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# Longitudinal Analysis of COVID-19 Impacts on Mobility: An Early Snapshot of the Emerging Changes in Travel Behavior

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**Abstract**

The COVID-19 pandemic has caused a huge disruption worldwide with direct and indirect effects on travel behavior. In response to extensive community spread and potential risk of infection, during the early stage of the pandemic many state and local governments implemented non-pharmaceutical interventions that restricted non-essential travel for residents. This study evaluates the impacts of the pandemic on mobility by analyzing micro panel data ($N = 1{,}274$) collected in the United States via online surveys in two periods, before and during the early phase of the pandemic. The panel makes it possible to observe initial trends in travel behavior change, adoption of online shopping, active travel, and use of shared mobility services. This analysis intends to document a high-level overview of the initial impacts to spur future research to dive deeper into these topics. With the analysis of the panel data, substantial shifts are found from physical commutes to teleworking, more adoption of e-shopping and home delivery services, more frequent trips by walking and biking for leisure purposes, and changes in ride-hailing use with substantial variations across socioeconomic groups. The social and environmental implications of these findings are discussed and suggestions for effective policy and directions for future research are made in the conclusion.

**Keywords**

planning and analysis, effects of information and communication technologies (ICT) on travel choices, eshopping/e-shopping, on-demand mobility, telecommuting, traveler behavior and values, behavior analysis, COVID-19 pandemic

The outbreak of COVID-19, the illness that is caused by the SARS-CoV-2 virus, first appeared in Wuhan, China, in December, 2019. Initial cases and community spread in the United States were first reported during the week of February 23, 2020, in California, Oregon, and Washington, and by March 7 COVID-19 cases were reported in 19 states (*1*). In mid-to-late March, 2020, in response to extensive community spread and potential risk of infection, many state and local governments implemented stay-at-home orders along with restrictions on activities such as going to school, eating at restaurants and bars, attending large gatherings, and making cross-border travel (*2*, *3*). These travel advisories imposed broad restrictions on millions of Americans resulting in drastic changes in mobility and disruptions to economic activity. Because of the rarity of this type of event, there are limited studies that investigate the various impacts of an extreme event like the current global pandemic on travel behavior. While popular media often reported empty trains and highways as evidence for substantial disruption in the transportation sector under the

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pandemic, this paper focuses on behavioral changes at a deeper level which may lead to longer-term shifts in activity-travel patterns in coming years. Firstly, there is an examination of the adoption of two measures that help "avoid/reduce" physical contact through information and communication technology (ICT) devices and services, working from home, and online shopping. In addition, changes are examined in the use of two modes, ridehailing and active modes for leisure purposes, mainly because of their potential for less car-oriented lifestyles after the pandemic.

To achieve these research objectives, data are combined from two before-pandemic surveys and a during-pandemic data collection (in spring 2020) conducted by the research team at the University of California, Davis, and form micro panel data. Using panel data is preferred over cross-sectional, retrospective data, as it directly asks and reports behavior at the time it is taking place rather than having respondents recall details on past behaviors, thus limiting a source of error. The panel makes it possible to observe initial trends in commuting travel behavior (physically or telecommuting), online shopping, active travel for leisure purposes, and use of shared mobility services during the early phase of the pandemic. These topics were selected as they provide a simplified yet holistic view of life's basic mobility needs for working, shopping, and leisure/exercise. While the observed changes might initially be temporary, they have the potential to become established behaviors that have a longer-term effect. To examine these initial changes attributable to the pandemic, a descriptive statistical analysis of several target variables was conducted, and comparisons were made across household income levels and worker occupation categories. Results are presented in cross-tabulation tables with key results visualized in alluvial diagrams to show the change in behavior over time. Several significant differences across these groups are observed. The environmental and social equity implications of these findings are discussed in the paper.

This paper is structured in the following manner. The next section summarizes the initial wave of research on the impact of COVID-19 on mobility and related studies. Next, the methodology and framework are introduced, the main results of the analysis are presented, and the paper concludes with implications and directions for future research.

## Literature Review

Extreme events such as the COVID-19 pandemic are major disruptors to transportation supply, work activities, economic activity, supply chains, and personal health. Note that pandemics are not new in human history, and previous pandemics in the U.S. also led to similar restrictions on travel and shrunken economic activities for the reduction in virus spread (*4*, *5*). During the 1918 Spanish flu pandemic, U.S. cities imposed public health interventions such as the closure of schools and churches, banning of mass gatherings, and mandatory mask wearing, although the impact and timing of these interventions varied by city, with cities that introduced measures early on receiving moderate but significant reductions in overall mortality rates. Similar recommendations were observed during the H1NI virus in 2009, along with a hesitancy among certain groups, such as parents with children, about getting vaccinated, which was mainly because of concerns about the safety of the vaccine. However, the COVID-19 pandemic is quite challenging, if not more so than its predecessors, given the widespread practice of long-distance domestic and international travel and continued gaps in medical resources and healthcare capacities within and across countries. Thus, until most countries become safe via mass vaccination to go back to "new" normalcy, no single country alone can do so.

The COVID-19 pandemic disrupts many individuals' daily routines and activity-travel patterns, which may make them reconsider existing travel habits. By definition, travel-related habits (e.g., commute mode choice, work arrangement of physical commutes versus remote work, and travel modes for attending social gatherings) are consistent once established and less responsive to minor changes in surroundings. However, once disruptive events of substantial size (e.g., wide spread of the novel coronavirus) take place, individuals can no longer hold their habits, and adopt temporary strategies which may lead to longer-term changes in routines or the formation of new habits. In other words, disruptive events may generate a window of opportunity in which individuals become more sensitive to the context in which they make travel-related decisions (*6*). For instance, life stage events are found to influence the way individuals make travel-related decisions, leading to changes in travel behavior at that moment and for a longer-term (*7*).

