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Publication Date

2021-02-25

Peer reviewed

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Word Count: 5308 word + 5 tables (250 words per table) = 6,558 words

SUBMITTED (AUGUST 1, 2020)

ABSTRACT

The COVID-19 pandemic has caused huge disruption to society with, among other impacts, direct and indirect effects (*e.g.* through public health measures) on travel behavior. Since its initial outbreak, COVID-19 has manifested itself into a global pandemic. In response to extensive community spread and potential risk of infection, many state and local governments implemented stay-at-home orders along with measures for social distancing restricting non-essential travel for residents. These travel advisories imposed broad restrictions on millions of Americans resulting in drastic changes in mobility and disruptions to economic activity. In our study we use a combination of data from two previous online surveys and a current data collection conducted to evaluate the impacts of the pandemic on mobility to form a unique longitudinal panel. The use of a longitudinal panel provides us the ability to observe initial trends in travel behavior change, adoption of online shopping, active travel and use of shared mobility services. In our analysis present initial descriptive statistics from the sample to examine the changes in various components of travel behavior in the sample (N=1,274) and for each income/occupation group separately. We find substantial shifts 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. Also, we discuss implications of these findings from the perspectives of environmental sustainability and social equity. This study concludes with suggestions of directions for effective policy and future research.

Keywords: COVID-19, Longitudinal Data, Travel Behavior, E-Shopping, Telecommuting, Active Travel, Disruption, Shared Mobility

INTRODUCTION

While the COVID-19 pandemic has been a devastating event, it has provided researchers a somber opportunity to examine the direct and indirect effects of public health measures on travel behavior. 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, in response to extensive community spread and potential risk of infection, many state and local governments implemented stay-at-home orders along with measures for social distancing restricting nonessential travel for residents in their respective jurisdictions. These restrictions tended to vary by state, but generally targeted activities and locations such as schools, large gatherings, restaurants and bars and 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. While many residents were advised to stay home, many of those employed continued to travel to work for essential operations and services amid statewide lockdowns (*4*). Given the rarity of this event, there are limited studies that have been conducted to investigate the various impacts of an extreme event like the current global pandemic on travel behavior, particularly in the United States. Our research seeks to describe the impacts of the pandemic across a variety of travel behaviors and establish the initial trends in these changes.

To achieve this research objective, we use a combination of data from two previous online surveys and a current data collection conducted by our researchers at the University of California, Davis to form a longitudinal panel. The use of a longitudinal panel provides us the unique ability to observe initial trends in travel behavior change, online shopping, active travel for leisure purposes and use of shared mobility services. To examine these changes, we conducted a descriptive statistical analysis of our target variables and made comparisons across household income level and worker occupation categories.

The following sections are structured as follows. In the next section we summarize earlier research on the impact of important life events on travel, extreme events, and recent COVID-19 studies related to economic and mobility impacts. After presenting our literature review, we will discuss our methodology and framework for analysis ending with a summary of our findings and concluding remarks.

LITERATURE REVIEW

The novel coronavirus was declared a global pandemic on March 11, 2020 by the World Health Organization and the disease has since then spread to more than 114 countries with millions of cases (*5*). Extreme events such as the current pandemic are major disruptors to transportation supply, work activities, economic activity, supply chains and personal health. Pandemics are nevertheless common events in human populations and previous pandemics in the U.S. revealed similar needs to restrict travel along with behavior responses to reduce the spread of the virus (*6,7*). Despite the existence of past pandemics, COVID-19 has proven to be a major disruption to the travel of many Americans; unique in its impacts when compared to similar events. The impacts that are experienced are derived from sudden changes in habits due to the many factors associated with COVID-19. It is assumed that these habits, particularly those related to travel commutes, working from home and social gatherings, were maintained under stable conditions prior to the outbreak of COVID-19; however, once community spread increased, many habits relating to travel started to change. Relevant to these changes in habits, previous studies (*8*) have discussed the application of the habit discontinuity hypothesis to observed changes in travel. It states that once individuals experience a disruption in habit, there is a window of opportunity in which the individual is more sensitive to making decisions affecting their behavior. In the case of the pandemic, individuals experienced one or more requirements to stay at home or continue their essential duties making them theoretically more salient and attentive to travel related information and risks. As such, other studies investigate similar changes in behavior during a person's life course and various turning points that affect long-term mobility decisions (*9*). Both studies show findings suggesting that disruptions

in a person's life course or certain life events can influence their behavior and travel-related decision making.

