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

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A Research Report from the National Center for Sustainable Transportation

Giovanni Circella, University of California, Davis
Xiatian Iogansen, University of California, Davis
Keita Makino, University of California, Davis
Junia Compostella, University of California, Davis
Mischa Young, Université de l'Ontario Français
Jai K. Malik, University of Michigan

National Center for Sustainable Transportation

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16. Abstract

This study investigates how the COVID-19 pandemic has transformed people's activity-travel patterns, using datasets collected through three waves of surveys in spring 2020, fall 2020, and summer 2021. With this dataset, it was possible to investigate evolving behavioral choices and preferences among respondents at different timepoints: fall 2019 (recollection of the past), spring 2020, fall 2020, summer 2021, and summer 2022 (future expectations). The study highlighted a large shift among California workers from physical commuting to working remotely in 2020, which was followed by a transition towards hybrid work by summer 2021. The shift to remote work and hybrid work varied considerably across population subgroups, and was most popular among higher-income, better-educated individuals, and urban residents. In terms of household vehicle ownership change, those tech-savvy and variety-seeking individuals were more likely to increase or replace household vehicles, while those who are pro-environment and pro-active are less likely to do so. COVID health concerns show concurrent effects of encouraging the adoption of a more pro-active lifestyle during the pandemic, but also leading to an increased desire to own vehicles in the future. Regarding shopping patterns, the number of respondents who shop online at least once per week increased nearly five-fold between fall 2019 and spring 2020, but such magnitude somewhat diminished by fall 2020. In general, the pandemic has generated a mix of short-lived temporary changes and potential longer-term impacts. The study provides various strategies to help increase transportation and social equity among various population groups as the communities recover from the pandemic.

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Disclaimer

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

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

Junia Compostella, PhD, Institute of Transportation Studies, University of California Davis

Mischa Young, PhD, Department of Urban Environments, Université de l'Ontario Français

Jai K. Malik, PhD, U-M LSA Center for the Study of Complex Systems, University of Michigan

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EXECUTIVE SUMMARY

The COVID-19 pandemic has disrupted travel behavior and the daily activities of communities across the world. Rather quickly after the emergence of the COVID-19 virus in early 2020, travel for all transportation modes fell dramatically. Car travel, public transportation, air travel, and commuting trips saw significant reductions, though travel by private vehicles in the United States started to recover more quickly than other modes with the reopening of activities. As the country emerges from the effects of the pandemic, there is evidence that some changes induced by the pandemic had short-term nature (and they could be largely reversible), while other changes might have long-term impacts on society, the economy, and mobility.

To better understand the impacts of the pandemic on transportation and society, three rounds of data collections were completed in California from May to August 2020 (we term it as "Spring 2020 Survey" in the remainder of the report), December 2020 to January 2021 ("Fall 2020 Survey") and later in August to October 2021 ("Summer 2021 Survey"). Specifically, the aim was to investigate the changes in employment, commuting and remote working status, vehicle ownerships, travel and shopping patterns in the state during these phases of the pandemic.

To the extent possible, the data collections attempted to recruit samples of respondents that mirror the characteristics of the residents in the state. To increase the representative nature of the sample and reduce sampling biases, respondents were recruited through multiple invitation channels. These included commercially available online opinion panels, as well as survey invitations shared on social media platforms and through email chains. During the fall 2020 and summer 2021 data collection, the survey was made available in both English and Spanish. During the third wave of data collection, in summer 2021, in addition to the previous recruitment channels used in spring 2020 and fall 2020, the research team also mailed printed invitations to complete the survey to the home addresses of a stratified random sample of households in California. Further, in the third wave of data collection, the best effort possible was made to oversample respondents from Hispanic and low-income communities in the state to counterbalance the low-response rate that is usually observed among these groups. Printed copies of the full questionnaires were also mailed to a smaller number of selected households, and printed copies of the questionnaires in Spanish language were mailed to households that live in census tracts were the predominant language spoken at home is Spanish. As such, the study was able to derive large repeated cross-sectional datasets (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) with a smaller longitudinal sample of 1092 respondents who completed at least two waves of those three surveys and 625 respondents who completed all three surveys.

All three surveys collected rich information from respondents on their sociodemographic characteristics, attitudes towards various topics, employment and work/student activities, shopping patterns, travel choices, vehicle ownership, the use of technology and emerging transportation options, and so forth. To better investigate the changes during the pandemic, some survey questions addressed topics in a time period close to when the surveys were administered, in the past before the pandemic (i.e., retrospective recall), and in the future (i.e., expectation). Based on this information, it was possible to investigate evolving behavioral choices and preferences among respondents at different timepoints: fall 2019 (recollection of the past), spring 2020, fall 2020, summer 2021, and summer 2022 (future expectations). After the completion of the data collection, various data processing tasks, including data cleaning, recoding and imputing missing values for key variables, data weighting to reduce the departure from the distribution of sociodemographic characteristics of the population of California, and geocoding participants' current home and work locations were conducted. The dataset was also enriched with built environment variables characterizing the home locations of the survey respondents from external datasets, such as Smart Location Database (SLD) maintained by the United States Environmental Protection Agency (US EPA).

Using these datasets, the research team conducted five quantitative studies to answer the following research questions:

- How have commuting and remote working status, activity patterns, vehicle ownership, shopping behaviors changed during the COVID-19 pandemic?
- What factors impact those changes and how those impacts differ temporally, geographically and socio-demographically, in regard to the topics listed above?
- What are the implications of those changes for travel behavior in the state?
- What policies could make the state-wide transportation system more sustainable and equitable during the recovery from the pandemic?

Among California workers, the study highlighted a large shift from physical commuting to remote working (exclusively) in 2020, which was followed by a transition towards hybrid working schedules by summer 2021. The proportion of workers who exclusively or mainly remote work increased significantly, from 4.1% of all respondents in fall 2019 to a high of 25.7% in fall 2020, before dropping in summer 2021 to 21.6% (with the expectation of a further reduction, to 9.7%, by summer 2022). On the contrary, hybrid workers (who combine physical commute and remote work) continuously increased from 14.5% of all respondents in fall 2019 to 21.7% in fall 2020, to 27.1% in summer 2021, and were expected for a further increase to 36.6% by summer 2022. Not surprisingly, the shift to remote work and hybrid work varied considerably across population subgroups. Lower-income, less-educated individuals, and rural residents reported substantially lower adoption of remote work at any time. By summer 2021, only 17.2% of individuals living in households with an annual income of less than $50,000 (referred as "low-income individuals" in the remainder of the report) were remote workers, whereas 26.4% of individuals living in households with an annual income of $100,000 or more (referred as "high-income individuals" henceforth) were remote workers. Similarly, 17.0% of less-educated individuals were remote workers (vs. 24.9% of more-educated individuals), and

15.8% of rural residents (vs. 22.1% of urban residents) were remote workers. Similar differences were observed for the adoption of hybrid forms of work. Different factors have been found to impact one's adoption of hybrid and remote work at different timepoints, before the pandemic, in 2021, and 2022 (expectation). Also, respondents from different survey recruitment channels (e.g., online opinion panel vs. mail-based survey) show different propensity towards adopting hybrid and remote work. This is something that needs to be considered and could be assessed as part of this study, but that has been largely ignored in other studies on the impacts of the COVID-19 pandemic on transportation, to date.

In terms of household vehicle ownership, the analysis of a longitudinal sample from of U.S. respondents the fall 2020 and summer 2021 datasets indicated an upward trend in vehicle ownership among respondents. Please note that this portion of the analysis was carried out also including respondents from outside of California, to obtain a larger sample of respondents who had completed both surveys. Approximately 7.9%, 5.1% and 19.2% of them reported to have increased, decreased or replaced their vehicles, respectively, from before the pandemic to summer 2021, and 8.4%, 3.8% and 21.4% of them expected to increase, decrease or replace their vehicles, respectively, from summer 2021 to summer 2022. We identify significant effects of latent attitudes, sociodemographic characteristics, life-events and COVID health concerns on vehicle ownership changes. Specifically, tech-savvy and variety-seeking individuals were more likely to increase or replace household vehicles, while those who are pro-environment and pro-active are less likely to do so. Increases in education attainment and household income were associated with a higher propensity to acquire a vehicle, while decreases in household size led to a reduction in vehicle ownership. Households with multiple family members showed greater volatility in their vehicle ownership, likely to meet more dynamic travel needs. Additionally, individuals transitioning to become students or workers tended to adopt more vehicles. COVID health concerns have led to an increased desire to own vehicles for some, but have also encouraged the adoption of a more pro-active lifestyle for others. The findings from this study and their associated policy implications can be valuable for policymakers and other stakeholders that are endeavoring to understand car ownership and use in the post-pandemic era.

Regarding shopping patterns, the number of respondents (among a longitudinal U.S. sample from spring 2020 and fall 2020 datasets) who shop online at least once per week increased nearly five-fold between fall 2019 (11.6%) and spring 2020 (51.2%). However, the proportion of respondents that shop online at least once a week diminishes to 25.1% in the fall 2020 period, which remains considerably higher than in fall 2019, but also indicates that the initially reported growth in e-shopping may have been short-lived. This result further suggests that the longer-term impacts of the COVID-19 pandemic on e-shopping may have been more modest than reported in earlier studies, which relied solely on data pertaining from the initial months of the pandemic. Higher levels of income and education continue to be positively associated with online shopping frequency. The recent rise in e-shopping induced by the COVID-19 pandemic was largely caused by an increase in units purchased by experienced online shoppers.

More specific to grocery shopping patterns, the analysis of the California sample from spring 2020 dataset highlighted an increase in online purchases during the early stages of the pandemic among people who have a consumerist nature, while a decrease among those who tend to be more financially conservative and/or were financially struggle during the pandemic. People tended to buy more items per purchase (in bulk) either at the store or online, while they physically visited stores less often than before the pandemic. Those who used to dine out frequently have increased grocery shopping in general, confirming the transition from dining out to preparing food at home during the first stage of the pandemic. Those who enjoy driving (a latent construct derived from a series of attitudinal survey questions) and those who like to be physically active kept traveling to the store at higher rates than others. Frequent use of social media was positively associated with a decrease in physical visits to the grocery store and an increase in online grocery shopping. Health concerns affected the way people shopped for groceries during the pandemic. Not surprisingly, some socio-demographics, such as household income and race were also found to have significant impacts on these changes in shopping patterns.

Overall, the analysis of the data collected in this study reveals the impacts that the pandemic has had on transportation among various segments of the population in the state, and the changes that emerged from the peak of the pandemic through the following phases. The analysis also helps inform policy recommendations that address key challenges brought by the pandemic -- for example, on both equity and environmental impacts of transportation. The massive transition to remote work and hybrid work during the pandemic highlighted huge differences in accessing forms of remote work across various types of workers and sociodemographic groups. It also highlighted the critical nature of access to reliable and affordable high-speed internet service ("broadband"). Tracking broadband coverage accurately in the state and expanding broadband access in unserved areas remains a critical task to allow forms of remote work also among groups that do not currently have the ability to work remotely due to limitations in their access to the internet. Members of disadvantaged population groups with certain occupation types (such as retail and blue-collar jobs), however, could not shift to remote work and hybrid forms of work. As a result, these workers have had higher rates of potential exposure to COVID-19.

Due to changes of commuting patterns during the pandemic, there is an opportunity for transportation agencies to reduce the emphasis on peak-hour planning, engineering, and investment decisions, but take advantage of additional roadway capacity across the day to reduce the need for roadway capacity expansion. Public transit agencies could consider redistributing services and resources to achieve a better balance between peak and non-peak times, as well as between regional and local services. This approach might be more cost-effective for transit agencies since it reduces the need for splitting employee shifts while encourages more bi-directional ridership (as opposed to trains/buses being packed in one direction but empty in the other). However, it might prove challenging as transit systems in the US are typically designed to serve commuting trips and tend to struggle to attract non-work related trips.

We see household vehicle ownership became more extreme, with an increased proportion of individuals from zero-vehicle households as well as households with three or more vehicles. Those who transitioned from car-owners to non-car-owners during the pandemic may need to rely on mass transit in a time when they are concerned about contracting the virus while public transit does not provide as frequent and reliable services as before, due to health concerns, driver shortages, financial uncertainty and other factors. More travel alternatives need be provided to this group of workers to increase mobility and accessibility. At the same time, we need policies to prevent society from becoming overly car-dependent, especially for those with multiple cars in the household. Increasing support for the use of public transit, active modes, and other shared mobility options, as the risk of severe COVID symptoms decrease with vaccines and previous exposure, could be considered as a way to reduce the use of private vehicles.

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, all of which are emerging areas for decision making and policy development. Physical retailers, including those operating in the grocery businesses investigated in this study, also need to investigate shoppers' evolving shopping behavior and demand volatility.

With the increased remote work and online shopping, and the persistence of high cost of living in Californian cities, many cities may continue to experience a population exodus as individuals begin to find that the advantages of living in remote areas outweigh its disadvantages. As the decision to relocate during the pandemic might have been a temporary change for many individuals, policymakers will need to develop strategies to combat this technology-induced urban sprawl. One potential solution to make cities more attractive is to convert vacant office space in the center city into housing or encourage its replacement with housing, and deploy efforts to retain nearby stores and amenities, by providing tax incentives or rent subsidies. At the same time, policymakers can consider implementing policies to incorporate smaller outlying communities with multi-use town centers and user-friendly transit options, while diminishing the appeal of lower-density and more distant housing locations which leads to more car-dependent lifestyles.

Finally, as the pandemic has continued to evolve, and its effects mix with additional changes happening in society—including the increased cost of living and high gas prices—it will be important to continue to study the evolving transportation patterns in the state. For instance, a great proportion of residents (36.6%) in the 2021 data collection expected to engage in hybrid work by summer 2022. It will be essential to learn if their preferences align with employers' remote working policies, and how further modifications in activity patterns, and the impacts of the high cost of driving and modifications in other transportation options, will impact future travel patterns. We also need to investigate individuals' longer-term decisions, such as home relocation, which can modify individuals' activity-travel patterns. Suburbanization and the continuing reliance on private vehicles may shift many of the societal costs of such behaviors to the most disadvantaged and vulnerable population groups, unless proper policies are enacted.

1 Introduction

The COVID-19 pandemic and related countermeasures such as stay-at-home orders, curfews, and capacity restrictions have significantly disrupted the daily activities and travel routines of most individuals around the world (Liu, Miller, & Scheff, 2020; Wilder-Smith & Freedman, 2020). In April 2020, during the first peak of the pandemic, daily average number of people in the U.S. staying home increased by nearly half (+46%) compared to the 2019 baseline (Bureau of Transportation Statistics, 2022). A vast number of students and workers had to transition to primarily remote learning and remote working within a short period of time. The advent of the pandemic also accelerated the adoption of online shopping and food delivery. As a result, the nationwide passenger vehicles miles traveled (VMT) in the U.S. during the same time period were as low as 40% of the value expected had there been no pandemic (Bureau of Transportation Statistics, 2020). While the VMT bounced back gradually after that, it was still below the baseline most of the time during the rest of 2020 and early 2021. However, the VMT trend started to grow beyond the baseline since March 2021. Especially as new COVID vaccines were introduced and transportation carriers such as airlines prioritized rigid sanitizing procedures to reduce exposure risk, both long-distance travel by air and daily passenger vehicle travel rebounded and thus VMT started to surge. In the meanwhile, however, the pandemic pushed transit ridership to historic lows, with a much slower recovery compared to car travel by 2022. By mid-August 2022, the nationwide monthly transit ridership was still 36% below the baseline and it had great variations across different transit modes serving in different geographic locations (Bureau of Transportation Statistics, 2022).

Public transit agencies, planning companies, mobility-service providers and private businesses have been eager to understand the ways the pandemic has affected individuals' activity patterns and travel behaviors and predict possible short- and long-term travel demand as the pandemic progresses (Irawan, Rizki, Joewono, and Belgiawan, 2020). A review of the literature on related topics is provided in Section 2 of this report. The longer-term implications of such drastic changes for the transportation sector, and more broadly for society, however, still remain largely unknown. For instance, transportation professionals are concerned that the reduced demand for public transit and other shared modes of travel, and the increases in remote work during the pandemic, may lead to further suburbanization and car-oriented lifestyles (Habib et al., 2021). In the meantime, cities have repurposed some existing infrastructure to better promote walking and cycling, which enables travelers to better practice social distancing (Marsden, 2020). To support positive changes in travel behaviors and inform transportation policy and infrastructure management, it is critical to understand individuals' behavioral changes during the pandemic. Moreover, understanding whether these changes are temporary or more enduring is of paramount importance.

Gaining a better understanding of the implications of the pandemic on activity and travel patterns is especially important for Caltrans, which, among other things, is committed to reducing traffic congestion on its roadway network, improving efficiency in transportation, reducing system-level VMT and greenhouse gas (GHG) emissions, and improving access to opportunities, especially for low-income communities and communities of color. To support these goals, three large survey-based data collections were launched in the California state from May to August 2020 (with a sample size of 3813), December 2020 to January 2021 (with a sample size of 5521), and from August to October 2021 (with a sample size of 6400), as a part of a larger COVID mobility study. These three surveys form a large repeated cross-sectional sample, with a smaller longitudinal sample of 1092 respondents who completed at least two waves of those surveys and 625 respondents who completed all three surveys. All surveys collected a range of self-reported information, including activity patterns and travel choices during and before the pandemic, the use of technology, shopping patterns, use of various travel modes, vehicle ownership, and individual and household socio-demographic characteristics, as well as each respondent's level of agreement with a series of statements designed to measure latent attitudinal constructs on topics including environmental issues, preferences for home location, concerns regarding the pandemic, and so forth. Detailed explanations on the survey, data collection and data processing are provided in Section 3 and Section 4 of the report.

The main component of this report (Section 5 to Section 7) includes five studies with the goals (1) to better understand individuals' behavioral changes during the pandemic and potential persistence of some of these patterns after the pandemic; (2) to identify mobility barriers and service gaps; and (3) to inform policy recommendations to improve equity, environmental sustainability, and efficiency of the regional transportation system in a post-pandemic future.

The following are more specific objectives of these studies:

- To understand how physical commute and remote work patterns changed during the pandemic, including the extent to which remote work induced by the COVID-19 pandemic may persist into the future;
- To understand changes in vehicle ownership during the pandemic;
- To understand changes in physical/online shopping patterns;
- To further investigate the variation in these patterns across different timepoints and various demographic groups (e.g., by income category);
- To inform policies that are tailored for different population segments in the state.

We analyze those topics primarily among Californian residents, but there are some cases when we analyze the nationwide trends with the majority of respondents coming from California, but also including respondents from other states, to allow for larger sample sizes. As we keep track on those topics in different timepoints of the pandemic, they all use lightly different datasets. As such, we provided detailed explanations on the motivation, background, data, method and findings of each of those five studies. Section 8 will then provide a discussion on the implications of those studies. We conclude this report with policy recommendations, limitations and future works in Section 9.

Overall, some findings from these studies confirm commonly accepted trends that are consistent with empirical observations in the state regarding changes in activity and travel patterns. However, these studies provide more rigorous quantitative analyses into the reasons behind these observations and the differences across groups. Still, there were some limitations that affected the study, including the survey contents, data collection method, and analyses. First, the data was collected through self-reported surveys. These may be subject to recall and response biases and are subject to certain limitations (and measurement errors), especially in measuring activity schedules and travel patterns (as the surveys did not include a full travel diary). Second, the study is subject to the typical limitations affecting data collection of this size, including potential sampling biases (e.g., self-selection of respondents that decide to participate in the study), which might limit the ability to generalize the results to the entire population in the state and to use the data to analyze smaller sub-groups within the region. Third, differences in the methods of sampling and recruitment of participants during the three rounds of data collection in this project might make the three samples not perfectly comparable. Fourth, while great efforts were made (especially in the third round of data collection in summer 2021) to recruit traditionally harder-to-reach segments of the population, such as people of color and residents from rural areas, these targets were not fully achieved due to low response rates, especially among these groups. As a result, those studies feature relatively small sample sizes from these demographics. Finally, while repeated cross-sectional analysis enables a larger sample size, it attempts to compare behavioral patterns of essentially two different samples at different points in time and the internal validity of the analysis may be limited. In contrast, although the longitudinal dataset by construction has strong internal validity, the small sample size and the potential impact of self-selection might limit the generalizability (and external validity) of the results from the analysis of that subsample. Readers are cautioned to interpret the findings from this study considering these limitations.

2 Literature Review

On March 13, 2020, the U.S. declared a national emergency for the COVID-19 pandemic. Many state governments developed health safety measures to combat the spread of COVID-19. A variety of response strategies and measures emerged that ranged dramatically in duration and severity. The pandemic and these response measures prompted a lifestyle transition for many Americans who sought to comply with public health guidelines. These response strategies and measures had strong impacts on personal health, work activities, economic activities, daily routines, and travel behavior, as well as longer-term household decisions such as residential relocation and vehicle ownership change. Average travel distances began to fall as travel concentrated in a small radius around households. The following reviews the existing papers, reports and online blogs on the impacts of the pandemic on various aspects of life and society.

2.1 Commuting and Remote Working Behavior

One of the most visible responses to the pandemic was a dramatic substitution of virtual activities for physical travel (e.g., substantial decreases in commuting and wide adoption of remote work in the American workforce) (Abdullah et al., 2020; Beck & Hensher, 2020). A Chicago study reported a 33% increase in remote work for April-June 2020 compared to before the pandemic (Shamshiripour et al., 2020). Guyot and Sawhill (2020) suggest that by April 2020, about half of the employed adults in the country were working from home. This proportion has steadily decreased as many people have returned to in-person work, though the long-term impacts are yet to be fully understood. According to Brenan (2020), among those who have worked remotely during the pandemic, approximately 35% simply preferred to do so, 30% wanted to do so primarily out of concern about COVID-19, and the remaining 35% would prefer to return to in-person work.

How does remote work impact travel demand? Studies prior to the pandemic have claimed both decreases (Koenig, Henderson, and Mokhtarian 1996; Ory and Mokhtarian 2006) and increases (Ravalet and Rérat 2019) in individual travel due to remote work. A recent Chicago based study, (Shabanpour et al. 2018), which incorporated a surge in the engagement in non-work activities due to flexible work schedules, found that an increase in flexible work time hours from the baseline of 12% to 50% could result in up to 2% reduction in system-level VMT, resulting in about 0.71% and 1.14% reduction in GHG emissions and particulate matter emissions, respectively. Studies are needed to confirm whether those effects of remote work exist during the pandemic and whether they will last after the pandemic.

2.2 Trip Generation and Mode Use

Gao et al. (2020) showed that just after the declaration of the pandemic, most states saw a massive reduction in daily mobility. In general, people began giving pandemic-related factors a greater priority in their travel decisions (Abdullah et al. 2020). For the duration of the pandemic, activities became increasingly centered around the household. This led to a variety of new preferences in trip patterns, destination choices, and means of transportation. Individuals' spontaneous behavioral changes are more likely to be determined by their own “perceived” risk of infection (Poletti and Ajelli, 2009), which can be significantly affected by the timing and the course of a pandemic (Funk et al. 2010).

For long-distance travel, Fatmi (2020) reported that in the early stages of the pandemic, a large proportion of long-distance travel was done by private vehicle. Air travel saw a dramatic drop in passenger thoroughfare as demand for domestic and international flights plummeted. This, combined with travel restrictions, led to the largest drop in passenger traffic on record in the United States (Bureau of Transportation Statistics, 2020). However, impacts varied across different commercial airports. Larger airports saw a greater reduction in departure operations and passenger traffic. With the widespread availability of vaccines, air travel began to rebound, and many Americans engaged in “binge” travel behavior after over a year of significant restrictions. Interestingly, Bui and Kliff (2021) report that, as of the spring of 2021, airports in major cities were still struggling, but some smaller airports connected with vacation destinations were even busier than before the pandemic.

In terms of daily travel, studies have examined the changes in the number of trips to various destinations like residences, workplaces, and retail. The trends show modest changes in mobility, but notable reductions in time spent away from residences (Wellenius et al., 2020; Luther, 2020). While there was a significant decline in mobility from March to April 2020, there were only negligible declines from June to September 2020 (Kim & Kwan, 2021). Observed decreases in trip rates were accompanied by shifts in mode choice from public transportation to more socially distant travel modes such as private vehicles, walking, and bicycling. Some cities, such as New York, saw drops in personal vehicle trips as high as 58% (Wang et al., 2020), though private vehicle use rebounded quickly as many began to view car travel as the safest option for daily travel needs. A Swiss study presented initial reductions in distance traveled 2 weeks before the official lockdown, followed by substantial increases in travel by bike and a return to baseline levels by car 4 months after the initial lockdown (Molloy et al., 2020).

Shared mobility, in particular, was deeply impacted by the COVID-19 pandemic. Ridehailing and taxis experienced a huge drop in demand, especially in the early phase of the pandemic. In addition, pooled ridehailing services (e.g., UberPool and Lyft Line) were suspended in most markets due to concerns over virus contraction across passengers. Matson et al. (2022) found that from 2019 to Spring 2020, ridehailing use among their survey respondents fell from 18.7% to 7%. Uber reported that by August 2020, demand for their ridehailing services had fallen by 73% when compared with the previous year (Kolodny, 2020). Carsharing initially saw large declines in use, but after the initial months, many companies such as Zipcar reported a significant growth in demand as stay-at-home orders began to be lifted.

Shared bike and e-scooter services, however, were impacted differently across regions. Some saw massive declines in use if not outright pandemic-related bans from city governments. In New York City, Teixeira and Lopes (2020) observed a 71% decrease in the use of the city’s bikesharing service. With this, they also observed growth in average trip duration, leading to some speculation that a modal transfer occurred from public transportation to bikesharing. Other bike and e-scooter share services gained in popularity for recreational and leisure purposes (Bliss et al., 2020), as well as for work purposes mainly for essential workers (Glusac, 2021; Schrimmer, 2021).

There was a widespread phenomenon of Americans biking using personal bikes, walking, and jogging far more frequently during the pandemic. In a year-over-year comparison, a study using bicycle count data from Eco-Counter found increases in bicycling rates between 5%-20% in major European countries and selected regions in the U.S. and Canada with most of the increases occurring on weekends (Buehler & Pucher, 2021). Trips to public parks increased substantially with the onset of the pandemic (Volenec et al., 2021). To meet this growing demand for human-scaled travel, several U.S. cities began reclaiming space for pedestrians along their streets, in what Nurse and Dunning (2020) describe as the "taking back" of road space.

2.3 Vehicle Miles Traveled, Congestion and Emissions

The impacts of travel behavior change on VMT, congestion, and GHG emissions varied with mode shift and period of the pandemic. From early March 2020 to the end of April 2020, nationwide VMT fell by an average of 39% (Lindquist and Jiao, 2020). With less driving, cities began to see declines in air pollution. Across the United States, Brodeur et al. (2021) observed a 25% reduction of $PM_{2.5}$. They also observed that counties with younger populations and a greater share of remote-work capable jobs saw a greater reduction in air pollution. However, early reductions in VMT during the pandemic have largely been reversed, with VMT reaching historically high levels during the past year.

As vehicle trip duration and frequency fell across the U.S., many states saw a significant reduction in average traffic collisions as well. Using data from Alabama, Connecticut, Kentucky, Missouri, and Vermont, Brodeur et al. (2021) observed a 50% reduction in vehicle collisions immediately after the declaration of a national emergency. Personal vehicles began to be increasingly used for long-distance travel as many Americans avoided air travel.

The COVID-19 pandemic has radically changed the lifestyles of nearly all Americans, as people have had to learn new ways to work, shop, travel, interact with others, and entertain themselves.

2.4 Shopping Behaviors

While the ability to purchase goods and services online has existed for over two decades, it has recently become more popular with the advent of the COVID-19 pandemic, due to its perceived safety with low infection risk and easy home delivery. Whereas it took the U.S. e-commerce sector five years (2013-2018) to increase from $263.3 billion to $513.6 billion, it only took the sector an additional two years to increase by a same margin, reaching $791.7 billion in 2020 (U.S. Department of Commerce, 2013, 2019, 2021).

