# The Pulse of the Nation on 3 Revolutions: Annual Investigation of Nationwide Mobility Trends

September 2022

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#### 16. Abstract

This study investigates the disruptive changes brought to transportation by emerging technologies and the COVID-19 pandemic through the analysis of repeated cross-sectional datasets that were collected with multiple survey waves administered in various regions of the United States and Canada. The first data collection was administrated in 2019 through the recruitment of respondents with an online opinion company. As the COVID-19 pandemic started to disrupt the world starting in 2020, two additional rounds of data collection were carried out in Spring 2020 and Fall 2020, to study the disruptions in activity and travel patterns that were caused by the pandemic. Starting in 2020, the data collection was extended to 15 U.S. regions: Los Angeles, Sacramento, San Diego and San Francisco in California; Atlanta, Boston, Chicago, Denver, Detroit, Kansas City, New York, Salt Lake City, Seattle, Tampa and Washington D.C. in other U.S. regions. In addition, the study covered also Toronto and Vancouver in Canada. Several thousands of respondents participated in the various waves of surveys. Some of these respondents were part of the longitudinal component of the dataset, built through inviting previous survey respondents to participate in the new waves of data collection. Additional respondents were recruited using online opinion panels and convenience sampling. The study enabled by the analysis of the data collected with this series of surveys helps understand how mobility patterns are evolving in the country as new technologies disrupt the transportation sector and they evolve from the pre-pandemic to the post-pandemic era. It helps make planning decisions and guide policymaking through an annual data collection that allows us to collect criticallyneeded information on the evolution of travel patterns and the adoption of new transportation technologies and trends in the selected regions, every year. In this report, we briefly describe the series of data collection and present some summary findings from the analysis of the data collected before and during the COVID-19 pandemic.

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September 2022

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### The Pulse of the Nation on 3 Revolutions: Annual Investigation of Nationwide Mobility Trends

#### **EXECUTIVE SUMMARY**

In this study, we investigate the disruptive changes brought to transportation by emerging technologies and the COVID-19 pandemic through the analysis of repeated cross-sectional datasets that were collected with multiple survey waves administered in various regions of the United States and Canada. The first data collection was administrated in 2019 through the recruitment of respondents with an online opinion company. We used quota sampling to recruit 3,410 respondents from the following eight metropolitan areas in the U.S.: Los Angeles, Sacramento, and San Francisco in California, and Boston, Kansas City, Salt Lake City, Seattle, and Washington D.C. in other regions of the United States. For each region, we defined quotas based on socio-demographic factors, for age, gender, race, ethnicity, presence of children, household income, and student/employment status. The survey asked the participants questions on a variety of topics, including socio-demographic traits, travel behavior patterns, vehicle ownership, long-distance travel, the expectations regarding the adoption of shared mobility services and/or alternative-fuel vehicles, and attitudinal questions that revealed the personal characteristics of the participants toward several important aspects of transportation, including environmental friendliness, cost-sensitivity, car dependency, and/or use of active modes of travel.

In 2020, however, the COVID-19 pandemic hit the world, which caused a lot of typical behaviors in transportation to drastically change. Among various disruptions caused by the pandemic, most of the airline services canceled or significantly reduced their operation, and people started to avoid using public transit and ridehailing services due to the risk of being exposed to pathogens from strangers. During the same time, the remote-work practice quickly spread out throughout the world. To capture data on such significant changes in transportation, another round of data collection was carried out using the same recruitment channel in Spring 2020. For this round of data collection, we extended the area of study to 15 U.S. regions, which were Los Angeles, Sacramento, San Diego, and San Francisco in California; Atlanta, Boston, Chicago, Denver, Detroit, Kansas City, New York, Salt Lake City, Seattle, Tampa and Washington D.C. in other U.S. regions. In addition, we also studied Toronto and Vancouver in Canada. A total of 3,483 people was recruited in these metropolitan areas, using quotas for neighborhood types (urban, suburban and rural) and socio-demographic factors (age, gender, race, ethnicity, presence of children, household income, and student/employment status). In addition, we resampled respondents from previous surveys who agreed to be contacted again to participate in follow-up surveys. This helped build a longitudinal dataset for studies related to the impact of the pandemic on transportation. Moreover, we also used convenience sampling for a part of the data collection for this survey iteration by sharing the invitation to participate in this survey through several listservs and with the general public through advertisements on social media.



The Spring 2020 survey shared most of the core content with the pre-pandemic survey but included several new topics specially designed for the pandemic situation, such as anxiety of health impacts by COVID-19, environment for remote work, modifications in travel patterns during the pandemic, and the expectations for travel choices in the near-term future (i.e., in Fall 2020). The analysis of the dataset has brought a wealth of information on the evolving travel patterns and lifestyles of people in California, the United States, and Canada and is expected to scaffold the insights on the impact of the COVID-19 pandemic as combined with the previous/later data collections.

Finally, we launched another round of data collection in Fall 2020 to further investigate how COVID-19 *kept impacting* transportation. The survey invitations for this round of survey were sent to the same respondents from the previous waves of the survey, thus creating a longitudinal dataset with information from before as well as during two early stages of the pandemic. In addition to these efforts, a parallel effort was carried out to recruit additional respondents through the opinion panel and with convenience sampling in the greater Los Angeles region, as part of a related project funded by the Southern California Association of Governments (SCAG). The survey content was kept aligned with those of the previous iteration to precisely examine the evolving change in transportation as the pandemic period lasted. Additional data collection efforts in Summer 2021 and beyond were also carried out by the research team to further investigate the changes brought by the long-lasting COVID-19 pandemic, as part of further phases of the research that are building on this project (which are not further described in this report).

The study powered by this series of surveys helps understand how mobility patterns are evolving in the country as new technologies disrupt the transportation sector and they evolve from the pre-pandemic to the post-pandemic era. It helps make well-informed decisions in planning and policymaking through an annual data collection that will allow us to collect critically-needed information on the evolution of travel patterns and the adoption of new transportation technologies and trends in the selected regions, every year. Although the COVID-19 pandemic made a significant impact on our initial plan, we have already made several iterations of data collection through the opinion panel in 2020 and 2021 with an adjusted research objective of the project. In this report, we briefly describe the series of data collection and present some summary findings from the analysis of the data collected before and during the COVID-19 pandemic.



#### I. Annual Investigation of Nationwide Mobility Trends

#### Introduction

In the last decade, the revolution of digital devices and online services has been playing a significant role in changing how people get around and travel. Among one of the most revolutionary technologies, ridehailing services such as Uber and Lyft are nowadays widely used by the public, counting more than 6.9 billion Uber rides in 2019 [1]. Micromobility services such as shared e-scooters, ridesharing services such as Waze carpool, and car-sharing services including Zipcar or Turo have become other common ways to travel in the last few years. However, there is ample evidence that the adoption of these new transportation services happens differently over various generations and/or socio-demographic groups [2]. Even though some studies investigated the impact of specific mobility services in selected regions [3]-[5], it is still unclear whether the current trend of emerging mobility, including not only ridehailing but also shared micromobility services (shared e-scooters and bikesharing), electric and other alternative-fuel vehicles, and/or even e-shopping behavior would lead to more sustainable transportation in the nationwide scale. For instance, a higher adoption rate of ridehailing services (and in the future autonomous vehicles) could eventually reduce vehicle ownership, or on the contrary, could strengthen car dependence and increase vehicle miles traveled, as the evidence from current research on the impacts of ridehailing adoption seems to suggest.

In order to build the foundation of this research, we have administrated a series of surveys since 2018 that focus on the current and future changes in the transportation industry. The study aimed to reveal the generational effect on the adoption of new mobility services, changes in vehicle ownership and adoption of alternative fuels, e-shopping patterns, travel patterns with various modes including private vehicles, public transits, and active modes, and so on. The study builds on a first survey that was launched in 2018 for California residents (California Mobility Panel Study, [6]). As part of this project, we built on that previous work, to launch a nationwide survey, which was administered in eight large U.S. cities in 2019.

The research team initially planned to collect a dataset with a survey that was very similar to the previous 2018 California survey to examine how the changes in transportation evolved over the recent years. However, the COVID-19 pandemic that has disrupted society since early 2020 also impacted the study research plan. The pandemic has brought a challenging situation to the transportation industry as several severe restrictions were enforced by governments [7] and many other changes were made in individuals' behaviors. Work from home, online meetings, eshopping, and indoor recreations have seen an unprecedented demand due to the anxiety and the need for social distancing to reduce exposure to pathogens [8]–[10]. Accordingly, in this study, we launched a new survey in Spring 2020 that also collected detailed information on short-term modifications brought by the pandemic on travel behavior, e-shopping patterns, vehicle ownership, individual lifestyles, and other household and individual activities in addition to the original set of questions from the pre-pandemic survey.