Concurrent studies on COVID-19, and in some instances, addressing possible limitations to associations between stay-at-home or social distancing orders and changes in behavior, have investigated impacts of the pandemic on economic and transportation related factors. Of these factors, a significant observation is the negative financial effects induced by the temporary shutdown of industries such as tourism, hospitality and airline travel as well as ancillary effects to, for example, agriculture and manufacturing resulting in the loss of income for many Americans (*10*). Various studies have used aggregated and anonymized data produced by Google to examine changes in the number of trips to specific categories of locations like residences, workplaces and retail with trends showing modest changes in mobility and notable reductions in time spent away from residences (*11,12*). When examining changes in use of certain travel modes, a study conducted in Switzerland observed initial reductions in distance traveled two weeks prior to the official lockdown followed by substantial increases in travel by bike and a return to baseline levels for car travel 4 months after the initial lockdown (*13*). Findings from recent COVID-19 studies are at present, mostly preliminary and rely on retrospectively collected data, therefore more detailed analyses are needed to provide conclusive evidence of changes in travel behavior.

DATA AND METHODS

Our unique longitudinal dataset is the combination of research projects that our research team at the University of California, Davis conducted during 2018, 2019 and 2020. Data collections prior to the pandemic consisted of the 2018 California Mobility Survey and 2019 8 Cities Travel Survey, resulting in 3,767 and 3,410 responses, respectively. The 2018 California Mobility Study was a statewide sample of California while the 2019 8 Cities Travel Survey sampled from the Boston, Kansas City, Los Angeles, Sacramento, Salt Lake City, San Francisco, Seattle, and Washington D.C. regions. The surveys were designed to allow for a longitudinal study by maintaining consistent questions and structure, where appropriate, across the questionnaires. The surveys collected information on a broad variety of topics including regular travel patterns, vehicle ownership, household organization, telecommuting patterns, e-shopping behaviors, emerging delivery services, use of shared mobility, and active modes of transportation. Respondents were asked if they would like to participate in future studies related to travel behavior and provided the researchers the means to directly contact them. The COVID-19 pandemic provided a unique event for the research team to study so new data collection was conducted for the 2020 COVID-19 Mobility Study. The participants that opted into the panel were contacted as part of the data collection utilized our study, resulting in 1,274 respondents for the longitudinal panel. There were two other data collections as part of the larger research project which utilized quota sampling via an online opinion panel vendor (N=8,353) and a convenience sample (N=1,266). These datasets were not used in our research as they lacked the longitudinal data collected in one of the prior research projects. Utilizing these datasets, a longitudinal panel with two time periods was created with the California Mobility Survey and the 8 Cities Travel Survey representing time period before the pandemic (T_1) and the 2020 COVID-19 Mobility Study representing the time period during the pandemic (T_2). Specific to the COVID-19 survey questionnaire, respondents were asked to report responses during the pandemic in the period between March-April 2020 to ensure they reported their activities during the lockdown period.