Abdullah et al. (2020) observed that in the absence of work and study-related trips, shopping became the primary purpose for traveling during the early stages of the pandemic. Some studies suggest that food purchasing was the most frequently mentioned reason for going out during the pandemic (Rieger, 2020). Although research showed that some people still preferred in-store shopping even during the pandemic (Soper and Boyle, 2020), there was a major transition to online shopping (Shamshiripour et al., 2020). Grashuis et al. (2020) reported that the market shares of online shopping grew from 3%–4% to 10%–15% and he found that when the virus spread at an increasing rate, consumers were less likely to do in-person grocery shopping. A survey using data based on more than 2000 Americans found that approximately 25% of respondents shopped online more frequently since the beginning of the pandemic (Ecola et al., 2020). Although it is unclear what long-term impacts the pandemic will have on people's habits, some customers may become accustomed to e-shopping and reduce in-store shopping in the future (De Vos, 2020).

Previous literature shows that many factors influence individuals' online shopping behaviors In terms of sociodemographic characteristics, education and income are both shown to be positively associated with the frequency of online shopping (Etminani-Ghasrodashti & Hamidi, 2020; Lee et al., 2015; Matson et al, 2022). Most studies further find age to be a primary determinant of online shopping likelihood and have put forth several arguments to support older consumers reluctance to shop online, which include the presence of a digital divide as well as older consumers' reported preference for trying out products in-person before purchasing them (Hernández et al., 2011; Lee et al., 2015; Trocchia & Janda, 2000; Zhang, 2009; Matson et al, 2022). The effect of gender appears to be more convoluted, if at all present, as several earlier studies find men to be the primary users of e-commerce (Farag et al., 2007), but more recent research suggesting a reversal of this trend (Jaller & Pahwa, 2020; Sener & Reeder, 2012) or reporting no gender effect at all (Lee et al., 2015; Song, 2021).

Findings from the literature also show conflicting results in terms of the built environment's impact on online shopping behaviors. Both low access to in-person shopping and limited access to brick-and-mortar stores are associated with a higher adoption of e-commerce (Ren & Kwan, 2009; Zhiqun et al., 2009), but living in large urban areas is also shown to increase one's likelihood to shop online (Cao et al., 2013; Farag et al., 2007; Jaller & Pahwa, 2020; Matson et al, 2022). This apparent discrepancy explains Zhen et al. (2018) is likely due to residents of urbanized areas generally having faster internet access, which facilitates the online shopping process and may lead to a high rate of e-purchases, despite them living in proximity to stores. Cities often also house better educated and more affluent people, which are found to be more likely to be early adopters of new technologies (Boschma & Weltevreden, 2008).

The decision to shop online also depends on consumers' attitudes and personal preferences. Those who perceive purchasing goods online as relaxing (Swinyard, 2003) or more efficient (Li et al., 1999), especially in comparison to in-person shopping, are more likely to partake in this behavior. In contrast, those who enjoy shopping or categorize themselves as impulsive buyers are more likely to shop in person (Cao et al., 2010). One's trust, familiarity, and attitude towards technology also influence this decision. For instance, Lee et al. (2017) find that individuals who have a positive attitude towards technology are also more likely to shop online. Lastly, past experiences also influence one's likelihood to purchase goods online; a positive past e-shopping experience will increase the chances of partaking in this behavior again (Dijst et al., 2008; Farag et al., 2007)

3 Data Collection

The research team has collected three waves of survey data for the COVID-19 Mobility Study, aiming to research on the temporary, but also longer-term impacts of the pandemic in various aspects. Built on existing research projects that were administered by the research team before the pandemic, three waves of survey-based data collection were carried out in Spring 2020, Fall 2020 and Summer 2021, targeting data collection in 15 regions of the US and two regions in Canada. As Figure 3-1 depicts, we attempt to build repeated cross-sectional surveys by re-contacting respondents in previous survey waves.

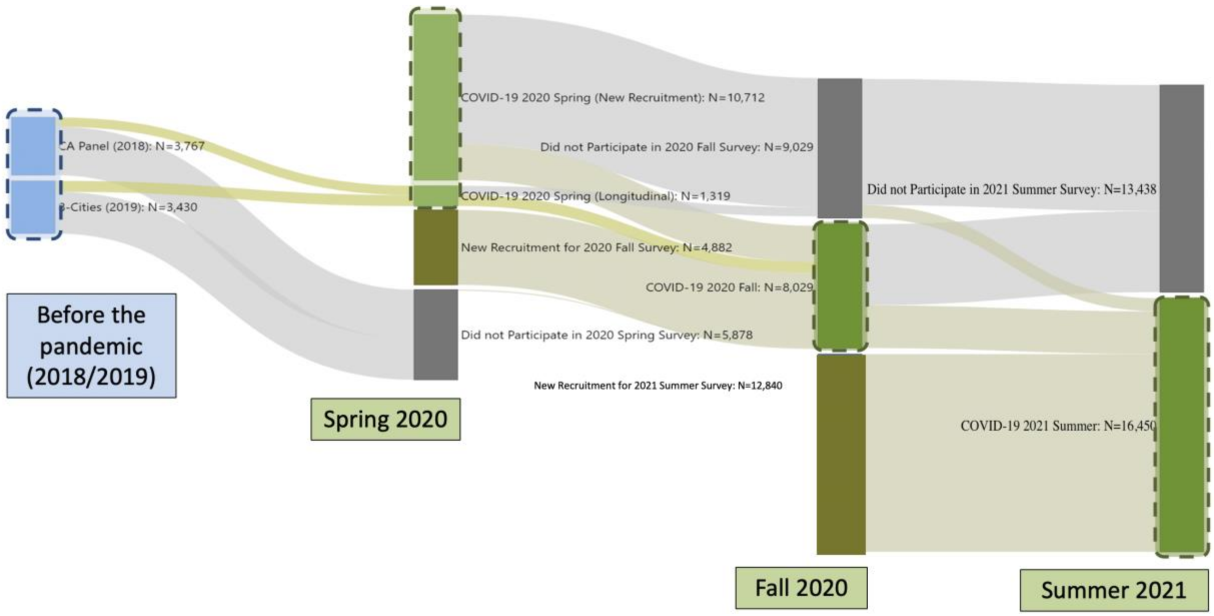


Figure 3-1. Repeated cross-sectional survey data collection

The team used multi-channel sampling and recruitment methods to generate robust samples. Table 3-1 summarizes the sampling and recruitment methods used for the administration of the surveys in spring 2020, fall 2020 and summer 2021, as well as other details on the data collection within California state. The data collection process was similar among these three surveys with mostly consistent structure and set of questions, but latter waves of data collection incorporated important lessons learned during the former waves of data collection. As part of the bigger data collection effort in the California state and in the US, the Southern California Association of Governments (SCAG) partnered with our research team to launch dedicated data collections targeting residents in Southern California in fall 2020 and summer 2021. This initiative aimed to assess the modified travel behavior and resulting impacts of the pandemic on equity and the environment at SCAG region, in support of their specific policy goals. The SCAG region encompasses six counties (Imperial, Los Angeles, Orange, Riverside, San Bernardino and Ventura). As a result, the samples for those years tend to be skewed toward SCAG residents. However, we introduce weights to increase the representativeness of our sample in each dataset and mirror the socio-demographic characteristics of California residents.

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

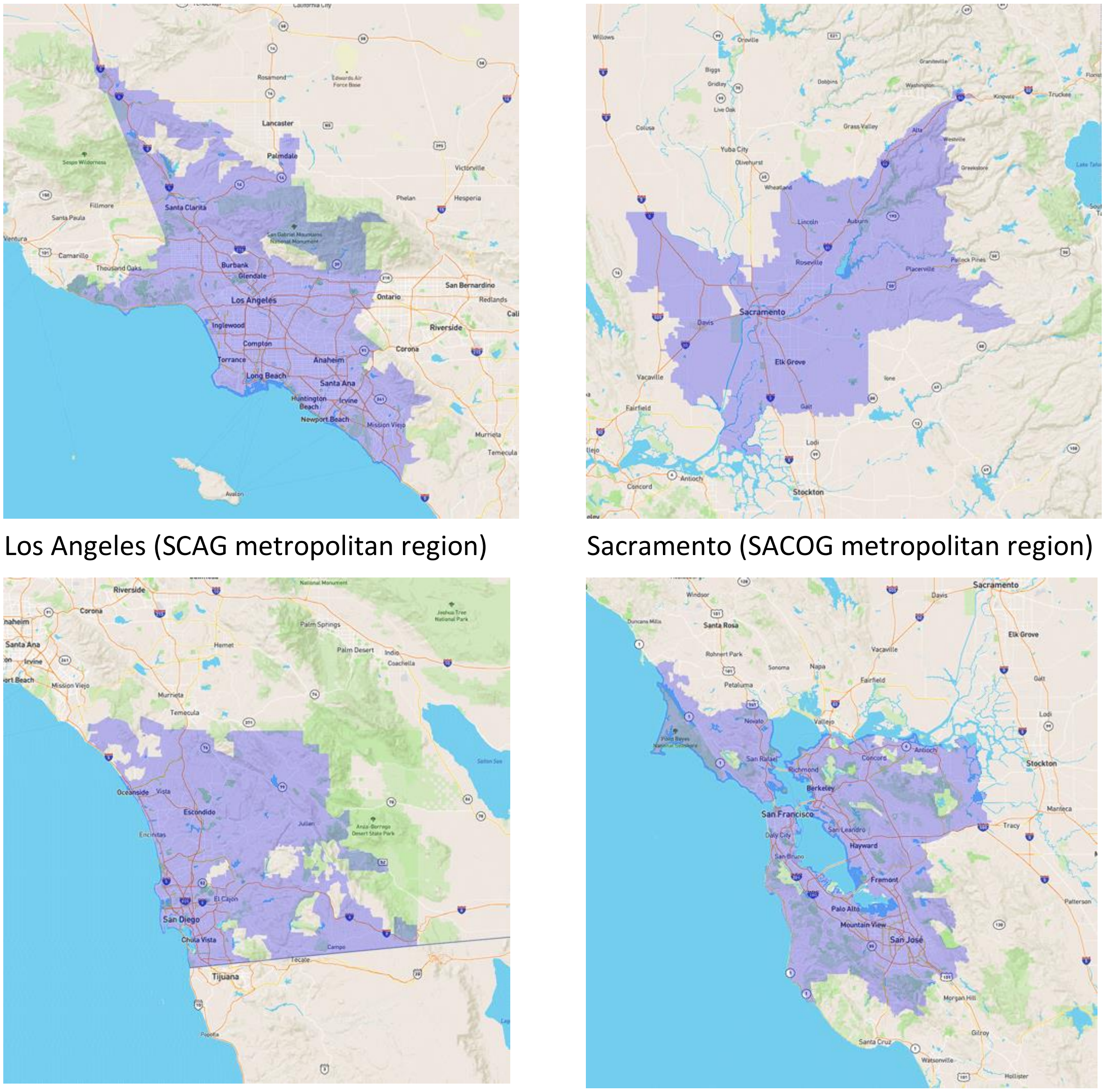
		Spring 2020 Survey	Fall 2020 Survey	Summer 2021 Survey
Sampling Methods		Recall of previous survey participants + online opinion panel + convenience sample	Recall of previous survey participants + online opinion panel + convenience sample	Recall of previous survey participants + online opinion panel + 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 within California	**SCAG region**	943 (24.7%)	4568 (82.7%)	3142 (50.9%)
	Non-SCAG region	2870 (75.3%)	953 (17.3%)	3258(49.1%)
	Total	3813(100%)	5521(100%)	6400 (100%)
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

For all three rounds of data collection, we used mixed sampling methods, including: (1) new recruitment of participants through a commercial online opinion panel; (2) recontacting previous respondents from other surveys administered by the research team in the state (i.e., use of a longitudinal panel); and (3) 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 (4) stratified random sample of local residents through mailing of printed invitations to complete the online survey, sent to the mailing addresses of randomly selected households in the state. In addition, we also 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 certain segments of the population (e.g., tech-savvy internet users, and individuals who 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. Instead, the recruitment through stratified random sampling of respondents using a paper survey questionnaire can reach other segments of the population that are missing from the previous channel, it relies on probabilistic sampling and eliminates many of the sampling biases that affect the previous channel, but is much more resource-intensive, in terms of the resources required to prepare, print and mail out the survey, the time required to collect the responses, and the need to input the data from the printed questionnaires to a digital.

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 the summer 2021 data collection. Respondents from this channel completed the survey either via the online platform or returning the printed questionnaires by mail. Follow-up postcards were sent in 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. Following sections provide more details on each of sampling and recruitment method.

3.1 Online Opinion Panel Survey Dataset

For the online opinion panel recruitment, we implemented a quota sampling approach, which sets up quotas for sociodemographic groups in the sample based on their distribution in the population based on the American Community Survey (ACS) 2019 1-year data. In spring 2020, the geographic quotas were estimated based on the distribution of the respondents in four metropolitan regions as shown in Figure 3-2, including SCAG region and non-SCAG California region that contains the San Diego Association of Governments (SANDAG), Sacramento Area Council of Governments (SACOG) and Metropolitan Transportation Commission (MTC).



Los Angeles (SCAG metropolitan region) Sacramento (SACOG metropolitan region)

San Diego (SANDAG metropolitan region) San Francisco (MTC metropolitan region)

Figure 3-2. Quota sampling of four metropolitan regions in spring 2020 data collection

In fall 2020 and summer 2021 data collection, we expanded the quota sampling approach to six regions of the entire state as Figure 3-3 suggested, with a main focus on SCAG region. Population targets by county, neighborhood type, age, gender, race and ethnicity, employment status, and annual household income from the ACS 2020 5-year data was used. For more information, please refer to another COVID project report that we prepared for SCAG (Circella et al., 2022).

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

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

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

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

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

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

Figure 3-3. Quota sampling of four metropolitan regions in fall 2020 and summer 2021 data collection

3.2 Longitudinal Survey Dataset

The second component of our three data collections was achieved through the longitudinal panel. This was built in continuation of a larger research project at UC Davis, which included data collections carried out for the 2018 California Mobility Study (Circella et al., 2019), the 2019 8-Cities Study, and COVID-19 Mobility Study since spring 2020. These studies provided a database of previous respondents within the state that agreed to be contacted again to participate in additional transportation-related studies. An email containing a unique survey link to each respondent in the email list was sent to those who lived within the state from an official study email address at UC Davis (mobilitystudy@ucdavis.edu). The message invited the previous respondents to participate in the COVID survey during all three rounds of data collection. An incentive of $10 was offered to all respondents for completing the survey. With this component, we were able to construct a dataset with the rotating panel structure to monitor the evolving behavior of same individuals.

3.3 Convenience Sample Survey Dataset

In addition, we used the convenience sampling method to recruit additional respondents, focusing, to the extent possible, on groups that tend to be underrepresented in the online opinion panel sampling frame. Various methods were used to distribute the survey, including online social media ads on Facebook and Instagram, social media posts, and invitations to complete the survey shared through professional email lists, listservs and newsletters managed by partner agencies in the state. Given the nature of the online-based convenience sampling being open to whoever received the link, efforts were to distribute the survey link only to California residents through methods such as geofencing the social media ads. Additional data quality checks were performed based on the respondents' self-reported home addresses to ensure they were indeed residents of California. To incentivize their participation, we offered each respondent the possibility to be included in a random drawing for a chance to win one of 10 $100 gift cards and 200 $10 gift cards for completing the survey.

3.4 Mail-based Survey Dataset

Finally, another component for the summer 2021 data collection was the use of mail-back printed questionnaires as well as a mailed invitation letter providing residents with the option to complete the online version of the questionnaire. We added this recruitment channel to improve the representativeness of the sample and in response to the difficulty of recruiting Hispanic residents in the previous round of data collection.

We drew a stratified random sample in the SCAG region and non-SCAG region, respectively, which were selected to receive a printed invitation by mail, containing an access code and the online link to complete the survey. Local households were selected to be invited in the study based on the census tract in which they live, with higher sampling rates for priority areas with high proportions of Hispanics and low-income households (which are traditionally difficult to reach in similar studies). The invitations were printed in both English and Spanish and mailed via the United States Postal Service (USPS) to the household home address, inviting the member of the household whose birthday was closer to the date they received the invitation to complete the survey. The letter informed the reader that they could complete the survey in their language of choice at the online link, or they could also request a printed copy of the questionnaire to be mailed to their home by calling a toll-free number that was activated for the study.

In addition, we drew a stratified random sample of local households in the SCAG region and non-SCAG region, respectively, using the same sampling method described above. These households received a printed copy of the questionnaire via the USPS with a prepaid return envelope to return the completed questionnaire. A list of census tracts with high proportions of Spanish-speaking households was identified. Residents from these census tracts received a copy of the printed questionnaire in Spanish, while residents in other census tracts in the region received a copy of the printed questionnaire in English. All invitation packages contained instructions to complete the survey, as an alternative, at the online link, if they preferred, or to contact the toll-free number for the study to request a printed copy of the questionnaire in the other language. The use of stratified random sampling to recruit respondents for this study resulted in a relatively low response rates, which is however not surprising. Considering the targeted effort that was made to recruit respondents among the members of Hispanic population and low-income groups, there were higher sampling rates in the census tracts with high proportions of households from these groups which are traditionally difficult to reach in this type of studies.

Though the data collection strategy was largely successful, it still had two major limitations in terms of geographic and demographic sampling. Despite the efforts to recruit survey respondents from all regions in the state, the number of respondents from rural counties remained below expectations, and small group sizes were obtained. Demographically, respondents in the Hispanic demographic group were underrepresented in the final sample for both rounds of data collection. Nevertheless, the study was able to improve upon these limitations in the summer 2021 data collection thanks to more targeted invitations, the use of stratified random sampling, and higher sampling rates in areas with high proportions of

Hispanics who were reached with printed invitations and printed questionnaires via mail to their home addresses and recruiting respondents via local organizations.

4 Data Handling and Processing

4.1 Data Cleaning

After completing each wave of data collection, the data was cleaned and filtered out incomplete and potentially invalid responses. This process was carried out in a similar way for the datasets collected in spring 2020, fall 2020 and summer 2021. Particular attention was paid to severely incomplete or inconsistent responses, mistakenly-input responses, responses with flatlining answers to matrix-type questions, and gibberish responses to open-ended questions. A series of data imputation and recoding tasks to convert the raw data into a format that could be more easily used for data analyses was performed. The below sections provide some examples.

4.1.1 Attitudinal Questions

To measure individual attitudes on various topics, we asked respondents to report their level of agreement with various attitudinal statements distributed in various sections of the survey, on a scale from "Strongly disagree" to "Strongly agree." For instance, the self-reported agreement with the statement "I like riding a bike" should reflect respondents' inclination toward bicycling and active modes. The layout for these types of questions were in a matrix format (i.e., each row corresponds to a statement and each column to a potential answer the respondent can select). These types of questions usually require a greater amount of time for respondents to answer than other questions do. It is common, in survey-based research, to observe how some survey respondents give a single answer to multiple questions or follow certain response patterns to run through the section (e.g., they answer that they "strongly disagree" to all the questions or repeat "strongly disagree" and "strongly agree" alternatively to a batch of attitudinal statements). This behavior becomes more common when respondents get tired or are subject to the fatigue of completing a particularly long questionnaire. The research team was particularly concerned that this behavior might be more commonly observed among respondents recruited through online opinion panels, who are often interested in completing surveys to obtain incentives for completing surveys, typically in the form of money, gift cards, or airline miles. Respondents recruited through online opinion panels might also include "professional" survey takers, or even bots programmed to answer surveys in an automated way.

To prevent, and detect, these behaviors, the survey was designed to try to minimize the survey fatigue, make the content as interesting to the respondents as possible, provide variety across sections (to break the monotony of the sequence of questions), and limit the total length of the questionnaire. Some statements ("trap questions") were added in the series of attitudinal statements which required a specific answer (e.g., "To confirm you're really reading this, please select 'Somewhat disagree' here."), to determine if the participants were paying attention to those questions and the content of the survey. The survey logic was designed so that those who responded incorrectly to the trap questions in very early sections of the survey exited the survey at the end of that section and would be prevented from completing the rest of the survey on the online platform. Respondents who answered the trap question at the end of the survey incorrectly were marked as potentially subject to survey fatigue and their responses to the questions in the late sections of the survey were potentially invalid. Respondents who gave the same response to all the matrix-type questions or failed the trap questions in the end of the survey were flagged for further investigation of the quality of their responses to the remaining questions in the survey. The responses of the flagged respondents were reviewed to determine whether the respondent was not taking the entire questionnaire seriously, got fatigued towards the end of the survey, did not understand some of the questions that were asked, etc. Based on this assessment, we determined when to completely remove certain responses from the dataset, report a section of their responses as invalid, or recode certain answers to some of the questions.

4.1.2 Household Composition

Respondents were asked survey questions about household composition, with instructions to consider the members of the households as those who live together and share financial resources. Respondents were asked to report the separate numbers of adults, children under 18, elderly people over 65, and the individuals with a valid driver's license. The validity of those responses was checked in several ways. For instance, the sum of children, adults, and elderly people in the household should match the reported household size. If these values did not match, the household size was recoded or assigned manually as deemed appropriate. Otherwise, cases with any gibberish inputs were flagged as they required extra attention during data analysis.

4.1.3 Job Category

In the survey, workers were asked to self-describe their job details. Since those responses were in open-ended text form, numerous cases needed recoding or re-classification. During this process, thirteen (13) broad occupation categories and 116 specific categories were created based on the classifications provided by the U.S. Bureau of Labor Statistics. For instance, "Website producer", "software manager", and "IT Software" were recoded into the "science, technology, engineering, and mathematics (STEM)" broad occupation category and "Software/Programming" as the specific category. Based on this re-classification, the job category became a much more useful variable used for quantitative analyses. Cases whose occupation could not be classified into a certain category of were also flagged as these cases could not be included in analyses requiring detailed information on occupation.

4.2 Geocoding and Integration with Built Environment Variables

In the survey, respondents self-reported their current home and regular work locations (i.e., the primary place where the person would eventually commute to work in person, if any, after any 'work-from-home' requirements were lifted for those working remotely during the pandemic), either through the street address or the 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) (Cooley, 2018) was used to convert the address into latitude and longitude. Using these geocodes, the census tract and block group IDs of the home locations of the respondents were appended using the ‘CensusAPI’ package in the R software (Recht, 2019).

With such geolocation information, additional built environment variables were then incorporated into the dataset. Following the definitions in Salon (2015), each census tract in California was classified into one of the five neighborhood types—‘urban’, ‘central city’, ‘suburban’, ‘rural’ and ‘rural-in-urban.’ The five categories were further collapsed to three simpler categories by merging the ‘urban’ and ‘central city’ into ‘urban,’ 'rural' and ‘rural-in-urban’ into 'rural,’ and maintaining ‘suburban.’ The SLD maintained by the USEPA (US EPA, 2021) was used to integrate information on the activity density, employment entropy, and intersection density of the block groups of respondents’ home locations, where:

- Activity density is the gross population density (people/acre) on unprotected land;
- Employment entropy is the relative mix of employment within an analysis zone. These measures acted as proxies for land use diversity by quantifying the relative blend of the number of jobs in different employment sectors. Since there is not a uniformly measured, publicly available national land use parcel database that can be allocated to the census block group (CBG), assumptions were made about the mixture of land uses based on counts of job by employment sector. Using these employment characteristics, the SLD includes a variety of alternative metrics to measure entropy. In this case, the employment mix (or entropy) variable uses the five-tier employment categories to calculate employment mix. The entropy denominator is set to observed existing employment types within each CBG.
- Intersection density is the number of street intersections per acre of land.

4.3 Weighting

Efforts were made to recruit respondents from the entire state and cover the demographic diversity of the state. However, a major challenge in making comparisons over time is that the samples (i.e., people who were invited to participate and responded to the surveys) differed at the three time points. 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 hold. 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 within the state. Table 12-1 to Table 12-3 in the Appendix list the attributes that were included in the weighting process, with the distribution of these variables in the target population, and in the unweighted and weighted datasets. As expected, the distribution of demographic characteristics in the weighted sample is much closer to the population characteristics in the state than the unweighted sample. Below is a detailed description of the weighting process.

4.3.1 Variable Selection for Weighting

The distributions of key demographic variables (i.e., household annual income, age, gender, work status, race, ethnicity, and county) in the unweighted data with the population targets that were obtained from the ACS 2019 1-year estimates were compared first.

In addition to these conventional variables that are commonly used for developing sample weights and correcting for a lack of representativeness of a dataset, respondents' work from home (WFH) status before the pandemic was also included as important additional information. This was due to the risk of oversampling respondents that are able to work remotely, especially among the respondents to the online survey (where every respondent was expected to be rather familiar with technology and has good access to the internet). This is a common problem affecting many studies carried out to investigate the impacts of the COVID-19 pandemic—due to the importance of studying the adoption of remote work as one of the main impacts of the pandemic on activities—and the reliance of many studies on the administration of on online surveys at a time in which in-person interactions were limited. The weighting process for the spring 2020 and fall 2020 datasets are identical, but it was slightly different for summer 2021 dataset due to some adjustments we made in the language used to the survey question(s) related to remote work.

For this portion of the weighting process, information from the ACS question "How did you usually get to work last week?", where "worked from home" was one of the available options when asking respondents their means of commuting to work was used. Although commutes may involve multiple means of travel (e.g., driving to a train station and then taking a train), respondents were restricted to indicating the single means of travel used for the longest distance. Further, by asking respondents to report how they "usually" go to work, they were induced to report the means of travel they use most often during the week. This implies that if somebody, for example, works from home only for one or two days a week but physically commutes to work by a certain means of travel on the other days, they would likely not report the information about remote work in this question. Therefore, workers who selected "worked from home" as their usual commute means of travel were considered as "usual telecommuters" and those who selected another means of travel in that question as "non-usual telecommuters". The proportion of "usual telecommuters" in the ACS survey could be considered as the upper bound of the proportion of workers who frequently telecommute in a week (at least 2-3 days a week, to be considered as the "usual" option).

In the spring 2020 and fall 2020 survey, workers and student-workers (i.e., who work and go to school at the same time) were asked whether they had the option to work/study from home and on how many days they worked from home in a work/school week in fall 2019 (retrospectively). Based on the responses to these questions, three remote work statuses were defined:

- Unemployed: currently do not work and are not students.

- Non-usual-WFH workers: work/study from home 0 or 1 days a week.
- Usual-WFH workers: work/study from home 2 or more days a week.

In the summer 2021 survey, however, workers and student-workers were asked to report their frequency of remote work in the month prior to the pandemic with response frequencies ranging from "Never" to "less than once a month", "1-3 times a month", "1-2 times a week", "3-4 times a week" and "5 or more times a week".

To obtain information that could be directly comparable to the classification for work from home as the "usual" means to go to work used in the ACS survey, we analyzed the frequency of using each travel means for commuting for each respondent, including remote work as a commute mode. The "usual travel means to work" was then identified for each respondent as the one that was used with the highest frequency. In the case of a tie between a travel means used for a physical commute and remote work, the travel means used for the physical commute. This decision was made because the ACS survey asks the respondents to select the travel means that is used as the usual means of travel to go to work, which seems to induce respondents to report the means of travel they used for their physical commute in similar cases.

Accordingly, the following seven variables were included into weighting process: household income, age, gender, employment status (before pandemic), ethnicity, remote work status (before pandemic) and county in which the respondent lives.

4.3.2 Weighting Process

The weighting process was all implemented at the state level. In the first stage, respondents' county and WFH status was used in a cell weighting step by dividing population proportions by sample proportions. The second stage in the weighting process was based on matching the sample joint distribution on the selected variables with the population joint distribution. The iterative proportional fitting (IPF) algorithm (i.e., raking) with the mipfp package in R (Barthelemy, Suesse, & Namazi-Rad, 2018; Lovelace & Dumont, 2018), was employed to complete this step. The entire process was iterated until convergence was reached and the sample weights would not vary beyond a certain degree with each additional iteration.