Transportation patterns, and related restrictions and regulations, evolved rapidly over the past 1.5 years. California, for instance, started to lift the first stay-at-home orders in early Summer 2020 [11], [12]. Many activities started to reopen, and travel patterns also changed as a result. Therefore, to capture the fast-changing trends in transportation with the country still under the effects of the COVID-19 pandemic, we administrated another iteration of the survey in Fall 2020.

At the time of writing this report, the world is still struggling to strike a balance between enforcing enough social restrictions to limit the spread of COVID-19 and the need (and desire) to return to a new "normal" to keep the economy alive. Some countries such as the United States have loosened restrictive orders despite high daily cases while others such as Germany still observe a strict operation of businesses while they are pushing the vaccination process, including the use of a vaccination passport [13], which has now been adopted in most EU countries as a way to safely reopen activities and allow travel while trying to contain the spread of the virus. Our research team has further built on this project, and has launched additional waves of the COVID-19 survey in Summer 2021 and beyond, to obtain additional data and continue monitoring the evolution of travel behaviors and transportation patterns during the following phases of the pandemic (however, this report does not include details on these following phases of the research).

This project report summarizes findings obtained from the analysis of the datasets obtained from this series of survey projects. The study and the data assembled as part of the research: 1) provide longitudinal data that enable the analysis of emerging changes in transportation patterns, including the adoption of new mobility services and/or alternative-fuel vehicles, use of public transit, e-shopping, and/or general travel pattern, 2) reveal the effect of generational or social-status differences on such changes, 3) investigate the impact of the COVID-19 pandemic on transportation patterns starting in Spring 2020 and onward. The following sections introduce the overview of the series of surveys and provide descriptive statistics of the dataset collected with each survey, before diving into more in-depth data analyses created with these data.

#### **Data Structure**

To investigate the shift in transportation patterns associated with emerging transportation and technology trends and the impacts of the COVID-19 pandemic, in this study we could rely on a series of datasets collected at the following times:

- 1) 8-Cities Mobility Survey in 2019
- 2) COVID-19 Mobility Survey in Spring 2020
- 3) COVID-19 Mobility Survey in Fall 2020

In addition, information from the California Mobility Panel Study in 2018 was also available, which provides additional information on travel behaviors before the COVID-19 pandemic. Additional rounds of data collection (not included in this report, but building on this study) are



being carried out to continue to monitor the evolution of travel patterns during the following stages of the pandemic.

In this report, we focus on the data collected in the three time periods of 2019, Spring 2020, and Fall 2020. The longitudinal component of the datasets is shown in Figure 1. The following sections review the content of each survey and the structure of each dataset collected in the project.

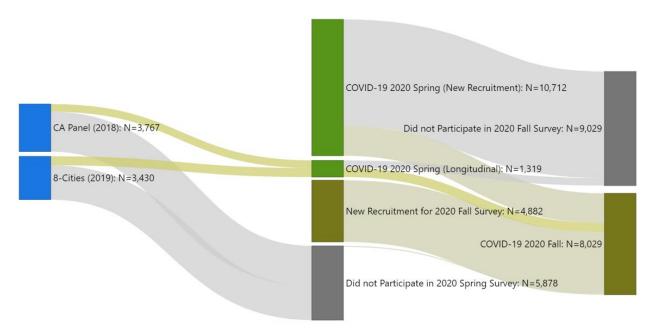


Figure 1. Longitudinal component of the survey datasets from 2018 to 2020

#### 2019 8-Cities Mobility Survey

#### **Data Collection Methodology**

A first mobility survey was administrated in late 2019 as part of this project. The content of this survey is largely built on the previous surveys that were administered in 2015 and 2018 in previous related projects [6], [14]. The final version of the 2019 survey was distributed through the Qualtrics online opinion panel platform and collected information on several groups of variables, including:

- (a) individual attitudes and preferences, and environmental concerns,
- (b) adoption of various technologies, personal lifestyles, and work styles (including telecommuting and mobile work, and adoption of e-shopping),
- (c) residential location and living arrangements,
- (d) current travel behavior, use of cars vs. non-motorized transportation modes,
- (e) availability and use of new transportation options and shared mobility services, including ridehailing, shared ridehailing, carsharing, and micromobility (bikesharing and



- e-scooter sharing), and effects of the use of these services on other components of travel,
- (f) interest in the adoption (purchase or lease) of electric and other alternative-fuel vehicles,
- (g) aspirations for future travel, attitudes towards automated vehicles (AVs), and
- (h) sociodemographic traits.

The survey was distributed through the online panel platform to residents in the following eight regions:

California: Los Angeles, Sacramento and San Francisco

Other USA: Boston, Kansas City, Salt Lake City, Seattle, and Washington D.C.

Each region was defined including not only the central city but also its metropolitan area and identified by a list of 5-digit zip codes included in the area of study. The following figure illustrates the boundary of each study region.



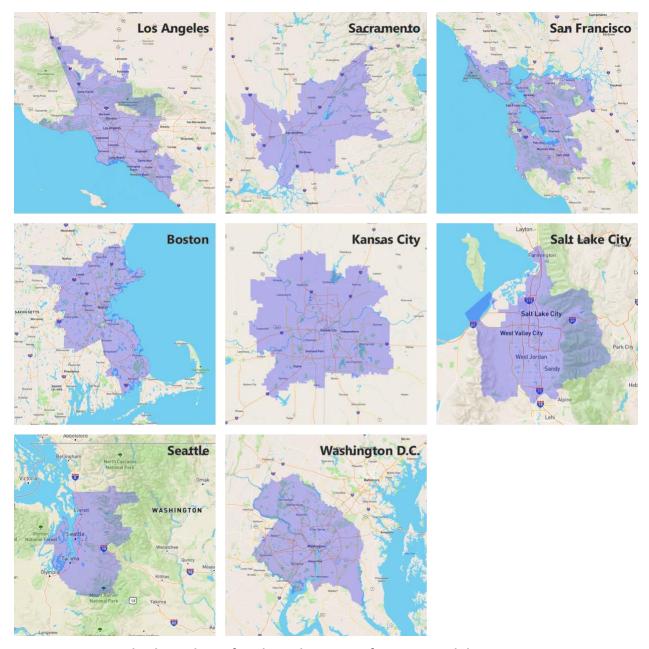


Figure 2. Geographic boundary of each study region of 8-Cities Mobility Survey

For sampling and recruitment purposes, a quota of 500 new respondents was set for each region. Additionally, each region had several targets, which work as a soft quota, by socio-demographic factors, i.e., gender, race, Hispanic ethnicity, age, household income, and employment status. The soft quotas were set using region-specific information from the American Community Survey (ACS).



Table 1. Socio-demographic targets for the opinion panel data collection in the 2019 8-cities study