Following the creation of the merged dataset, we identified our target variables as those consistent in all three datasets. This was necessary as there were changes to the survey content based on the main purpose of the studies (*e.g.* micro-mobility for the 8 Cities Study and COVID impacts for the COVID-19 study), thus we could not use all the available variables as they were not collected in all three studies. The research team conducted exploratory analysis on all viable variables to aid in the selection of the variables to be studied. Five variables were identified that yielded intriguing insights into the respondents travel behavior which included number of days commuting to work, number of days working from home, type of delivery option chosen for purchases in the last 30 days, use of active travel modes for leisure purposes (as defined in the survey, leisure trips include not only recreational trips but also

purposes such as shopping, errands, and social trips) and use of ride-hailing services. Once identified, analysis was conducted on each variable by creating subsamples based on the respondents' household income level and occupation group. The categorization for household income was defined as:

- Low income (<=$49,999)
- Middle income ($50,000-$74,999)
- High income (>=$75,000)

Categorizing by occupation required a recoding process as the question was asked with an open-ended response. Four occupation groups were used as it provided a manageable amount for the researchers to implement in an efficient manner without being too granular. The four categories used were:

- White collar (*e.g.* Attorney, Manager, Accountant, Engineer)
- Blue collar (*e.g.* Waiter, General Contractor, Cashier)
- Teacher (*e.g.* Grade School to High School Teachers College and University Professors)
- Other (*e.g.* Peace officer, Judge, Musician).

As the object of the research is to identify early trends in travel behavior change between the two time periods the researchers created contingence tables for each variable with the T_1 and T_2 results paired together. To ensure that the results were significantly different from one another and not homogeneous a Pearson's Chi^2 test was conducted. Alluvial diagrams were created to visualize the changes between the time periods as they are an effective means to depict the overall percent change in responses between the two time periods while also tracking flows between categories.

SUMMARY OF FINDINGS

Sociodemographics

A summary of the sociodemographic statistics is presented in TABLE 1. The sample consists of 58.2% female, 41.2% male, and 0.5% respondents that prefer to self-describe. The age of the sample skews older with the mean age 53.22 years old. The panel is highly educated with only 7% having no college or technical schooling. Household income levels are equally distributed with 34.9% below $50,000, 30% between $50,000 and $75,000, 30.7% above $75,000, and 4.4% preferring not to provide this information. More than half of the panel (54.6%) are currently not working directly because of COVID-19 or previously not being employed. 61.3% of panel is not under financial stress while 36.6% have some level of stress associated with paying monthly bills.

TABLE 1 Sociodemographic summary statistics (Sample Size N = 1,274)

Variable	Response	Frequency (%)
Age groups	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%)
	Self Describe	7 (0.5%)
Hispanic or Latino	Yes	145 (11.4%)
	No	1129 (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%)
Household Income	<= $49,999	382 (34.9%)
	$50,000 - $74,999	391 (30.0%)
	>= $75,000	445 (30.7%)
	Prefer not to answer	56 (4.4%)
Current Employment Status	Full time	441 (34.6%)
	Part time	135 (10.6%)
	COVID: Not working	94 (7.4%)
	Not working/Retired	601 (47.2%)
	2 or more jobs	3 (0.2%)
Current Financial Stress	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 worries about my monthly bills	399 (31.3%)
	I prefer not to answer	28 (2.2%)

Commuting and Telecommuting

Commute trips and telecommuting presented changes that were in line with our expectations given the stay-at-home orders preventing non-essential workers from traveling to their typical workspace. See FIGURE 1 for a graphic representation of this data and TABLE 2 for the underlying data. The whole panel results suggest that most respondents changed from traveling 5 days a week in T_1 (54.22%) to 0 days in T_2 (54.05%). When examining by income bracket we observe a pattern of the high income having the largest shift to 0 days commuting to the office while the middle income had a smaller proportion and the low income smaller yet again. This is likely due to the nature of their jobs which is confirmed when examining the data by occupation group. The white-collar workers resemble the previously discussed high income level while the blue-collar workers follow similar trends as the middle- and low-income categories. This is in line with expectations as higher income tends to be related to white collars jobs more so than with blue collar jobs. Teachers presented a clear picture as most schools were closed explaining the drop in travel to work from 77.78% commuting 5 days a week to 2.22% and the increase in 0 days commuting from 6.67% to 64.44%.