Concurrent studies on COVID-19 have investigated the impacts of the pandemic on the economy, society, and travel behavior. As regards economic impacts, the temporary shutdown hit transportation-related industries—such as tourism, hospitality, and airline—hard, resulting in income loss for many Americans (*8*). As for mobility impacts, studies have used aggregated and anonymized data produced by Google to examine changes in the number of trips to specific categories of locations—such as residences, workplaces, and retail—with trends showing modest changes in mobility and notable reductions in time spent away from residences (*9*, *10*). While many studies have focused on the early phase of the pandemic, one study examined longer-term trends and reports a significant decline in mobility from March to April 2020, followed by negligible declines from June to September 2020 (*11*). In addition, other studies reported the substitution of virtual activities for physical travel; for example, substantial decreases in commuting and grocery shopping and wide adoption of working from home and online shopping (*12*, *13*). For instance, a Chicago study reports a 33% increase in working from home and a 65% growth in online shopping for April–June, 2020, compared with before the pandemic (*14*). 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. A Swiss study presented initial reductions in distance traveled two weeks before the official lockdown, followed by substantial increases in travel by bike and a return to baseline levels by car four months after the initial lockdown (*15*). Other commonly reported patterns include active travel gaining in popularity for recreational and leisure purposes in the early stage of the pandemic, with shared mobility services such as bike sharing serving additional travel demand for essential workers (*16*, *17*). In a year-over-year comparison, a study using bicycle count data from Eco-Counter found increases in bicycling rates between 5% and 20% in major European countries and selected regions in the U.S. and Canada, with most of the increases occurring on weekends (*18*). In contrast, public transit, ridehailing, and taxis experienced a huge drop in demand, especially in the early phase of the pandemic. Among them, pooled ridehailing services (e.g., UberPool and Lyft Line) were hit the hardest because of concerns over virus contamination across passengers; however, major transportation network companies were optimistic of a complete rebound by the end of 2021 as trips started to slowly grow back to pre-pandemic levels (*19*).

As a complement to the present study, additional studies have leveraged the use of panel data to investigate the impacts of the pandemic on travel behavior, with similar approaches to the analysis of impacts as well as unique contexts that are examined. One panel study conducted in the Netherlands examined the impact of the Dutch "intelligent lockdown" on travel behavior, whereas another study in Japan observed behavior changes with a focus on risk perception and social influence between two waves during the pandemic (*20*, *21*). In the U.S., panel studies, such as the one by researchers at Arizona State University and the University of Illinois at Chicago, are useful references for a comparison with the present study and future findings that will emerge as future waves of data collection are conducted (*22*). The present study contributes to the existing literature on the impacts of the COVID-19 pandemic on travel behavior and will broaden the understanding of the impacts of the pandemic on telecommuting, online shopping, active travel, and ridehailing usage.

## Data and Methods

This study analyzes a two-wave individual-level panel ($N$ = 1,274), which a team of researchers at the University of California, Davis, built via survey administration in the U.S. before and during the pandemic. The panel contains rich information on a broad range of topics including regular travel patterns, vehicle ownership, household organization, telecommuting patterns, e-shopping behaviors, use of emerging delivery services, and use of shared mobility and active modes of transportation.

To build the panel, in March, 2020, the team re-contacted participants of two surveys before the pandemic, the 2018 California Mobility Survey ($N$ = 3,767, collected for June–October, 2018) and the 2019 8 Cities Travel Survey ($N$ = 3,410, collected for March–April, 2019). The former survey was a statewide survey in California that utilized two sampling methods: a stratified random sample for mailed survey recruitment and a quota sampling approach through the use of an online opinion panel. The latter survey recruited individuals across the country from the Boston, Kansas City, Los Angeles, Sacramento, Salt Lake City, San Francisco, Seattle, and Washington D.C. regions via an online opinion panel using quota sampling to account for key socio-demographic characters, such as age, race, and employment status. For additional information, please read the project report for the 2018 California Mobility Survey and the forthcoming project report for the 2019 8 Cities Travel Survey (*23*). At the time of these two surveys, the team envisioned building a panel and asked respondents if they would be interested in participating in similar surveys. When the COVID-19 pandemic started in the U.S. in spring, 2020, the team launched the 2020 COVID-19 Mobility Study and re-contacted those previous respondents who opted in for later surveys. By doing so, the team could build a panel dataset including information collected in June–October, 2018, or May–July, 2019, as *before the pandemic* (referred to as the time $T_1$ in the remainder of the paper) and for March–April, 2020, as *during the pandemic* ($T_2$). Merging the 2018 and 2019 data was possible, as the variables analyzed were from identically worded questions, the surveys were administered on the same survey platform, and similar sampling methodologies were used. Out of a total of 3,273 previous respondents who provided a valid email address and were recontacted for this study, a total of 1,274 respondents participated in the 2020 COVID-19 Mobility Study (with a response rate of 38.9% in this survey wave). Of these, 568 cases were recruited from the 2018 California Mobility Survey ($T_1$ = June–October, 2018), and the remaining 706 cases from the 2019 8 Cities Travel Survey ($T_1$ = May–July, 2019). No respondents took part in both the 2018 and 2019 surveys.

In the 2020 COVID-19 Mobility Study, the survey questionnaire asked respondents to report typical travel behaviors from March to April 2020—the initial lockdown period with non-pharmaceutical interventions in the study regions. Since the three survey questionnaires are not entirely identical but slightly different depending on the purpose of each project (detailed information on micromobility was added to the 2019 8 Cities Study and variables measuring the COVID-19 impacts were introduced in the 2020 COVID-19 survey), travel outcomes of interest are selected among those identical or consistent in all three datasets after conducting exploratory analysis on all viable variables. By doing this, five variables are identified, which help understand changes in travel behavior and activity organization during the early stage of the pandemic. These include: (1) the number of days commuting to work in a typical week; (2) the number of days working from home in a typical week; (3) the type of delivery option chosen for online/remote purchases in the last 30 days; (4) typical frequency of active trips for leisure purposes (i.e., not only for recreational trips but also for shopping, errands, and social trips); and (5) the use of ridehailing services in the past 30 days. Travel behavior was measured via self-reported frequencies with which the individuals engaged in several activities: for example, individuals were asked about the number of days they physically commuted and/or telecommuted from home "separately." Given this structure, the responses to these questions were analyzed separately, without the ability to check whether, perhaps, an individual might have worked remotely and also physically commuted to work on the same day (e.g., carrying out each activity for half a day). Similarly, travel behavior patterns were measured through a series of questions asking for the self-reported frequency of use for each mode (by trip purpose) in a given period. Each outcome is analyzed by segmenting the sample based on the respondents' household income level and occupation group. After all, several sources have suggested that the impacts of the pandemic differ greatly across various socioeconomic groups, and the goal is to understand its social implications (i.e., if and how the disadvantaged group struggles more, and what policies could be implemented to mitigate these impacts).