| Region    |             | Los Angeles | Sacramento  | San<br>Francisco | Boston      | Kansas City | Salt Lake<br>City | Seattle     | Washington D.C. | Total N |
|-----------|-------------|-------------|-------------|------------------|-------------|-------------|-------------------|-------------|-----------------|---------|
| Gender    | Male        | 49.0% (245) | 49.0% (245) | 49.0% (245)      | 48.0% (240) | 49.0% (245) | 50.0% (250)       | 50.0% (250) | 49.0% (245)     | 1,965   |
| Gender    | Female      | 51.0% (255) | 51.0% (255) | 51.0% (255)      | 52.0% (260) | 51.0% (255) | 50.0% (250)       | 50.0% (250) | 51.0% (255)     | 2,035   |
| Hispanis  | Yes         | 45.0% (225) | 21.0% (105) | 22.0% (110)      | 11.0% (55)  | 10.0% (50)  | 18.0% (90)        | 10.0% (50)  | 16.0% (80)      | 765     |
| Hispanic  | No          | 60.0% (300) | 79.0% (395) | 78.0% (390)      | 89.0% (445) | 90.0% (450) | 82.0% (410)       | 90.0% (450) | 84.0% (420)     | 3,260   |
|           | White       | 56.0% (280) | 70.0% (350) | 54.0% (270)      | 78.0% (390) | 79.0% (395) | 83.0% (415)       | 75.0% (375) | 50.0% (250)     | 2,725   |
|           | Black       | 7.0% (35)   | 8.0% (40)   | 8.0% (40)        | 9.0% (45)   | 14.0% (70)  | 2.0% (10)         | 6.0% (30)   | 31.0% (155)     | 425     |
| Race      | Asian       | 16.0% (80)  | 14.0% (70)  | 27.0% (135)      | 8.0% (40)   | 3.0% (15)   | 2.0% (10)         | 14.0% (70)  | 12.0% (60)      | 480     |
|           | N. American | 12.0% (60)  | 5.0% (25)   | 7.0% (35)        | 3.0% (15)   | 3.0% (15)   | 6.0% (30)         | 3.0% (15)   | 4.0% (20)       | 215     |
|           | Other       | 12.0% (60)  | 5.0% (25)   | 7.0% (35)        | 3.0% (15)   | 3.0% (15)   | 6.0% (30)         | 3.0% (15)   | 4.0% (20)       | 215     |
|           | 18-24       | 13.0% (65)  | 13.0% (65)  | 13.0% (65)       | 13.0% (65)  | 11.0% (55)  | 13.0% (65)        | 11.0% (55)  | 12.0% (60)      | 495     |
|           | 25-34       | 20.0% (100) | 23.0% (115) | 19.0% (95)       | 19.0% (95)  | 19.0% (95)  | 23.0% (115)       | 21.0% (105) | 21.0% (105)     | 825     |
| Age       | 35-44       | 18.0% (90)  | 20.0% (100) | 18.0% (90)       | 16.0% (80)  | 18.0% (90)  | 20.0% (100)       | 18.0% (90)  | 18.0% (90)      | 730     |
|           | 45-54       | 18.0% (90)  | 16.0% (80)  | 17.0% (85)       | 18.0% (90)  | 18.0% (90)  | 16.0% (80)        | 18.0% (90)  | 18.0% (90)      | 695     |
|           | 55+         | 31.0% (155) | 28.0% (140) | 33.0% (165)      | 34.0% (170) | 34.0% (170) | 28.0% (140)       | 32.0% (160) | 31.0% (155)     | 1,255   |
| Employed  | Yes         | 65.0% (325) | 61.0% (305) | 67.0% (335)      | 69.0% (345) | 69.0% (345) | 71.0% (355)       | 68.0% (340) | 72.0% (360)     | 2,710   |
| Employed  | No          | 35.0% (175) | 39.0% (195) | 33.0% (165)      | 31.0% (155) | 31.0% (155) | 29.0% (145)       | 32.0% (160) | 18.0% (90)      | 1,240   |
|           | ~ \$24,999  | 20.0% (100) | 19.0% (95)  | 14.0% (70)       | 17.0% (85)  | 18.0% (90)  | 14.0% (70)        | 14.0% (70)  | 11.0% (55)      | 635     |
|           | ~ \$49,999  | 20.0% (100) | 20.0% (100) | 14.0% (70)       | 15.0% (75)  | 23.0% (115) | 21.0% (105)       | 18.0% (90)  | 13.0% (65)      | 720     |
| Household | ~ \$74,999  | 16.0% (80)  | 17.0% (85)  | 13.0% (65)       | 14.0% (70)  | 18.0% (90)  | 20.0% (100)       | 17.0% (85)  | 14.0% (70)      | 645     |
| Income    | ~ \$99,999  | 12.0% (60)  | 13.0% (65)  | 11.0% (55)       | 12.0% (60)  | 13.0% (65)  | 15.0% (75)        | 14.0% (70)  | 12.0% (60)      | 510     |
|           | ~ \$149,999 | 15.0% (75)  | 16.0% (80)  | 18.0% (90)       | 18.0% (90)  | 16.0% (80)  | 17.0% (85)        | 18.0% (90)  | 20.0% (100)     | 690     |
|           | \$150,000~  | 17.0% (85)  | 15.0% (75)  | 29.0% (145)      | 24.0% (120) | 12.0% (60)  | 13.0% (65)        | 19.0% (95)  | 29.0% (145)     | 790     |
| Total N   |             | 500         | 500         | 500              | 500         | 500         | 500               | 500         | 500             | 4,000   |



Table 2. Distribution of socio-demographics in the 2019 8-cities sample

| Region    |             | Los Angeles | Sacramento  | San<br>Francisco | Boston      | Kansas City | Salt Lake<br>City | Seattle     | Washington D.C. | Total N |
|-----------|-------------|-------------|-------------|------------------|-------------|-------------|-------------------|-------------|-----------------|---------|
| Gender    | Male        | 48.6% (205) | 42.5% (191) | 44.1% (204)      | 44.4% (210) | 38.7% (162) | 37.7% (154)       | 44.8% (191) | 48.4% (169)     | 1,486   |
| Gender    | Female      | 50.9% (215) | 56.8% (255) | 55.1% (255)      | 55.0% (260) | 60.9% (255) | 61.1% (250)       | 54.9% (234) | 51.6% (180)     | 1,904   |
| Hispanis  | Yes         | 33.9% (143) | 12.0% (54)  | 16.2% (75)       | 8.5% (40)   | 4.5% (19)   | 9.5% (39)         | 9.6% (41)   | 6.9% (24)       | 435     |
| Hispanic  | No          | 66.1% (279) | 88.0% (395) | 83.8% (388)      | 91.5% (433) | 95.5% (400) | 90.5% (370)       | 90.4% (385) | 93.1% (325)     | 2,975   |
|           | White       | 66.4% (280) | 75.1% (337) | 58.3% (270)      | 82.5% (390) | 83.8% (351) | 92.9% (380)       | 75.1% (320) | 48.4% (169)     | 2,497   |
|           | Black       | 8.3% (35)   | 8.9% (40)   | 8.6% (40)        | 7.8% (37)   | 12.9% (54)  | 2.4% (10)         | 7.0% (30)   | 44.4% (155)     | 401     |
| Race      | Asian       | 11.6% (49)  | 15.6% (70)  | 29.2% (135)      | 8.5% (40)   | 2.4% (10)   | 2.4% (10)         | 16.4% (70)  | 5.7% (20)       | 404     |
|           | N. American | 4.5% (19)   | 4.2% (19)   | 3.0% (14)        | 2.1% (10)   | 3.6% (15)   | 2.0% (8)          | 3.3% (14)   | 2.0% (7)        | 106     |
|           | Other       | 13.3% (56)  | 5.6% (25)   | 7.6% (35)        | 3.2% (15)   | 1.2% (5)    | 3.7% (15)         | 3.5% (15)   | 4.0% (14)       | 180     |
|           | 18-24       | 15.4% (65)  | 14.5% (65)  | 11.4% (53)       | 10.6% (50)  | 13.1% (55)  | 13.9% (57)        | 12.4% (53)  | 15.2% (53)      | 451     |
|           | 25-34       | 23.7% (100) | 17.6% (79)  | 16.2% (75)       | 17.5% (83)  | 15.8% (66)  | 22.7% (93)        | 24.6% (105) | 30.1% (105)     | 706     |
| Age       | 35-44       | 21.3% (90)  | 19.4% (87)  | 19.4% (90)       | 16.9% (80)  | 21.5% (90)  | 24.4% (100)       | 21.1% (90)  | 24.9% (87)      | 714     |
|           | 45-54       | 16.4% (69)  | 15.1% (68)  | 15.1% (70)       | 18.0% (85)  | 16.0% (67)  | 14.2% (58)        | 17.6% (75)  | 10.6% (37)      | 529     |
|           | 55+         | 17.8% (75)  | 31.2% (140) | 35.6% (165)      | 35.9% (170) | 30.5% (128) | 20.5% (84)        | 23.5% (100) | 16.9% (59)      | 921     |
| Employed  | Yes         | 74.9% (316) | 61.2% (275) | 64.8% (300)      | 67.2% (318) | 63.5% (266) | 65.3% (267)       | 70.4% (300) | 80.5% (281)     | 2,323   |
| Employed  | No          | 25.1% (106) | 38.8% (174) | 35.2% (163)      | 32.8% (155) | 36.5% (153) | 34.7% (142)       | 29.6% (126) | 19.5% (68)      | 1,087   |
|           | ~ \$24,999  | 17.1% (72)  | 21.2% (95)  | 15.1% (70)       | 18.0% (85)  | 21.7% (91)  | 17.4% (71)        | 16.7% (71)  | 16.3% (57)      | 612     |
|           | ~ \$49,999  | 23.2% (98)  | 22.5% (101) | 15.1% (70)       | 16.1% (76)  | 27.7% (116) | 26.4% (108)       | 21.1% (90)  | 18.6% (65)      | 724     |
| Household | ~ \$74,999  | 17.1% (72)  | 18.9% (85)  | 14.3% (66)       | 15.2% (72)  | 21.7% (91)  | 24.9% (102)       | 19.5% (83)  | 20.3% (71)      | 642     |
| Income    | ~ \$99,999  | 14.2% (60)  | 14.5% (65)  | 11.9% (55)       | 13.5% (64)  | 15.3% (64)  | 14.2% (58)        | 13.6% (58)  | 12.3% (43)      | 467     |
|           | ~ \$149,999 | 17.1% (72)  | 12.9% (58)  | 19.4% (90)       | 19.2% (91)  | 10.7% (45)  | 12.0% (49)        | 18.8% (80)  | 14.0% (49)      | 534     |
|           | \$150,000~  | 11.4% (48)  | 10.0% (45)  | 24.2% (112)      | 18.0% (85)  | 2.9% (12)   | 5.1% (21)         | 10.3% (44)  | 18.3% (64)      | 431     |
| Total N   |             | 422         | 449         | 463              | 473         | 419         | 409               | 426         | 349             | 3,410   |