The order of the steps in the weighting procedure was selected to start with the most unbalanced distributions in the sample (e.g., the variables for which the distributions in the sample diverged the most from the population). Using the output of each step as the seed (i.e., input) for the next step, the IPF process iterated among the rest of variables until the change in the weights was negligible. Following the guidelines from the literature, at the end of the process, the eventual presence of extreme weights was also controlled for.

4.4 Descriptive Statistics

Using the entire sample available for analysis, Table 4-1 summarizes the key sociodemographic characteristics of respondents within the California state for the spring 2020, fall 2020 and summer 2021 weighted datasets. The information reported in the table 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 and the characteristics of the sample from three timepoints are reasonably consistent for us to make cross-comparison.

Table 4-1. Descriptive statistics with the weighted datasets collected in spring 2020, fall 2020 and summer 2021 in California

		Spring 2020		Fall 2020		Summer 2021	
		n	%	n	%	n	%
Region	Central Valley	340	6.2%	305	8.1%	596	10.0%
	MTC	1187	21.5%	762	20.4%	1186	19.9%
	NorCal and Others	322	5.8%	264	7.1%	399	6.7%
	SACOG	380	6.9%	247	6.6%	387	6.5%
	SANDAG	498	9.0%	327	8.7%	509	8.5%
	SCAG	2794	50.6%	1839	49.1%	2887	48.4%
Age	18-34	1796	32.5%	1212	32.4%	1893	31.7%
	35-64	2704	49.0%	1850	49.4%	2890	48.4%
	65 or over	1021	18.5%	683	18.2%	1182	19.8%
Ethnicity	Non-Hispanic, Latino, or Spanish origin	3500	63.4%	2332	62.3%	3753	62.9%
	Hispanic, Latino, or Spanish origin	2021	36.6%	1413	37.7%	2212	37.1%
Race	Asian pacific islander	1244	22.5%	709	18.9%	1234	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	3068	55.6%	2036	54.4%	3131	52.6%
	Other	181	3.3%	612	16.3%	557	9.4%
Gender	Female	2811	50.9%	1880	50.2%	2955	49.6%
	Not-female	2710	49.1%	1865	49.8%	3006	50.4%
Educational Background	Lower than bachelors	2476	44.9%	1604	42.8%	2641	44.4%
	Bachelor or higher	3045	55.1%	2141	57.2%	3312	55.6%
Student Status	Not a student	4396	79.6%	2941	78.5%	4452	74.6%
	Student	1125	20.4%	804	21.5%	1512	25.4%

		Spring 2020		Fall 2020		Summer 2021	
		n	%	n	%	n	%
Employment Status	Non-workers	2237	40.5%	1520	40.6%	2535	42.5%
	Full-time workers	2306	41.8%	1445	38.6%	2222	37.2%
	Part-time workers or other	979	17.7%	780	20.8%	1208	20.2%
Annual Household Income	Less than $50,000	1773	32.1%	1195	31.9%	1902	32.4%
	$50,000 - $99,999	1591	28.8%	1056	28.2%	1580	26.9%
	$100,000 or over	2156	39.1%	1494	39.9%	2388	40.7%
Household vehicle ownership	Zero vehicle household	363	7.3%	22	0.7%	170	3.3%
	Household with vehicle	4596	92.7%	3241	99.3%	5047	96.7%
Household composition	Live alone	892	16.2%	553	15.4%	1061	17.8%
	Live with other household members	4629	83.8%	3047	84.6%	4904	82.2%
Housing Tenure	Rent	2042	39.3%	1382	38.3%	1966	33.0%
	Own	2722	52.4%	1883	52.1%	3561	59.7%
	Other	426	8.2%	347	9.6%	438	7.3%
Neighborhood Type	Urban	1901	35.6%	1463	40.5%	2290	38.4%
	Suburban	2653	49.7%	1655	45.8%	2845	47.7%
	Rural	781	14.6%	495	13.7%	829	13.9%

5 Impact of the COVID-19 Pandemic on Work Arrangement

This section includes two related studies. The first study investigates the changes among various groups of population in the state in terms of work arrangement, employment status, commuting and remote work patterns. At the heart of many unknowns lies the following key questions for us to explore:

(1) How to identify different population segments based on individuals' student/worker status, as well as commuting and remote work patterns during the various phases of the pandemic? Who were responsible for the rise in remote work and hybrid work, and what are their characteristics? To what extent will the growth in remote work and hybrid work induced by COVID-19 persist into the future?

(2) What was the percentage of workers who physically commuted versus remotely worked during the various phases of the pandemic? What were the frequencies with which they commuted physically versus worked remotely? How did these patterns differ among individuals with different household income level?

To the extent possible with the repeated cross-sectional data collected within California state in fall 2020 and summer 2021, these topics were compared at four timepoints (collected through the two different surveys): fall 2019 (recollection from pre-pandemic patterns in fall 2020 survey), fall 2020 (during a relatively early stage of the pandemic), summer 2021 (during a later stage of the pandemic), and summer 2022 (expectations for the future, as reported in the summer 2021 survey).

The second study utilizes the summer 2021 dataset collected within California to explore different factors that impact workers' remote work practice at different timepoints (pre-pandemic, summer 2021 and summer 2022). The study also compares remote work patterns among respondents from different recruitment channels including online opinion surveys and mail-based surveys to stress the importance of implementing multi-channel recruitment method to reduce biases and increase validity of survey data.

5.1 A Large Shift to Remote Work and Hybrid Work[1]

5.1.1 Introduction

Exploring how individuals changed their employment and commuting status during the pandemic is important to understand their changes in travel behavior and decisions towards the use of various means of travel. As a lot of businesses transitioned to remote work and hybrid work models during the pandemic, it is especially important to understand workers'

[1] The following section implements a similar methodology of a paper that was prepared for publication in journal *Transportation Research Interdisciplinary Perspectives*. Please use the following citation to cite the full paper: *Iogansen, X; Lee, Y; Malik, J; Circella, G & Lee, Y. (2022). Change in Work Arrangement during the COVID-19 Pandemic: A Large Shift to Remote Work and Hybrid Work (working paper).*

preference towards and practice of these new work arrangements in order to establish effective managerial and organizational support.

It remains unclear that to what extent will the growth in remote work entirely and hybrid work (i.e., combining physical commute and remote work) induced by the COVID-19 pandemic persist into the future and how the transition differs across various population segments. One of the most important impacts of the uptake of remote work on transportation system is through the changing patterns of commuting trips, including travel demand, trip frequency, trip distance and mode use. However, few studies have delved into the changes in work arrangement in different phases of the pandemic, and more importantly, its connection to the shift in travel demand and trip-making. Such information is crucial for formulating effective managerial and organizational policies. At the heart of many unknowns lie the following key questions, which are the focus of this study:

(1) How has the COVID-19 pandemic affected physical commute, remote work and hybrid work status during various phases of the pandemic? Who embraced remote work and hybrid work the most and what are their characteristics?
(2) How did the adoption and frequency of physical commute and remote work change during various phases of the pandemic?

5.1.2 Data and Method

5.1.2.1 Classifying Different Types of Work Arrangement

This study exploits the repeated cross-sectional data encompassing two survey waves (collected in fall 2020 and summer 2021) to monitor the changes in work arrangement among residents in the California state across four timepoints, fall 2019, before the pandemic; fall 2020 and summer 2021, during the pandemic; and summer 2022, near-future from the 2nd survey timepoint. Descriptive analyses of this dataset have been presented in previous sections of this report in Section 4.4.

Despite the growing consensus on a general concept of “remote work” and “hybrid work” in the academic and media, so far, they do not have a universal definition. As these forms of work arrangement provide workers with greater flexibility in terms of work location and working hours, it is challenging to identify clear-cut typologies. If someone works from home just once a month while physically travel to workplace the rest of time, should we classify him/her as a “hybrid worker”? But what if he/she splits the month into half and half? As such, establishing consistent definitions is a critical step of our work. Our study came up a quantitative and systematic way to classify different types of work arrangement based on how frequent workers actually engage in work activities in all alternatives of work location and working hours.

Table 5-1 and Table 5-2 summarize the criteria that were used to define the four categories of commuters, hybrid workers, remote workers, and non-students and non-workers based on individuals’ self-reported employment and commuting statuses:

(1) Commuters: students/workers who <u>mainly/entirely</u> physically travel to traditional school/work location.

(2) Remote workers: students/workers who mainly/entirely study/work remotely in locations separated from traditional school/work location (Olson 1983).
(3) Hybrid workers: students/workers who both physically travel to traditional school/work location and study/work remotely in similar frequency.
(4) Non-students and non-workers.

Note that "commuters," "hybrid workers," and "remote workers" include both workers and students, but for the sake of brevity, we refer them all as "workers".

Table 5-1. Definition of commuting status in fall 2020 survey

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="8">Commuting frequency in most recent school/work week</th></tr>
<tr><th>0</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th><th>7</th></tr>
<tr><td rowspan="8">Remote working frequency in most recent school/work week</td><td>0</td><td>Non-students and non-workers</td><td colspan="7">Commuters</td></tr>
<tr><td>1</td><td rowspan="7">Remote workers</td><td colspan="7" rowspan="7">Hybrid workers</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
</table>

Table 5-2. Definition of commuting status in summer 2021 survey

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="6">Commuting frequency in June/July 2021</td></tr>
<tr><td>Never</td><td>Less than once a month</td><td>1-3 times a month</td><td>1-2 times a week</td><td>3-4 times a week</td><td>5 or more times a week</td></tr>
<tr><td rowspan="6">Remote working frequency in June/July 2021</td><td>Never</td><td>Non-students and non-workers</td><td colspan="5"></td></tr>
<tr><td>Less than once a month</td><td rowspan="2"></td><td colspan="2" rowspan="2">Hybrid workers</td><td colspan="3" rowspan="2">Commuters</td></tr>
<tr><td>1-3 times a month</td></tr>
<tr><td>1-2 times a week</td><td colspan="3" rowspan="3">Remote workers</td><td colspan="3" rowspan="3">Hybrid workers</td></tr>
<tr><td>3-4 times a week</td></tr>
<tr><td>5 or more times a week</td></tr>
</table>

The survey questions related to commuting status were asked differently in the fall 2020 survey than in the summer 2021 survey. Therefore, the definition of the employment and commuting categories also had to be adjusted accordingly. In fall 2020, respondents were asked "In your most recent school/work week, how many days have you studied/worked from home and physically traveled to school/a work location outside of home?" (with the emphasis of the bold and underlined content, as in the original question). In summer 2021, respondents were asked "In June/July summer 2021, how often do you generally study/work…" with the categories including: (1) primary workplace/school location, (2) other workplace/school location, (3) home, (4) temporary location such as coffee shops, parks and public library. The frequency was measured by the following categories: never, less than once a month, 1-3 times a month, 1-2 times a week, 3-4 times a week, or 5 or more times a week. This adjustment was made while designing the summer 2021 survey, to better capture general commuting behavior rather than commuting behavior during the holiday/vacation season when the survey was administered (i.e., June–July 2021).

5.1.2.2 Quantifying the adoption and frequency of remote work versus physical commute

To further study the commuting and remote working patterns, as well as the connections between each other, the second part of the study focuses on two main variables: 1) the percentages of workers who physically commuted versus remotely worked at various timepoints during the pandemic, and 2) the frequency with which they physically commuted vs. remotely worked, if at all.

As Table 5-1 and Table 5-2 listed, we collected frequency of activities in Likert scale. In order to make the frequency categories calculable and comparable, they were first converted into the median of that category in terms of monthly frequency (e.g., 1–3 times a month → 2 times a month, 3–4 times a week →14 times a month) (Lee et al. 2020). Further, Table 5-3 summarizes the conversion. As such, self-reported monthly frequency of physical commute and remote work corresponding to all timepoints can be compared.

Table 5-3. Proxy values for the monthly frequency

Fall 2020 Survey (in the recent week of fall 2020)	Summer 2021 Survey (in June/July 2021)	Proxy for the number of days per month
0 days		0
	Less than once a month	0.5
	1-3 times a month	2
1 day		4
	1-2 times a week	6
2 days		8
3 days		12
	3-4 times a week	14
4 days		16
5 days	5 or more times a week	20
6 days		24
7 days		28

5.1.3 Results

5.1.3.1 Transition in Work Arrangements and Commuting Patterns

Figure 5-1 illustrates the transition patterns among the four timepoints using the repeated cross-sectional datasets. Commuters were the dominant group pre-pandemic (48.2% of respondents, or 72.0% of students/workers), yet by fall 2020, full-time commuters were reduced to 16.7% of respondents due to stay at home policies. Most commuters shifted to more remote work, with 25.7% of the respondents (40.1% of students/workers) being remote workers, while 21.7% of the respondents (33.9% of students/workers) reported being hybrid workers. By summer 2021, slightly fewer individuals (21.6% of respondents, or 33.6% of students/workers) were remote workers as some businesses resumed in-person work to some degree, yet more individuals engaged in hybrid work schedules. Based on respondents' expectations, the share of hybrid work is expected to continue increasing through summer 2022. However, this does not mean that hybrid work schedules will be an option for everyone who prefers it. Engaging in remote work or hybrid forms of work will depend on employers/companies' policies, and support from managers.

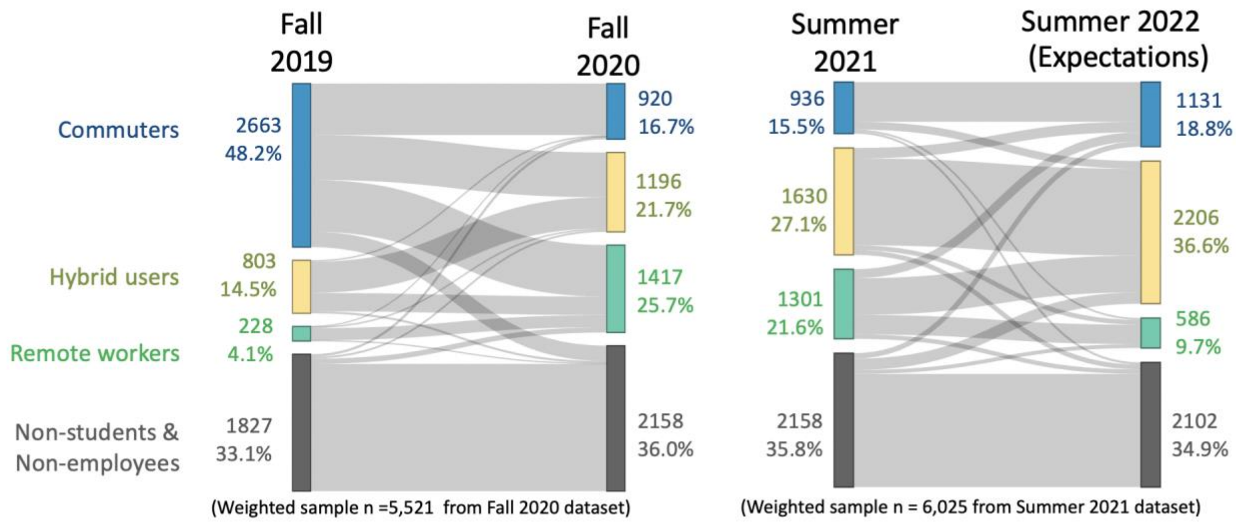


Figure 5-1. Transition of commuting status in the CA state (weighted repeated cross-sectional data)

5.1.3.2 Sociodemographic Characteristics of Remote and Hybrid Workers

Table 5-4 below compares the likelihood of adopting remote work and hybrid work among individuals from each category of socio-demographic categories across four timepoints. Several key findings can be drawn from this analysis. Among workers/students, including both full-time and part-time students/workers, the proportion of those working or studying remotely entirely increased considerably during the pandemic and accounted for the largest share of students/workers in fall 2020 (40.2%). By summer 2021, there was a substantial shift to a hybrid work model among students/workers (42.2%). They expected to continue remote work in the near future, with 56.2% responding that they expect to have a hybrid work model in summer 2022, driven by remote workers returning to the office on a hybrid work model if company policies allow. These general trends consistently apply to different population groups in terms of age, ethnicity, race, gender, and other categories. When we compare the likelihood of adopting remote work and hybrid forms of work by socio-demographic categories, the following key findings emerge:

- Individuals from the younger age group (18-34 years) had a higher share of remote workers compared to other age groups at all timepoints (from 4.9% in fall 2019 to 34.9% in fall 2020, 27.8% in summer 2021 and 10.8% in summer 2022). They also had a higher share of hybrid workers at all timepoints (from 16.9% in fall 2019 to 26.1% in fall 2020, 39.8% in summer 2021 and 57.8% in summer 2022). With comparison, individuals from the middle age group (35-64 years) had a low share of remote workers pre-pandemic, but also increased dramatically during the pandemic (from 4.0% in fall 2019 to 25.1% in fall 2020, to 24.4% in summer 2021, and to 11.2% in summer 2022). However, despite of the increasing popularity of hybrid work among middle age group (from 16.3% in fall 2019 to 24.4% in fall 2020, to 31.8% in summer 2021, and to 40.1% in summer 2022), it is not expected to be as prominent as the younger age group.

- During the pandemic, individuals with Hispanic, Latino, or Spanish origin had a slightly lower share of remote workers than their counterparts at all timepoints, but they had a higher share of hybrid workers than their counterparts.
- African Americans had the lowest share of remote workers at all timepoints. Asian pacific islanders had high share of remote workers, but low share of hybrid workers at most timepoints.
- Females had a larger share of remote workers, but a smaller share of hybrid workers compared to their counterparts in fall 2019 and fall 2020, but this trend reversed by summer 2021 when not-females had a higher share of remote workers while females had a higher share of hybrid workers. By summer 2022, females were expected to have a higher share of both remote workers (9.8% vs. 9.7%) and hybrid workers (39.0% vs. 34.9%) comparing to their counterparts.
- Individuals with higher levels of education (i.e., Bachelor's degree or higher) had a much larger share of hybrid workers before and during the pandemic compared to their counterparts, increasing from 19.0% in fall 2019 to 26.2% in fall 2020, 29.7% in summer 2021 and 39.8% in summer 2022.
- Students had much higher shares of remote workers and hybrid workers most of the time compared to non-students. Their proportion of remote workers increased from 7.5% in fall 2019 to 44.8% in fall 2020, but decreased to 30.3% in summer 2021 and to 9.4% in summer 2022. Their proportion of hybrid workers increased from 25.5% in fall 2019 to 39.3% in fall 2020, to 49.8% in summer 2021 and to 60.5% in summer 2022.
- The share of remote workers and hybrid workers increased dramatically among workers during the peak pandemic in fall 2020, but the proportion of remote workers gradually declined after that (among full-time workers: from 3.8% in fall 2019 to 35.9% in fall 2020, 30.2% in summer 2021 and 12.4% in summer 2022; among part-time workers: from 7.4% in fall 2019 to 27.5% in fall 2020, 29.2% in summer 2021 and 11.6% in summer 2022), while the proportion of hybrid workers had kept increasing (among full-time workers: from 22.3% in fall 2019 to 34.5% in fall 2020, 43.1% in summer 2021 and 53.8% in summer 2022; among part-time workers: from 18.7% in fall 2019 to 35.2% in fall 2020, 43.4% in summer 2021 and 52.7% in summer 2022).
- Except for fall 2019, members of high-income (with annual household income of $100,000 or more) households had the highest share of remote workers in other three timepoints compared to individuals from other income groups. Their share of remote workers increased from 3.6% in fall 2019 to 32.3% in fall 2020, 26.4% in summer 2021 and 11.3% in summer 2022. They also had a higher share of hybrid workers at all timepoints which also kept increasing during the pandemic (22.0% in fall 2019, 28.9% in fall 2020, 30.5% in summer 2021 and 41.1% in summer 2022).
- Household vehicle owners had a higher share of remote workers before the pandemic and all timepoints during the pandemic. Their proportion of remote workers increased from 4.3% in fall 2019 to 26.9% in fall 2020, 22.5% in summer 2021 and 10.1% in summer 2022. Vehicle non-owners, however, had a much higher share in hybrid

workers by summer 2021 (68.2% vs. 25.8%) and summer 2022 (67.3% vs. 35.6%), compared to vehicle owners.

- Individuals living with other household members had a higher share of remote workers and hybrid users than their counterparts at all timepoints. Their proportion of remote workers increased from 4.3% in fall 2019 to 26.0% in fall 2020, 22.6% in summer 2021 and 9.9% in summer 2022. Their proportion of remote workers increased from 15.7% in fall 2019 to 23.4% in fall 2020, 28.5% in summer 2021 and 38.5% in summer 2022.
- Housing renters had a higher share of remote workers during the pandemic and started to have higher share of hybrid users in both summer 2021and summer 2022.
- Urban (as compared to suburban and rural) residents had a higher proportion of hybrid workers at all timepoints, which increased from 20.0% in fall 2019 to 27.0% in fall 2020, 36.9% in summer 2021 and 47.3% in summer 2022. Rural residents had a higher share of remote workers in fall 2019 (4.6%), but urban and suburban residents had much more drastic increase in remote workers during the pandemic (among urban residents, their share increased from 3.8% in fall 2019 to 27.4% in fall 2020, then 22.1% in summer 2021 and 9.0% in summer 2022; among suburban residents, their share increased from 4.4% in fall 2019 to 26.8% in fall 2020, 22.7% in summer 2021 and 10.8% in summer 2022).

The differences in adopting remote work and hybrid work across groups mirror the inherent nature of the different job types and their ability to transition to remote work. In particular, those in lower-income, lower-education groups are more likely to have essential jobs and blue-collar jobs that more often require employees to be on site. High-income full-time workers are much more likely to have white-collar office jobs, STEM and government jobs, while low-income part-time workers are employed in a large variety of jobs, including a larger proportion of jobs that are classified as essential and that require in-person presence. These differences between work patterns across different sociodemographic groups raises potential equity concerns, both in the short-term in facing risks in the pandemic and in the long-term ability for recovery.

Table 5-4. Percentage distributions of remote workers and hybrid workers for each category of socio-demographic variables in each timepoint

		Remote workers				Hybrid Workers			
		Fall 2019	Fall 2020	Summer 2021	Summer 2022	Fall 2019	Fall 2020	Summer 2021	Summer 2022
n		228	1417	1301	586	803	1196	1630	2206
% of all students/workers		6.1%	40.2%	33.6%	14.9%	21.7%	33.9%	42.2%	56.2%
% of all respondents		4.1%	25.7%	21.6%	9.7%	14.5%	21.7%	27.1%	36.60%
Age	18-34	4.9%	34.9%	27.8%	10.8%	16.9%	26.1%	39.8%	57.8%
	35-64	4.0%	25.1%	24.4%	11.2%	16.3%	24.4%	31.8%	40.1%
	65 or more	3.0%	9.7%	9.5%	5.8%	4.8%	5.2%	4.2%	6.7%
Ethnicity	Non-Hispanic, Latino, or Spanish	3.9%	25.8%	21.6%	9.8%	14.8%	21.4%	24.3%	33.0%
	Hispanic, Latino, or Spanish	4.9%	25.2%	21.4%	9.3%	13.7%	22.5%	35.4%	47.5%
Race	Asian pacific islander	5.0%	37.4%	28.3%	9.8%	12.3%	19.1%	24.9%	37.1%
	African American	1.9%	18.0%	18.8%	7.7%	15.1%	22.7%	37.5%	46.8%
	Native American	4.3%	23.2%	23.7%	10.3%	20.7%	25.0%	37.1%	49.6%
	White	4.1%	23.7%	20.3%	9.7%	14.8%	22.0%	26.0%	34.8%
	Other	4.8%	20.6%	24.8%	11.4%	14.3%	23.8%	28.5%	40.0%
Gender	Female	4.4%	27.2%	20.4%	9.8%	11.3%	17.5%	30.0%	39.0%
	Not-female	3.8%	23.5%	22.5%	9.7%	19.2%	27.6%	24.9%	34.9%

		Remote workers				Hybrid Workers			
		Fall 2019	Fall 2020	Summer 2021	Summer 2022	Fall 2019	Fall 2020	Summer 2021	Summer 2022
Education	Lower than Bachelor’s	4.5%	20.2%	17.0%	8.0%	9.1%	16.0%	23.3%	32.1%
	Bachelor’s or higher	3.8%	30.2%	24.9%	10.9%	19.0%	26.2%	29.7%	39.8%
Student Status	Non-student	3.3%	21.2%	19.0%	9.8%	12.0%	17.5%	20.3%	29.6%
	Student	7.5%	44.8%	30.3%	9.4%	25.5%	39.3%	49.8%	60.5%
Worker Status	Non-workers	2.9%	13.3%	5.1%	3.0%	4.0%	1.3%	3.7%	12.3%
	Full-time workers	3.8%	35.9%	30.2%	12.4%	22.3%	34.5%	43.1%	53.8%
	Part-time workers	7.4%	27.5%	29.2%	11.6%	18.7%	35.2%	43.4%	52.7%
	Other	7.1%	31.1%	44.8%	23.5%	19.7%	34.4%	39.5%	48.7%
Household Income	Less than $50,000	4.9%	19.5%	17.2%	8.7%	8.6%	15.3%	21.6%	30.9%
	$50,000 to $99,999	3.8%	25.3%	19.8%	8.6%	13.2%	21.0%	28.7%	37.4%
	$100,000 or more	3.6%	32.3%	26.4%	11.3%	22.0%	28.9%	30.5%	41.1%
Household Vehicle Ownership	Zero vehicle household	2.3%	23.9%	7.3%	3.6%	12.1%	12.5%	68.2%	67.3%
	Household with vehicle	4.3%	26.9%	22.5%	10.1%	15.1%	22.3%	25.8%	35.6%
Household composition	Live alone	3.2%	23.9%	17.7%	9.0%	9.0%	13.4%	21.6%	29.1%
	Live with other members	4.3%	26.0%	22.6%	9.9%	15.7%	23.4%	28.5%	38.5%

		Remote workers				Hybrid Workers			
		Fall 2019	**Fall 2020**	**Summer 2021**	**Summer 2022**	**Fall 2019**	**Fall 2020**	**Summer 2021**	**Summer 2022**
Housing Tenure	Rent	4.2%	27.1%	23.1%	11.0%	11.8%	18.4%	27.9%	39.2%
	Own	4.3%	25.9%	20.1%	9.0%	17.9%	24.7%	26.9%	34.5%
	Other	3.0%	28.6%	28.4%	10.7%	9.4%	17.1%	23.9%	44.0%
Neighborhood Type	Urban	3.8%	27.4%	22.1%	9.0%	20.0%	27.0%	36.9%	47.3%
	Suburban	4.4%	26.8%	22.7%	10.8%	11.9%	19.0%	20.9%	30.5%
	Rural	4.6%	18.4%	15.8%	7.8%	8.9%	15.0%	20.9%	27.8%

Note: please refer to Table 4-1 for the weighted sample size of each sociodemographic category at different timepoints.

5.1.3.3 Changes in Commuting and Remote Work Adoption and Frequency

Understanding the changes over time in the adoption and frequency of in-person work (requiring physical commute) and/or remote work helps better evaluate the shift in travel demand and trip-making, and the potential continuation of some of these trends in the future.

This section focuses on two main variables: 1) the percentages of workers who physically commuted vs. remote worked during the various phases of the pandemic, and 2) the frequency with which they physically commuted vs. remote worked, if at all. Again, this section discusses the commuting/remote work patterns across four timepoints (collected through two different surveys): (1) fall 2019 (pre-pandemic), (2) fall 2020 (during pandemic), (3) summer 2021 (during pandemic), and (4) summer 2022 (expectation for the future).