To group households into income groups, the reported current household income (as of March–April, 2020) is adjusted based on the size of each household, the age of each household member, and residential location (*24*). In so doing, "equivalence scales" are applied by assuming that, with each additional member in a household, the needs of the entire household increase, but not in a proportional way. Because of economies of scale in consumption and the sharing of resources, households of different compositions have variations in need to maintain a certain standard of living, and the equivalence scale assigns a value corresponding to that need. Among available approaches for equivalence scales (see Atkinson et al. (1995) for a review), the three-parameter scale, commonly used by the U.S. Census Bureau, is chosen (*25*, *26*). This scale allows for the adjustment of income for three groups of households: adults with no children, single parents, and all other families (i.e., any combination of more than one adult and one child). As a second adjustment, to account for regional differences in the prices of goods and services across Metropolitan statistical areas (MSAs), the regional price parities (RPP) of the U.S. Bureau of Economic Analysis are used. RPP is a measure of the average prices for the mix of goods and services consumed in a region for a given year (*27*). With the two-step adjustment, households are grouped into the following three categories:

- Low: $23,400–$31,900
- Medium: $31,901–$63,600
- High: $63,601–$186,000

The categorization for occupation required a recoding process, as the question was asked with an open-ended response. Four occupation groups were used, as they provided a manageable amount to be implemented efficiently without being too granular. The four categories used are:

- White collar (e.g., attorney, manager, accountant, engineer)
- Blue collar (e.g., waiter, retail worker, cashier)
- Teacher (e.g., grade school to high school teacher, college and university professor)
- Other (e.g., peace officer, coach, musician)

See Table 1 for the cross-tabulation of two categories in the sample ($N$ = 1,274).

As the objective of the research is to identify early trends in travel behavior change between the two time periods, contingency tables are created for each variable, with the $T_1$ and $T_2$ results paired together. To identify statistically significant differences among categories between two periods, a series of Pearson's chi-square tests are conducted. Chi-square tests were conducted also within each variable for each period to measure if the intra-variable observations were significantly different. These are not presented in the paper for brevity, as all results exceeded a p-value of $<0.01$. Alluvial diagrams are created to visualize the changes between the periods, as they are an effective means to depict the overall percent change in responses between the two time periods, while also tracking individual-level flows between categories.

**Table 1.** Number of Cases by Current Occupation and (Adjusted) Household Income Level

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

## Summary of Findings

### Sociodemographics

A summary of the major sociodemographic statistics for this dataset is presented in Table 2. The sample consists of 58.2% female, 41.2% male, and 0.6% respondents that prefer to self-describe, instead of choosing from the two. The age of the sample is rather skewed toward older respondents, with the mean age 53.2 years old. The panel is highly educated with only 7% having no college or technical schooling. Household income levels are equally distributed, with 32.5% of the respondents living in a household with an annual household income below $31,901; 30.7% between $31,901 and $63,600; 31% above $63,600; and 5.8% preferring not to provide this information. More than half of the respondents in the panel dataset (53.2%) reported that they were currently not working at the time of completing the 2020 survey either because of COVID-19 or not being employed from before the pandemic. A total of 61.3% of the respondents report that they do not feel under financial stress, while 36.6% of the cases have some level of stress associated with paying monthly bills (either as a direct result of the pandemic or because of pre-existing financial difficulties).

Considering the unique nature of the panel, consisting of cases recruited from two separate pre-pandemic surveys—one throughout California and the other from the eight large metropolitan areas in the U.S.—it was decided not to weight the panel, even though there is an awareness of its non-representativeness. After all, certain subgroups have only a small number of cases in the panel, and it is not straightforward which sociodemographic targets to establish across different regions and pre-pandemic data collection periods. Still, the authors believe a comparison for the same individuals before and during the pandemic provides useful insights. Note that the sociodemographic deviation of the sample from the population in the studied area should be considered before any generalization is made of the findings from the research to the entire population (which lies beyond the scope of the current paper).

### Commuting and Telecommuting

Commute trips and telecommuting patterns presented changes that were in line with expectations, given the stay-at-home orders preventing non-essential workers from traveling to their typical workspace during the time of the 2020 data collection. (See Figure 1 for a graphic representation of this data and Table 3 for the underlying data with detailed comparisons across groups.) The information for respondents that regularly commute in the sample ($N = 592$) suggests that many respondents changed from traveling to work 5 days a week in $T_1$ to 0 days in $T_2$, during the pandemic. Not surprisingly, though, when examining these results by income bracket, a pattern is observed of the high-income workers having the largest shift to 0 days commuting to the work location, while the middle-income group had a smaller proportion making the same shift, and the low-income workers smaller yet again. This is likely because of the nature of their jobs which is confirmed when examining the data by occupation group. White-collar workers resemble the previously discussed high-income pattern (as this job occupation is indeed positively correlated with household income), while blue-collar workers follow trends that are more similar to the middle- and low-income categories of workers. Teachers also reported a very clear and distinguished pattern in their reported commuting behaviors, as most schools were closed during the time of the 2020 data collection, explaining the large drop in "travel to work" from 77.8% of the respondents in this group at $T_1$ commuting 5 days a week to only 2.2% that do so at $T_2$, and an increase in the number of respondents who physically commute to work 0 days per week from 6.7% to 64.4% during the same time interval. It should be noted that, in all the statistics that have been presented on employed individuals, respondents that either temporarily (e.g., because of the pandemic) or permanently (e.g., because they retired) ceased to work from $T_1$ to $T_2$ were not included in the dataset for the "employed" individuals, which thus only includes respondents that did work at both times, for a more appropriate comparison.

**Table 2.** Summary Statistics of Socioeconomics as of May, 2020 (Sample Size $N = 1,274$)

| Variable and Response | Frequency (%) |
|---|---|
| Age group | |
| 18–24 | 41 (3.2%) |
| 25–34 | 154 (12.1%) |
| 35–44 | 229 (18.0%) |
| 45–54 | 217 (17.0%) |
| 55–64 | 252 (19.8%) |
| 65 and older | 381 (29.9%) |
| Gender | |
| Female | 742 (58.2%) |
| Male | 525 (41.2%) |
| Prefers to self-describe | 7 (0.6%) |
| Hispanic or Latino | |
| Yes | 145 (11.4%) |
| No | 1,129 (88.6%) |
| Race | |
| Asian | 125 (9.8%) |
| Black | 56 (4.4%) |
| Native American | 17 (1.3%) |
| White | 986 (77.4%) |
| Multiple | 55 (4.3%) |
| Other | 35 (2.7%) |
| Education | |
| Some grade/high school | 8 (0.6%) |
| Completed high school or GED | 81 (6.4%) |
| Some college/technical school | 390 (30.6%) |
| Bachelor's degree | 457 (35.9%) |
| Graduate degree | 268 (21.0%) |
| Professional degree | 70 (5.5%) |
| Adjusted household income[a] | |
| Low (≤$31,900) | 414 (32.5%) |
| Medium ($31,901–$63,600) | 391 (30.7%) |
| High (≥$63,601) | 395 (31.0%) |
| Prefer not to answer | 74 (5.8%) |
| Current employment status[a] | |
| Full time | 441 (33.8%) |
| Part time | 139 (10.7%) |
| Two or more jobs | 30 (2.3%) |
| Worked at $T_1$, but not working at $T_2$ | 94 (7.2%) |
| Not working at both times/retired | 601 (46.0%) |
| Current financial stress[a] | |
| Paying bills is a major struggle and worry | |
| Paying bills is a major struggle and worry | 119 (9.3%) |
| Paying bills is tough and on my mind, but I get by | 346 (27.2%) |
| My monthly bills are affordable and I don't worry too much about paying them | 382 (30.0%) |
| I am not worried about my monthly bills | 399 (31.3%) |
| I prefer not to answer | 28 (2.2%) |

*Note*: GED = General Educational Development.
[a]Responses are from $T_2$, during the early phase of the pandemic.