So how did people still work if they could not go to their office space? It appears that telecommuting quickly filled the need as seen in the full sample trend through the transition from 0 days a week (63.99%) to 5 or more days a week (61.48%). The shift to 5 or more days telecommuting had the largest portion in the high-income group at 63.39% followed in descending order by income level at 45.09% and 30.47%, respectively. When examined by occupation group, white-collar workers changed to telecommuting 5 or more times a week (56.7%) at a greater rate than the blue-collar works (22.22%). Teachers embraced telecommuting even more than white collar workers as they transitioned from 79.07% telecommuting 0 days a week to 74.42% telecommuting 5 or more days a week.

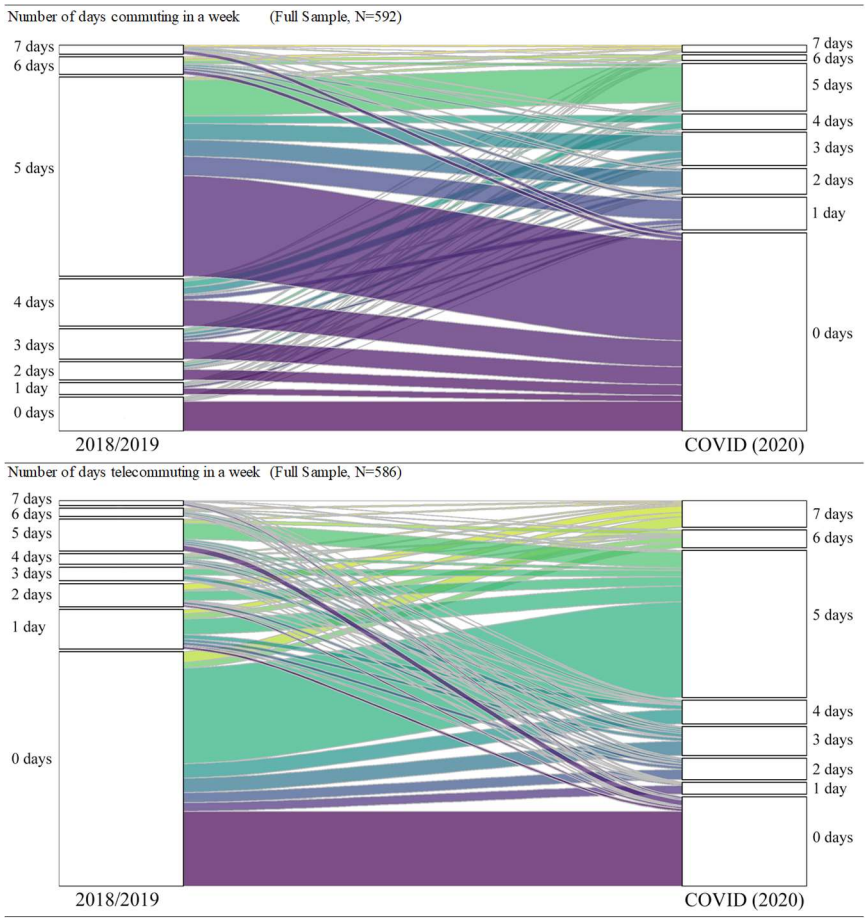

FIGURE 1 Alluvial diagrams for number of days commuting and telecommuting in a week