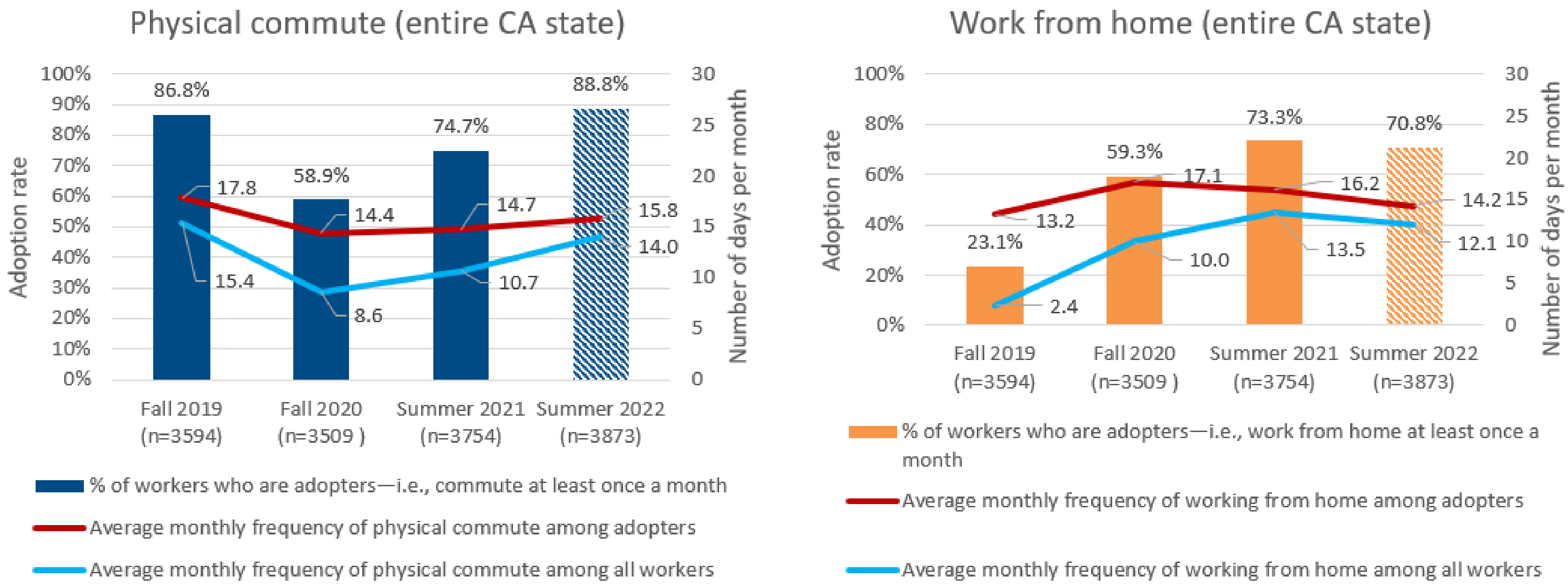
Figure 5-2 compares the shares of workers who physically commuted (left figure) vs. remotely worked (right figure) and their average monthly frequency of doing so during various phases of the pandemic. It provides a deeper understanding of the pandemic's impact on commute trips.

Let us first focus on the chart on the left. The blue bars represent the percentage of workers who physically commuted to their workplace at least once a month in each timepoint (i.e., were adopters of in-person work). The hatched blue bar indicates a future percentage based on individual predictions, i.e., what respondents in summer 2021 expected do to in summer 2022. The light blue line represents the average monthly frequency of physical commutes among those adopters. This provides a measure of the commuting trips among those commuters and hybrid workers. The red line represents the average monthly commute frequency among all workers in that timepoint. Since this also includes remote workers, it can provide insight into the changing number of commuting trips across the entire working population.

The bar chart indicates that the proportion of workers who commuted to work at least once a month declined sharply from fall 2019 (86.8%) to fall 2020 (58.9%) as expected and likely included a certain bounce back after the initial impact of the pandemic on commuting in spring 2020. As the pandemic progressed, the percentage of those physically commuting to work at least once a month partially recovered (74.7%), but still remained approximately 10 percentage points lower in summer 2021 than the pre-pandemic level. The adopters of in-person work were expected to increase more by summer 2022. Consistent trends are observed for commuting frequency shown by the line chart. Among workers who commuted to work at least once a month, the mean commuting days per month dropped from 17.8 from pre-pandemic to only 14.4 in fall 2020 and then increased slightly to 14.7 by summer 2021 which is still 17.4% below the pre-pandemic level. Among all workers, the average number of commuting days per month dropped dramatically from 15.4 from pre-pandemic to 8.6 in fall 2020. It then increased slightly to 10.7 by summer 2021 and was expected to increase to 14.0 by summer 2022.

The chart on the right reports analogous information, but this time for remote work. The orange bars represent the proportion of workers who are adopters of remote work, i.e., who remote work at least once a month in each timepoint. The light blue line represents the average monthly frequency of remote work among those adopters, while the red line represents the average monthly frequency among all workers in that timepoint.

Consistent with the expectations of the increased remote working during the pandemic, the trends of remote working were the opposite (and complementary) of the trends of physical commuting. The percentage of those who remote worked at least once a month increased substantially from only 23.1% pre-pandemic to 59.3% in fall 2020, stayed high at 73.3% in summer 2021 and was expected to remain high in the future. However, among adopters, the frequency of remote working increased initially in the early phase of the pandemic (from an average of 13.2 to 17.1 days/month) but declined in the later phase in summer 2021 (to 16.2 day/month). We observe the same trend among all workers. The above trends are not surprising: they represent a reality in which many individuals shifted to remote working entirely during the "peak COVID-19 time", but later transitioned to hybrid forms of work, i.e., combining remote and in-person work. In the future, individuals expect to continue to engage in hybrid forms of work, either on different days of the week/month, or during the same day.



Note: The hatched blue bar indicates a future percentage based on individual predictions, i.e., what respondents in summer 2021 expected do to in summer 2022.

Figure 5-2. Changes in the adoption and frequency of physical commute and work from home (weighted repeated cross-sectional data)

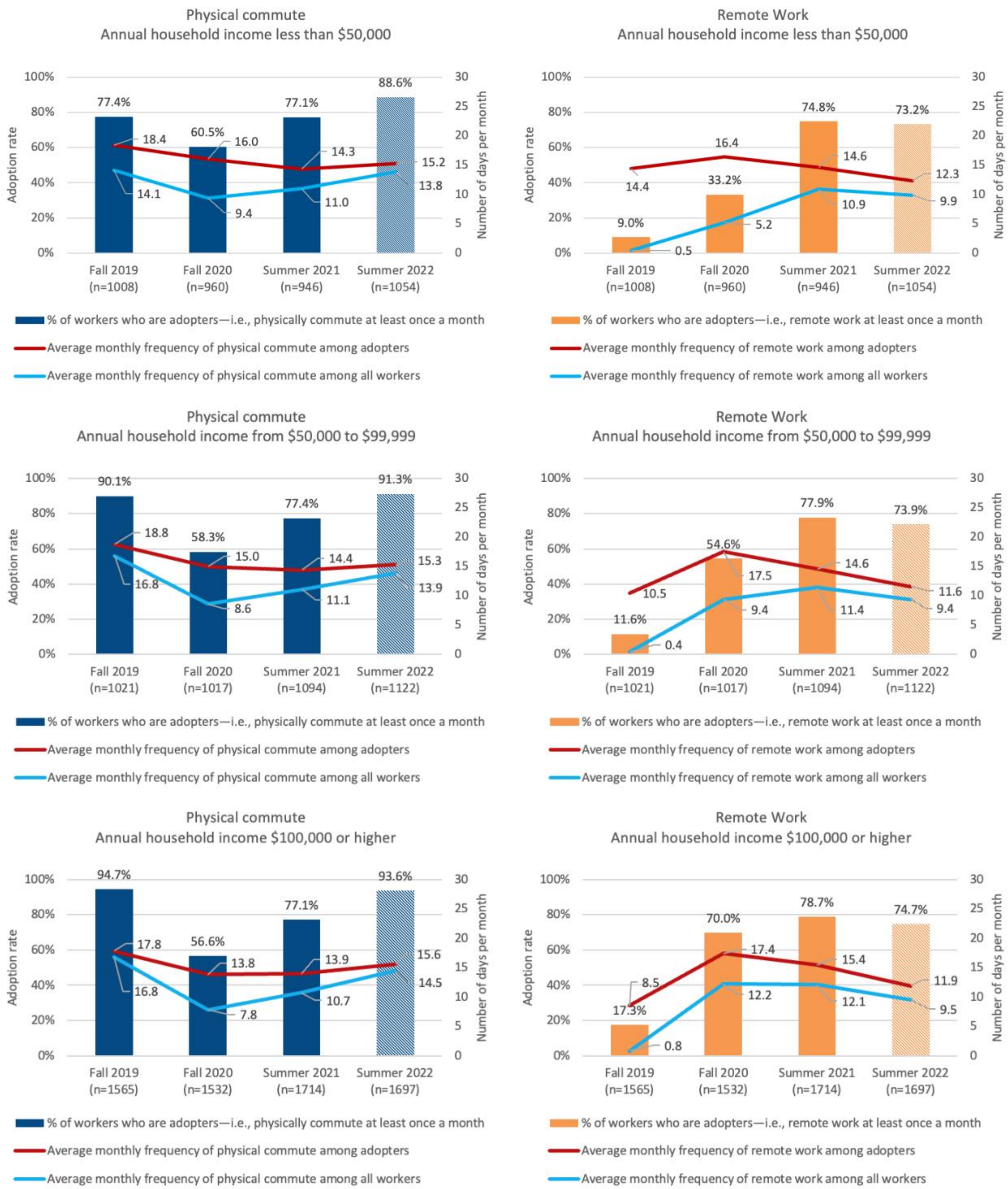
In Figure 5-3 we also compare the changes in physical commute and remote work across various income groups.

Let us first focus on patterns of physical commute that are illustrated by the three figures on the left side. Based on the blue bar charts, workers from high-income household (with an annual income of more than $100,000) had the highest adoption of physical commutes before the pandemic (94.7% physically commuted to work at least once a month), compared to the workers in the low-income category (77.4% physically commuted to work at least once a month). Interestingly, among those who did commute to work at least once a month in fall 2019, those in the high-income category had the lowest average monthly frequency (17.8 days/month) of commutes compared to their lower-income counterparts (18.4 days/month). This finding highlights a greater ability among higher income earners to replace their physical commute with other forms of work (e.g., remote work, or hybrid work) even before the pandemic. From fall 2019 to fall 2020, workers in the highest-income group experienced the most substantial reduction in the percentage of physical commuters (−38.1 percentage points [p.p.] from 94.7% to 56.6%). By contrast, this percentage of physical commuter declined only −16.9 p.p. from 77.4% to 60.5% in the low-income group. Respondents' expectations about whether they would physically commute at least once a month in summer 2022 were largely in line with pre-pandemic percentages, with a slight increase for those in the lowest income category.

The frequency of physical commutes (shown by the line charts) also decreased the most among the high-income individuals between fall 2019 and fall 2020, reaching an average of only 13.8 days/month among adopters of physical commute and 7.8 days/month among all workers in fall 2020 in that income group. These frequencies were much higher than those reported by workers in the low-income group, respectively at 16.0 days/month among adopters of physically commute, and 9.4 among all workers in fall 2020 in that income group. The recovery in the physical commutes by summer 2021 was observed among workers in all income groups, though the high-income workers who resumed physical commuting continued to do so less often than those in the low-income group.

Now let us shift to the patterns of remote work that are illustrated by the three figures on the right side of Figure 5-3. The adoption of remote work (shown in the orange bar charts) was the highest among the high-income group (17.3%) and lowest in the low-income group (9.0%) before the pandemic. The adoption also increased, from fall 2019 to fall 2020, by the most and least in these high- and low-income groups respectively (+52.7 vs. +24.2 p.p.). In terms of frequency that are shown in the line charts, among all workers, those in the high-income category always reported higher frequency of remote work than their counterparts. The blue and red lines in the figures are getting closer over time in each chart, which indicates that the differences in the frequency of remote working among workers were reducing.

In total, the trends in the adoption rate and average monthly frequency among adopters of physical commute were opposite to those in the trends of these parameters of remote work. These findings indicate that high-income workers are more able to adopt remote work and hybrid work. Instead, low-income workers either fully physically commute (if their job requires them to be in person onsite all the time) or fully remote work (if they do not have good mobility options and/or have certain jobs that can be performed remotely, and for which an office space might not even be available).



Note: The hatched blue bar indicates a future percentage based on individual predictions, i.e., what respondents in summer 2021 expected do to in summer 2022.

Figure 5-3. Changes in the adoption and frequency of physical commute and work from home by household income groups (weighted repeated cross-sectional data)

5.2 Differences in Remote-work Adoption among Respondents from Different Survey Recruitment Methods[2]

5.2.1 Introduction

In previous section of the report, we have found that capability and practice of remote work vary greatly among workers with different socio-demographic characteristics. In this part of study, we aim to further explore the differences in remote work practice in the pre-COVID, 2021, and 2022 (expected) periods among respondents from 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. This perspective has become even more important during the COVID-19 pandemic, as the limitations to in-person interactions and the capability of quicker data collection accelerated the use of online opinion panels. However, the emphasis on, for instance, the remote-work practice raises serious concerns about potential differences between opinion panel respondents and the general population.

This is an important research topic, because to date, only a few studies in the transportation literature examined the validity of a dataset taken from the source of an online opinion panel. While online opinion panels have many advantages include minimizing the cost of reaching out to survey participants (Buhrmester, Kwang, and Gosling, 2016), accessing them without geographical restrictions, and/or accessing hard-to-reach population segments in society (Smith et al., 2015) with saving researchers' valuable time (Paolacci, Chandler, and Ipeirotis, 2010). 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. Even though bias from the coverage and/or nonresponse may happen regardless of the recruitment method, the magnitude is potentially severer when using an opinion panel than in other recruitment channels (Baker et al., 2010). There could be two types of biases among opinion panel datasets: 1) a bias in the composition of survey participants, such as age, income, occupation, race, or educational attainment (Berrens et al., 2003; Paolacci, Chandler, and Ipeirotis, 2010) and 2) a bias in the qualitative aspects of behaviors and choices, including personality (Valentino et al., 2020), willingness to pay (Gao, House, and Bi, 2016), or political opinion (Berrens et al., 2003). Even if researchers perfectly adjust the quotas of a survey project via an online opinion panel to the population, the latter bias, which depends on what type of people joins the panel, may largely affect the survey outcome.

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[2] 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: *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.*

Especially, since COVID-19 pandemic started in early 2020, the interest in the literature has shifted to social media (Bisanzio et al., 2020), remote work practice (Brynjolfsson et al., 2020; Wang et al., 2021), or online activities such as virtual meetings (Porpiglia et al., 2020). In the assessment of these behaviors, biases that may exist in online opinion panels could lead to inaccurate modeling estimates and implications for policy and practice.

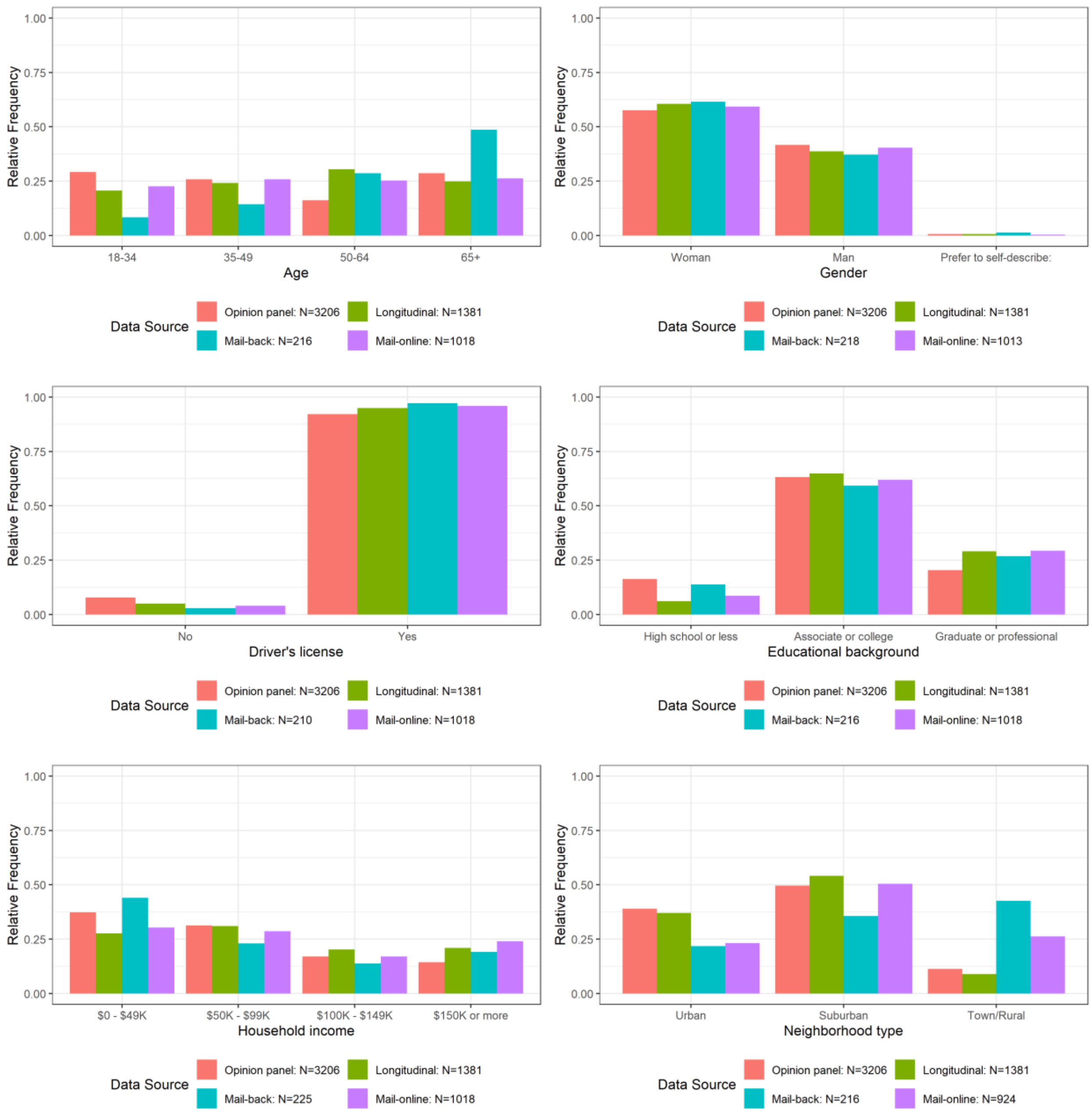
By implementing a series of linear regression models, we have revealed that opinion panel users had a stronger practice of hybrid or remote work before the COVID-19 pandemic, while non-opinion-panel users showed a stronger shift to such a home-based workstyle during the pandemic. Future research in transportation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

5.2.2 Data and Method

In this study, we analyze the COVID dataset collected in summer 2021. The survey was administered through five distribution channels (i.e., recruitment methods) to obtain a more comprehensive sample from a wide range of segments in the population. In this study, we will use four out of the five datasets, including opinion panel (n=3,206), longitudinal(n=1,381), mail-back (n=225), and mail-online (1,018), but excluding those on convenience sampling.

We use the following socio-demographics to explain individuals' remote work behaviors: age (18-34, 35-49, 50-64, or 65+), gender (male, female, or non-binary), possession of a driver's license (yes or no), education (high school or less, college, or graduate), neighborhood type (urban, suburban, or town/rural), and the dataset type (longitudinal, opinion panel, mail-back, or mail-online).

Figure 5-4 illustrates the different distributions of the socio-demographics over the four datasets. First, the opinion panel dataset contains slightly more younger people while the mail-back dataset has much more older adults. The opinion panel dataset contains more less-educated people. This result is consistent with the literature (Zhang & Gearhart, 2020). Opinion panel dataset also contains more low-income people, but the mail-back dataset has a larger share of high-income individuals. Finally, the longitudinal and opinion panel dataset contains more urban residents while the mail-back and mail-online datasets have more participants from rural areas.



Notes: 1. Top-left: Age, Top-right: Gender, Middle-left: Possession of a driver's license, Middle-right: Educational background, Bottom-left: Household income, Bottom-right: Neighborhood type. 2. The sample size of Mail-back and Mail-online differs slightly across six panels because of cases with missing values. 3. The vertical axis indicates percentage values ranging from 0 (0%) to 1 (100%).

Figure 5-4. Descriptive statistics of socio-demographic factors of four datasets

We first classify respondents into Non-workers, Commuters, Hybrid workers, or Remote workers based on the same method that we discussed in Section 5.1.1. We then estimate a series of multinomial logit model examined the remote-work practice of people from different recruitment methods in the pre-COVID, 2021, and 2022 (expected) periods.

5.2.3 Results

For the remote-work status in pre-COVID, 2021, and 2022, Table 5-5 summarizes the coefficients and significance of the independent variables in the multinomial logit model. There are three models in total and each model has coefficients for the level of hybrid workers and that of remote workers, constructing two columns in the table. First of all, in all the models for the three time periods, gender was removed by the stepwise variable selection as it did not contribute to the model AIC. In the literature, there are mixed results about the significance of the effect of gender on the adoption of remote work (Tremblay and Thomsin, 2012; Walls, Safirova, and Jiang, 2007).

The first model estimates one's remote-work status before the COVID-19 pandemic started. In this model, education was not significant, although some prior studies reported a significant positive effect of higher degrees (Shabanpour et al., 2018; Walls, Safirova, and Jiang, 2007). On the other hand, it is natural that 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 need to obtain it. The effect of age group is somehow hard to interpret, but one hypothesis is that older adults, especially those who are 65 or older, are more likely to adopt a bipolar workstyle than younger adults. Income has an overall negative effect on one's hybrid-work practice, while a higher income encourages remote-work practice. The latter result is aligned with literature but the former one is not (He and Hu, 2015). About the difference between the datasets, people in the opinion panel dataset are the most typical hybrid and remote workers. This could be associated with the finding that the population is more technology-oriented than people in other datasets. Especially, mail-back dataset shows the greatest negative coefficient, indicating that there is a non-negligible effect on those who cannot be contacted by online survey distributions.

The second model estimates one's remote-work status in 2021. In this model, being an older adult or in a more rural area was determined as a negative factor for both workstyles. Those cohorts could have fewer opportunities to adopt off-site 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 be more likely to work remotely. Regarding the datasets, there are some opposite results for hybrid and remote workstyles. It implies that, while overall the remote work practice spread to society, people in the longitudinal or mail-online datasets shifted to remote-work more strongly than those in the opinion panel dataset. Meanwhile, mail-back dataset did not show significance, suggesting that people who do not have access to the web would overlap with on-site workers.

The last model estimates one's expectation of their work status in 2022 (i.e., one year from when they participated in the survey). In this model, the variable of the dataset was removed by the variable selection. This means that the nature of people reached by different distributions does not quite vary about the expectation. Meanwhile, younger adults, high-educated or high-income workers expect more off-site workstyle in the future. The effect of the neighborhood seems complex, but it seems that urban workers would prefer to continue hybrid work practice.

The models indicate that in the pre-COVID period, online panel users have a stronger orientation to hybrid- or remote-work practice as suggested by their trait of tech-savviness. However, as of 2021 in the pandemic era, people in the longitudinal and mail-online datasets showed more intense remote-work practice, potentially in a bipolar selection with regular commuting (i.e., less chance of adopting a hybrid workstyle). Regarding one's expectation of their workstyle in 2022 (one year from participating in the survey), we did not find a significant relationship between the datasets so the effect from socio-demographics would be much larger. Even though the four subsamples have different characteristics or practices in general, the expectation or forecast of one's future situation may not differ among them.

Table 5-5. Results of multinomial logit models for remote work status in the pre-COVID period, 2021 and 2022 (expected)

Explanatory Variable	Levels	Coefficients					
		Pre-COVID		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	
Alternative Specific Constant (ASC)		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+	-1.217***	0.150	-1.452***	-0.631**	-1.262***	-0.390
Gender (base: Female)	Male	---	---	---	---	---	---
	Prefer-to-self-describe	---	---	---	---	---	---
Driver license (base: No)	Yes	-0.857***	-0.742*	---	---	---	---
Education (base: High school or less)	College	-0.119	-0.412	0.085	0.366	-0.089	0.842**
	Graduate	0.254	-0.217	0.550**	0.558*	0.315	0.699*
Income (base: less than $50K)	$50K -$99K	-0.310**	-0.512**	0.146	0.624***	0.003	0.299
	$100K - $150K	-0.339**	-0.113	0.167	0.743***	0.037	0.546**
	$150K or more	-0.270*	0.290	0.558***	1.309***	0.372**	1.097***
Neighborhood type (base: urban)	Suburban	-0.235**	-0.025	-0.430***	-0.172	-0.326***	0.086
	Town or rural	0.034	-0.245	-0.497**	-0.591***	-0.433**	-0.077
Dataset (base: opinion panel)	Longitudinal	-0.710***	-0.613***	-0.376**	0.453***	---	---
	Mail-back	-0.457*	-1.286**	0.074	-0.158	---	---
	Mail-online	-0.552***	-0.844***	-0.372**	0.437***	---	---
Log-likelihood (null model with only ASC)		-2254.322		-2107.166		-2105.493	
Log-likelihood (full model)		-2142.689		-1989.703		-2034.94	
Number of parameters estimated		30		28		22	

Note:

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

6 The Impact of COVID-19 on Household Vehicle Ownership Changes[3]

6.1 Introduction

A number of studies have suggested the increasingly prominent role of private vehicles during the pandemic (Fatmi 2020; Abdullah et al. 2020; Loa et al. 2021; Zhang, Hayashi, and Frank 2021) as large segments of the population began to view car travel as the safest option for daily travel needs. Comparing to the rather consistent observation of the increasing travel demand with private vehicles globally, car sale statistics display a more complex and region-specific trends and they are also evolving quickly with the pandemic situation.

On the supply side, business shutdown and shortage of raw materials during the pandemic has upended the automotive industry, resulting in a significant decline in vehicle production among most auto manufactures (Krolikowski & Naggert, 2021). However, from the demand side, the demand for cars has remained strong during the pandemic (Krolikowski & Naggert, 2021). According to a national survey conducted by Cars.com, 60% of car buyers among their respondents said that the pandemic influenced their decision to purchase a vehicle, and over 50% bought a car sooner than originally planned (Auto Remarketing, 2021). Some individuals who did not previously own a car may have been compelled to buy or lease one to avoid using mass transportation, which may have contributed to the boom in used car sales during the pandemic (Rosenbaum, 2020). In the meanwhile, economic uncertainty during the pandemic may have prevented some consumers from incurring unnecessary expenses on buying or replacing cars (de Palma, Vosough, & Liao, 2022).

Given the volatility of the consumer market, automotive manufacturers, car dealers, and government officials must understand how consumers' vehicle ownership change decisions have been affected by the pandemic and what the "new normal" might entail. However, there are some research gaps in this topic. Firstly, although vehicle ownership has been well-studied before the pandemic, limited research has been focused on the situations during the pandemic in the US. Secondly, many existing studies on vehicle ownership rely on cross-sectional data, which may obscure potential variations in vehicle ownership within households over time (Klein & Smart, 2017). Besides, cross-sectional data often do not capture the impact of life events on vehicle ownership, which can be critical in understanding how and why household make decisions about vehicle ownership. Finally, to the best of the authors' best knowledge, no prior study has simultaneously modeled both actual vehicle ownership changes in the past and anticipated vehicle ownership change in the future. This comprehensive approach can not only yield valuable insights into individuals' vehicle ownership decision patterns over a longer time

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[3] The following section is a short version of a paper that was peer-reviewed and has been presented in 2023 Transportation Research Board annual meeting in Washington D.C. Please use the following citation to cite the full paper: *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 annual meeting, Washington D.C.*

horizon, but also reveals heterogenous impact of certain variables on the past and future vehicle ownership decisions.