So how did people still work if most could not go to their physical workspace? It appears that telecommuting quickly filled the need, as shown in the full-sample trend through the transition from the respondents who reported they were telecommuting "0 days a week" in $T_1$ to those that reported they did so "5 or more days a week" in $T_2$. The largest portion of individuals reporting the shift to five or more days telecommuting in a week was observed in the high-income group, followed, in descending order, by middle- and low-income levels. When examined by occupation group, white-collar workers switched to telecommuting five or more times a week at a much greater rate than blue-collar workers. Because of the cessation of on-site schooling, teachers were forced to embrace telecommuting even more than white-collar workers, as most reported 0 days of telecommuting a week before the pandemic (79.1%), but now a similar share of them (to that of white-collar workers) telecommute five or more days a week (74.4%).

## *E-Shopping*

Another effect that can be attributed to many U.S. states imposing statewide lockdowns, and more in general to the precautions that residents took to protect their health, is the reduced access to in-person shopping, which potentially shifted pre-COVID-19 shopping behaviors increasingly toward e-shopping. This is largely consistent with expectations, and it highlights one case in which the pandemic somehow accelerated a pre-existing trend in society, with the gradual growth of e-shopping which has been growing its user base significantly already in the past years. In this context, the analysis shows how the patterns of e-shopping adoption differ by the type of delivery. The use of priority 1- or 2-day shipping saw an increase in the frequent users (≥4 times a month) from 14.2% to 24.2%, while the occasional users (up to 3 times a month) dropped from 57.9% to 29.6%. One explanation for the latter trend could be the reduction in the availability of priority shipping because it would require high capacities, but the workforce was limited across the freight system during the early stage of the pandemic (*28*). Another factor influencing the reported pattern is that the March/April, 2020, data collection largely happened at a time in which many people were still hunkered down and not frequently shopping. This is supported by the growth in frequent users of regular delivery methods (>2 days) from 8.3% to 22.1%, as this was the delivery method used by most online retailers during the pandemic.

The delivery method that saw the largest drop in usage was the delivery at a pick-up location, which 28.3% of the sample used in some capacity before the pandemic, but which almost disappeared during the peak pandemic months, at only 5.4% of the respondents. This is consistent with expectations, as people were reducing trips to the types of places where these pick-up lockers are located (e.g., gas stations and grocery stores). Conforming to social distancing guidelines, and the reactions that were observed in the population in the early

**Table 3.** Summary of Number of Days Commuting and Telecommuting in a Week

| Question | Subsample | Time period | Response | | | |
|---|---|---|---|---|---|---|
| | | | 0 days (%) | 1–2 days (%) | 3–4 days (%) | 5+ days (%) |
| Average number of days commuting in a week | All workers*** (*N* = 592) | $T_1$ | 9.3 | 8.1 | 21.1 | 61.5 |
| | | $T_2$ | 54.1 | 16.0 | 13.3 | 16.6 |
| | HHI: high income** (*N* = 237) | $T_1$ | 10.1 | 6.3 | 24.5 | 59.1 |
| | | $T_2$ | 63.3 | 15.2 | 10.5 | 11.0 |
| | HHI: middle income*** (*N* = 201) | $T_1$ | 7.5 | 8.0 | 17.9 | 66.7 |
| | | $T_2$ | 48.3 | 18.4 | 15.4 | 17.9 |
| | HHI: low income*** (*N* = 126) | $T_1$ | 8.7 | 10.3 | 17.5 | 63.5 |
| | | $T_2$ | 42.1 | 15.9 | 15.9 | 26.2 |
| | Occupation: white collar*** (*N* = 421) | $T_1$ | 8.6 | 7.8 | 24.2 | 59.4 |
| | | $T_2$ | 57.5 | 15.9 | 12.8 | 13.8 |
| | Occupation: blue collar*** (*N* = 82) | $T_1$ | 14.6 | 11.0 | 14.6 | 59.8 |
| | | $T_2$ | 34.1 | 12.2 | 20.7 | 32.9 |
| | Occupation: teacher (*N* = 45) | $T_1$ | 6.7 | 2.2 | 6.7 | 84.4 |
| | | $T_2$ | 64.4 | 24.4 | 6.7 | 4.4 |
| | Occupation: other (*N* = 43) | $T_1$ | 7.0 | 11.6 | 18.6 | 62.8 |
| | | $T_2$ | 46.5 | 16.3 | 11.6 | 25.6 |
| Average number of days telecommuting in a week | All workers*** (*N* = 586) | $T_1$ | 64.0 | 17.1 | 6.7 | 12.3 |
| | | $T_2$ | 24.4 | 9.0 | 14.3 | 52.2 |
| | HHI: high income*** (*N* = 235) | $T_1$ | 61.7 | 21.3 | 5.5 | 11.5 |
| | | $T_2$ | 13.6 | 9.4 | 11.9 | 65.1 |
| | HHI: middle income*** (*N* = 197) | $T_1$ | 66.5 | 15.2 | 7.6 | 10.7 |
| | | $T_2$ | 22.3 | 10.2 | 16.8 | 50.8 |
| | HHI: low income*** (*N* = 125) | $T_1$ | 65.6 | 12.0 | 6.4 | 16.0 |
| | | $T_2$ | 47.2 | 8.0 | 16.0 | 28.8 |
| | Occupation: white collar*** (*N* = 418) | $T_1$ | 62.4 | 19.1 | 7.7 | 10.8 |
| | | $T_2$ | 20.6 | 8.4 | 14.4 | 56.7 |
| | Occupation: blue collar*** (*N* = 81) | $T_1$ | 60.5 | 13.6 | 4.9 | 21.0 |
| | | $T_2$ | 56.8 | 8.6 | 12.3 | 22.2 |
| | Occupation: teacher (*N* = 43) | $T_1$ | 79.1 | 9.3 | 2.3 | 9.3 |
| | | $T_2$ | 2.3 | 9.3 | 14.0 | 74.4 |
| | Occupation: other** (*N* = 43) | $T_1$ | 69.8 | 11.6 | 4.7 | 14.0 |
| | | $T_2$ | 23.3 | 14.0 | 18.6 | 44.2 |