TABLE 2 Summary of number of days commuting and telecommuting in a week

Question	Subsample	Time Period	Response							
Avg. number of days commuting in a week			0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
	*Full Sample****	T_1	9.29%	3.21%	4.90%	8.28%	12.84%	54.22%	4.73%	2.53%
	(N=592)	T_2	54.05%	8.95%	7.09%	9.12%	4.22%	13.01%	1.52%	2.03%
	*HH Income - High Income**	T_1	7.93%	2.41%	4.48%	8.97%	13.79%	55.17%	3.79%	3.45%
	(N=290)	T_2	60.69%	8.62%	8.28%	7.93%	3.10%	9.31%	1.03%	1.03%
	*HH Income - Middle Income****	T_1	9.71%	2.86%	4.57%	6.29%	13.14%	59.43%	2.86%	1.14%
	(N=175)	T_2	46.29%	9.71%	8.00%	10.29%	3.43%	18.29%	0.57%	3.43%
	*HH Income - Low Income***	T_1	9.35%	3.74%	6.54%	8.41%	10.28%	48.60%	10.28%	2.80%
	(N=107)	T_2	42.99%	9.35%	3.74%	12.15%	9.35%	14.95%	4.67%	2.80%
	*Occupation - White Collar****	T_1	8.55%	3.33%	4.51%	9.26%	14.96%	53.21%	4.04%	2.14%
	(N=421)	T_2	57.48%	9.03%	6.89%	8.79%	4.04%	11.40%	1.19%	1.19%
	*Occupation - Blue Collar****	T_1	14.63%	3.66%	7.32%	8.54%	6.10%	46.34%	9.76%	3.66%
	(N=79)	T_2	31.65%	6.33%	6.33%	13.92%	7.59%	22.78%	5.06%	6.33%
	Occupation - Teacher	T_1	6.67%	0.00%	2.22%	4.44%	2.22%	77.78%	2.22%	4.44%
	(N=45)	T_2	64.44%	11.11%	13.33%	4.44%	2.22%	2.22%	0.00%	2.22%
	Occupation - Other	T_1	6.98%	4.65%	6.98%	2.33%	16.28%	55.81%	4.65%	2.33%
	(N=43)	T_2	46.51%	11.63%	4.65%	9.30%	2.33%	23.26%	0.00%	2.33%
Avg. number of days telecommuting in a week			0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
	*Full Sample****	T_1	63.99%	10.75%	6.31%	3.75%	2.90%	8.70%	2.22%	1.37%
	(N=586)	T_2	24.40%	3.24%	5.80%	7.85%	6.48%	40.10%	4.78%	7.34%
	*HH Income - High Income****	T_1	61.32%	12.54%	8.36%	4.53%	1.39%	8.71%	2.09%	1.05%
	(N=287)	T_2	11.50%	3.48%	5.92%	8.36%	7.32%	48.08%	6.62%	8.71%
	*HH Income - Middle Income****	T_1	67.63%	10.98%	4.62%	4.05%	3.47%	8.09%	0.58%	0.58%
	(N=173)	T_2	32.95%	2.31%	7.51%	5.78%	6.36%	34.68%	4.05%	6.36%
	*HH Income - Low Income****	T_1	66.67%	5.71%	3.81%	1.90%	4.76%	8.57%	5.71%	2.86%
	(N=105)	T_2	45.71%	3.81%	3.81%	10.48%	5.71%	23.81%	1.90%	4.76%
	*Occupation - White Collar****	T_1	62.44%	12.20%	6.94%	4.31%	3.35%	8.13%	1.91%	0.72%
	(N=418)	T_2	20.57%	3.11%	5.26%	7.42%	6.94%	44.02%	5.74%	6.94%
	*Occupation - Blue Collar****	T_1	60.49%	8.64%	4.94%	2.47%	2.47%	12.35%	2.47%	6.17%
	(N=81)	T_2	56.79%	3.70%	4.94%	8.64%	3.70%	13.58%	1.23%	7.41%
	Occupation - Teacher	T_1	79.07%	4.65%	4.65%	2.33%	0.00%	6.98%	2.33%	0.00%
	(N=43)	T_2	2.33%	0.00%	9.30%	9.30%	4.65%	55.81%	6.98%	11.63%
	*Occupation - Other***	T_1	69.77%	6.98%	4.65%	2.33%	2.33%	9.30%	4.65%	0.00%
	(N=43)	T_2	23.26%	4.65%	9.30%	9.30%	9.30%	37.21%	0.00%	6.98%

Note: Signficance of homogenetiy between T_1 and T_2 as based on Person's Chi^2 test, ***p < .01; **p < .05; * p < .10.