To address these research gaps, this study employs a two-wave panel survey collected in the U.S., to simultaneously investigate individuals' past changes in vehicle ownership from months shortly before the COVID-19 pandemic struck the US (referred to as "pre-pandemic") to June/July 2021 (referred to as "summer 2021") and expected future changes in vehicle ownership from June/July 2021 to June/July 2022 (referred to as "summer 2022"). Four levels of vehicle ownership changes are measured: (1) increase in the number of vehicles, (2) decrease in the number of vehicles, (3) keeping the same total but replacing one or more vehicles, and (4) no change. Our approach is to estimate an integrated choice & latent variable (ICLV) model to identify the factors that impact vehicle ownership changes, focusing on latent attitudes (e.g., tech-savviness), socio-demographics, life events (e.g., starting a job), and COVID-related factors (e.g., COVID health concern). While we cannot account for the complexities of the global auto market, our study seeks to shed light on the individual-level factors driving observed vehicle transactions and to provide valuable insights for policy and business strategy related to vehicle ownership in the post-pandemic era.

6.2 Data and Method

This study focuses on 2,283 longitudinal respondents who participated in both fall 2020 and summer 2021 COVID data collection in the US. Respondents self-reported their vehicle ownership (i.e., number of household vehicles at specific timepoints), as well as changes in vehicle ownership (i.e., increase, decrease, replace household vehicles during specific time periods) of each respondent from our two waves of survey. To ensure that the sample's composition reflects the US adult population, the panel data were weighted and controlled for age, gender, race/ethnicity, education level, employment status, household income, and number of household vehicles, census divisions based on 2021 American Community Survey (ACS) 1-year Estimates. All summary statistics presented in this paper henceforth are computed based upon the weighted sample.

The proportion of respondents who reported living in households without a vehicle decreased from 7.2% in winter 2020 to 5.0% in summer 2021. The fraction of those from households with one or two vehicles also decreased slightly during this time period. However, the decrease in these three groups is balanced by the increase in the proportion of respondents from households with three or more cars (from 25.7% to 29.2%). Overall, the average number of household vehicles among respondents increased from 1.97 in winter 2020 to 2.11 in summer 2021.

Figure 6-1 shows the distribution of responses to questions about their recent vehicle ownership changes *before the pandemic to summer 2021*, 7.9%, 5.1% and 19.2% of respondents reported to have increased, decreased, or replaced their vehicles, respectively. *Looking one year ahead from summer 2021 to summer 2022*, 8.4%, 3.8% and 21.4% of respondents expected to increase, decrease, or replace their vehicles, respectively. Once again, more respondents expected to increase their vehicle ownership then decrease it. Even though it is very rare to observe someone relinquished their vehicle and turned into non-car-household by summer 2021 (0.3%), more non-car-owners expected to add a car by summer 2022 (1.4%). Within expectation, the rate of vehicle replacement was much larger than that of acquisition and disposal.

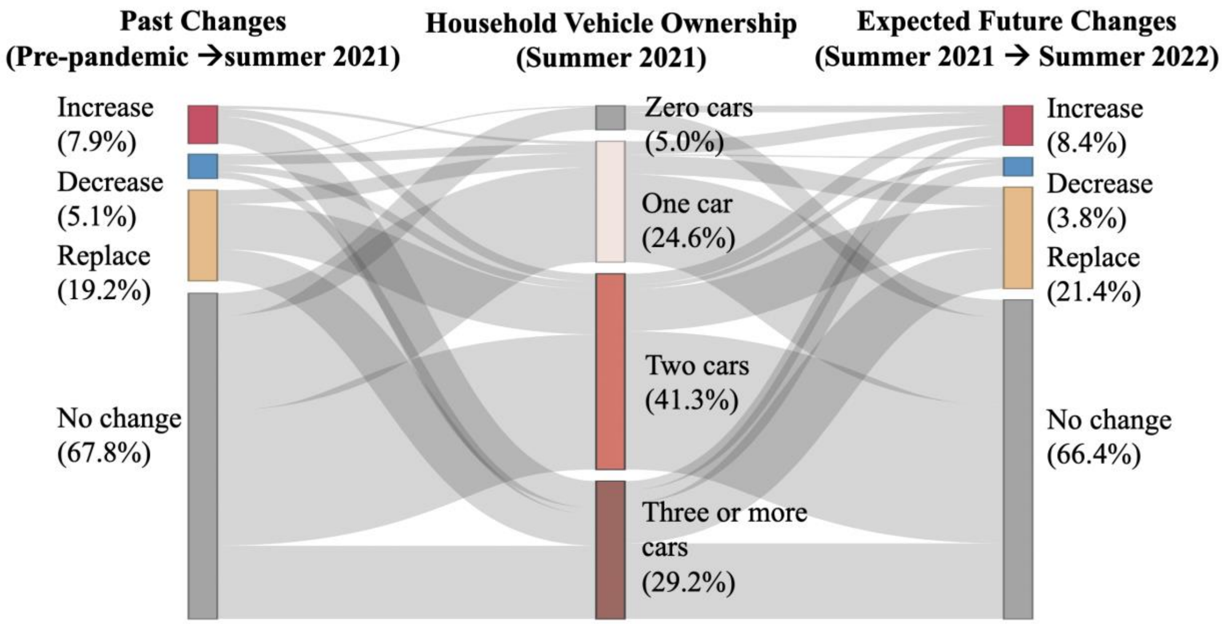

Figure 6-1. Recent and expected vehicle ownership changes

To measure individuals' attitudes, we analyze the attitudinal statements in the survey, to which individuals responded on the five-point semantic scale from "strongly disagree" to "strongly agree". Through an exploratory factor analysis (EFA), 22 statements were distilled into seven underlying dimensions. Table 6-1 presents the results from EFA done by *psych* R package. The *car-affine & pro-driving* latent factor indicates people's strong preference to own a vehicle and their enjoyment from driving. The *tech-savvy & variety-seeking* factor reflects individual's familiarity and proficiency with new technologies, as well as their inclination and openness to new things and experience. The *pro-environment* factor encompasses individuals' attitude towards environmental regulations to raise the cost of driving in order to reduce the negative impacts of transportation on the environment, while to provide funding for better public transportation. The *pros and cons of urban life* factor reflects individuals' opinions and experience when living in an urban setting. Individuals with high scores on this factor like some aspects of urban life, such as better public transportation network and infrastructure, while dislike other aspects of urban life, such as traffic congestion and parking issues. The *pro-active* factor pertains to people's value on active lifestyle through regular walking and exercising. Finally, *car-dependent* factor indicates people's dependence on their vehicle in daily life due to limited access to alternative modes.

Table 6-1. Results from exploratory factor analysis (“promax” rotation)

	Attitudinal Statements	Latent Factors						
		Car-affine & pro-driving	Tech-savvy & variety-seeking	Pro-environment	Pros and cons of urban life	Pro-active	Pro-biking	Car-dependent
1	I like driving a car.	0.95						
2	I prefer to be a driver rather than a passenger.	0.67						
3	I definitely want to own a car.	0.49						
4	To me, a car is just a way to get from place to place.	-0.34						
5	I like to be among the first people to have the latest technology.		0.7					
6	I ’ll stretch my budget to buy something new and exciting.		0.68					
7	Having Wi-Fi and/or good internet access on my mobile phone everywhere I go is essential to me.		0.51					
8	I like trying things that are new and different.		0.37					
9	We should raise the cost of driving to provide funding for better public transportation.			0.88				
10	We should raise the cost of driving to reduce the negative impacts of transportation on the environment.			0.81				
11	I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.				0.49			
12	I like the idea of public transit as a means of transportation for me.				0.48			
13	Traffic congestion is a major problem in the region where I live.				0.35			
14	I am less likely to drive if parking is difficult or expensive.				0.34			
15	I am generally satisfied with my transportation options.				-0.46			-0.31
16	I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.				-0.49			
17	I like walking.					0.74		

	Attitudinal Statements	Latent Factors						
		Car-affine & pro-driving	Tech-savvy & variety-seeking	Pro-environment	Pros and cons of urban life	Pro-active	Pro-biking	Car-dependent
18	Getting regular exercise is very important to me.					0.74		
19	If I felt protected from car traffic, I would ride a bicycle more often.						0.77	
20	I like riding a bike.						0.74	
21	Most of the time, I have no reasonable alternative to driving.							0.7
22	My schedule makes it hard or impossible for me to use public transportation.							0.57

[1] Numbers in the table are factor loadings of attitudinal statements, which quantifies the extent to which a given attitudinal statement is related to a given latent factor. Factor loadings with an absolute value lower than 0.30 are omitted from the table.

Mathematically, we utilized an integrated choice and latent variable (ICLV) model, which combines two sub-models: a latent variable model and a traditional discrete choice model (Abou-Zeid & Ben-Akiva, 2014). The latent variable model evaluates the relationship between observable features of individuals (such as sociodemographic and neighborhood characteristics, as well as COVID-19 health concerns) and their underlying psychometric factors. The discrete choice model estimates the utility of different vehicle ownership change decisions in relation to these observable factors, life events and latent factors. Figure 6-2 depicts the conceptual framework of the model.

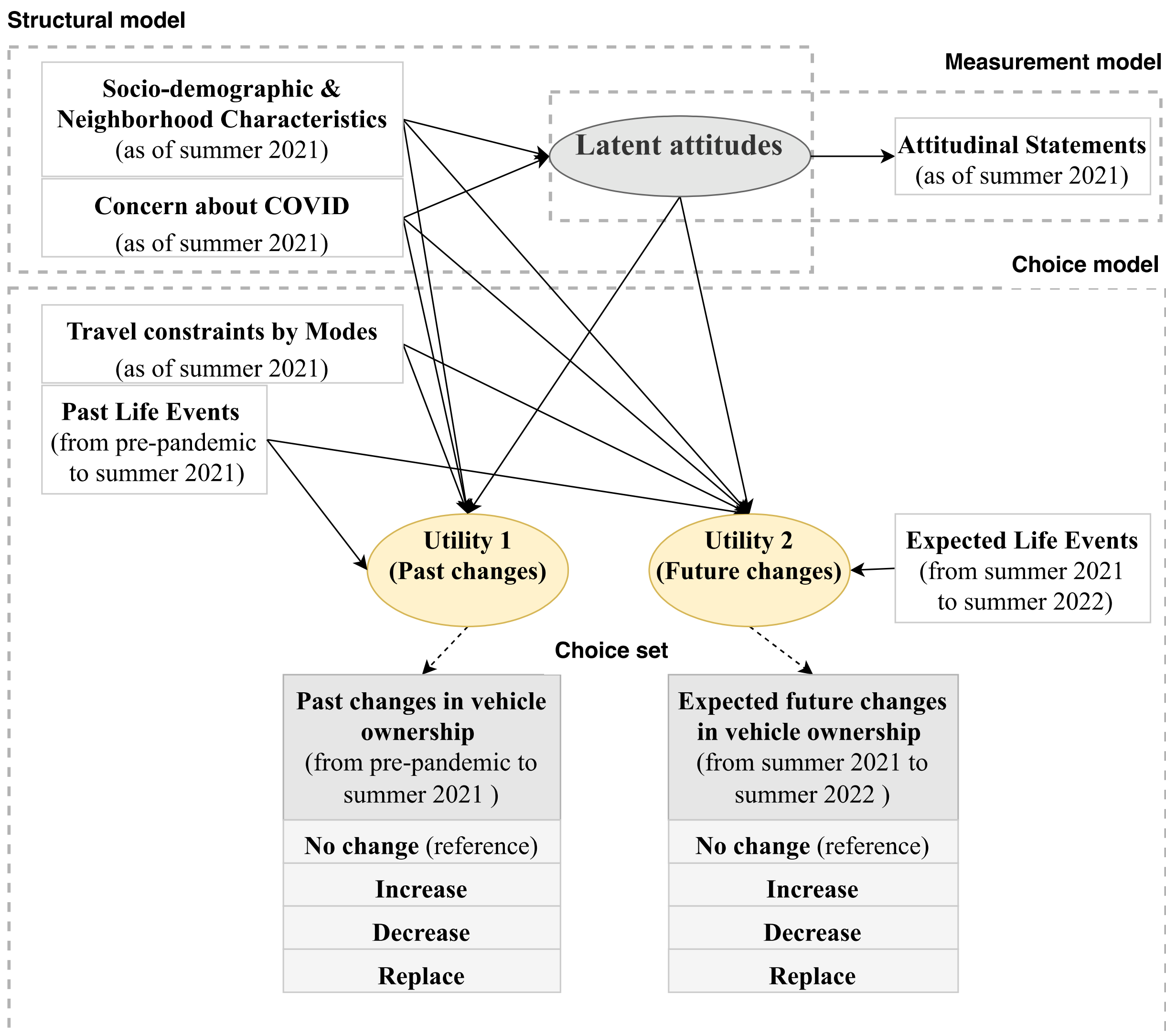

Figure 6-2. Conceptual framework of the ICLV model

6.3 Results

The final model was obtained after a systematic process of testing alternative specifications. We present the results of three sub-models separately, although all sub-models are estimated simultaneously. Only variables that are statistically significant at 10% are included in the final model specification. However, in the case when two levels of a categorical variables have different level of significance (e.g., middle age group is not statistically significant while old age group is statistically significant), we loosen this criterion and report coefficients of both levels for comparisons.

6.3.1 Identification of Related Latent Attitudes

The choice model revealed three significant latent variables: *tech-savvy & variety-seeking*, *pro-environment* and *pro-active lifestyle*. The results are more or less consistent with initial factor analysis. The estimated coefficients for the structural equations are presented in Table 6-2 confirming the hypothesis that the socio-demographic attributes have a significant impact on attitudes and lifestyles. The results reveal that certain groups are more likely to be tech-savvy and variety-seeking than others, including those with Hispanic, Latino or Spanish origin, white, females, students, homeowners, and those with children and higher incomes. Pro-environment attitudes were found to be more common among females, individuals with higher education levels, and those with higher household incomes (Dietz, Kalof, & Stern, 2002), while suburban and rural residents were less likely to exhibit these attitudes (Ambrosius & Gilderbloom, 2015). In contrast, a pro-active lifestyle was found to be more prevalent among white individuals, those with higher education levels, workers, high-income earners, those with multiple household members, and homeowners. These findings are in line with the literature which reveal more walking among adults with high income and socio-economic status (Mondschein, 2021). Notably, we also found that those who are more concerned about the health impacts of the COVID by summer 2021 are more likely to embrace pro-active lifestyle. As they practice social distancing, reducing the use of shared travel modes and public indoor spaces (e.g., gyms, fitness centers), many people have resorted to alternative ways, such as walking or biking, for traveling, engaging activities and keeping physical fitness (Cusack, 2021).

Table 6-2. Estimation results from the structural equations

Variables	Categories	Tech-savvy and variety-seeking	Pro-environment	Pro-active lifestyle
Ethnicity (ref: Non-Hispanic, Latino, or Spanish)	Hispanic, Latino, or Spanish	0.44 (4.58)***		
Race (ref: non-white)	White	1.08 (13.97)***		1.58 (6.61)***
Gender (ref: non-female)	Female	0.74 (12.36)***	0.22 (3.28)***	
Education attainment (ref: lower than bachelor's degree)	Bachelor's degree or higher		0.51 (6.68)***	0.88 (4.84)***
Student status (ref: non-students)	Student	0.73 (6.19)***		
Employment status (ref: non-workers)	Full-time workers			0.79 (4.61)***
	Part-time workers			1.22 (5.63)***
Household Annual income (ref: less than $50,000)	$50,000 - $99,999	0.97 (10.60)***	0.32 (3.83)***	0.74 (4.72)***
	$100,000 or more	0.87 (8.75)***	0.20 (2.14)**	0.25 (1.90)*
Household size (ref: one member)	Two members			1.21 (6.29)***
	Three or more members			1.32 (6.53)***
Presence of kid(s) (ref: no)	Yes	0.48 (6.81)***		
Housing Tenure (ref: rent or other)	Own	0.51 (7.16)***		0.35 (3.39)***
Neighborhood type (ref: rural)	Suburban		-0.18 (-2.38)**	
	Rural		-0.33 (-2.89)***	

Variables	Categories	Tech-savvy and variety-seeking	Pro-environment	Pro-active lifestyle
Concern about health impacts of the COVID (ref: not concern)	Somewhat concern			2.37 (6.71)***
	Strongly concern			2.61 (6.95)***

Note: Statistics in the table represent coefficients, robust t-statistics, significance level (*10%, **5%, ***1%).

6.3.2 Factors Impacting Vehicle Ownership Change

Table 6-3 reports the results from the two multimodal logit models concurrently modeling past and expected future vehicle ownership change and no change is the reference category. For dummy or categorical independent variables that representing two or more population segments, one of the segments is set as the reference category. Therefore, a positive parameter in the table indicates that compared to the individuals in the referenced group, this group of individuals have higher likelihood of changing their vehicle ownership (e.g., increase/decrease/replace) than no change.

It is not surprising that individuals who are *tech-savvy and variety-seeking* tend to have more fluctuating vehicle ownership status. These attitudes often result in them acquiring new vehicles, disposing of their old vehicles, or "updating" their existing ones during the pandemic. This trend was expected to continue in the coming year, although they may not decrease their vehicle. On the other hand, those who are more *pro-environment* were more likely to have reduced during the pandemic or expected to decrease their vehicle, yet not replace their vehicles in the future. This makes sense considering that they are more willing to raise the cost of driving to subsidize public transit and minimize the impact of transportation on the environment, as discussed previously. We also found that *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, 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 their vehicle ownership patterns. In fact, our survey found that older individuals were less likely to have increased or decreased their vehicle ownership in the past, and were also less likely to plan to increase their ownership in the future. This is because their household structure, financial status, lifestyle, and travel needs tend to be more stable. Interestingly, our survey revealed that a disproportionate number of car augmenters (i.e., those planning to increase their vehicle ownership) were aged 18 to 34. This age group accounted for only 23.8% of the total population surveyed, yet represented 37.3% of car augmenters. These findings are consistent with a global survey conducted in August 2020, which suggested that Millennials are likely to spearhead a COVID-induced car ownership surge (EY Global, 2021). Females were less likely to consider increasing or replacing their vehicle in the future. This is in line with previous research indicating that females tend to exhibit less car dependency than males, even though the gender gap in private transport use may be narrowing over time (den Braver et al., 2020; Guan & Wang, 2019). Individuals with higher educational attainment status by summer 2021 were less likely to plan on decreasing their vehicles 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 during the pandemic 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. This may be because part-time workers often have multiple jobs in different locations that require in-person attendance, making personal vehicle ownership a necessity. In fact, among our survey respondents, part-time workers were more likely to be essential workers in education, healthcare and retail sectors. As alternative means of travel (e.g., public transit) were limited due to reduced capacity, some might have to add vehicles into their household, even if they are not in the best financial situations. Furthermore, our study found that those who transitioned from workers to non-workers tend to decrease their vehicle ownership, while those who transitioned from non-workers to workers were more likely to replace their vehicles.

Individuals with a driver's license were more likely to anticipate replacing their vehicle within a year compared to those without a license. On the other hand, individuals with physical or personal conditions that prevent or limit their ability to drive were more likely to plan on reducing their vehicle ownership.

Individuals from households with higher annual income, particularly those earning $100,000 or more, 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 (Goodwill, 1993). Interestingly, we also found that, in general, 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 may have more dynamic travel needs and preferences, as well as greater financial burden of vehicle ownership and maintenance, making them more likely to adjust their vehicle ownership based on changing circumstances.

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 also more were more likely to report plans to increase their vehicles in the future. These findings are consistent with previous research that has highlighted the impact of children on household vehicle ownership decisions (Lee & Goulias, 2018). This is likely because households with children have more complex travel needs, such as transporting children to school, extracurricular activities, and medical appointments, which is harder to manage using alternative modes. Additionally, households with children may feel a greater sense of responsibility to ensure reliable transportation for their family. Consistent with a previous study (Yamamoto, 2008), we found that decrease in household size is associated with a reduction in vehicles.

Somewhat surprisingly, houseowners were found to be less likely to increase their vehicle ownership. We believe this again highlights the nuanced relationship between certain variables and vehicle ownership change, which may not always align with their effect on overall ownership statues. In this case, it is well-established that homeowners generally own more vehicles already, but their travel needs are likely met without adding more vehicles. Related to this, 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 individuals who somewhat or strongly concern about the health impact of COVID-19 by summer 2021 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 the lingering concerns about the pandemic (Loa et al., 2021; Zhang et al., 2021).

Table 6-3. Estimation results from the discrete choice model

Variables	Categories	Past changes in vehicle ownership (Pre-pandemic→ summer 2021, "no change" as the reference)			Expected future changes in vehicle ownership (Summer 2021→ summer 2022, "no change" as the reference)		
		Increase	**Decrease**	**Replace**	**Increase**	**Decrease**	**Replace**
Constants		-4.71 (-7.80)***	-5.39 (-6.73)***	-3.42 (-9.49)***	-3.39 (-5.56)***	-5.01 (-5.77)***	-3.39 (-6.79)***
Attitudes (as of summer 2021)							
Tech-savvy & variety-seeking		0.56 (3.11)***	0.48 (2.43)**	0.44 (3.74)***	0.59 (3.29)***		0.44 (3.91)***
Pro-environment			0.28 (2.16)**			0.31 (1.91)*	-0.15 (-2.30)**
Pro-active lifestyle					-0.24 (-2.89)***		
Sociodemographic Characteristics (as of summer 2021)							
Age (ref: 18-34)	35-64	-0.27 (-1.29)	-0.26 (-1.12)		-0.31 (-1.71)*		
	65 or over	-0.87 (-2.20)**	-0.73 (-2.19)**		-1.66 (-3.98)***		
Gender (ref: non-female)	Female				-0.39 (-2.50)**		-0.23 (-2.05)**
Education attainment (ref: lower than bachelor's degree)	Bachelor's degree or higher					-0.54 (-2.11)**	
Student status (ref: non-students)	Student				0.54 (2.34)**		
Employment status (ref: non-workers)	Full-time workers	-0.54 (-2.44)**	-0.54 (-1.91)*		-0.01 (-0.03)		0.33 (2.32)**
	Pat-time workers	-0.08 (-0.35)	0.19 (0.71)		0.67 (2.85)***		0.47 (2.89)***
Having a driver's license (ref: no)	Yes						0.67 (1.83)*
Constraints on driving (ref: no)	Yes		0.93 (3.48)***				

Variables	Categories	Past changes in vehicle ownership (Pre-pandemic→ summer 2021, "no change" as the reference) Increase	Decrease	Replace	Expected future changes in vehicle ownership (Summer 2021→ summer 2022, "no change" as the reference) Increase	Decrease	Replace
Household Annual income	$50,000 - $99,999	0.36		0.27			
(ref: less than $50,000)		(1.3)		(1.62)			
	$100,000 or more	0.7		0.41			
		(2.44)**		(2.45)**			
Household size	Two members	0.81	0.9	0.68	0.86	0.50	0.37
(ref: one member)		(2.31)**	(3.06)***	(3.78)***	(2.91)***	(1.27)	(2.15)**
	Three or more members	1.08	1.09	0.54	1.05	0.80	0.92
		(2.85)***	(3.37)***	(2.61)**	(3.48)***	(2.08)**	(5.4)***
Presence of kid(s)	Yes	0.47	-0.59	0.33	0.45		
(ref: no)		(2.07)**	(-2.20)**	(2.02)**	(2.22)**		
Housing Tenure	Own	-0.48					
(ref: rent or other)		(-2.33)**					
Past (between pre-pandemic and summer 2021) and Expected (between summer 2021 and summer 2022) Life Events							
Change in education attainment	Increase		-0.99				
(ref: no change)			(-1.84)*				
Change in student status	Student to non-student	0.76	0.88		0.27	1.10	
(ref: no change)		(2.17)**	(2.43)**		(0.77)	(2.36)**	
	Non-student to student	-0.67	0.32		0.77	-0.15	
		(-1.06)	(0.71)		(2.42)**	(-0.2)	
Change in work status	Worker to non-worker		1.12				-0.50
(ref: no change)			(3.58)***				(-1.44)
	Non-worker to worker		-0.1				0.76
			(-0.19)				(2.81)**
Change in household size	Decrease		1.05				
(ref: no change)			(3.81)***				
	Increase		0.1				
			(0.27)				

		Past changes in vehicle ownership (Pre-pandemic→ summer 2021, "no change" as the reference)			Expected future changes in vehicle ownership (Summer 2021→ summer 2022, "no change" as the reference)		
Variables	**Categories**	**Increase**	**Decrease**	**Replace**	**Increase**	**Decrease**	**Replace**
Change in household income	Decrease	0.00		0.31			
(ref: no change)		(0.01)		(1.96)*			
	Increase	0.47		0.06			
		(2.23)**		(0.38)			
Residential relocation	Moved		0.59				
(ref: did not move)			(1.7)*				
COVID-related Factor (as of summer 2021)							
Health Concerns about COVID	Somewhat concern				0.57		
(ref: not concern)					(1.96)*		
	Strongly concern				0.52		
					(1.79)*		
# of Observation		(Increase: Decrease: Replace: No change=145:121:418:1599)			(Increase: Decrease: Replace: No change=193:70:439:1581)		
LL(equally-likelihood model)				-3049.15			-3049.15
LL(final model)				-1890.37			-1894.35

Note: Statistics in the table represent coefficients, robust t-statistics, significance level (*10%, **5%, ***1%).

7 Impacts of the COVID-19 Pandemic on Shopping Patterns

The pandemic-related lockdown measures have significantly limited people's ability to shop in-person. This has led to an increase in e-shopping. However, there remains much uncertainty surrounding the ways in which these new shopping behaviors have and may continue to transform our day-to-day activities, travel behaviors, and urban landscapes. One of the big questions related is whether new e-commerce habits that have been eventually established during the pandemic might carry forward once life will go back to "normal". Some new e-customers could go back to shopping in person, others will stick to it. Understanding the factors that influence the changes in grocery shopping behavior due to the COVID-19 is crucial for business development and public entities to better tackle situations of crisis and high stress.

In this section, we will present two studies to address following questions: How in-person and online shopping patterns changed during the pandemic and how may it evolve into the future? who has adjusted their grocery shopping patterns during the early stage of the pandemic, and what factors affected their changes.

7.1 The increase in online shopping during COVID-19[4]

7.1.1 Introduction

The e-commerce sector has caught the attention of policymakers and has led many to examine the determinants of new shopping behavior during the pandemic, due to its broader socioeconomic and behavioral implications, which may include influencing residential location decisions, modifying travel mode preferences, and changing day-to-day retail activities (Circella & Mokhtarian, 2017). We attempt to explore two fundamental questions: 1) who is responsible for the recent rise in e-commerce, and 2) to what extent will the growth in online shopping induced by COVID-19 persist into the future?

Our study proposes to compare the use and frequency of e-shopping before COVID-19 (Fall 2019) to both the Spring 2020 and Fall 2020 periods in order to uncover the short- and longer-term impacts of the pandemic on individuals' e-shopping habits. Beyond descriptively presenting which factors have influenced the likelihood to partake in online shopping during the early and later months of the COVID-19 pandemic, the longitudinal nature of our dataset also enables us to model changes in the frequency of e-shopping over time and hypothesize on the role it will play in our economy going forward. Using the breadth of attitudinal questions in our survey, we will further examine whether—and to what extent—personal preferences, including users' satisfaction with online and in-person shopping, influence their use and frequency of e-shopping. We will also be comparing the behaviors of respondents from 11 U.S. cities and will be controlling for city-specific characteristics to account for potential differences in the severity of COVID-19-related restriction measures and the ways in which these may have

[4] 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: *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*

led respondents to experiment with online shopping different. In the next section we describe our dataset and the cities included in this study and present the modeling approach employed for this research.

Our results indicate that the rate of online shopping has increased approximately five-fold between Fall 2019 and the early months of the pandemic (Spring 2020). Benefiting from responses over a longer period of time, we are further able to examine whether this increase persists throughout the pandemic and find it to be rather short-lived, as the frequency of e-shopping decreases to more modest levels in the Fall 2020 period. We further establish that experienced online shoppers (i.e., those frequently partaking in this behavior prior to the start of the pandemic) account for the majority of the growth in online shopping in the longer term. Findings from this study will prove valuable to researchers interested in the economic implications of the pandemic and to policymakers seeking to properly regulate the online shopping sector to ensure it aligns with cities' equitable and sustainable objectives. Transportation and city planners also have much to gain from this analysis, as the transition towards e-shopping is poised to lead to a sizable reduction in the frequency of shopping-related trips and influence residents' housing location decisions and understanding whether these changes are temporary or long lasting is of paramount importance.