*Note*: HHI = household income level.
Homogeneous distributions across different response levels between $T_1$ and $T_2$ are tested with Person's chi-square test, ***$p < .01$; **$p < .05$; $p < .1$.

stage of the pandemic, people were told to minimize this sort of non-essential travel, and, if a purchaser was going to be at home all day they might not have the same delivery issues that required the use of the lockers. On the other hand, in the later stages of the pandemic, with the reopening of many non-essential stores, a sizable increase in pick-up services at curbside and physical store locations was seen, which is not covered in this paper. Note that, for all three delivery methods, the share of 0 times increased substantially. One possibility is that occasional e-shoppers, likely those who shop online selectively, may have chosen not to do so to save money or because of fear of outsiders visiting their homes. Last, but more importantly, the availability and service quality of e-shopping vary by location, so future research is called for on the ways its adoption differs among cities, suburbs, and rural communities. (See Table 4 for a complete summary of the results.) When these data were analyzed by the adjusted household income and occupation categories the trends followed the same patterns as the whole sample, that is, occasional use for delivered purchases reduced by half and frequent use doubling, and therefore are not presented in detail in the paper because of length limitations. However, one important finding in that area relates to how the substantial increase in the use of e-shopping also points to the somewhat "democratization" of e-shopping patterns, with users from more social groups and income categories now accessing the service, beyond the early adopters that were already buying online in previous years.

## Active Leisure Travel

Reports in popular media made claims of large increases in biking and walking as leisure activities during the pandemic (*29*). Consistent with these claims, the sample

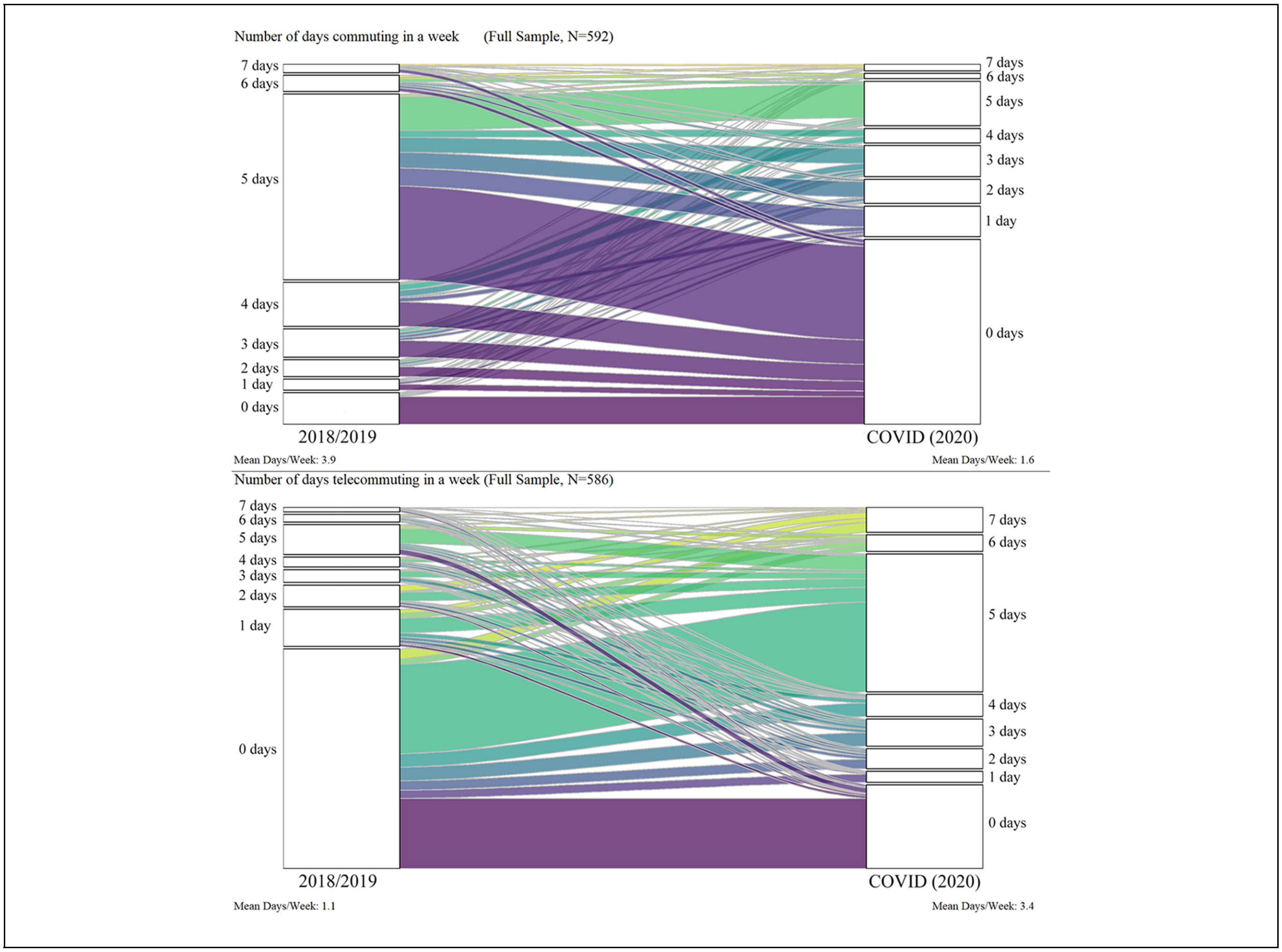


**Figure 1.** Alluvial Diagrams for Number of Days (top) Commuting and (bottom) Telecommuting in a Week.

reported significant gains in the portion of frequent walkers (i.e., those that engage in this behavior at least 1–2 times a week) from 28.9% to 41.5% in the sample. The largest increases in walking leisure trips (in percentage) were found for the category of the "five or more times a week," from 9.6% to 16.1% (i.e., 66% increase) of respondents in the sample. It is speculated that these results are related to walkability around their home and the pandemic amplifying the importance of walkability. While a recent study by Hook et al. did not find evidence of land use affecting "undirected trips," more research is needed to determine the ways such relationships vary by location or country (*30*).