E-Shopping

Another effect that can be attributed to many U.S. states imposing statewide lockdowns is reduced access to in-person shopping, which potentially shifted pre-COVID shopping behaviors to e-shopping. The use of priority 1- or 2-day shipping saw an increase in the frequent users (>= 4 times a month) from 14.23% to 24.21% while the occasional users (>= to 3 times a month) dropped from 57.86% to 29.64%. One explanation for this could be the reduction in availability of priority shipping given the high capacity and limited workforce across the freight system (*14*). This is supported by the growth in frequent users of regular delivery methods (>2 day) from 8.27% to 24.51% as it was the delivery method used by most online retailers during the pandemic. The shipping method that saw the largest drop in usage was for delivery to a pick-up location, which 28.3% of the sample used in some capacity prior to the pandemic, but during the peak pandemic months this dropped to 5.35%. 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 groceries stores). Consistent with many social distancing guidelines, this sort of non-essential travel was told to be minimized, 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. See TABLE 3 Summary of e-shopping delivery frequency of use for complete summary of results. When this data was analyzed by the household income and occupation groups the trends followed the same patterns as the whole sample and therefore are not presented in this paper.

TABLE 3 Summary of e-shopping delivery frequency of use

Question	Subsample	Time Period	Response		
			0 times	>0 to 3/month	>=4/month
How often do you purchase any product online with 1 or 2 day delivery?	*Full Sample**** (N=1272)	T_1	27.91%	57.86%	14.23%
		T_2	46.15%	29.64%	24.21%
How often do you purchase any product online with regular delivery (>2 days)?	*Full Sample**** (N=1270)	T_1	10.39%	81.34%	8.27%
		T_2	32.44%	45.43%	22.13%
How often do you purchase any product online with delivery to pick-up location?	*Full Sample**** (N=1272)	T_1	71.70%	25.63%	2.67%
		T_2	94.65%	3.85%	1.49%

Note: Significance of homogeneity between T_1 and T_2 as based on Person's Chi^2 test, ***p < .01; **p < .05; * p < .10.

Active Leisure Travel

Reports in popular media made claims of large increases in biking and walking as a leisure activity during the pandemic (*15*). Consistent with the popular media, the sample reported significant gains in the number of leisure walking trips for frequent walkers (> 1-2 times a week) from 28.81% to 41.47%. The largest increases were in the >5 times a week category with a 66% increase to 16.07% of the sample. However, the reported increase in use of biking for leisure trips does not seem to hold for true for our sample. Respondents displayed an increase in not biking from 78.2% to 84.61%. There were minimal increases in the more frequent users (>1-2 times a week) from 6.49% to 8.07%. Both increases were at the expense of the infrequent bikers opting to take less rides. This indicates that these changes were likely predicated on a predisposition to already enjoying biking and the pandemic did not change this underlying attitude. See TABLE 4 for a summary of results. For both walking and biking leisure trips no clear patterns were observed when compared across household income and occupation and therefore are not presented in this paper.

TABLE 4 Summary 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***	T_1	40.80%	16.74%	13.66%	11.16%	7.99%	9.66%
	(N=1201)	T_2	39.05%	8.66%	10.82%	13.99%	11.41%	16.07%
Biking leisure trips								
	*Full Sample****	T_1	78.20%	10.32%	4.99%	2.83%	2.41%	1.25%
	(N=1202)	T_2	84.61%	3.16%	4.16%	4.08%	2.41%	1.58%

Note: Signficance of homogenetiy between T_1 and T_2 as based on Person's Chi^2 test, ***p < .01; **p < .05; * p < .10.

Ride-hailing

With the rapid growth of ride-hailing services in the years leading up to the pandemic and these services beginning to establish themselves as core aspect of transportation system it is important to see how users have reacted in the face of a massively disruptive event. This is of even more importance than other modes as the major players in this segment are funded by venture capital and were already hemorrhaging money (*16*) and understanding the impacts of the pandemic on ride-hailing may be an indicator of the long term viability of these companies. See TABLE 5 for a summary of the data. For the full sample, the "Never Used" category has dropped from 44.9% to 40.11% and that difference represents the adoption rate growth in the sample over the two time periods. While the share of users is increasing, the portion of the sample that has used a ride-hailing service in the last 30 days has dropped from 18.68% to 6.99% which suggests a reduced travel demand and/or an aversion to ride-hailing due to the shared nature of the service.