7.1.2 Data and Method

To conduct our longitudinal analysis, we restricted our analysis to those recruited through the Fall 2020 re-contact method who had also 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 the Fall 2019 responses collected in the Fall 2020 COVID-19 Mobility Study serving as the time period before the pandemic (T_1), the Spring 2020 COVID-19 Mobility Study representing the time period during the early months of the pandemic (T_2), and the 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 specifically asked to report responses during the period between March-April 2020, whereas participants in the Fall 2020 version of the survey were asked to report responses in the period between October-December 2019 and 2020.

Following the creation of the merged dataset and the removal of entries with missing values and/or non-responses, we chose to restrict our analysis to cities with at least 100 respondents as to avoid an insufficient sample size biasing our results. This includes four cities in California (Los Angeles, San Francisco, San Diego, and Sacramento), as well as seven other cities across the U.S. (New York City, Chicago, Boston, Washington D.C., Atlanta, Seattle, and Detroit). A summary of respondents' online shopping frequency per time periods in our study is presented in Table 7-1.

Table 7-1. Online shopping frequency per timepoint

Online Shopping Frequency	Fall 2019 (n = 1,722)	Spring 2020 (n = 1,722)	Fall 2020 (n = 1,722)
Never	25.9%	18.4%	10.8%
Less than once per month	24.9%	10.0%	20.1%
1–3 times per month	37.6%	20.4%	44.0%
1-2 times per week	8.6%	32.7%	18.5%
3 or more times per week	3.0%	18.5%	6.6%
Total	100.0%	100.0%	100.0%

Table 7-1 reveals that the proportion of respondents that shop online at least once a week has increased nearly five-fold between the Fall 2019 (11.6%) and Spring 2020 (51.2%) periods. This proportion has since diminished to 25.1% in the Fall 2020 period, which remains sizably more than in Fall 2019, but also suggests that the large initial rise in e-shopping observed in the early months of the pandemic may have been short-lived and that the longer-term impacts of COVID-19 on the frequency of e-shopping may have been more modest. Moreover, while the five-fold increase in online shopping may have been temporary, the proportion of respondents who indicate that they never shop online appears to have diminished throughout our study period. This in turn may imply that e-commerce is now reaching a broader base of users and is something we will explore in more detail in the Result subsection.

To model online shopping frequency during the three time periods of analysis, a set of consecutive Ordinal Logit Models were estimated (McCullagh, 1980). We opted for this method as the nature of our variable of interest, namely online shopping frequency, is ordered and discrete, as presented in Table 7-1. 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 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.

7.1.3 Results

7.1.3.1 Extent to which the e-shopping sector was able to capture and retain new users

In Table 7-2 we present the descriptive characteristics of respondents and separate them based on their online shopping frequency per time period in our dataset. In accordance with previous studies, we find that prior to the pandemic (Fall 2019), wealthier and higher educated individuals are more likely to shop online and that older individuals are less likely to partake in this behavior. In this initial time period, we further find men to be slightly more likely to shop online than women. However, this trend appears to reverse itself once the pandemic starts (i.e., Spring 2020), as men become notably more likely to report never shopping online whereas women now indicate doing so more frequently. In the early stages of the pandemic, all age and income categories increase their online shopping frequency. The only partial exception is younger individuals (aged 18-24), which despite exhibiting an increase in online shopping frequency, do not display a reduction in the proportion of non-users. Education is also found to be positively correlated with online shopping frequency in the Spring 2020 period, with respondents holding undergraduate or graduate degrees being more than twice as likely to frequently shop online (i.e., 3 or more times per week) in comparison to those who have started or only completed high school.

As the pandemic progresses, the effect of gender eventually subsides. In the longer-term (i.e., Fall 2020), men and women become just as likely to shop online and while the frequency at which they do so diminishes in comparison to the Spring 2020 period, It remains well above their pre-pandemic levels. The share of men and women who have never purchased goods online also diminishes throughout the pandemic and falls to approximately 10% for both genders in Fall 2020. The older, less wealthy, and less educated segments of the population remain the least likely to shop online in the Fall 2020 period, but along with all other age, income, and education categories, they appear to have increased their e-shopping frequency in comparison to the pre-pandemic level—although at a more modest rate than in Spring 2020.

Together, this descriptive analysis suggests that the COVID-19 pandemic has led to a significant increase in online shopping frequency, particularly in the short term, as the magnitude of this increase also appears to have become less pronounced over time. The temporal variation in online shopping frequency is presented in Figure 7-1, and 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 in the longer-term, while not giving up this behavior entirely.

In Table 7-3, we further explore respondents' online shopping behaviors by grouping them based on their e-shopping frequency over time. Only 32.9% of respondents who never shopped online in the Fall 2019 period continue to do so in the early months of the pandemic (Spring 2020). Unsurprisingly, 51.9% of those who shopped online frequently (3 or more times per week) before the pandemic continue to do so in Spring 2020, and this increases to 65.4% in the Fall 2020 period. A closer examination of the group that never shopped online in Fall 2019 reveals that 37.2% began shopping online at least once per week at the onset of the COVID-19 pandemic, which suggests that at least in the short-term, the e-commerce sector was able to reach a broader share of the population. However, the magnitude of this finding does subside in the longer-term, as 57.9% of the respondents in this group revert to never shopping online or doing so less than once per month in the Fall 2020 period. A similar result is established when examining the group of respondents who frequently shopped online (3 or more times per week) in the early stages of the COVID-19 pandemic; only a quarter of them were found to also shop online at least once per week prior to the pandemic. This finding once again, support the hypothesis that the e-commerce sector was able to capture a share of the population that previously did not use this service, but that in the longer-term, the majority (59.3%) of respondents continue to frequently shop online are those that did so at least once per week prior to the pandemic.

Table 7-2. Descriptive characteristics of online shopping frequency per time period

		Never			Less than once a month			1-3 times a month			1-2 times a week			3 or more times a week			Total
Time period		F19 (%)	S20 (%)	F20 (%)	F19 (%)	S20 (%)	F20 (%)	F19 (%)	S20 (%)	F20 (%)	F19 (%)	S20 (%)	F20 (%)	F19 (%)	S20 (%)	F20 (%)	N. of obs.
Gender	Male	23.1	21.2	10.5	25.9	10.0	21.7	37.3	18.8	44.2	9.5	32.9	17.7	4.1	17.1	6.0	702
	Female	27.9	16.5	11.1	24.2	10.0	19.1	37.6	21.6	43.8	7.9	32.5	19.0	2.3	19.4	7.0	1,020
Age	18-34	19.2	14.8	8.4	19.2	12.1	14.5	42.4	18.9	46.8	12.5	36.4	21.9	6.7	17.8	8.4	297
	35-64	25.9	18.4	9.3	25.3	8.5	20.5	37.0	19.8	43.6	9.0	32.4	19.0	2.8	21.0	7.6	997
	65+	30.8	21.0	16.1	28.0	11.9	23.4	35.3	23.1	42.8	4.9	30.8	15.0	0.9	13.1	2.8	428
Income	Less than $50,000	31.6	28.0	15.3	26.3	11.5	25.1	33.6	18.6	43.1	5.6	28.6	12.7	2.9	13.3	3.8	339
	$50,000 to $99,999	24.6	14.1	11.0	26.4	11.5	20.5	34.9	24.9	42.3	11.8	31.8	19.7	2.3	17.7	6.4	390
	$100,000 to $149,999	24.1	13.4	10.0	27.2	10.0	20.7	35.5	23.8	46.2	9.3	32.8	16.6	3.8	20.0	6.6	290
	$150,000 or more	19.4	12.7	5.3	22.6	5.7	14.1	43.5	16.6	43.5	10.2	35.0	25.8	4.2	30.0	11.3	283
	Prefer not to answer	25.5	17.6	11.8	21.6	11.8	15.7	37.3	15.7	39.2	11.8	37.3	25.5	3.9	17.6	7.8	51
Education	Started/completed high school	29.8	25.5	12.6	27.1	11.0	21.7	33.6	20.5	43.8	7.4	29.8	16.9	2.1	13.3	5.0	420
	Some college/technical school	33.6	29.7	17.2	27.3	9.4	23.4	28.9	18.0	41.4	7.0	33.6	13.3	3.1	9.4	4.7	128
	Bachelor's degree(s)	24.8	16.8	10.0	22.5	9.0	21.1	41.5	21.7	42.1	8.4	32.3	20.8	2.8	20.1	6.0	653
	Graduate degree(s)	17.7	8.9	3.8	22.8	6.3	12.7	40.5	15.2	46.8	11.4	39.2	25.3	7.6	30.4	11.4	79
	Professional degree(s)	23.3	12.4	10.0	26.0	11.3	17.6	37.3	20.1	47.1	10.0	34.6	16.7	3.4	21.5	8.6	442
Number of observations (count)		447	317	187	429	172	347	646	352	757	148	563	318	52	318	113	1,722

Table 7-3. Respondents online shopping behavior over time (column-wise percentages in parenthesis)

		Spring 2020					
		Never (n = 317)	**Less than once a month (n = 172)**	**1-3 times a month (n = 352)**	**1-2 times a week (n = 563)**	**3 or more times a week (n = 318)**	**Total (n = 1,722)**
Fall 2019	Never (n = 447)	32.9% (46.4%)	12.8% (33.1%)	17.2% (21.9%)	24.2% (19.2%)	13.0% (18.2%)	100.0%
	Less than once a month (n = 429)	21.9% (29.7%)	13.8% (34.3%)	27.5% (33.5%)	25.9% (19.7%)	11.0% (14.8%)	100.0%
	1-3 times a month (n = 646)	10.8% (22.1%)	7.9% (29.7%)	20.0% (36.6%)	40.7% (46.7%)	20.6% (41.8%)	100.0%
	1-2 times a week (n = 148)	2.0% (0.9%)	3.4% (2.9%)	14.2% (6.0%)	44.6% (11.7%)	35.8% (16.7%)	100.0%
	3 or more times a week (n = 52)	5.8% (0.9%)	0.0% (0.0%)	13.5% (2.0%)	28.8% (2.7%)	51.9% (8.5%)	100.0%
	Total (n = 1,722)	(100.0%)	(100.0%)	(100.0%)	(100.0%)	(100.0%)	

		Fall 2020					
		Never (n = 187)	**Less than once a month (n = 347)**	**1-3 times a month (n = 757)**	**1-2 times a week (n = 318)**	**3 or more times a week (n = 113)**	**Total (n = 1,722)**
Fall 2019	Never (n = 447)	34.2% (81.8%)	23.7% (30.5%)	30.4% (18.0%)	8.7% (12.3%)	2.9% (11.5%)	100.0%
	Less than once a month (n = 429)	4.0% (9.1%)	43.4% (53.6%)	41.3% (23.4%)	9.1% (12.3%)	2.3% (8.8%)	100.0%
	1-3 times a month (n = 646)	1.9% (6.4%)	7.7% (14.4%)	64.4% (55.0%)	22.4% (45.6%)	3.6% (20.4%)	100.0%
	1-2 times a week (n = 148)	2.7% (2.1%)	2.0% (0.9%)	15.5% (3.0%)	57.4% (26.7%)	22.3% (29.2%)	100.0%
	3 or more times a week (n = 52)	1.9% (0.5%)	3.8% (0.6%)	9.6% (0.7%)	19.2% (3.1%)	65.4% (30.1%)	100.0%
	Total (n = 1,722)	(100.0%)	(100.0%)	(100.0%)	(100.0%)	(100.0%)	

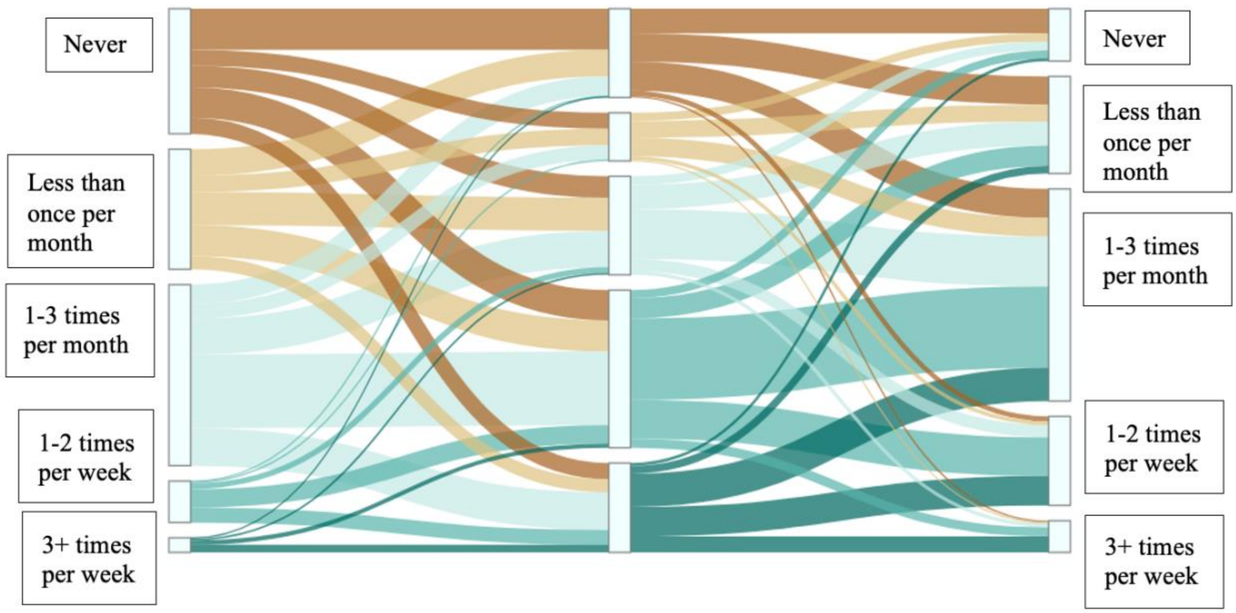

Figure 7-1. Visualization of online shopping frequency over time (n = 1,722)

7.1.3.2 An examination of who changed their e-shopping behavior during the pandemic

With an understanding of the factors that may influence the likelihood to shop online both before and during the COVID-19 pandemic, as well as an awareness that the increase in e-shopping observed in the earlier months of the pandemic may have been short-lived, we now conduct 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, namely: "never", "less than once per month", "1-3 times per month", "1-2 times per week", and "3 or more times per week". Regression coefficients are presented in Table 7-4 and Table 7-5 are subsequently presented as marginal effects in which particular emphasis placed on explanatory variables that influenced the likelihood to "Never" shop online or do so "3 or more times per week" over the three time periods in our study.

Prior to the start of the pandemic, younger respondents (aged 18 to 34) where more likely to shop online. However, the significance of this relationship subsides once the pandemic starts, as respondents from all age categories become confronted with the same COVID-19 restriction measures and many resort to shopping online instead. Interestingly, with regards to gender we find that men were more likely to shop online in the Fall 2019 period, but that women became significantly more likely to do so once the pandemic began. Indeed, women were 4% more likely than men to "never" have shopped online in Fall 2019 but became 2.6% and 1.7% less likely to belong to this category in the Spring and Fall 2020 periods, respective. This result corroborates recent research by Jaller and Pahwa (2020) that also finds a reversal in the impact of gender on e-shopping frequency in recent years, and may suggest that this trend was occurring even before the start of the pandemic. Education, which was not significant in Fall 2019, does appear 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 likelihood to do so at least 3 times per week. Using the adjusted income variable, modified to account for household composition and regional cost of living, we find that respondents from the highest income group (those with an annual household income over $89,377) were more likely to shop online in the Fall 2019 and Fall 2020 periods, in comparison to those belonging to the lowest income group (those with an annual household income $24,943). Also noteworthy is that this relation is not significant in the Spring 2020 period, when 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. (2013) we find that respondents living in urban neighborhoods shop online more frequently than their suburban or rural counterparts in the Fall 2019 period. However, this relation appears to reverse itself once the pandemic begins as suburbanites become 2.6% and 1% more likely to frequently shop online in Spring 2020 and Fall 2020, respectively, when compared to those living in urban areas. This, we surmise, may perhaps be due to the proliferation of malls in suburban areas, which often could not facilitate curbside pickup (in comparison to centrally located stores which were more likely to provide this service) and may have led some shoppers to feel unsafe and unwilling to shop in-person. The reduction in this effect over time further supports this hypothesis, as malls were gradually able to reopen.

Owning digital devices also appears to have had an effect on the frequency of online shopping. Prior to the start of the pandemic, owning fast Internet significantly increased the likelihood that respondents would shop online. A responded with out 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 frequently online (3+ times per week) in the Spring 2020 period.

Attitudes towards e-shopping also influence the likelihood that respondents will shop online. Respondents who indicated being satisfied with online shopping options available to them are also more likely to use this service. In contrast, those who state that they are able to find everything they need when physically going to the grocery store are significantly less likely to shop online, particularly in the early months of the pandemic when agreeing with this statement leads to a 3.3% increase in the likelihood that respondents have never shopped online. Although our survey does not ask respondents whether they were able to find non-grocery items when shopping in-person, we believe this grocery question serves as an adequate proxy for consumers' attitudes towards in-person shopping.

Despite COVID-19 lockdown measures varying quite drastically among cities and regions in the U.S., we do not find much variation in terms of online shopping frequency at a city-level. This finding supports the notion that the severity of the COVID-19 pandemic led many to change their purchasing behaviors in favor of online shopping, and that controlling for city-specific features—such their Covid-19 restriction measures—may not be necessary.

Lastly, to account for respondents' initial online shopping behavior, we also include their Fall 2019 online shopping frequency levels in the Spring 2020 and Fall 2020 models. We find that those who frequently shopped online in Fall 2019 were also more likely to continue doing so in the subsequent time periods. Indeed, respondents who shopped online 1-3 times per month in the Fall 2019 were 12.1% more likely to shop online 3+ times per week in Spring 2020 and 7.7% more likely to do so in the Fall 2020 period. These rates increased even higher for respondents who already shopped online 1-2 times per week in Fall 2019, as the likelihood of them doing so 3+ times per week in Spring 2020 was 29.7% and rose to 47.6% in Fall 2020. This finding is of particular importance for this study, as it suggests that the recent rise e-commerce induced by COVID-19 was, especially in the longer-term, primarily caused by an increase in purchasing frequency of experienced online shoppers rather than the result of this sector now reaching a broader share of the population.

Table 7-4. Ordered logistic regressions to determine who modified their online shopping behavior during the COVID-19 pandemic

		Likelihood to shop online		
		Fall 2019	**Spring 2020**	**Fall 2020**
Age	18-34 [Reference]			
	35-64	-0.517**	0.137	0.227
	65+	-0.897**	-0.097	-0.168
Gender	Male [Reference]			
	Female	-0.226*	0.210*	0.291**
Education	Started/completed high school or GED [Reference]			
	Some college/technical school	0.005	0.019	-0.322
	Bachelor's degree(s)	0.246	0.227	-0.062
	Graduate degree(s) (e.g., MS, PhD, MBA)	0.369	0.935**	0.402
	Professional degree(s) (e.g., JD, MD, DDS)	0.115	0.477**	0.096
Adjusted income [a]	Less than $24,943 [Reference]			
	24,943 to $39,349	0.203	0.066	0.208
	39,349 to $59,714	0.342*	0.247	0.020
	59,714 to $89,377	0.269	0.361*	0.258
	More than $89,377	0.372*	0.146	0.358*
Neighborhood type	Urban [Reference]			
	Suburban	-0.321**	0.190*	0.382**
	Rural or small town	-0.442	0.088	0.384
Attitudes	Own a smartphone	0.416	0.903**	0.534
	Own fast internet	0.857**	0.282	-0.299
	Satisfied with online shopping	0.219**	0.242**	0.250**
	Able to find everything in grocery store	-0.188**	-0.266**	-0.204**
	Able to find everything while shopping online	0.106	0.018	0.080

		Likelihood to shop online		
		Fall 2019	Spring 2020	Fall 2020
City	Los Angeles [Reference]			
	Atlanta	-0.252	-0.304	-0.252
	Boston	-0.022	-0.434	-0.515*
	Chicago	-0.400	-0.270	-0.554*
	Detroit	-0.520*	-0.687**	-0.399
	New York	-0.426*	-0.139	0.018
	Sacramento	-0.236	0.048	-0.344
	San Diego	-0.111	-0.169	-0.288
	San Francisco	-0.488**	-0.062	-0.334
	Seattle	0.125	-0.072	-0.556*
	Washington DC	-0.086	0.240	0.206
E-shopping freq. Fall 2019	Never [Reference]			
	Less than once a month		-0.028	0.671**
	1-3 times per month		0.824**	1.993**
	1-2 times a week		1.544**	3.915**
	3 or more times a week		1.966**	5.144**
Number of observations		1,302	1,302	1,302
Never | < 1 time per month		-0.128	0.417	-0.199
< 1 time per month | 1-3 times per month		1.086*	1.082*	1.455**
1-3 times per month | 1-2 times per week		3.110**	2.159**	4.043**
1-2 times per week | 3+ times per week		4.601**	3.834**	6.124**
Log-Likelihood (null)		-1,750.627	-1,876.863	-1,551.164
Log-Likelihood (final)		-1,817.643	-2,012.880	-1,849.327
R-squared		0.037	0.068	0.161

[a] The income variable was adjusted to account for household composition and regional cost of living.

Table 7-5. Ordered logistic regressions corresponding marginal effects (depicting the likelihood to "Never" shop online and to do so "3+ times per week" across study periods)

		Fall 2019		Spring 2020		Fall 2020	
		Never	3+ times a week	Never	3+ times a week	Never	3+ times a week
Age	18-34 [Reference]						
	35-64	0.091	-0.015	-0.017	0.019	-0.013	0.006
	65+	0.180	-0.020	0.012	-0.013	0.010	-0.004
Gender	Male [Reference]						
	Female	0.040	-0.006	-0.026	0.028	-0.017	0.008
Education	Started/completed high school) [Reference]						
	Some college/ technical school	-0.001	0.000	-0.002	0.003	0.021	-0.008
	Bachelor's degree(s)	-0.044	0.007	-0.027	0.032	0.004	-0.002
	Graduate degree(s)	-0.061	0.012	-0.085	0.165	-0.019	0.013
	Professional degree(s)	-0.021	0.003	-0.054	0.070	-0.005	0.003
Adjusted income	Less than $24,943 [Reference]						
	$24,943 to $39,349	-0.035	0.006	-0.008	0.009	-0.011	0.006
	$39,349 to $59,714	-0.058	0.010	-0.029	0.035	-0.001	0.001
	$59,714 to $89,377	-0.047	0.008	-0.041	0.053	-0.014	0.007
	More than $89,377	-0.063	0.011	-0.017	0.021	-0.018	0.011
Neighborhood	Urban [Reference]						
	Suburban	0.057	-0.009	-0.024	0.026	-0.022	0.010
	Rural or small town	0.088	-0.010	-0.011	0.012	-0.019	0.012
Attitudes	Own a smartphone	-0.082	0.009	-0.146	0.092	-0.038	0.011
	Own fast internet	-0.183	0.016	-0.038	0.035	0.015	-0.009
	Satisfied with online shopping	-0.040	0.006	-0.030	0.033	-0.014	0.007
	Able to find everything in grocery store	0.034	-0.005	0.033	-0.036	0.012	-0.005
	Able to find everything when e-shopping	-0.019	0.003	-0.002	0.002	-0.005	0.002
City	Los Angeles [Reference]						
	Atlanta	0.048	-0.006	0.041	-0.038	0.016	-0.006
	Boston	0.004	-0.001	0.061	-0.052	0.035	-0.011
	Chicago	0.079	-0.009	0.036	-0.034	0.039	-0.012
	Detroit	0.105	-0.011	0.104	-0.076	0.026	-0.009
	New York	0.083	-0.010	0.018	-0.018	-0.001	0.000
	Sacramento	0.045	-0.006	-0.006	0.007	0.022	-0.008
	San Diego	0.021	-0.003	0.022	-0.022	0.018	-0.007

		Fall 2019		Spring 2020		Fall 2020	
		Never	3+ times a week	Never	3+ times a week	Never	3+ times a week
	San Francisco	0.095	-0.011	0.008	-0.008	0.021	-0.008
	Seattle	-0.022	0.004	0.009	-0.010	0.039	-0.012
	Washington DC	0.016	-0.002	-0.028	0.035	-0.011	0.006
E-shopping freq. Fall 2019	Never [Reference]						
	< 1 a month			0.004	-0.004	-0.033	0.021
	1-3 times a month			-0.094	0.121	-0.099	0.077
	1-2 times a week			-0.123	0.297	-0.082	0.476
	3+ times a week			-0.127	0.412	-0.070	0.780

7.2 The Change in in-store and online grocery shopping during COVID-19[5]

7.2.1 Introduction

In this study, we are interested in analyzing grocery shopping behavior changes, focusing on both in-store and online grocery shopping during vs. before the pandemic. It investigates the factors that influenced this change, for example, buying more items per visit might lead to decreasing in-store visits, or visiting only one store that offers everything vs. a variety of stores (e.g., visit one store for produce and another one for baked products) also might lead to decreasing in-store visits. We study the causal effect of the change of various activities during the pandemic, personal attitudes around lifestyle, mobility and the environment, as well as socio-demographic characteristics.

Although it is unclear what long-term impacts the pandemic will have on people's habits, some customers may become accustomed to e-shopping and reduce in-store shopping in the future (De Vos, 2020; Watanabe & Omori, 2020; Chang & Meyerhoefer, 2020; Renner et al, 2020; Severson, 2020; Redman, 2020; Mckinsey & Company, 2020). With this hypothesis in mind, we estimate a bivariate binary probit model to explore the factors that influenced the behavior change with in-store and online grocery shopping behavior using data collected from a behavioral survey relative to previous (February 2020 or earlier) and during the first phase of the pandemic (March - June 2020) in the state of California.

Findings from this investigation may be timely and crucial to provide public authorities and regulators with insights to improve the readiness of society to respond to situations of great sudden stress (e.g., a pandemic), as well as market research teams with a better understanding

[5] 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: *Compostella, J; Wang, K; Iogansen, X & Circella, G. (2023). Trips to the Grocery Store and On-line Grocery Shopping: A Comparison of Individual Behaviors Before vs. During the First Wave of the COVID-19 Pandemic. Transportation Research Record.*

of their customers' needs and changing habits, some of which might extend beyond the end of the current pandemic.

7.2.2 Data and Method

We base this study on the spring 2020 COVID dataset with the focus on the state of California. Specifically, the respondents were resided in the counties of: Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara, El Dorado, Los Angeles, Orange, Placer, Sacramento, Yolo, and San Diego.

The survey contains questions that investigate two timeframes: "before" COVID-19 (February 2020 or before) and "during" COVID-19 (March-June 2020). A total, 2,961 respondents who live in the study area completed the survey. The cleaning process left us with 2,948 complete cases. We acknowledge that only 0.02% of sample do not own a smart technology (a phone, laptop, computer desk, and tablet). This may limit the representativeness of the analysis as regard to the segment of population that were still not "connected" at the time of the data collection, or simply live without information and communication technology. Table 7-6 shows the socio-demographic traits of the group of respondents who completed the survey.