Table 3. Difference between actual distribution in the 2019 8-cities sample vs. targets

| Region      |             | Los Angeles  | Sacramento   | San Francisco | Boston      | Kansas City      | Salt Lake<br>City | Seattle          | Washington D.C.   | Total         |
|-------------|-------------|--------------|--------------|---------------|-------------|------------------|-------------------|------------------|---|---------------|
| Gender      | Male        | -0.4% (-2)   | -6.5% (-33)  | -4.9% (-25)   | -3.6% (-18) | -10.3% (-<br>52) | -12.3% (-<br>62)  | -5.2% (-26)      | -0.6% (-3)  | -24.4% (-479) |
|             | Female      | -0.1% (-1)   | 5.8% (29)    | 4.1% (21)     | 3.0% (15)   | 9.9% (50)        | 11.1% (56)        | 4.9% (25)        | 0.6% (3)  | -6.4% (-131)  |
| Hispania    | Yes         | -11.1% (-56) | -9.0% (-45)  | -5.8% (-29)   | -2.5% (-13) | -5.5% (-28)      | -8.5% (-43)       | -0.4% (-2)       | -9.1% (-46)   | -43.1% (-330) |
| Hispanic    | No          | 6.1% (31)    | 9.0% (45)    | 5.8% (29)     | 2.5% (13)   | 5.5% (28)        | 8.5% (43)         | 0.4% (2)         | D.C.<br>-0.6% (-3)<br>0.6% (3)  | -8.7% (-285)  |
|             | White       | 10.4% (52)   | 5.1% (26)    | 4.3% (22)     | 4.5% (23)   | 4.8% (24)        | 9.9% (50)         | 0.1% (1)         | -1.6% (-8)  | -8.4% (-228)  |
|             | Black       | 1.3% (7)     | 0.9% (5)     | 0.6% (3)      | -1.2% (-6)  | -1.1% (-6)       | 0.4% (2)          | 1.0% (5)         | 13.4% (67)  | -5.6% (-24)   |
| Race        | Asian       | -4.4% (-22)  | 1.6% (8)     | 2.2% (11)     | 0.5% (3)    | -0.6% (-3)       | 0.4% (2)          | 2.4% (12)        | -6.3% (-32)   | -15.8% (-76)  |
|             | N. American | -7.5% (-38)  | -0.8% (-4)   | -4.0% (-20)   | -0.9% (-5)  | 0.6% (3)         | -4.0% (-20)       | 0.3% (2)         | -2.0% (-10)   | -50.7% (-109) |
|             | Other       | 1.3% (7)     | 0.6% (3)     | 0.6% (3)      | 0.2% (1)    | -1.8% (-9)       | -2.3% (-12)       | 0.5% (3)         | 0.0% (0)  | -16.3% (-35)  |
|             | 18-24       | 2.4% (12)    | 1.5% (8)     | -1.6% (-8)    | -2.4% (-12) | 2.1% (11)        | 0.9% (5)          | 1.4% (7)         | 3.2% (16)   | -8.9% (-44)   |
|             | 25-34       | 3.7% (19)    | -5.4% (-27)  | -2.8% (-14)   | -1.5% (-8)  | -3.2% (-16)      | -0.3% (-2)        | 3.6% (18)        | 9.1% (46)   | -14.4% (-119) |
| Age         | 35-44       | 3.3% (17)    | -0.6% (-3)   | 1.4% (7)      | 0.9% (5)    | 3.5% (18)        | 4.4% (22)         | 3.1% (16)        | 6.9% (35)   | -2.2% (-16)   |
|             | 45-54       | -1.6% (-8)   | -0.9% (-5)   | -1.9% (-10)   | 0.0% (0)    | -2.0% (-10)      | -1.8% (-9)        | -0.4% (-2)       | -7.4% (-37)   | -23.9% (-166) |
|             | 55+         | -13.2% (-66) | 3.2% (16)    | 2.6% (13)     | 1.9% (10)   | -3.5% (-18)      | -7.5% (-38)       | -8.5% (-43)      | % (25) 0.6% (3) % (-2) -9.1% (-46) % (2) 9.1% (46) % (1) -1.6% (-8) % (5) 13.4% (67) % (12) -6.3% (-32) % (2) -2.0% (-10) % (3) 0.0% (0) % (7) 3.2% (16) % (18) 9.1% (46) % (16) 6.9% (35) -7.4% (-37) % (-2) -7.4% (-37) % (12) 8.5% (43) % (14) 5.3% (27) % (16) 5.6% (28) % (13) 6.3% (32) % (-2) 0.3% (2) % (4) -6.0% (-30) % (-44) -10.7% (-54) .8% (- | -26.6% (-334) |
| Francis vod | Yes         | 9.9% (50)    | 0.2% (1)     | -2.2% (-11)   | -1.8% (-9)  | -5.5% (-28)      | -5.7% (-29)       | 2.4% (12)        | 8.5% (43)   | -14.3% (-387) |
| Employed    | No          | -9.9% (-50)  | -0.2% (-1)   | 2.2% (11)     | 1.8% (9)    | 5.5% (28)        | 5.7% (29)         | -2.4% (-12)      | 1.5% (8)  | -12.3% (-153) |
|             | ~ \$24,000  | -2.9% (-15)  | 2.2% (11)    | 1.1% (6)      | 1.0% (5)    | 3.7% (19)        | 3.4% (17)         | 2.7% (14)        | 5.3% (27)   | -3.6% (-23)   |
|             | ~ \$49,000  | 3.2% (16)    | 2.5% (13)    | 1.1% (6)      | 1.1% (6)    | 4.7% (24)        | 5.4% (27)         | 3.1% (16)        | 5.6% (28)   | 0.6% (4)      |
| Household   | ~ \$74,000  | 1.1% (6)     | 1.9% (10)    | 1.3% (7)      | 1.2% (6)    | 3.7% (19)        | 4.9% (25)         | 2.5% (13)        | 6.3% (32)   | -0.5% (-3)    |
| Income      | ~ \$99,000  | 2.2% (11)    | 1.5% (8)     | 0.9% (5)      | 1.5% (8)    | 2.3% (12)        | -0.8% (-4)        | -0.4% (-2)       | 0.3% (2)  | -8.4% (-43)   |
|             | ~ \$149,000 | 2.1% (11)    | -3.1% (-16)  | 1.4% (7)      | 1.2% (6)    | -5.3% (-27)      | -5.0% (-25)       | 0.8% (4)         | -6.0% (-30)   | -22.6% (-156) |
|             | \$150,000 ~ | -5.6% (-28)  | -5.0% (-25)  | -4.8% (-24)   | -6.0% (-30) | -9.1% (-46)      | -7.9% (-40)       | -8.7% (-44)      | -10.7% (-54)  | -45.4% (-359) |
| Total       |             | -15.6% (-78) | -10.2% (-51) | -7.4% (-37)   | -5.4% (-27) | -16.2% (-<br>81) | -18.2% (-<br>91)  | -14.8% (-<br>74) | ,   | -14.8% (-590) |



#### **Spring 2020 COVID-19 Mobility Survey**

#### **Data Collection Methodology**

Following the 8-cities survey project in 2019, the research team has administered a new series of surveys since the COVID-19 pandemic hit the society in March 2020 to examine the impact of the pandemic on individuals' travel behaviors and needs. The first iteration of the online survey was launched in May 2020, using three recruitment channels.