The reported increase in the use of biking for leisure trips (also reported in the media) does not seem to hold true for the sample in this study, though different measurement methods and definitions of trip purposes might be partially behind these findings. Respondents displayed an increase in "not biking at all" from 78.2% to 84.6%. There were minimal increases in the higher-frequency categories (i.e., those that ride a bicycle at least 1–2 times a week) from 6.4% to 8.1%. Both increases were at the expense of many infrequent bikers opting to take fewer rides. This may suggest that these changes were likely predicated on a predisposition to already enjoying biking and the pandemic did not change this underlying attitude. (See Figure 2 for a graphic representation of this data and Table 5 for the underlying data). For both walking and biking leisure trips, no major significant differences were observed when comparing reported responses across household income and occupation groups, and therefore those comparisons are omitted in this paper.

## *Ridehailing*

With the rapid growth of ridehailing services in the years leading up to the pandemic, and these services beginning to establish themselves as a core component of the

**Table 4.** Summary of E-Shopping Delivery Frequency in Last 30 Days

| Question | Subsample | Time period | Response: 0 times (%) | 1–3 times (%) | 4 or more times (%) |
|---|---|---|---|---|---|
| How often did you purchase any product online with... | | | | | |
| 1- or 2-day delivery? | Full sample*** ($N$ = 1,272) | $T_1$ | 27.9 | 57.9 | 14.2 |
| | | $T_2$ | 46.1 | 29.6 | 24.2 |
| Regular delivery (>2 days)? | Full sample*** ($N$ = 1,270) | $T_1$ | 10.4 | 81.3 | 8.3 |
| | | $T_2$ | 32.4 | 45.4 | 22.1 |
| Delivery to pick-up location? | Full sample*** ($N$ = 1,272) | $T_1$ | 71.7 | 25.6 | 2.7 |
| | | $T_2$ | 94.7 | 3.9 | 1.5 |

*Note*: Homogeneous distributions across different response levels between $T_1$ and $T_2$ are tested with Person's chi-square test, ***$p < .01$.

**Table 5.** Summary of Frequency of Leisure Active Travel

| Question | Subsample | Time period | Response: 0 times (%) | <1/month (%) | 1–3/month (%) | 1–2/week (%) | 3–4/week (%) | >5/week (%) |
|---|---|---|---|---|---|---|---|---|
| Walking leisure trips | Full sample*** ($N$ = 1,201) | $T_1$ | 40.8 | 16.7 | 13.7 | 11.2 | 8.0 | 9.7 |
| | | $T_2$ | 39.1 | 8.7 | 10.8 | 14.0 | 11.4 | 16.1 |
| Biking leisure trips | Full sample*** ($N$ = 1,202) | $T_1$ | 78.2 | 10.3 | 5.0 | 2.8 | 2.4 | 1.2 |
| | | $T_2$ | 84.6 | 3.2 | 4.2 | 4.1 | 2.4 | 1.6 |

*Note*: Homogeneous distributions across different response levels between $T_1$ and $T_2$ are tested with Person's chi-square test, ***$p < .01$.

transportation system, it is important to study how users might have reacted in the face of a disruptive event. This is even more important than other modes, as the major players in this segment are funded by venture capital and were already hemorrhaging money before the pandemic (*31*). Thus, understanding the impacts of the pandemic on ridehailing services may be an indicator of their long-term viability. (See Table 6 for a summary of the data.) For the full sample, the "never used" category has dropped from 44.9% to 40.1%, and that difference highlights the growth in the overall adoption rate in the sample (and in general in the population) between 2018/2019 and 2020. While the share of those that have used ridehailing at least once ("users") keeps increasing, the portion of the sample that reported that they have used a ridehailing service "in the last 30 days" dropped from 18.7% to only 7.0% during spring, 2020, which highlights the large reduction in the demand and/or an aversion to ridehailing because of the shared nature of the service.

It was found that ridehailing use patterns differ statistically by income and occupation at the same timepoint (chi-square test results not included in Table 6 for brevity). When the use patterns are compared across income levels, some interesting results are revealed. The adoption rate (non-zero responses) is greater in the high-income level compared with the middle- and low-income levels. This is consistent with the literature that high-income people use ridehailing more often than other groups (*32*). Interestingly, however, the high-income group also had the greatest portion of *inactive* users at $T_2$ (at 66.8%), as their occupation allows for telecommuting, with 76.6% of them telecommuting four or more times a week. Alternatively, they may have more flexibility in their travel choices, in particular, the mode to use, as they were not locked into ridehailing services for transportation and have reasonable access to other options. A household car(s) would be the primary alternative and 95.5% of high-income, inactive transportation network company (TNC) users have access to at least one car, and 66.7% have access to two or more cards. Also, the other side of this pattern is demonstrated by the low-income group, among which the largest percentage of users actively used the service in the last 30 days during the peak of the pandemic, at 11.4%. This suggests an important role for ridehailing that has continued to meet the travel demand of many low-income users, consistent with findings in a study of Toronto, Canada (*33*). Many of the

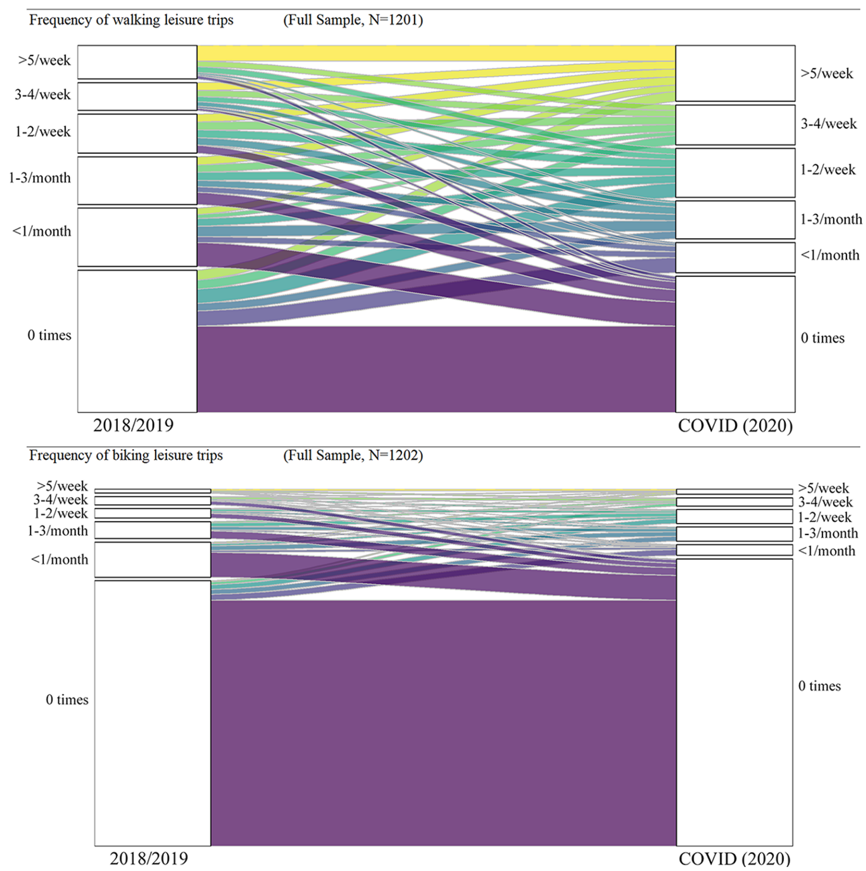


**Figure 2.** Alluvial Diagrams for Frequency of (top) Walking Leisure Trips and (bottom) Biking Leisure Trips.

low-income cases in the sample have no regular access to a household vehicle (e.g., 55.3% without a car), and they still needed to commute to work (e.g., 47.4% telecommuted zero times a week). To further understand the extent to which income and vehicle access account for ridehailing adoption during the pandemic, a follow-up study based on the estimation of the changes in the use of ridehailing is called for.