Table 7-6. Socio-demographic characteristics of the sample (n= 2,948)

		Sample	Population[6]
Gender			
	Female	1,732 (59.2%)	12,905,825 (50.5%)
	Male	1,195 (40.8%)	12,670,689 (49.5%)
Race			
	White/Caucasian	2,075 (70.4%)	15,154,197 (59.3%)
	Non-White/Caucasian	873 (29.6%)	10,422,317 (40.7%)
Ethnicity			
	Hispanic	635 (21.5%)	9,139,229 (35.7%)
	Non-Hispanic	2,313 (78.5%)	16,437,285 (64.3%)
Age			
	Youngest (18-34)	844 (28.6%)	6,357,097 (31.5%)
	Middle (35-54)	999 (33.9%)	6,872,590 (34.1%)
	Oldest (55+)	1,105 (37.5%)	6,923,718 (34.4%)
2019 annual household income (before taxes)			
	Lower (<$25,000 - $49,999)	895 (30.8%)	2,543,648 (29.1%)
	Middle ($50,000 - $99,999)	864 (29.7%)	2,309,668 (26.5%)
	Higher ($100,000+)	1,147 (39.5%)	3,875,746 (44.4%)

In this study we implement a bivariate probit model to jointly model the changes in visiting grocery stores and on-line grocery shopping during vs. before the COVID-19 pandemic as a function of some explanatory variables. The following paragraphs describe our dependent and independent variables used in the model, and then the model specifications.

[6] 2019 American Community Survey (ACS) (5-years 2019)

Dependent variables: We studied the difference between (i) change of in-store trips frequency and (ii) change of frequency in online grocery shopping. Table 7-7 shows counts and percentages of our response variables. About half of the respondents in our sample (52.7%) decreased their visits to the grocery store, while 30.80% increased online grocery shopping.

Table 7-7. Distribution of the response variables across the sample (count and % or total) (n= 2,948)

			Grocery shopping online			
			Other (0)		**Increased (1)**	
			Decreased	**Same**	**Increased**	**Total**
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%)	**1,216 (41.2%)**
		Increased	24 (0.8%)	107 (3.6%)	46 (1.6%)	**177 (6%)**
		Total	**227 (7.7%)**	**1,813 (61.5%)**	**908 (30.8%)**	**2,948 (100%)**

Independent variables: Specifically, the study includes whether having children, who are forced to stay at home during the pandemic, leads busy parents to change grocery activity. We investigate whether those who were affected by unemployment, applied for unemployment benefits, and are concerned about paying bills during the pandemic changed their grocery activities. The model includes the change in grocery shopping habits i.e., visiting only one vs. a variety of grocery stores and purchasing more items per visit. We investigate whether the reduction of going to the restaurant impacted the grocery shopping style. The model estimates the effect of the concern on the health impacts of the COVID-19 pandemic. The study observes the association between the change in long distance travel (for work or leisure) and the change in visiting grocery stores. Our expectation is that people who no longer can travel due to the pandemic make more frequent trips to the grocery store as an excuse to get out of the house. Following the methodology developed by Makino et al. (2022), the model includes the long-distance travel for work or leisure variables. We created six independent categorical variables that reflected the change of long-distance trips for work and leisure with three modes: “car”, “air” and “other”. We also investigate if traveling to work during the pandemic (including essential and non-essential workers) have an effect on the visits to the grocery store.

More on independent variables: We also observe the relationship of continuous variables with our responses. We study whether who has the tendency of doing a lot of online shopping in the past 30 days (of various type: clothing, medicines, etc.), also tends to increase online grocery shopping. We study the association between staying informed on the COVID-19 updates through media and our responses. A number of studies have shown the importance of individual attitudes in predicting behavior (Malik, Alemi & Circella, 2021). We included individual attitudes performing a factor analysis on a set of survey questions that explored respondents’ opinions during the pandemic time on issues related to transportation, residential location and lifestyles. We performed oblique rotation because we observed that the variables' correlation exceeded 0.32 in the majority of the cases meaning that there is 10% (or more) overlap in variance among them; enough variance to justify oblique rotation. The correlated variables are found to be linearly related to a smaller number of unobservable (latent) factors. In our model we only include those that theoretically support our hypotheses:

- Active lifestyle desirability: people who like to have an active lifestyle
- Material and new things desirability: people who like to have the latest, new and different things
- Environmental consciousness desirability: people who align with environmentally friendly rules.

Figure 7-2 reports the conceptual model of this study, and Table 7-8 summarizes the hypotheses.

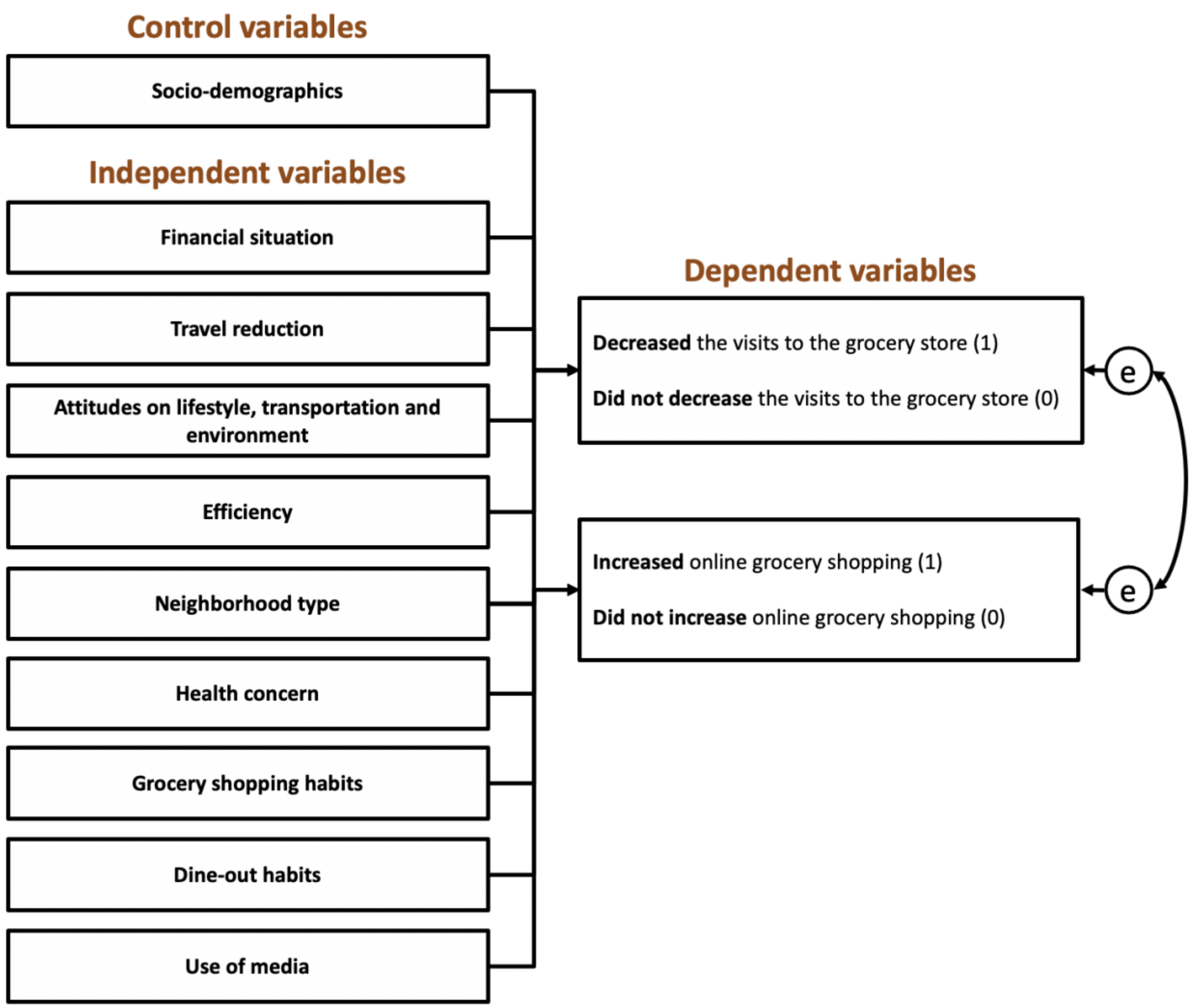

Figure 7-2. Conceptual model

Table 7-8. Hypotheses summary

Variable	Hypothesis
Older people	Decreased in-store visits
Financial situation jeopardized by the pandemic	Led not to increase on-line grocery
Having children in the household	Led to increase on-line grocery
Living in rural areas	Led not to decrease in-store visits
Keep traveling to work during the pandemic	Led not to decrease in-store visits
Long distance travel (for work or leisure) reduced by the pandemic	Led not to decrease in-store visits
Having a consumerist nature	Led not to decrease in-store visits, and increase online grocery
Buying more grocery item per purchase (bulk) vs. before the pandemic	Led to decrease in-store visits
Visiting less stores vs. before the pandemic (one single store that sells everything vs. a variety (e.g., a store for produce, another one for meat).	Led to decrease in-store visits
Reducing dining-out during the pandemic	Led not to decrease in-store visits, and increase on-line grocery
Enjoying active lifestyle	Led not to decrease in-store visits
Conforming to environmental conscious behavior	Led to decrease in-store visits
Driving and car desirability	Led not to decrease in-store visits
Media use	Led to decrease in-store visits, and increase on-line grocery
Health concern	Led to decrease in-store visits

7.2.3 Results

We found evidence that confirms the hypothesis that those who still travel to work during the pandemic are less likely to decrease their visits to the grocery stores. This is intuitive, since these people might be linking their out of home trips in one chain that includes going to the grocery store. So, keep travelling to work may also cause the person to stop off at the grocery store while out of their home. Similarly, we justify people who like to drive to be associated with visiting the grocery store despite the pandemic. These findings may be supported by the work of Martarelli & Wolff (2020) who pointed out that boredom can be a motivator for people to keep visiting stores as an escape from spending longer time at home (and ignore social distancing rules). Their point may support our other finding that people who enjoy an active lifestyle are less likely to reduce visiting grocery stores and go to the store. Perhaps this is a form of entertainment during the quarantine and as a reaction to travel restrictions during the pandemic. We find an association between the inclination towards doing a lot of online shopping of various kind (clothing, medicines, etc.), and increasing grocery shopping online; as suggested by Ruvio & Somer (2014), individuals who have a consumerist nature, if experience stress from traumatic event (e.g., a pandemic), are more likely to spend compulsively as a result. We found evidence to support our hypothesis, based on the work of other authors (Al-Dmour et al, 2020; Eriksson & Stenius, 2022; Sahni & Sharma, 2020; Yum, 2020), that the use of media platforms has a powerful effect on the awareness around the pandemic and consequent public behavior; our data show that people who use media more frequently tend to decrease their visits to the store and increase online shopping. Perhaps, those who do the transition are the most tech savvy. Our findings support the hypothesis that those who applied for an unemployment benefit are less likely to increase online grocery shopping. The reasoning behind this result could be due to the fact that online shopping tends to be costlier, as also specified by (Shamshirpour, 2020). The results support our hypothesis, and the study of (Shamim, Ahmad & Alam, 2021), that how the risk of infection is perceived influences people's activities. Those who reported to be concerned about the health impact of the pandemic are more likely to decrease in-person visits to the grocery store and more likely to increase online grocery shopping vs. the non-concerned. They indeed might feel inhibited by staying at home orders and follow social distance rules; people who do not have a strong opinion (the neutrals) were not significant. Our findings confirm the hypothesis that says that trips to the store during the pandemic are fewer (Severson, 2020). We indeed found that people who visited less stores vs. a variety (i.e., visiting one store that sells everything vs. visiting one store for produce and another for households' supplies, etc.) are more likely to decrease in-person visits to the grocery store. Our research also highlighted that people who purchase more items per time (vs. before the pandemic) are more likely to increase online grocery shopping and confirms results from other sources (Severson, 2020; Clark, 2020) that the number of items purchased per visit went up and people tend to buy more in bulk. During the pandemic, many restaurants closed, so many people who would normally eat at restaurants opted to eat at home (besides, perhaps, using takeout service instead) and engage in new culinary activities at home. As supported by the United States department of agriculture (USDA) data (Economic Research Service, 2021), that reported that consumers increased their expenditures on groceries while decreased food-away-from-home expenditures, we found that those who decreased dining-out are more likely to increase online grocery shopping and decrease their visits to the store. The latter perhaps in respect of staying at home rules.

In addition, we found some other correlations with our responses: non-white Caucasian, who represent the minority in our sample, are less likely to increase online grocery shopping as compared to white Caucasians. We found that, although in absolute terms higher-income people increased online shopping more that middle-income people, the latter group increased the shopping frequency (multiple times per week vs. monthly) more than the former. This justifies the finding that people in the middle-income group are found to be more associated with online grocery shopping than higher income people. On the contrary, lower income people are found to be less associate with online shopping than the higher income group (although not statistically significant in the model).

To make sure we do not run into an endogeneity problem, we ran the model without three variables that might lead to some reversed causality issues, these are: Go to the restaurant, Fewer grocery stores visited during the pandemic, and More grocery items bought per time during the pandemic. Results did not show any noticeable differences (instability) in the coefficients, in terms of their magnitude and sign. We deduce that our model is not considerably affected by endogeneity issues and the presence of these variables in the model is not of big concern.

Table 7-9. Bivariate Binary Probit Model Results (n = 2,948)

	Decreased in-person visits to the grocery store		Increased online grocery shopping	
	Coeff.	p-value	Coeff.	p-value
Socio-demographics				
Race (reference: White/ Caucasian)				
Non-White/Caucasian	-0.147	**	-0.141	*
2019 annual household income (before taxes) (reference: Higher)				
Low (<$25,000 - $49,999) (not significant)			-0.066	
Middle ($50,000 - $99,999)			0.176	**
Individual specific variables				
(Have a job and) Travel to work during pandemic (reference: No)				
Yes	-0.181	***		
Applied to pandemic unemployment benefits (reference: Not applied)				
Applied			-0.227	***
Fewer grocery stores visited during the pandemic vs. normal life (reference: Same or more)				
Fewer (tend to visit only one grocery store vs. multiple as before pandemic)	0.271	***		
More grocery items bought per time during the pandemic vs. before pandemic (reference: Same or fewer)				
More items per visit vs. before pandemic	0.337	***	0.212	***
Dine out vs. before pandemic (reference: No change nor increased)				
Decreased	0.770	***	0.324	***
Concern about the health impacts of the pandemic (reference: Disagree)				
Agree	0.411	***	0.330	**
Neutral	0.253			
N. of online purchases (of any kind) in the past 30 days			0.009	***
Material and new things desirability			0.024	
Car and driving desirability	-0.032	**		
Active lifestyle desirability (not significant)	-0.011			
Use of social media	0.014	***	0.014	***
Log-likelihood (Null model)	-3787.84			
Log-likelihood (Final model)	-3490.22			
ρ^2 (Mc Fadden test)	0.0785			
ρ (correlation coefficient between the two equations)	0.29 (p-value = 0.000)			

Note: Statistics in the table represent coefficients and significance level (*10%, **5%, ***1%).

8 Key Findings and Discussions

8.1 A Large Shift to Remote work and Hybrid Forms of Work

We measured the transformational impacts of the pandemic on work organization and commuting patterns using data from four timepoints: fall 2019 (recollection of pre-pandemic activities), fall 2020, summer 2021 and summer 2022 (expectations for the future). Residents in the state experienced a large shift from physical commuting to remote work, or to hybrid work schedules, during the pandemic.

The number of fully remote workers increased significantly from a negligible share in pre-pandemic (4.1% of all respondents in the weighted data) to a larger share in fall 2020 (25.7%). It then declined by summer 2021 and was expected to shrink further by summer 2022, as additional activities re-open and employers facilitate the (at least partial) return to in-person work activities. Meanwhile, the percentage of hybrid workers continually increased, from 14.5% of all respondents pre-pandemic to 27.1% in summer 2021, and is expected by respondents to continue increasing through summer 2022.

This shift towards remote work and hybrid work was not consistent across sociodemographic groups. Lower-income, less-educated individuals and rural residents reported substantially lower adoption of remote work. By summer 2021, remote workers constituted 17.2% of low-income individuals vs. 26.4% of high-income individuals, 17.0% of lower-education individuals vs. 24.9% of higher-education individuals, and 15.8% of rural residents vs. 22.1% of urban residents. Similar patterns occurred among hybrid workers. The differences across groups mirror the inherent nature of the different job types and their ability to transition to remote work. In particular, those in lower-income, lower-education groups are more likely to have essential jobs and blue-collar jobs that more often require employees to be on site. High-income full-time workers are much more likely to have white-collar office jobs, STEM (science, technology, engineering, and mathematics) and government jobs, while low-income part-time workers are employed in a large variety of jobs, including a larger proportion of jobs that are classified as essential and that require in-person presence. These differences between work patterns across different sociodemographic groups raises potential equity concerns, both in the short-term in facing risks in the pandemic and in the long-term ability for recovery that increases equitable mobility.

One of the most important impacts of the adoption of remote work on transportation is through its impact on the frequency and total number of commuting trips in the region. Understanding the frequency of trips made by hybrid workers, which can range from one to more days per week, may provide a deeper understanding of the pandemic's impact on total commute trips and the potential of policies that support remote work to reduce VMT, in the region. When focusing on individuals that commute at least once per month in each period, the analysis highlighted how the frequency of commuting trips declined from an average of 17.8 days per month per active commuter before the pandemic to only 14.4 days per month in fall 2020. Despite the rebound in the number of active commuters by summer 2021, their average frequency of commuting to work reached only 14.7 day per month, highlighting the persistence of reduced commuting activity (in particular during the peak time), in part due to the adoption of hybrid forms of work.

Not surprisingly, not only did the percentage of workers who remote work at least one day per month increase during the pandemic, but their average number of days also worked remotely increased from 13.2 per month before the pandemic to 17.1 in fall 2020. The prevalence of remote work in the state remained high in summer 2021, at 13.5 day per month among all workers. The sustained high adoption rates and frequency of remote work, and the expectation among respondents that they would be able to continue to work from home (including partial remote work) in the future, highlight the current (and potential future) persistence of hybrid forms of work. This includes working from home on some days of the week and commuting on others. Others hybrid options would involve working from home for part of the day and in-person another part of the day, potentially avoiding peak traffic congestion. Similar to the adoption of remote work during the early stages of the pandemic, the transition to forms of hybrid work is more common among higher-income, more educated workers, and those that have STEM, white collar office jobs, and government jobs.

In addition, our statistical models show that different factors have impacted individuals' remote-work practice in different timepoints of the pandemic. Before the pandemic, possession of a driver's license has a negative effect on hybrid or remote work. Income is negatively associated with one's adoption of hybrid-work while encourages the adoption of remote work. In summer 2021 during the pandemic, individuals who are younger, with higher education and higher income, living in more urban regions are more likely to adopt hybrid and remote work. In terms of the expectations of work status in 2022, younger adults, high-educated or high-income workers expect more off-site workstyle in the future, but urban workers would prefer to continue hybrid work practice.

Our study also shows that hybrid and remote work practice differs among respondents from the opinion panel dataset and other recruitment channel. In the pre-COVID period, online panel users have a stronger orientation to hybrid- or remote-work practice which is associated with their trait of tech-savviness. However, as of 2021 in the pandemic era, people in the longitudinal and mail-online datasets showed more intense remote-work practice, potentially in a bipolar selection with regular commuting (i.e., less chance of adopting a hybrid workstyle).

8.2 An Upward Trend in Household Vehicle Ownership

Our study investigated the factors that influence household vehicle ownership changes, including additions, deletions and replacements, focusing on socio-demographic characteristics, attitudes, life events, and COVID health concerns. Our analyses covered two distinct time periods: the pre-pandemic period leading up to summer 2021, and in the expected future period from summer 2021 to summer 2022. We found an upward trend in vehicle ownership among respondents, with an increasing number of individuals who own three or more vehicles (rising from 25.7% in fall 2020 to 29.2% in summer 2021), and more individuals reported to increasing rather than decreasing their vehicle, both in the past (7.9% versus 5.1%) and in the expected future (8.4% versus 3.8%). These results suggest that automobiles continue to hold a prominent position in American society, even among those who previously did not own a car. Such proliferation may have detrimental effects on the environment and the health of our cities.

Using an ICLV model, we found that the factors influencing past changes in vehicle ownership can differ from those affecting expected future changes in vehicle ownership. This may be attributable to various factors, such as the evolving situation of the pandemic, changes in demand-supply trends of the automobile industry, and shifting travel needs of individuals. For instance, household income and changes in household income had a significant impact on individuals' vehicle ownership decisions during the pandemic. Specifically, only individuals in the highest income bracket (earning $100,000 or more annually) or those who experienced an increase in their household income were more likely to increase or replace their vehicles during the financially strapped COVID-19 period. However, interestingly, we also found that the income variable was not significant when it came to expected future vehicle ownership decisions. This suggests that individuals' financial status was expected to improve by summer 2022, and therefore, all other things being equal, high-income individuals were not statistically more likely to acquire a vehicle. These results demonstrate the complex nature of the factors influencing vehicle ownership decisions, and how they can vary over time. Policymakers and industry stakeholders must consider these trends to ensure that policies and services align with the evolving needs and circumstances of individuals and households.

Our study highlights that vehicle ownership dynamics differ significantly among population groups with varying characteristics. In terms of latent attitudes, individuals who are tech-savvy and variety-seeking were more likely to experience changes in vehicle ownership during the pandemic and are also more inclined to consider increasing or replacing their vehicle in the future. In contrast, individuals who are pro-environment and pro-active lifestyle are less likely to do so. In terms of socio-demographics, we observed that younger individuals, males, students, workers, individuals with higher education and higher income, households with children and those with concerns about the health impact of COVID-19 were more likely to increase or replace their vehicles, or less likely to decrease their vehicles, compared to their counterparts. Moreover, individuals who increased their education attainment, transitioned to students or workers, or experienced an increase in their household income exhibited similar patterns in their vehicle ownership decisions.

Moreover, our study provided some evidence showing that although current vehicle ownership status and changes in vehicle ownership change are closely related, they involve different decision mechanisms, with different factors come into play. As a result, some factors that are well-established in existing literature to impact vehicle ownership may have a different impact or have no impact on vehicle ownership change. For instance, our analysis did not detect the impact of certain car-related attitudinal factors, such as car-affine & pro-driving and car-dependent, on vehicle ownership changes. We believe that these factors may have had a stronger impact on individuals' existing ownership and use of their vehicle (Lee & Goulias, 2018), in terms of the absolute number of vehicles they own, but not necessarily on their willingness to change their vehicle ownership. In fact, since these individuals are obsessed with and highly dependent on their cars, it is likely that their car needs have already been met. Therefore, there is no reason for them to acquire additional cars, and at the same time, it is also unlikely for them to get rid of any cars they already own.

8.3 The Growth of E-Commerce

New online shopping habits have been established during the pandemic, in part reinforcing pre-existing trends such as the growth in the use of e-shopping solutions that predated the impacts of the COVID-19 pandemic. Our study shows that the proportion of respondents that shopped online at least once per week in Fall 2019 (11.6%) to those who did so in Spring 2020 (51.2%)—a near fivefold increase. That being said, by tracking respondents over a longer period of time, we are also able to examine whether this behavior holds true in the longer-term and find that the proportion of respondents that shop online at least once a week diminishes to 25.1% in the Fall 2020 period, which remains considerably higher than in Fall 2019, but also indicates that the initially reported growth in e-shopping may have been short-lived. This result further suggests that the longer-term impacts of the COVID-19 pandemic on e-shopping may have been more modest than reported in earlier studies, which relied solely on data pertaining from the initial months of the pandemic.

By examining the factors associated with the use of online shopping both before and during the COVID-19 pandemic, we find that higher levels of income and education continue to be positively associated with online shopping frequency. We also determined that younger individuals (18 - 34 years old), which were shown to be more likely to shop online prior to the COVID-19 pandemic, are no longer more likely to do so. This we surmise, maybe due to the fact that once the pandemic hit, respondents of all ages were confronted with similar COVID-19 restriction measures and had to quickly adapt their shopping behaviors. Older individuals, which prior studies had shown to be the group least likely to partake in online shopping (Hernández et al., 2011; Lee et al., 2015), were also the most at risk from contracting the COVID-19 virus and therefore had the most to gain from switching to online shopping.

Another determinant of online shopping frequency during COVID-19 was the rate at which respondents partook in this behavior before the pandemic. Indeed, respondents who shopped online at least once per week in the Fall 2019 were 29.7% more likely to do so 3+ times per week in Spring 2020 and 47.6% more likely to do so in the Fall 2020 period. Coupled with the finding that 51.9% and 65.4% of respondents who shopped online 3+ times per week during the Spring 2020 and Fall 2020 periods, respectively, also did so as frequently before the pandemic, we believe that the recent rise in e-shopping induced by the COVID-19 pandemic was largely caused by an increase in units purchased by experienced online shoppers. That is not to say that the COVID-19 pandemic has not led to an increase in the amount of people who now shop online, as we find that 37.2% of those who never shopped online in the Fall 2019 period started doing so at least once per week during the early months of the pandemic. But in accordance with our previous results, we find that the level at which the e-commerce sector was able to retain its expanded base of users dwindles over time, as 57.9% of respondents who never shopped online in Fall 2019 revert to never or doing so less than once per month in the Fall 2020 period. Individuals such as these that are unable or unwilling to make the transition towards e-shopping and continue to depend on brick-and-mortar stores are likely be made less well off, as experienced online shoppers begin to purchase more units and more people now start to partake in this behavior. While lower than initially expected, the COVID-19-induced growth in online shopping will have broader socioeconomic implications, as vendors who start witnessing a decrease in in-person sales at the expense of online shopping may decide to relocate away from city center to save on fixed costs such as rent, leaving the 10.8% of respondents who continue to never shop online in the Fall 2020 period with potentially fewer shopping options. Moreover, by no longer having to rent expensive store fronts in centrally located areas, commences that relocate will likely be able to reduce their per-unit purchasing costs, which may further stymie independent shops' ability to survive downtown and ultimately risks destroying the vibrancy and diversity of city life as we now know it (Moore, 2018; Young, 2021).

9 Conclusions, Policy Implications, Future Works, and Limitations

The COVID-19 pandemic has been disrupting various aspects of an individual's life. This has been observed in our study in the form of changes in travel behaviors and organization of activities that were measured in the analysis of three repeated cross-sectional data collected in spring 2020, fall 2020 and summer 2021 in the state of California. In this final section of the report, we summarize some brief conclusions and policy implications of the findings from five studies presented in this report to inform planners and policy makers in California on the impacts that the COVID-19 pandemic has had, and will continue to have, on transportation and society. Policy implications in this section provide strategies to help increase transportation and social equity, support more informed decisions to meet the transportation needs of various groups in the population in the region, and make transportation more sustainable as the communities recover from the pandemic. In general, as the pandemic has generated a mix of short-lived temporary changes and potential longer-term impacts, policy makers should try to mitigate trends that may be harmful and support long-term beneficial changes that emerged.

9.1 Support Equitable Transition to New Work Arrangements

Among its major impacts, the pandemic led to a significant shift to remote work during its early phases, which has further transitioned during later phases (as shown in the analysis of the data from summer 2021 in this study) to more widespread adoption of forms of hybrid work among certain groups of workers (who combine some in-person work with some work for home), and the shift towards hybrid work is expected to continue in the future. The persistence of remote work and hybrid forms of work, and the way they will further evolve in the future, remain an important topic of relevance for planning and policy making. Among other considerations, the surveys that were administered as part of this project focused on workers' self-reported activities and preference towards remote work or hybrid work in the future and measured them using frequency. However, the way future work organization will evolve will also rely on company policies regarding the adoption of remote work and guidelines from employers and managers. Studying, including gathering and analyzing data from, both workers' and employers' perspectives would be essential to study the evolution of work organization, including remote work expectations and the reorganization of workspace (e.g., with more flexible office space and modified ratios of square footage and parking space per employee, among other things), and forecast future trends.

As our study has shown, an important portion of those whose jobs allow and encourage remote or flexible work schedules are interested in continuing to engage in these forms of work organization, with hybrid work schedules—either featuring remote work on certain days and in-person commute to work on others, or split time between remote work and in-person work on the same day—being particularly popular. These flexible forms of work organization are expected to remain popular among those that can work remotely, and government and planning agencies should continue to explore options to accommodate these modified patterns (and the implications they will cause on the use of the transportation system, among other things). Employers should also consider how effective policy for flexible work organization might fit in parts of strategies to organize their work units, increase efficiency, and make remote and hybrid work more effective, and attract and retain employees.