#### **Longitudinal Dataset**

This channel aimed to recruit survey participants that had already participated in at least one of our previous surveys (i.e., surveys conducted in 2018 and 2019). Previous survey respondents who opted to be contacted again to participate in future surveys were recontacted by email to participate in this new data collection. By the end of the data collection period, we had sent out survey invitations to 3,466 respondents from previous surveys. Among them, 1,440 participants completed the new survey, with a response rate of 41.5%. Since we recruited previous participants from the 2018 California Mobility Panel Study, which targeted the sample only in California, and from the 2019 8-cities Mobility Study, which targeted several regions across the United States, a large portion of this longitudinal sample is from California (i.e., all the participants from 2018 California Mobility Panel Study and those who were recruited in Los Angeles, Sacramento and San Francisco in the 2019 8-cities Mobility Study, unless they had relocated to another region by Spring 2020) with the rest from the non-California metropolitan regions of Boston, Kansas City, Seattle, Salt Lake City, and Washington DC.

#### **Opinion Panel**

The second distribution channel that was used in this data collection is an online opinion panel administered by Qualtrics. The recruitment process through this channel was very similar to the one used in the previous 2019 data collection campaign. However, in Spring 2020 we expanded the study region to include the following 15 metropolitan regions across the United States and 2 regions in Canada (with additional funding that was provided by the Canadian Smart Prosperity Institute and that completed this study) in this data collection:

California: Los Angeles (LA), Sacramento, San Diego and San Francisco (SF)

Other USA: Atlanta, Boston, Chicago, Denver, Detroit, Kansas City, New York City, Salt Lake

City, Seattle, Tampa, and Washington D.C. (DC)

Canada: Toronto and Vancouver

Similar to the 2019 8-cities Mobility Study, the online panel version of this data collection, adopted the following sociodemographics to mirror the distribution of the population in these regions for gender, race, Hispanic ethnicity, age, household income, and employment status. Table 4 to Table 6 summarize the sociodemographic targets, the characteristics of the sample that was collected, and the difference between them.

For this distribution channel, the online opinion panel company managed its own reward systems to motivate respondents to participate in the study. By the end of the data collection, a



total of 10,815 valid responses were collected (with 9,323 completed responses, and 1,492 partial responses that were still considered valid). As 58,496 individuals started the survey, this corresponded to a completion rate of 18.5%.

#### **Convenience Sampling**

The last distribution channel used a mix of convenience sampling methods that focused on the recruitment through social media, i.e., Facebook and Instagram, and the distribution of the email invitations through various listservs, and through various colleagues' professional networks. The primary recruitment channel was Facebook. The research team posted several series of Facebook ads. Some samples of the images used in the ads are shown in the figure below.



Figure 3. Images for advertisement on Facebook [15], [16]

To increase the conversion rate, we also advertised a drawing of Amazon gift cards among respondents who completed the survey and that were recruited through these channels. The ads received a total of 98,030 views. In total, 1,393 respondents were recruited through convenience sampling participated in the study by the end of the data collection period.



Table 4. Socio-demographic targets for the opinion panel data collection in the Spring 2020 survey

| Region                        |             | Atlanta     | Boston      | Chicago     | DC          | Denver      | Detroit     | Kansas      | LA          | New York    |
|-------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Condor                        | Male        | 47.4% (237) | 48.5% (242) | 48.0% (240) | 48.5% (243) | 49.5% (248) | 47.7% (239) | 49.0% (245) | 49.3% (246) | 47.3% (473) |
| Gender                        | Female      | 52.6% (263) | 51.5% (258) | 52.0% (260) | 50.5% (252) | 52.3% (261) | 51.0% (255) | 50.7% (254) | 52.7% (527) | 51.1% (255) |
| Gender Hispanic Race Employed | Yes         | 12.4% (62)  | 11.4% (57)  | 23.5% (117) | 25.7% (128) | 4.5% (23)   | 9.6% (48)   | 45.0% (225) | 27.1% (271) | 21.2% (106) |
| піѕрапіс                      | No          | 87.6% (438) | 88.6% (443) | 76.5% (383) | 74.3% (372) | 95.5% (477) | 90.4% (452) | 55.0% (275) | 72.9% (729) | 78.8% (394) |
|                               | White       | 44.8% (224) | 77.8% (389) | 59.8% (299) | 79.8% (399) | 66.6% (333) | 79.1% (395) | 56.4% (282) | 50.9% (509) | 70.3% (351) |
| Paca                          | Black       | 40.5% (202) | 9.1% (45)   | 20.7% (104) | 6.5% (32)   | 24.6% (123) | 14.3% (71)  | 6.9% (35)   | 19.6% (196) | 7.5% (38)   |
| Race                          | Asian       | 7.4% (37)   | 8.3% (42)   | 7.9% (39)   | 4.1% (21)   | 4.7% (23)   | 3.1% (16)   | 16.3% (82)  | 13.4% (134) | 13.8% (69)  |
|                               | Other       | 7.4% (37)   | 4.8% (24)   | 11.6% (58)  | 9.5% (48)   | 4.1% (20)   | 3.5% (18)   | 20.3% (102) | 16.2% (162) | 8.4% (42)   |
|                               | 18-34       | 32.8% (164) | 31.7% (159) | 32.0% (160) | 33.3% (167) | 28.2% (141) | 30.3% (151) | 32.9% (165) | 31.6% (316) | 31.2% (156) |
| Age                           | 35-54       | 38.0% (190) | 33.8% (169) | 34.0% (170) | 35.4% (177) | 34.1% (170) | 35.4% (177) | 35.6% (178) | 34.3% (343) | 33.9% (170) |
|                               | 55+         | 29.2% (146) | 34.5% (172) | 34.0% (170) | 31.3% (157) | 37.7% (189) | 34.3% (172) | 31.5% (157) | 34.1% (341) | 34.9% (174) |
| Employed                      | Yes         | 64.6% (323) | 68.9% (344) | 61.6% (308) | 68.1% (340) | 57.8% (289) | 68.6% (343) | 64.7% (323) | 60.4% (604) | 61.5% (307) |
| Employed                      | No          | 35.4% (177) | 31.1% (156) | 38.4% (192) | 31.9% (160) | 42.2% (211) | 31.4% (157) | 35.3% (177) | 39.6% (396) | 38.5% (193) |
|                               | ~ \$49,999  | 39.0% (195) | 32.1% (161) | 39.4% (197) | 34.6% (173) | 44.1% (221) | 40.8% (204) | 39.4% (197) | 37.9% (379) | 39.3% (196) |
| Household Income              | ~ \$100,000 | 30.1% (150) | 26.2% (131) | 28.3% (141) | 31.8% (159) | 29.0% (145) | 31.6% (158) | 28.3% (141) | 25.5% (255) | 30.0% (150) |
|                               | \$100,001~  | 30.9% (155) | 41.7% (208) | 32.4% (162) | 33.6% (168) | 26.9% (134) | 27.6% (138) | 32.3% (162) | 36.7% (367) | 30.7% (154) |
| Total N                       |             | 500         | 500         | 500         | 500         | 500         | 500         | 500         | 500         | 1,000       |