When the ride-hailing data is compared across income level some interesting results are revealed. The adoption rate (non-zero responses) is greater in the high-income level compared to the middle- and low-income levels. This is consistent with the literature that high-income people use ride-hailing more often (*17*). Interestingly, in the high-income group they had the greatest portion of inactive users at 67.87% which suggests they likely either had the means to not travel, *e.g.* occupation allows for telecommuting, or they were not locked into ride-hailing services for transportation. The other side of this is clearly demonstrated by the low-income group who have the largest percent of users actively using the service in the last 30 days at 11.52% which suggests that ride-hailing meets the travel demand of low-income users, who may lack access to household vehicles, and need to travel to locations that transit and active travel cannot serve.

Continuing this line of inquiry, the ride-hailing data was then sliced by the occupation category. White collar and blue-collar workers mirrored the trends seen in high/middle-income and low-income categories, respectively. While mirroring the trends in low-income user, the blue-collar trends have a larger magnitude. It has the greatest gain in adoption rate of any occupation group at 9.65% and the largest percent of active users at 14.91%. Teachers saw similar drops in usage as white collar works, but teachers did not adopt the services at a similar rate. Given the heterogenous nature of the Other occupation category it is not possible to confidently draw conclusions regarding their changes in travel behavior.

TABLE 5 Summary of ride-hailing use in last 30 days

Question	Subsample	Time Period	Response		
			Never used	Not in last 30 days	Used in last 30 days
Use of ride-hailing services in the last 30 days	*Full Sample****	T_1	44.90%	36.42%	18.68%
	(N=1274)	T_2	40.11%	52.90%	6.99%
	*HH Income - High Income****	T_1	31.91%	41.12%	26.97%
	(N=445)	T_2	26.97%	67.87%	5.17%
	*HH Income - Middle Income****	T_1	48.59%	36.32%	15.09%
	(N=391)	T_2	43.48%	51.41%	5.12%
	*HH Income - Low Income****	T_1	56.28%	29.84%	13.87%
	(N=382)	T_2	51.83%	36.65%	11.52%
	*Occupation - White Collar****	T_1	29.59%	39.96%	30.45%
	(N=463)	T_2	23.33%	68.90%	7.78%
	*Occupation - Blue Collar****	T_1	43.86%	40.35%	15.79%
	(N=114)	T_2	34.21%	50.88%	14.91%
	*Occupation - Teacher****	T_1	38.89%	44.44%	16.67%
	(N=54)	T_2	37.04%	57.41%	5.56%
	*Occupation - Other****	T_1	48.98%	28.57%	22.45%
	(N=49)	T_2	40.82%	46.94%	12.24%

Note: Significance of homogeneity between T_1 and T_2 as based on Person's Chi^2 test, ***p < .01; **p < .05; * p < .10.

DISCUSSION

In this section we further discuss the results of this study within the context of the policy implications from both a transportation and social equity perspective. The results showed there was a large shift from commuting to work to telecommuting. This trend was not consistent across income level and occupations with the lower-income and blue-collar workers reporting less telecommuting. The imbalance across groups highlights the inherent nature of the different job types' ability to utilize telecommuting, *i.e.* blue-collar jobs more often require the employee to be on site. To mitigate this inequity in essentially forced exposure to the potential COVID-19 carriers, policy should be enacted that would ensure the workers that are required to be on site are provided with all the viable precautionary measures (*e.g.* mask requirements for customers and employees), free access to personal protective equipment, and the legal means and protection to enforce the requirements without fear of repercussions for trying to ensure a safe place of business. Even though it does bring to light some inequities in the job market, the growth in telecommuting is something that should be encouraged as it has many co-benefits beyond reducing exposure to COVID-19, such as reduced congestion, reduced emissions, and costs savings. The potential cost savings benefit society through the positive externalities from reduced vehicle miles traveled and are enticing to individuals who previously endured commuting costs such as fuel, parking, loss in productivity, and stress. Such benefits unfortunately are distributed unequally due to the parallel existence

of individuals who are vulnerable to economic fluctuations and probably do not have the privilege to experience all these co-benefits. 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 (*18,19*).