Employees' preference towards remote and hybrid forms of work during the pandemic relate to various factors. As this study has shown, some such factors might have been only temporary, including safety concerns about exposure to the virus and about meeting with others outside of their household and using transportation options during the pandemic. As the pandemic is (hopefully) expected to further recede in the near future, the impacts of these temporary factors are expected to gradually disappear in the future. In fact, this study has already showed how the concerns about the potential exposure to the virus (and, for example, the use of public transportation, which is more conducive to contacts with strangers) have already declined as many activities reopened and a significant portion of the population got vaccinated. The study also highlighted the presence of other factors affecting the preference towards remote work, including commuters' desire to reduce commute time and costs, whose effect might further extend over time, or even increase—for example in a scenario of high gas prices and increasing costs of traveling, as it seems likely at the time of writing of this report. Accordingly, several employers and public agencies might consider extending policies for flexible form of work, including remote and hybrid work, as a way to fight higher costs of driving and to reduce the economic burden on commuters, as already experienced by some employers around the country. Additional considerations relate to the perceived efficiency at working from home vs. in the office, a topic that has been highlighted in the analysis of the attitudinal data collected as part of this project. Not surprisingly, after the initial shock of the disruption caused by the pandemic and the partial transition to hybrid work, a larger portion of workers reported increased efficiency of work from home in summer 2021 than in the first data collection carried out in fall 2020. This can be a sign of adjustment to changed working conditions, including increased work from home—which might lead to further persistence of at least partial forms of remote work in the future. More in-depth investigation of these topics will be beneficial for formulating individual-tailored policies on the path to a more flexible and efficient work environment.

The transition to remote work has not been similar for everyone. Not surprisingly, certain population segments (including low-income, less-educated individuals, part-time workers and rural residents) were either more likely to lose jobs during the pandemic or to have lower ability to adopt remote work and flexible work schedules. The impacts of the pandemic on employment and jobs are of extreme importance and should be central to the policies to support economic recovery including increased access to jobs, support for those temporarily out of employment, and promotion of opportunities to retrain those in search of a jobs. In addition, as the region emerges from this era of disruption, it will be important for transportation agencies to adjust transportation options and improve transportation accessibility for the various groups. This means, on one hand, adjusting to the modified needs of those that have transitioned to remote or hybrid forms of work, but on the other hand reimagining transportation options to serve those that continue to depend on physical commutes—for example, with the evolution of public transportation. In most cases, public transit has been traditionally designed primarily to serve commuting trips during peak times along radial corridors towards a central core (e.g., a central business district of a city), but its evolution in the future will likely pass through the need to adjust to the modified spatial and temporal distribution of trips in the future.

Among individuals that retained their occupation during the pandemic, the study highlighted how some of their occupation types (such as retail and health care) were not as able as others (such as white-collar office jobs) to shift to remote work. As a result, they usually had to commute physically to work and had greater exposure to the virus. Future preparedness to eventual disruptions or similar epidemics will need to consider ways to mitigate the forced exposure to the potential pathogens among essential workers, including enacting policies to provide viable precautionary measures to reduce commuters' potential exposure during travel. It is unfortunately not an easy task to improve the working flexibility of all sectors universally. Additionally, policy must support the mobility needs of these workers by providing sufficient safe travel choices, at a time in which the availability of certain services is reduced. The massive transition to remote work has also highlighted the critical nature of accessing high-speed and affordable internet service ("broadband") for all. Tracking broadband coverage accurately in California and expanding broadband network in unserved areas remains critical.

The growth in remote work and flexible work schedules is something that should be considered, and potentially encouraged, when and where appropriate, as it has many additional benefits beyond reducing exposure to COVID-19. For instance, remote work reduces traffic congestion on most congested corridors during peak time, and can lead to a reduction in GHG emissions and air pollution, important issues in California. Still, more studies would be needed to better understand the overall impacts of the adoption of remote work—or hybrid forms of work—on travel, in particular as work from home might lead to reduction in commuting trips but the generation of additional home-based trips for other purposes during certain portions of the day. Thus, it might lead to a certain redistribution of trips from peak hours to non-peak hours across the day or shift the overall time windows that define the "peak hours," in addition to a redistribution of the spatial-temporal patterns of trips, e.g., along the highway network vs. local roads. Likely, a combination of those scenarios might be in place. This information will be essential to support travel demand forecasting and implementing travel demand management policies to reduce congestion, increase efficiency of transportation, and promote social equity and environmental sustainability.

The changing commute patterns encourages us to rethink the industry standard for traffic analysis. So far, most transportation planning and evaluation processes and tools are structured around analysis of travel demand vs. capacity during the peak time. This process has already started to evolve recently, with the adoption of activity-based models that focus on activity participation and related travel choices during the various time periods of the day, and reduced emphasis on the transportation level of service. In the future, it will become particularly important to update such models to properly capture the changed conditions of work organization and to forecast individuals' formation of work and non-work activity patterns (and related travel activity). For example, California should accelerate the SB 743 (Steinberg, 2013) transition to using VMT (which accounts for all car travel) instead of level of service (primarily a peak-hour performance measure) for purposes of environmental analysis.

With the reduced commuting trips due to the shift to hybrid work schedules, transportation agencies should reduce transportation planning emphasis on peak-hour planning, engineering, and investment decisions, and take advantage of additional roadway capacity across the day to help avoid having to physically expand roadways. In the same vein, public transit agencies should also consider how to redistribute their services and resources, eventually with more balance between peak and non-peak time, and between regional and local services. This will include rethinking the way public transportation services are typically designed and operated. While peak-hour service is very expensive to operate, the changes could lead to good news if one consequence of the pandemic travel changes were to distribute demand over the course of the day. At the same time, most public transportation services are designed to primarily serve commuting trips during peak times on radial corridors to/from major centers of employment. In most locations, they are less able to capture demand for non-work purposes, including travel for shopping, leisure and socializing activities. The necessary evolution to serve these modified travel markets might require redesigning scheduled fixed-route service to align with current demand with high-capacity and cost-effective services, or in certain cases, thinking of ways to go beyond traditional forms of fixed-route, fixed-schedule transportation services on major corridors, with an increasing reliance on flexible, on-demand components of public transit, or better integration with on-demand mobility.

Our study also suggests that the factors impacting one's adoption of hybrid work and remote work vary across different timepoints prior to and during the pandemic. Therefore, it is important to study such changing patterns in the future to identify influencing factors of remote work and formulate more individually tailored policies to support such practices. In addition, as the study shows that the differences in socio-demographic characteristics and remote work practice between the subpopulation taken from online panel datasets and other sources, it emphasizes the importance of recruiting survey respondents through multiple channels to reduce potential sample biases.

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

Our study found that individuals with tech-savvy and variety-seeking attitudinal attributes were more likely to have changes in vehicle ownership. Previous studies also suggest that they are also more inclined to embrace new vehicle technologies, such as electric vehicles (Iogansen, Wang, Bunch, Matson, & Circella, 2023) and autonomous vehicles (Wang & Akar, 2019), as well as shared mobility services, such as ridehailing (Lavieri & Bhat, 2019), carsharing (Mueller, Schmoeller, & Giesel, 2015) and micromobility (Mahmoud, Chouaki, & Puchinger, 2021). Therefore, policies aimed at incentivizing these individuals to transition to cleaner vehicles or promoting mode shift away from private vehicles altogether, could be viable and have significant impact on reducing carbon emissions.

We also revealed that individuals who are pro-environment and agree on raise the cost of driving were more inclined to relinquish their vehicles. However, they are more prevalent among highly educated and high-income individuals, as well as urban residents. Therefore, it is important to raise environmental awareness among all individuals, regardless of their demographics. In addition, policymakers can also 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.

Moreover, we highlighted that the health concerns arising from the COVID-19 pandemic have partially attributed to the increase of pro-active lifestyle. This, in turn, has reduced the attractiveness of vehicle ownership for some. This presents a unique opportunity for some people to break long-held habits in travel patterns. Cities can invest better walking and biking infrastructure in the neighborhoods, to ensure individuals continue their active and sustainable options over cars. On the other hand, the health concerns of the COVID-19 have also been found to drive individuals to increase their private vehicle ownership, potentially due to the fear of virus transmission in public and shared travel modes. Transportation agencies and mobility providers should continue implementing and enforcing safety measures, including regular sanitization of the vehicles and providing sample space for physical distancing. As the COVID-19 vaccine becomes more widely available and misinformation about COVID-19 is increasingly studied and understood, public education is also needed to dispel unnecessary concerns.

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-induced car ownership boom, it is crucial to formulate policies that divert younger individuals away from increasing vehicle ownership, especially among those who are currently non-vehicle owners, while promote alternative modes of travel.

In general, students and workers tend to have higher level of personal mobility needs, making stable or increased vehicle ownership more desirable for them. Also, they tend to adapt new ownership patterns to reflect their changing student or worker status. Despite of the meteoric rise in remote work and reduced travel during the peak of the pandemic, many companies do not have a well-formulated remote working policy, let alone guaranteed long-term remote work options. 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 for sure how company's remote working policy would play out when the pandemic subsides. Therefore, governments should support companies in formulating concrete polices to effectively guide and manage remote and hybrid work arrangement, which in turn can help workers settle into their new normal of travel needs 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, as our study showed that those in the highest income category or those who experienced an increase in income during the pandemic had much more likelihood to acquire or replace vehicles compared to low-income individuals. Therefore, it is crucial to provide more travel alternatives for this group. Government and employers could consider offering incentives for active commuting, such as biking or walking, or providing subsidies for ride-hailing services with proper safety measures in place.

Furthermore, our research suggests that understanding household characteristics is crucial when analyzing vehicle ownership patterns. Specially, households with multiple family members exhibit greater variabilities in their vehicle ownership change patterns. 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 in future work is crucial to help policymakers and car manufacturers develop transportation policies and designing vehicles that meet the diverse needs of families.

Finally, we offer several ideas for future research. First, the landscape of auto industry is evolving rapidly, which vehicle transactions increasing in the past year compared to previous years due to gradual economy recovery. As policymakers and car manufacturers and dealers adjust their policies and marketing strategies, staying attuned to these trends will enable them to make more informed decisions accordingly. Therefore, continued efforts to study this topic could yield significant research dividends in the years ahead. Our new wave of survey data that will be collected in spring 2023 as a part of this multi-wave COVID mobility survey will allow us to better understand the relationships between vehicle ownership change intentions and actual vehicle transaction behavior. Furthermore, we can extend this research topic by investigating vehicle composition and fuel type choices. Along the line, mode choice and vehicle ownership are also interconnected. Therefore, investigating the links between mode choices and vehicle ownership could be an interesting extension of the current study. Second, our model did not detect the influence of neighborhood characteristics on vehicle ownership change. But perhaps, results could vary significantly for transit rich and transit poor cities if we introduce more spatial factors into the model. The hypothesis here is that residents of transit poor cities might be auto dominant to begin with, making the impact of the pandemic on vehicle ownership more subdued for them. Conversely, residents of transit-rich cities could be affected by a reduction in transit services due to the pandemic, leading them to purchase a vehicle to meet their work and leisure travel needs. Further research can shed more lights on this topic. Finally, although we used a longitudinal dataset, our analysis cannot distinguish causation from correlation. Therefore, a new research framework is needed to establish causal relationship between variables.

9.3 Accommodate and Drive the Growth of E-commence

In terms of online shopping, its adoption significantly increased during the pandemic, and remains above pre-pandemic levels. Transportation and city planners need to closely follow the growth in online shopping, as this may influence residents' housing location decisions and reduce the frequency of shopping-related trips. COVID-19 pandemic has led to an increase in remote work which removes the burden of commuting and increases the appeal of cheaper, distant housing locations. But when coupled with the ability to purchase all necessary goods and services online, the decision to relocate further away becomes even more enticing. This is particularly true for wealthier, well-educated individuals which are more likely to be able to work from home (Matson et al., 2021; Yilmazkuday, 2020), but also, as demonstrated in this study, display the highest likelihood 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 its disadvantages. To combat this technology-induced urban sprawl, policymakers will need to develop strategies to retain stores in central areas, such as providing tax incentives or rent subsidies, and simultaneously implement policies to diminish the appeal of distant housing locations, such as imposing higher gasoline taxes (Young et al., 2016) or implementing additional fees on home deliveries.

Fortunately, the speed at which individuals are transitioning towards online shopping is less than what was initially expected when only considering the earlier months of the pandemic, and that those responsible for the increase in online shopping during the COVID-19 pandemic are primarily experienced online shoppers. In other words, the rapid increase in e-shopping and ensuing potential implications this may have on households' housing location decisions and rate of shopping-related trips, may have been exaggerated and temporary, as the longer-term impacts of the pandemic on e-shopping frequency are found to be more modest. That is not to say that cities should not preemptively start thinking of solutions to avoid this impending exodus, but rather that they should seek out additional information such as findings provided in this study, to help them develop more informed policy decisions when required to regulate online shopping.

More specific to on-site and online grocery shopping, we suggest that grocery stores pay attention to their inventory as those who during the pandemic developed the habits to purchase in bulk and/or visit one store that sells everything vs. multiple stores (e.g., visit one store for produce, one for meat) might (or not) go back to old routines. Market research might help investigate these aspects and deal with demand volatility. Certain groups of people who showed to be keener to switch to online grocery shopping and who could be targeted to expand the online grocery marketplace. These groups include higher and middle-income individuals and the segment of society who tend to be more consumeristic, i.e., showed to be very active in purchasing online any sort of goods. Such groups could be more easily interested in newer forms of business or delivery apps because they are more likely they will end up shopping online.

As we move to exit the pandemic, we suggest grocery stores to advertise new safety and health protocols while shopping in a store; such measures might help those who were found to decrease in-person store visits because concerned about their health, to regain confidence. On the other side, the "health concerned" could be also the right people to target and make them stick to online grocery shopping with the right marking campaigns. We also identified that people who frequently use 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 to build rules that make mandatory for media to forge public awareness based on experts' advice who can correct any sort of misconceptions, and lead to a safe public behavior that help control states of emergency such as a pandemic.

It will be also important to identify the changing socio-demographics and geographic locations of those who changed their in-person and online shopping patterns and those who might continue to engage in these forms of shopping. While shopping online is still largely an urban phenomenon, our study highlighted how the adoption of online shopping increased in the U.S. and California during the pandemic. Current infrastructure and services may not be able to meet the demand for the sudden increase in demand for good delivery. The emerging e-commerce requires policies for better freight infrastructure, goods delivery services, and curb management.

Our studies have primarily focused on the behavior of online shoppers, but we believe there is an important yet overlooked dimension of inequality that pertains to couriers. As a result of the surge in demand for package delivery, the courier business is experiencing unprecedented growth. It is crucial to understand who is more likely to work as couriers during and after the pandemic (such as low-income workers) and how they go about fulfilling their duties (such as utilizing their own vehicles via Uber Eats platform). Such an investigation would not only shed light on issues of equality but also help us understand whether and why specific groups of workers have acquired additional automobiles.

9.4 Limitations

There are some limitations of our datasets and analyses. We attempted to generate a sample that mirrors the population in California to the extent possible, but self-selection bias is always a concern: individuals who choose to participant in our surveys may have certain characteristics, as well as behavioral and attitudinal predispositions. Although we made effort to collect data from all residents in the region, including those groups that are traditionally harder to reach, such as BIPOC, non-English speakers, and residents of rural areas, we did not completely achieve those targets. To give these typically underserved populations a stronger voice in this type of study, even more work needs to be done to recruit them and use alternatives tools (e.g., focus groups, and in-depth interviews) to collected information from these segments of the population. While the sample for the study was weighted to correct for the lack of representativeness, future studies should recruit additional respondents from these groups to generate a more realistic depiction of transportation in California. In particular, the recruitment of Hispanic respondents was below the study targets, despite the efforts that were made in this study to recruit more respondents in this category, highlighting existing difficulties to reach these groups in this type of study. Alternative recruitment channels should be used in the future to reach the Hispanic populations. It is also possible that the incentives redeemable with major retailers might not be appropriate. Possible alternative options including cash awards or prepaid credit cards that are not tied to a specific retailer should be considered. Another recruitment target that underperformed was the sampling from Imperial County. The methods of recruiting respondents for this study did not seem very successful in this region, given the low response rates, and alternatives should be explored in the future. Also, the survey undoubtedly reflects some non-response biases as some individuals did not respond to some of survey questions. We tried to overcome this limitation by using data imputation process for some key variables such as household income, neighborhood type and so forth.

Another limitation of this study is that in some analyses we presented in this report, we measure changes at four timepoints based on two repeated cross-sectional datasets. As a result, respondents were differed at the two time points. Thus, the internal validity of the comparisons might be somewhat compromised. Nevertheless, weights were applied to these two datasets to reduce their deviation from population distribution and improve the comparability of the two datasets. Also, we do have a small longitudinal sample that continuously participate the two surveys, but a future data collection with a larger longitudinal sample is needed to improve the generalizability of the findings.

Our studies describe the change activity patterns at the California or U.S. level; we acknowledge that the results may vary according to the various geographical areas within California and across different states that are notoriously associated with differences from a sociodemographic and economic perspective. This is a reminder of the different policy interventions that will be needed, reflecting local needs and focusing on areas where government can support beneficial changes in the post-pandemic future.

Finally, while this report has summarized findings from three waves of data collected in the study, the richness of the data will allow the development of many future analyses that can address a number of additional planning and policy-relevant questions that could not be included in the current report. The findings reported may indeed change as the pandemic evolved. We will actively monitor evolving situation with coming new waves of data collection. In addition, this study could be enriched also with other data collection that have a more qualitative approach, e.g., interviews or focus groups, that would allow to shed light on our findings more in-depth. Such a project would help to better study human behavior during situations of emergency such as a pandemic and potential future quarantine.

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11 Data Summary

Products of Research

As part of the COVID mobility study, the research team carried out several rounds of data collection through surveys administered among the general public in the state of California, other parts of the U.S. and worldwide.

The first COVID dataset was collected in spring 2020. We resampled respondents from the previous surveys that were administered by the research team in 2018 and 2019 in California and the U.S. to form a longitudinal sample. We also recruited new respondents through an online opinion panel targeting residents in 15 metropolitan areas in the United States and two regions in Canada (California: Los Angeles, Sacramento, San Diego, and San Francisco; Non-California: Atlanta, Boston, Chicago, Denver, Detroit, Kansas City, New York City, Salt Lake City, Seattle, Tampa, and Washington D.C.; Canada: Toronto, Vancouver). In addition, we included a convenience sampling method with which we reached out potential participants through professional email lists and online advertisements (e.g., Facebook Ads). The second and third data collection was administered in fall 2020 and summer 2021. We used similar sampling methods to resample previous respondents while adding new respondents to form a large dataset with a rotating panel structure. The survey administration also included the distribution of a (printed) paper questionnaire to recruit respondents that are conventionally hard to reach.

The survey content of all three survey was mostly consistent in order to keep track on the longitudinal impacts of the COVID-19 pandemic. All datasets feature a similar structure and contain information on similar topics related to transportation, including personal attitudes and preferences, adoption of mobile devices or social media, household composition, general travel patterns, vehicle ownership, use of new mobility services such as ridehailing, carsharing, or bikesharing, and household and individual socio-demographics. However, as the COVID-19 pandemic severely disrupted society, we accordingly modified some components of the survey.

Data Format and Content

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

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

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

Data Access and Sharing

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

Reuse and Redistribution

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

12 Appendix

Table 12-1. Unweighted and weighted sample, and target population in the state of California in the spring 2020 dataset

Demographics	Sub-categories	Population target	Percentage	Unweighted Sample size	Unweighted Sample percentage	Unweighted % difference	Weighted Sample size	Weighted Sample percentage	Weighted % difference
Age	Adult	15,012,733	49.4%	1890	50.5%	1.1%	1850	49.4%	0.0%
	Elderly	5,644,497	18.6%	707	18.9%	0.3%	683	18.2%	-0.3%
	Young	9,732,152	32.0%	1148	30.7%	-1.4%	1212	32.4%	0.3%
Work status (2020)	Non-workers	13,485,810	43.3%	1385	37.0%	-6.3%	1520	40.6%	-2.8%
	Workers	17,638,398	56.7%	2360	63.0%	6.3%	2225	59.4%	2.8%
Gender	Female	19,783,141	50.3%	1457	38.9%	-11.4%	1865	49.8%	-0.5%
	Male	19,562,882	49.7%	2288	61.1%	11.4%	1880	50.2%	0.5%
Household income	High income	5,201,713	39.7%	1543	41.2%	1.5%	1494	39.9%	0.2%
	Low income	4,277,540	32.6%	1074	28.7%	-4.0%	1195	31.9%	-0.7%
	Medium income	3,623,861	27.7%	1128	30.1%	2.5%	1056	28.2%	0.5%
Race and ethnicity	Non-white, Hispanic	7,692,353	19.6%	317	8.5%	-11.1%	685	18.3%	-1.3%
	Non-white, non-Hispanic	9,599,949	24.4%	811	21.7%	-2.7%	925	24.7%	0.3%
	White, Hispanic	7,688,576	19.5%	481	12.8%	-6.7%	728	19.4%	-0.1%
	White, non-Hispanic	14,365,145	36.5%	2136	57.0%	20.5%	1407	37.6%	1.1%
Region	Central Valley	4,225,143	10.7%	70	1.9%	-8.9%	305	8.1%	-2.6%
	MTC	7,713,510	19.6%	1070	28.6%	9.0%	762	20.4%	0.7%
	Northern California and Others	2,733,093	6.9%	126	3.4%	-3.6%	264	7.1%	0.1%
	SACOG	2,512,705	6.4%	842	22.5%	16.1%	247	6.6%	0.2%
	SANDAG	3,323,970	8.4%	709	18.9%	10.5%	327	8.7%	0.3%
	SCAG	18,837,602	47.9%	928	24.8%	-23.1%	1839	49.1%	1.2%
WFH status (pre-pandemic)	Not usual WFH workers	17,380,354	55.6%	1911	51.0%	-4.6%	2079	55.5%	-0.1%
	Non-workers	12,691,889	40.6%	1385	37.0%	-3.6%	1520	40.6%	0.0%
	Usual WFH workers	1,175,984	3.8%	449	12.0%	8.2%	146	3.9%	0.1%

Table 12-2. Unweighted and weighted sample, and target population in the state of California in the fall 2020 dataset

Demographics	Sub-categories	Population target	Percentage	Unweighted Sample size	Unweighted Sample percentage	Unweighted % difference	Weighted Sample size	Weighted Sample percentage	Weighted % difference
Age	Adult	15,012,733	49.4%	2773	50.2%	0.8%	3068	49.4%	0.0%
	Elderly	5,644,497	18.6%	946	17.1%	-1.4%	1192	17.8%	-0.7%
	Young	9,732,152	32.0%	1802	32.6%	0.6%	1988	32.8%	0.7%
Work status (2020)	Non-workers	13,485,810	43.3%	2152	39.0%	-4.4%	2718	40.0%	-3.4%
	Workers	17,638,398	56.7%	3369	61.0%	4.4%	3530	60.0%	3.4%
Gender	Female	19,783,141	50.3%	3256	59.0%	8.7%	3193	51.7%	1.4%
	Male	19,562,882	49.7%	2265	41.0%	-8.7%	3055	48.3%	-1.4%
Household income	High income	5,201,713	39.7%	1840	33.3%	-6.4%	2455	38.1%	-1.6%
	Low income	4,277,540	32.6%	1884	34.1%	1.5%	2048	32.2%	-0.4%
	Medium income	3,623,861	27.7%	1797	32.5%	4.9%	1746	29.7%	2.0%
Race and ethnicity	Non-white, Hispanic	7,692,353	19.6%	202	3.7%	-15.9%	1097	11.6%	-7.9%
	Non-white, non-Hispanic	9,599,949	24.4%	1194	21.6%	-2.8%	1558	26.3%	1.9%
	White, Hispanic	7,688,576	19.5%	1027	18.6%	-0.9%	1249	21.4%	1.9%
	White, non-Hispanic	14,365,145	36.5%	3098	56.1%	19.6%	2344	40.7%	4.2%
Region	Central Valley	4,225,143	10.7%	64	1.2%	-9.6%	633	3.8%	-6.9%
	MTC	7,713,510	19.6%	390	7.1%	-12.5%	1211	19.8%	0.2%
	Northern California and Others	2,733,093	6.9%	70	1.3%	-5.7%	426	3.8%	-3.1%
	SACOG	2,512,705	6.4%	238	4.3%	-2.1%	409	7.6%	1.2%
	SANDAG	3,323,970	8.4%	191	3.5%	-5.0%	534	9.0%	0.6%
	SCAG	18,837,602	47.9%	4568	82.7%	34.9%	3036	56.0%	8.2%
WFH status (pre-pandemic)	Not usual WFH workers	17,380,354	55.6%	2748	49.8%	-5.8%	3450	55.7%	0.1%
	Non-workers	12,691,889	40.6%	2152	39.0%	-1.6%	2557	40.0%	-0.7%
	Usual WFH workers	1,175,984	3.8%	621	11.2%	7.5%	241	4.4%	0.6%

Table 12-3. Unweighted and weighted sample, and target population in the state of California in the summer 2021 dataset

Demographics	Sub-categories	Population target	Percentage	Unweighted			Weighted		
				Sample size	Sample percentage	% difference	Sample size	Sample percentage	% difference
Age	Adult	15,012,733	49.4%	3027	47.3%	-2.1%	3068	49.1%	-0.3%
	Elderly	5,644,497	18.6%	1581	24.7%	6.1%	1192	19.1%	0.5%
	Young	9,732,152	32.0%	1792	28.0%	-4.0%	1988	31.8%	-0.2%
Work status (2021)	Non-workers	13,485,810	43.3%	2568	40.1%	-3.2%	2718	43.5%	0.2%
	Workers	17,638,398	56.7%	3832	59.9%	3.2%	3530	56.5%	-0.2%
Gender	Female	19,783,141	50.3%	3694	57.7%	7.4%	3193	51.1%	0.8%
	Male	19,562,882	49.7%	2706	42.3%	-7.4%	3055	48.9%	-0.8%
Household income	High income	5,201,713	39.7%	2273	35.5%	-4.2%	2455	39.3%	-0.4%
	Low income	4,277,540	32.6%	1918	30.0%	-2.7%	2048	32.8%	0.1%
	Medium income	3,623,861	27.7%	2209	34.5%	6.9%	1746	27.9%	0.3%
Race & ethnicity	Non-white, Hispanic	7,692,353	19.6%	406	6.3%	-13.2%	1097	17.6%	-2.0%
	Non-white, non-Hispanic	9,599,949	24.4%	1086	17.0%	-7.4%	1558	24.9%	0.5%
	White, Hispanic	7,688,576	19.5%	1198	18.7%	-0.8%	1249	20.0%	0.4%
	White, non-Hispanic	14,365,145	36.5%	3710	58.0%	21.5%	2344	37.5%	1.0%
Region	Central Valley	4,225,143	10.7%	426	6.7%	-4.1%	633	10.1%	-0.6%
	MTC	7,713,510	19.6%	1001	15.6%	-4.0%	1211	19.4%	-0.2%
	Northern California and Others	2,733,093	6.9%	329	5.1%	-1.8%	426	6.8%	-0.1%
	SACOG	2,512,705	6.4%	856	13.4%	7.0%	409	6.5%	0.2%
	SANDAG	3,323,970	8.4%	530	8.3%	-0.2%	534	8.5%	0.1%
	SCAG	18,837,602	47.9%	3258	50.9%	3.0%	3036	48.6%	0.7%
WFH status (pre-pandemic)	Not usual WFH workers	17,380,354	55.6%	2539	39.7%	-15.9%	3450	55.2%	-0.4%
	Non-workers	12,691,889	40.6%	2100	32.8%	-7.8%	2557	40.9%	0.3%
	Usual WFH workers	1,175,984	3.8%	1761	27.5%	23.8%	241	3.9%	0.1%