| Region  |             | Sacramento  | San Diego   | Seattle     | SF          | Salt Lake   | Tampa       | Toronto     | Vancouver   | Total N |
|---|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|---------|
| Gandar  | Male        | 48.9% (245) | 50.1% (250) | 50.0% (250) | 49.4% (247) | 50.2% (251) | 47.8% (239) | 48.0% (240) | 48.1% (240) | 4,375   |
| Region  Gender  Hispanic  Race  Age  Employed | Female      | 51.1% (255) | 49.9% (250) | 50.0% (250) | 50.6% (253) | 49.8% (249) | 52.2% (261) | 52.0% (260) | 51.9% (260) | 4,625   |
| Hispanis                                      | Yes         | 21.2% (106) | 33.5% (168) | 9.7% (49)   | 21.9% (109) | 17.6% (88)  | 19.4% (97)  | -           | -           | 1,630   |
| riispariic                                    | No          | 78.8% (394) | 66.5% (332) | 90.3% (451) | 78.1% (391) | 82.4% (412) | 80.6% (403) | -           | -           | 6,370   |
|   | White       | 70.3% (351) | 70.7% (354) | 75.1% (375) | 54.2% (271) | 83.2% (416) | 77.3% (386) | 49.1% (245) | 45.4% (227) | 5,706   |
| Paco  | Black       | 7.5% (38)   | 5.0% (25)   | 6.0% (30)   | 8.0% (40)   | 1.7% (9)    | 12.5% (63)  | 7.8% (39)   | 1.0% (5)    | 1,211   |
| Race  | Asian       | 13.8% (69)  | 11.8% (59)  | 13.7% (69)  | 26.9% (135) | 3.8% (19)   | 3.5% (18)   | 36.3% (181) | 49.5% (247) | 1,248   |
|   | Other       | 8.4% (42)   | 12.4% (62)  | 5.3% (26)   | 10.9% (54)  | 11.2% (56)  | 6.7% (34)   | 6.9% (34)   | 4.1% (21)   | 835     |
|   | 18-34       | 31.2% (156) | 34.7% (174) | 31.9% (159) | 32.3% (161) | 36.4% (182) | 26.8% (134) | 29.8% (149) | 30.5% (152) | 2,852   |
| Age   | 35-54       | 33.9% (170) | 33.3% (166) | 36.1% (180) | 34.9% (174) | 35.8% (179) | 32.9% (164) | 36.1% (181) | 34.3% (172) | 3,142   |
|   | 55+         | 34.9% (174) | 32.0% (160) | 32.0% (160) | 32.8% (164) | 27.9% (139) | 40.3% (202) | 34.1% (170) | 35.2% (176) | 3,006   |
| Employed                                      | Yes         | 61.5% (307) | 61.7% (308) | 68.1% (340) | 67.1% (336) | 71.1% (356) | 56.8% (284) | 60.8% (304) | 61.5% (308) | 5,779   |
| Lifipioyeu                                    | No          | 38.5% (193) | 38.3% (192) | 31.9% (160) | 32.9% (164) | 28.9% (144) | 43.2% (216) | 39.2% (196) | 38.5% (192) | 3,221   |
|   | ~ \$49,999  | 39.3% (196) | 33.6% (168) | 31.8% (159) | 28.5% (143) | 35.1% (175) | 47.1% (235) | 31.7% (158) | 37.6% (188) | 3,272   |
| Household Income                              | ~ \$100,000 | 30.0% (150) | 29.5% (147) | 30.4% (152) | 24.6% (123) | 35.3% (176) | 29.9% (150) | 31.1% (156) | 30.2% (151) | 2,619   |
|   | \$100,001~  | 30.7% (154) | 37.0% (185) | 37.8% (189) | 46.9% (235) | 29.6% (148) | 23.0% (115) | 37.2% (186) | 32.3% (161) | 3,110   |
| Total N                                       |             | 500         | 500         | 500         | 500         | 500         | 500         | 500         | 500         | 9,000   |

<sup>-:</sup> No quota is set.



Table 5. Distribution of socio-demographics in the Spring 2020 sample collected with the opinion panel

| Region                           |             | Atlanta     | Boston      | Chicago     | DC          | Denver      | Detroit     | Kansas      | LA   | New York    |
|----------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|--|-------------|
| Gender                           | Male        | 43.6% (218) | 40.0% (200) | 44.6% (223) | 43.0% (215) | 42.4% (212) | 45.0% (225) | 39.6% (198) | 45.6% (228)  | 47.8% (478) |
| Gender                           | Female      | 60.0% (300) | 61.4% (307) | 59.4% (297) | 63.4% (317) | 60.0% (300) | 61.2% (306) | 56.4% (282) | 58.3% (583)  | 63.0% (315) |
| Hispanis                         | Yes         | 9.6% (48)   | 7.2% (36)   | 20.4% (102) | 14.4% (72)  | 5.0% (25)   | 5.0% (25)   | 39.0% (195) | 27.0% (270)  | 18.0% (90)  |
| пізрапіс                         | No          | 94.4% (472) | 96.8% (484) | 83.6% (418) | 89.2% (446) | 99.0% (495) | 98.4% (492) | 65.0% (325) | 45.6% (228) 4<br>58.3% (583) (27.0% (270) 27.0% (770) 37.0% (770) 37.0% (210) 21.0% (210) 21.0% (140) 21.7% (127) 21.0% (349) 21.0% (390) 21 | 83.6% (418) |
|                                  | White       | 55.8% (279) | 83.6% (418) | 64.8% (324) | 83.0% (415) | 75.0% (375) | 85.0% (425) | 61.0% (305) | 56.3% (563)  | 70.4% (352) |
| Paco                             | Black       | 37.0% (185) | 7.0% (35)   | 22.0% (110) | 6.6% (33)   | 20.8% (104) | 12.8% (64)  | 8.0% (40)   | 21.0% (210)  | 7.4% (37)   |
| Race                             | Asian       | 8.0% (40)   | 9.0% (45)   | 9.0% (45)   | 6.6% (33)   | 5.4% (27)   | 3.4% (17)   | 17.0% (85)  | 14.0% (140)  | 14.8% (74)  |
|                                  | Other       | 3.2% (16)   | 4.4% (22)   | 8.2% (41)   | 7.4% (37)   | 2.8% (14)   | 2.2% (11)   | 18.0% (90)  | 12.7% (127)  | 9.0% (45)   |
|                                  | 18-34       | 35.8% (179) | 35.2% (176) | 34.2% (171) | 34.6% (173) | 27.6% (138) | 36.8% (184) | 36.6% (183) | 34.9% (349)  | 33.2% (166) |
| Age                              | 35-54       | 36.0% (180) | 36.2% (181) | 35.4% (177) | 41.4% (207) | 35.2% (176) | 39.8% (199) | 37.8% (189) | 39.0% (390)  | 33.4% (167) |
| Race  Employed  Household Income | 55+         | 32.2% (161) | 32.6% (163) | 34.4% (172) | 27.6% (138) | 41.2% (206) | 26.8% (134) | 29.6% (148) | 30.1% (301)  | 35.4% (177) |
| Employed                         | Yes         | 63.6% (318) | 65.8% (329) | 61.0% (305) | 64.2% (321) | 58.6% (293) | 65.2% (326) | 64.0% (320) | 62.3% (623)  | 56.2% (281) |
| Employeu                         | No          | 40.4% (202) | 38.2% (191) | 43.0% (215) | 39.4% (197) | 45.4% (227) | 38.2% (191) | 40.0% (200) | 41.7% (417)  | 45.4% (227) |
|                                  | ~ \$49,999  | 32.4% (162) | 28.2% (141) | 34.8% (174) | 33.8% (169) | 36.6% (183) | 39.0% (195) | 35.2% (176) | 33.6% (336)  | 38.8% (194) |
| Household Income                 | ~ \$100,000 | 34.6% (173) | 31.8% (159) | 33.0% (165) | 33.4% (167) | 34.0% (170) | 34.4% (172) | 32.2% (161) | 30.5% (305)  | 29.4% (147) |
|                                  | \$100,001~  | 37.0% (185) | 44.0% (220) | 36.2% (181) | 36.2% (181) | 33.4% (167) | 30.0% (150) | 36.6% (183) | 39.9% (399)  | 33.4% (167) |
| Total N                          |             | 520         | 520         | 520         | 520         | 518         | 520         | 517         | 520  | 1,040       |