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

## Discussion

This section further discusses the results of this study within the context of the policy implications from both transportation and social-equity perspectives. The results of this study showed that there was a large shift from commuting to work to telecommuting. This trend was not consistent across income levels, and occupation categories with the lower-income and blue-collar workers reporting substantially lower adoption of telecommuting. Given the lack of a representative sample for the entire U.S., the following policy implications may apply only to the study area, that is, California, and the Boston, Kansas City, Los Angeles, Sacramento, Salt Lake City, San Francisco, Seattle, and Washington D.C. regions. While no significant difference in the number of days

**Table 6.** Summary of Self-Reported Ridehailing Use in Last 30 Days

| Question | Subsample | Time period | Response: Never used (%) | Response: Not in last 30 days (%) | Response: Used in last 30 days (%) |
|---|---|---|---|---|---|
| Use of ride-hailing services in the last 30 days | Full sample*** (*N* = 1,274) | $T_1$ | 44.9 | 36.4 | 18.7 |
| | | $T_2$ | 40.1 | 52.9 | 7.0 |
| | HHI: high income*** (*N* = 395) | $T_1$ | 35.9 | 39.7 | 24.3 |
| | | $T_2$ | 28.4 | 66.8 | 4.8 |
| | HHI: middle income*** (*N* = 391) | $T_1$ | 42.7 | 38.1 | 19.2 |
| | | $T_2$ | 40.9 | 54.0 | 5.1 |
| | HHI: low income*** (*N* = 414) | $T_1$ | 54.1 | 31.6 | 14.3 |
| | | $T_2$ | 48.8 | 39.9 | 11.4 |
| | Occupation: white collar*** (*N* = 463) | $T_1$ | 29.6 | 40.0 | 30.5 |
| | | $T_2$ | 23.3 | 68.9 | 7.8 |
| | Occupation: blue collar*** (*N* = 114) | $T_1$ | 43.9 | 40.4 | 15.8 |
| | | $T_2$ | 34.2 | 50.9 | 14.9 |
| | Occupation: teacher*** (*N* = 54) | $T_1$ | 38.9 | 44.4 | 16.7 |
| | | $T_2$ | 37.0 | 57.4 | 5.6 |
| | Occupation: other*** (*N* = 49) | $T_1$ | 49.0 | 28.6 | 22.4 |
| | | $T_2$ | 40.8 | 46.9 | 12.2 |

*Note*: HHI = household income level.
Homogeneous distributions across different response levels between T1 and T2 are tested with Person's chi-square test, ***$p < .01$.

physically traveling to work was observed between high- and low-income individuals before the pandemic, the latter were much more likely to be considered essential workers and continue to report to work during the pandemic. The imbalance across groups highlights the inherent nature of the different job types' ability to utilize telecommuting, that is, blue-collar jobs more often require the employee to be on site. To mitigate this inequity in essentially forced exposure to potential COVID-19 carriers, policies should be enacted that would provide viable precautionary measures to reduce potential exposure during travel. 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. A potential policy includes the temporary opening of high-occupancy toll roads to all passengers. This approach will reduce the incentive to travel with others, which increases exposure as it is a challenge to maintain physical social distancing while in a personal vehicle. Given the greater reliance on public transit by blue-collar workers, another policy (which has been largely enacted in all major cities throughout the country) ensures public transit follows best practices, such as reducing seating capacity and regular disinfectant cleaning, to maintain health safety for workers and passengers. Many agencies have also considered it prudent to move to a contactless system (e.g., for fare payments) to further reduce potential contamination points, though this comes with its own equity concerns (e.g., access to banking service, smartphone access, learning curve related to using a new payment system) so this should only be implemented when these can be addressed in parallel. A temporary elimination of transit fares has been enforced by some transit authorities, though this policy has major negative consequences in relation to a reduction in revenues, at a time in which the budget of transit operators is already under pressure, and support from the federal and state governments has not always been sufficient to compensate for that reduction.

Even though it does bring to light some transportation-related inequities in the job market, the growth in telecommuting is something that should be encouraged whenever appropriate, as it has many additional benefits beyond reducing exposure to COVID-19, such as reduced congestion, reduced emissions, and cost savings (*34–36*). The potential cost savings benefit both society—through the reduction of the externalities from reduced vehicle miles traveled—and individuals who previously endured commuting costs related to fuel, parking, time, and stress. Such benefits, unfortunately, are not distributed evenly across various socioeconomic groups. In addition, these benefits are not without their own issues, as the greatly reduced congestion levels have led to higher speeds which could have a negative effect on road safety (*37*, *38*). Further, agencies, for example, the Metropolitan Transportation Commission (MTC) in the San Francisco Bay area, have started to explore policy frameworks to support the longer-term adoption of telecommuting in local businesses. However, these draft policies have been received with skepticism, if not total hostility, by certain segments of the business community, in particular because of the potential damages such a policy could bring to local businesses and real estate markets in the job-rich central cores of cities.