The results for the active leisure trips (*i.e.* recreational, shopping, errands, and social trips) suggest an increase in walking trips and an increase for people that already frequently bike. As modern society becomes increasingly sedentary these changes should be encouraged to persist past the pandemic for both its positive benefits on the transportation network and the positive health benefits. Continuing current efforts to expand biking infrastructure, both permanent and temporary, would create an environment where these changes in behavior are enduring. 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 (*21*). Furthermore, we would suggest policy makers to focus on non-work/school trips as they account for roughly 70% of all trips according to National Household Travel Survey data (*20*) to maximize the potential effect of any policy actions that would encourage mode shifts to active travel.

The impacts of COVID-19 on ride-hailing usage begins to illuminate some underlying inequities in the transportation network that need to be addressed with the data suggesting that lower income and blue-collar users are more dependent on ride-hailing as they maintained the highest level of use during the pandemic. It is important to recognize that these new services are clearly filling a demand in the market given the increase in adoption across all segments, but it is not without its issues. Ride-hailing services were quick to stop offering shared rides with other customers in an effort to limit the spread of the virus, while also maintaining access to their core service even though it is inherently a shared ride between the passenger and driver in close quarters where social and physical distance is not easily achieved. This puts the people still using the services into a position where it might be assumed to be safe as the clearly unsafe service, shared rides, 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, ride-hailing drivers are less encouraged to maintain participation with the services. This is where the continued efforts to get drivers (and other gig economy workers) properly reclassified as employees of the service play an important role, which would allow them to access the social safety nets, like unemployment insurance, that other traditional workers were able to utilize during this period.

CONCLUSION

The COVID-19 pandemic has been a tragic event with massive loss of life and effects that reach all aspects of life. With the stay-at-home orders issued across most of the United States, the transportation system has been greatly impacted 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 our study we observed this in the form of switching to telecommuting if available, changing e-shopping delivery preferences, an increase in walking for leisure, and a reduction of using ride-hailing services across most segments of the sample. While it is still early to definitively determine if these trends will be temporary or longer lasting it is important to begin this research to help inform policymakers and private industry on the immediate changes so measures can be taken to address any negative effects and maintain the positive behavioral changes.

There are some limitations to this study that warrant discussion. First, the dataset's sample is not representative of the whole country and as such generalizations need to be made cautiously as there are many pronounced differences in how different localities are responding to the pandemic. Also, this is being further exacerbated by the increasing politicization of the following public health guidelines. 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 or if they are lasting behavior changes. Third, while the original data collections where designed with specific quotas

and rational to achieve a robust and statistical sound sample, the nature of a voluntary longitudinal panel is the self-selection to remain in the panel begins to skew the sample towards a non-probabilistic convenience sample. The resampling effort achieved a retention rate of 38.5% which was encouraging for this wave of data collection, but if this rate continues, the later waves of data collection will have a greatly reduced dataset. 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.

ACKNOWLEDGEMENTS

This study was made possible through funding received by the University of California Institute of Transportation Studies from the State of California via the Public Transportation Account and the Road Repair and Accountability Act of 2017 (SB 1). Additional funding was provided by the California Air Resources Board. The contents of this paper reflect the views of the authors, who are responsible for the accuracy of the information presented. This document does not necessarily reflect the official views or policies of the State of California. The authors would like to thank Jai Malik, Keita Makino, Xiatan Wu, Rosa Dominguez-Faus, Erinne Boyd, Junia Sanguinetto, Tho Lee, and Kailai Wang for their contributions to the work presented in this paper.

AUTHOR CONTRIBUTIONS

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

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