| Region           |             | Sacramento  | San Diego   | Seattle     | SF          | Salt Lake   | Tampa       | Toronto     | Vancouver   | Total N |
|------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|---------|
| Gender           | Male        | 36.2% (181) | 42.6% (213) | 38.8% (194) | 38.8% (194) | 32.2% (161) | 43.6% (218) | 43.8% (219) | 42.2% (211) | 3,788   |
|                  | Female      | 63.0% (315) | 60.4% (302) | 62.4% (312) | 60.0% (300) | 66.0% (330) | 60.0% (300) | 59.6% (298) | 60.0% (300) | 5,449   |
| Hispanic         | Yes         | 18.0% (90)  | 24.8% (124) | 8.8% (44)   | 21.0% (105) | 9.6% (48)   | 13.6% (68)  | 4.8% (24)   | 3.8% (19)   | 1,346   |
|                  | No          | 83.6% (418) | 79.2% (396) | 95.2% (476) | 83.0% (415) | 91.2% (456) | 90.4% (452) | 99.2% (496) | 99.4% (497) | 7,977   |
| Race             | White       | 70.4% (352) | 75.4% (377) | 77.8% (389) | 59.0% (295) | 90.0% (450) | 83.8% (419) | 50.4% (252) | 45.4% (227) | 6,171   |
|                  | Black       | 7.4% (37)   | 4.8% (24)   | 5.6% (28)   | 7.4% (37)   | 2.0% (10)   | 11.2% (56)  | 8.8% (44)   | 1.6% (8)    | 1,154   |
|                  | Asian       | 14.8% (74)  | 13.0% (65)  | 15.0% (75)  | 28.0% (140) | 4.0% (20)   | 5.0% (25)   | 36.8% (184) | 51.2% (256) | 1,324   |
|                  | Other       | 9.0% (45)   | 10.8% (54)  | 5.6% (28)   | 9.6% (48)   | 4.8% (24)   | 4.0% (20)   | 8.0% (40)   | 5.0% (25)   | 674     |
|                  | 18-34       | 33.2% (166) | 38.4% (192) | 32.0% (160) | 36.6% (183) | 50.6% (253) | 23.8% (119) | 35.0% (175) | 44.0% (220) | 3,178   |
| Age              | 35-54       | 33.4% (167) | 33.8% (169) | 41.6% (208) | 36.2% (181) | 38.0% (190) | 39.2% (196) | 39.6% (198) | 35.0% (175) | 3,391   |
|                  | 55+         | 35.4% (177) | 31.8% (159) | 30.4% (152) | 31.2% (156) | 12.2% (61)  | 41.0% (205) | 29.4% (147) | 24.2% (121) | 2,756   |
| Employed         | Yes         | 56.2% (281) | 57.0% (285) | 62.6% (313) | 64.2% (321) | 66.6% (333) | 55.8% (279) | 66.0% (330) | 63.0% (315) | 5,637   |
| Employed         | No          | 45.4% (227) | 47.0% (235) | 41.4% (207) | 39.8% (199) | 34.2% (171) | 48.2% (241) | 38.0% (190) | 40.2% (201) | 3,686   |
|                  | ~ \$49,999  | 38.8% (194) | 33.6% (168) | 31.0% (155) | 24.2% (121) | 44.6% (223) | 43.0% (215) | 28.6% (143) | 32.6% (163) | 3,037   |
| Household Income | ~ \$100,000 | 29.4% (147) | 29.4% (147) | 30.6% (153) | 30.8% (154) | 37.6% (188) | 33.2% (166) | 35.6% (178) | 35.2% (176) | 2,927   |
|                  | \$100,001~  | 33.4% (167) | 41.0% (205) | 42.4% (212) | 49.0% (245) | 18.6% (93)  | 27.8% (139) | 39.8% (199) | 35.4% (177) | 3,358   |
| Total N          |             | 508         | 520         | 520         | 520         | 504         | 520         | 520         | 516         | 9,323   |



Table 6. Difference between actual distribution in the Spring 2020 sample collected with the opinion panel vs. targets

| Region           |             | Atlanta     | Boston      | Chicago     | DC           | Denver      | Detroit     | Kansas      | LA          | New York    |
|------------------|-------------|-------------|-------------|-------------|--------------|-------------|-------------|-------------|-------------|-------------|
| Gender           | Male        | -3.8% (-19) | -8.5% (-42) | -3.4% (-17) | -5.5% (-28)  | -7.1% (-36) | -2.7% (-14) | -9.4% (-47) | -3.7% (-18) | 0.5% (5)    |
|                  | Female      | 7.4% (37)   | 9.9% (49)   | 7.4% (37)   | 12.9% (65)   | 7.7% (39)   | 10.2% (51)  | 5.7% (28)   | 5.6% (56)   | 11.9% (60)  |
| Hispanic         | Yes         | -2.8% (-14) | -4.2% (-21) | -3.1% (-15) | -11.3% (-56) | 0.5% (2)    | -4.6% (-23) | -6.0% (-30) | -0.1% (-1)  | -3.2% (-16) |
|                  | No          | 6.8% (34)   | 8.2% (41)   | 7.1% (35)   | 14.9% (74)   | 3.5% (18)   | 8.0% (40)   | 10.0% (50)  | 4.1% (41)   | 4.8% (24)   |
| Race             | White       | 11.0% (55)  | 5.8% (29)   | 5.0% (25)   | 3.2% (16)    | 8.4% (42)   | 5.9% (30)   | 4.6% (23)   | 5.4% (54)   | 0.1% (1)    |
|                  | Black       | -3.5% (-17) | -2.1% (-10) | 1.3% (6)    | 0.1% (1)     | -3.8% (-19) | -1.5% (-7)  | 1.1% (5)    | 1.4% (14)   | -0.1% (-1)  |
|                  | Asian       | 0.6% (3)    | 0.7% (3)    | 1.1% (6)    | 2.5% (12)    | 0.7% (4)    | 0.3% (1)    | 0.7% (3)    | 0.6% (6)    | 1.0% (5)    |
|                  | Other       | -4.2% (-21) | -0.4% (-2)  | -3.4% (-17) | -2.1% (-11)  | -1.3% (-6)  | -1.3% (-7)  | -2.3% (-12) | -3.5% (-35) | 0.6% (3)    |
|                  | 18-34       | 3.0% (15)   | 3.5% (17)   | 2.2% (11)   | 1.3% (6)     | -0.6% (-3)  | 6.5% (33)   | 3.7% (18)   | 3.3% (33)   | 2.0% (10)   |
| Age              | 35-54       | -2.0% (-10) | 2.4% (12)   | 1.4% (7)    | 6.0% (30)    | 1.1% (6)    | 4.4% (22)   | 2.2% (11)   | 4.7% (47)   | -0.5% (-3)  |
|                  | 55+         | 3.0% (15)   | -1.9% (-9)  | 0.4% (2)    | -3.7% (-19)  | 3.5% (17)   | -7.5% (-38) | -1.9% (-9)  | -4.0% (-40) | 0.5% (3)    |
| Employed         | Yes         | -1.0% (-5)  | -3.1% (-15) | -0.6% (-3)  | -3.9% (-19)  | 0.8% (4)    | -3.4% (-17) | -0.7% (-3)  | 1.9% (19)   | -5.3% (-26) |
|                  | No          | 5.0% (25)   | 7.1% (35)   | 4.6% (23)   | 7.5% (37)    | 3.2% (16)   | 6.8% (34)   | 4.7% (23)   | 2.1% (21)   | 6.9% (34)   |
| Household Income | ~ \$49,999  | -6.6% (-33) | -3.9% (-20) | -4.6% (-23) | -0.8% (-4)   | -7.5% (-38) | -1.8% (-9)  | -4.2% (-21) | -4.3% (-43) | -0.5% (-2)  |
|                  | ~ \$100,000 | 4.5% (23)   | 5.6% (28)   | 4.7% (24)   | 1.6% (8)     | 5.0% (25)   | 2.8% (14)   | 3.9% (20)   | 5.0% (50)   | -0.6% (-3)  |
|                  | \$100,001~  | 6.1% (30)   | 2.3% (12)   | 3.8% (19)   | 2.6% (13)    | 6.5% (33)   | 2.4% (12)   | 4.3% (21)   | 3.2% (32)   | 2.7% (13)   |
| Total            |             | 4.0% (20)   | 4.0% (20)   | 4.0% (20)   | 4.0% (20)    | 3.6% (18)   | 4.0% (20)   | 3.4% (17)   | 4.0% (20)   | 0.4% (40)   |