The results for active leisure trips (i.e., recreational, shopping, errands, and social trips) suggest an increase in walking trips, and an increase in bicycling among those that already had a habit of frequently riding a bike. As modern society becomes increasingly sedentary, these changes should be encouraged to persist past the pandemic for their positive benefits for both the transportation system and public health. Ongoing efforts to expand bicycling infrastructure, both permanent and temporary, would create an environment where these changes in behavior can endure. One approach that seems to be gaining popularity in cities around the world during the pandemic is the implementation of car-free districts/corridors to promote active travel by making it safer and more convenient (*39*). The permanence of these districts has been, however, somewhat threatened in many locations during the later stages of the pandemic, because of the resurgence of car travel and the competing needs for space in cities. It is suggested that policymakers should increasingly focus on non-work/non-school trips, as they account for roughly 70% of all trips according to National Household Travel Survey data, to maximize the potential effect of any policy actions that would encourage mode shifts to active travel (*40*). For doing so, more research is needed on the socioeconomic profiles, residential neighborhoods, and travel patterns of those who adopted active travel during the pandemic, which helps identify target groups with greater potential for trip reduction by motorized modes and develop tailored approaches. The challenges of inclement weather and habit are hard to overcome, but the pandemic was a forced point of behavior change with the first lockdown orders, and lockdown orders were reinstated in winter 2020/2021, which provided another opportunity to establish new travel behaviors. As this potential is hindered by the winter season not being conducive to active travel, the topic warrants the need to find creative solutions. A potential set of solutions includes supporting local donation efforts for jackets and accessories (such as hats and gloves) to ensure all people that are outside are properly protected from the cold weather, while promoting a positive message that encourages active travel (e.g., bicycling-themed colorful hats and gloves that can be also easily seen by drivers), ensuring snow removal is conducted on sidewalks and bike paths, providing educational outreach on current programs and infrastructure that supports active travel, and possibly promoting less well-established modes for active winter travel such as cross-country skiing (where applicable). These are just a few (sometimes controversial) ideas that can get the conversation started, as any plans to encourage more active travel will require considering local factors including infrastructure, culture, and seasonal weather to develop a targeted strategy that is tailored to its locale.

The impacts of COVID-19 on ridehailing usage illuminate some underlying inequities in the transportation network that need to be addressed, with the data from this study highlighting that lower-income and blue-collar users are more dependent on ridehailing, as they maintained the highest level of use during the pandemic. It is important to recognize that these new services are filling a demand in the market given the increase in adoption across all segments, but it is not without its issues. Ridehailing services were quick to stop offering shared rides with other customers to limit the spread of the virus, while they maintained their core single-travel-party services, even though it is inherently a shared ride between the passenger(s) and driver in close quarters where physical distance is not easily achieved. This puts those still using the services into a position where it might be incorrectly assumed to be safe, as the unsafe service, that is, shared ridehailing, was shuttered. This puts a burden on both the driver and rider to be extra cautious, while the users that were able to completely stop using the services would not be exposed to this potential transmission vector.

Another aspect to consider is that, with the reduced demand, ridehailing drivers are less encouraged to maintain participation with the services. The continued efforts to get ridehailing drivers and other gig-economy workers reclassified as employees and not independent contractors will play an important role, as it would allow them better access to labor and social safety nets, such as unemployment insurance, which other traditional workers were able to utilize during this period. Recently, California passed a ballot measure (Proposition 22) exempting certain gig-economy workers from such benefits as established in California's 2019 Assembly Bill 5 which reclassified many gig-economy workers as employees. The evolution of this topic will need to be observed closely to see the ramifications of these policy changes. Hopefully, it does not set a precedent for other jurisdictions seeking a more equitable and safer labor market for TNC drivers and other gig economy workers.

Unfortunately, the limited number of respondents in the sample that used transit regularly did not make it possible to reliably assess the behavior change. Another limitation of the study relates to the respondents' perception of COVID-19, as this has largely been a highly politicized topic in the U.S., with some segments of the population even questioning if the virus is real, and/or expressing doubts about how it is transmitted, and so forth. This topic was less of a concern at the time of the data collection in March/April, 2020, but, according to many reports and news media, it has since become a driving factor in how people are currently changing or not changing their behaviors because of COVID-19. This latter aspect could not be evaluated in this paper.

## Conclusions

The COVID-19 pandemic has been a disruptive event with effects that have reached all aspects of an individual's life. With the stay-at-home orders issued across most of the U.S. enforced in various parts of 2020, the transportation system has been greatly affected and the pandemic has reverberated across most aspects of society as it underpins the mobility that is crucial for most life activities to take place. In this study, this has been observed in the form of changes in travel behaviors and organization of activities that were measured in the analysis of panel data from 2018/2019 and the first peak of the pandemic in spring, 2020, in the U.S. The major observed changes included a significant shift to telecommuting, if available, changing e-shopping delivery frequencies, an increase in walking for leisure trips, and a reduction in the use of ridehailing services across most income and population groups. While it is still too early to definitively determine if these trends will be temporary or long-lasting, it is important to make sure research in this area can help inform policymakers and private industry on the immediate changes and beneficial policy needs, so measures can be taken to address any negative effects and maintain any positive behavioral changes that might be arising during the pandemic. The study also highlighted significant equity issues that were caused by the pandemic, with lower-income groups and blue-collar workers in many cases being more exposed to the more negative transportation-related externalities from the pandemic. The research team will conduct new waves of data collection in 2021 and future years, and continue to analyze evolving changes in travel behavior, and identify any potential longer-lasting impacts.

Finally, there are some limitations to this study that warrant discussion. First, the dataset is not representative of the whole country, and, as such, the generalizations derived from the results need to be made cautiously, as there are many pronounced differences in how different localities have been responding to the pandemic. The research team is developing a weighting scheme to address the lack of representativeness of the sample. Second, all trends suggested in this study should only be taken as initial, as further data collections will be needed to determine if they were merely temporary shifts in response to the pandemic during the initial spring 2020 peak, or if they are gradually turning (at least in part) into lasting changes in individual behaviors. Third, while the original data collections were designed with a combination of a stratified random sample of households in California and quota sampling through an online opinion panel to achieve a robust and statistically sound sample, the nature of a voluntary longitudinal panel inherently causes potential biases in the data. This is because of the panel attrition and the self-selection of those who decide to continue to participate in the panel study, which can potentially skew the sample toward a non-probabilistic convenience sample. The resampling effort achieved a retention rate of 38.5% which was encouraging for this wave of data collection. However, if the current attrition continues to manifest, as expected, in later waves of data collection, this will lead to smaller sample sizes and reduced generalizability of the results from the analysis of future rounds of data collection in the study. Nurturing the panel to maintain participation in the panel will be of great importance to the research team to ensure the long-term viability of this line of study, while additional data collection efforts and the recruitment of new respondents to *refresh* the panel are also being deployed, to ensure that future rounds of data collection in the study will contribute to answering the standing research questions that have only partially been answered in this initial study.

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### Author Contributions

The authors confirm contributions to the paper as follows: study conception and design: G. Matson, G. Circella; data collection: G. Matson, S. McElroy, Y. Lee, G. Circella; analysis and interpretation of results: G. Matson, S. McElroy, Y. Lee, G. Circella; draft manuscript preparation: G. Matson, S. McElroy, Y. Lee, G. Circella. All authors reviewed the results and approved the final version of the manuscript.

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