| Region           |             | Sacramento   | San Diego   | Seattle      | SF           | Salt Lake    | Tampa       | Toronto     | Vancouver    | Total         |
|------------------|-------------|--------------|-------------|--------------|--------------|--------------|-------------|-------------|--------------|---------------|
| Gender           | Male        | -12.7% (-64) | -7.5% (-37) | -11.2% (-56) | -10.6% (-53) | -18.0% (-90) | -4.2% (-21) | -4.2% (-21) | -5.9% (-29)  | -6.5% (-587)  |
|                  | Female      | 11.9% (60)   | 10.5% (52)  | 12.4% (62)   | 9.4% (47)    | 16.2% (81)   | 7.8% (39)   | 7.6% (38)   | 8.1% (40)    | 9.2% (824)    |
| Hispanic         | Yes         | -3.2% (-16)  | -8.7% (-44) | -0.9% (-5)   | -0.9% (-4)   | -8.0% (-40)  | -5.8% (-29) | -           | -            | -3.2% (-284)  |
|                  | No          | 4.8% (24)    | 12.7% (64)  | 4.9% (25)    | 4.9% (24)    | 8.8% (44)    | 9.8% (49)   | -           | -            | 17.9% (1,607) |
| Race             | White       | 0.1% (1)     | 4.7% (23)   | 2.7% (14)    | 4.8% (24)    | 6.8% (34)    | 6.5% (33)   | 1.3% (7)    | 0.0% (0)     | 5.2% (465)    |
|                  | Black       | -0.1% (-1)   | -0.2% (-1)  | -0.4% (-2)   | -0.6% (-3)   | 0.3% (1)     | -1.3% (-7)  | 1.0% (5)    | 0.6% (3)     | -0.6% (-57)   |
|                  | Asian       | 1.0% (5)     | 1.2% (6)    | 1.3% (6)     | 1.1% (5)     | 0.2% (1)     | 1.5% (7)    | 0.5% (3)    | 1.7% (9)     | 0.8% (76)     |
|                  | Other       | 0.6% (3)     | -1.6% (-8)  | 0.3% (2)     | -1.3% (-6)   | -6.4% (-32)  | -2.7% (-14) | 1.1% (6)    | 0.9% (4)     | -1.8% (-161)  |
|                  | 18-34       | 2.0% (10)    | 3.7% (18)   | 0.1% (1)     | 4.3% (22)    | 14.2% (71)   | -3.0% (-15) | 5.2% (26)   | 13.5% (68)   | 3.6% (326)    |
| Age              | 35-54       | -0.5% (-3)   | 0.5% (3)    | 5.5% (28)    | 1.3% (7)     | 2.2% (11)    | 6.3% (32)   | 3.5% (17)   | 0.7% (3)     | 2.8% (249)    |
|                  | 55+         | 0.5% (3)     | -0.2% (-1)  | -1.6% (-8)   | -1.6% (-8)   | -15.7% (-78) | 0.7% (3)    | -4.7% (-23) | -11.0% (-55) | -2.8% (-250)  |
| Employed         | Yes         | -5.3% (-26)  | -4.7% (-23) | -5.5% (-27)  | -2.9% (-15)  | -4.5% (-23)  | -1.0% (-5)  | 5.2% (26)   | 1.5% (7)     | -1.6% (-142)  |
|                  | No          | 6.9% (34)    | 8.7% (43)   | 9.5% (47)    | 6.9% (35)    | 5.3% (27)    | 5.0% (25)   | -1.2% (-6)  | 1.7% (9)     | 5.2% (465)    |
| Household Income | ~ \$49,999  | -0.5% (-2)   | 0.0% (0)    | -0.8% (-4)   | -4.3% (-22)  | 9.5% (48)    | -4.1% (-20) | -3.1% (-15) | -5.0% (-25)  | -2.6% (-235)  |
|                  | ~ \$100,000 | -0.6% (-3)   | -0.1% (0)   | 0.2% (1)     | 6.2% (31)    | 2.3% (12)    | 3.3% (16)   | 4.5% (22)   | 5.0% (25)    | 3.4% (308)    |
|                  | \$100,001~  | 2.7% (13)    | 4.0% (20)   | 4.6% (23)    | 2.1% (10)    | -11.0% (-55) | 4.8% (24)   | 2.6% (13)   | 3.1% (16)    | 2.8% (248)    |
| Total            |             | 1.6% (8)     | 4.0% (20)   | 4.0% (20)    | 4.0% (20)    | 0.8% (4)     | 4.0% (20)   | 4.0% (20)   | 3.2% (16)    | 3.6% (323)    |

<sup>-:</sup> Cannot be computed as no quota is set.



#### Fall 2020 COVID-19 Mobility Survey

The last survey that was administered as part of this project was launched in Fall 2020 to study the evolution of travel patterns during the continuing COVID-19 pandemic. With the pandemic lasting beyond the summer of 2020, this survey was conducted to continue our efforts to observe the impacts of the pandemic over time.

#### **Data Collection Methodology**

The data collection method for this survey iteration was primarily carried out through recontacting respondents from previous surveys, including the Spring 2020 survey. In addition, new respondents were recruited through the online opinion panel and with convenience sampling in the greater Los Angeles area, as part of a related research effort funded by the Southern California Association of Governments (SCAG).

#### **Longitudinal**

Similar to the Spring 2020 iteration, we again recruited a longitudinal panel of the survey participants from the earlier rounds of data collection. An invitation email was sent out to those who had opted to participate in future surveys in one of the previous survey waves, including the 2018 California Mobility Study, 2019 8-cities Mobility Study, and the Spring 2020 COVID-19 Mobility Study. Since this longitudinal sample now includes people from the convenience-sampling channel of Spring 2020 data collection which is spread out over the world, the geographical region of the participants is not limited to specific metropolitan areas. Further, the presence of some respondents that participated in both the Spring 2020 and Fall 2020 surveys allows for studying differences in travel patterns during the two phases of the pandemic. By the end of the data collection period, we obtained 3,385 valid responses.

#### **Opinion Panel and Convenience Sampling**

In addition to the recruitment of previous participants in the longitudinal component of the study, additional respondents were recruited using an online opinion panel and convenience sampling channels in the greater Los Angeles region, as part of a separate, related project funded by the Southern California Association of Governments (SCAG). Due to the priorities for the contract with SCAG, the study area was limited to the six counties in their jurisdiction, which are Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura. Note that although we had recruited respondents from the *Los Angeles* region in the previous survey iterations (and in the longitudinal component for the Fall 2020 dataset), those respondents were located in the metropolitan area of Los Angeles (i.e., Los Angeles also contains Orange County and some other parts of the metropolitan area), while in the SCAG data collection respondents are usually labeled as from Los Angeles if they are located in the Los Angeles County. In addition, in the SCAG project, additional respondents were also recruited through online advertisements on social media and the distribution of survey invitations through listservs and other local networks in the region.



#### II. Data Analysis

In this section, we summarize several analyses of the data collected as part of this project. Some components of the analyses use one dataset, either the pre-COVID-19 one or one of the 2020 datasets collected during the COVID-19 pandemic, and some use more than one survey wave as part of longitudinal analyses.

#### **Descriptive Statistics from the Pre-COVID-19 and During-COVID-19 Datasets**

First of all, in this subsection, we provide some comparisons between the dataset collected before the COVID-19 pandemic and the ones taken during the pandemic in 2020, to help better understand how the trends in various aspects around transportation have changed due to the COVID-19 pandemic.

#### Remote-Work Behavior before and after the COVID-19 Pandemic

One of the most significant changes that the COVID-19 pandemic brought to society is in how people work and communicate with each other. Since the pandemic started, the idea of remote work and online meetings became more widely adopted by many companies and workplaces. Figure 4 clearly illustrates this trend, showing that many workers started the habit of remote work in Spring 2020. Before the pandemic, the majority of workers did not work remotely at all, followed by full-time remote workers and workers who work remotely one day a week. However, after the pandemic hit society, full-time remote workers became the majority, followed by full on-site workers.

Figure 5 illustrates how, among those that participated in all three surveys in 2019, Spring 2020, and Fall 2020, most full-remote workers kept their routine in the Fall-2020 data collection. Meanwhile, the workstyle of those that are partly-remote workers has become more popular in Fall 2020, which implies that people got used to balancing the workload between home and workplace.



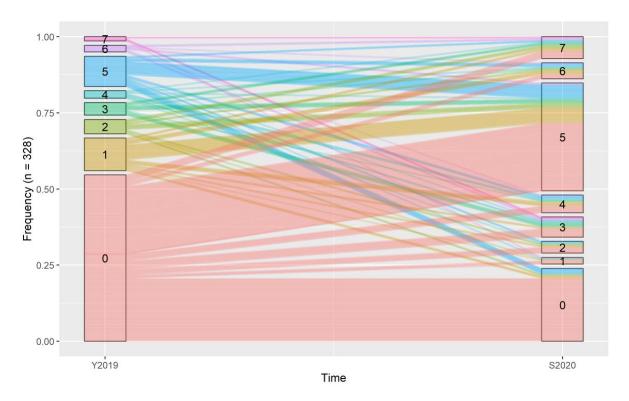


Figure 4. Change in the frequency of remote work (in number of days per week) in 2019 vs. Spring 2020

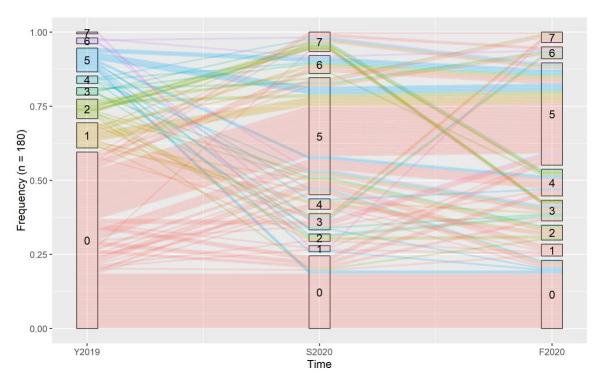


Figure 5. Change in the frequency of remote work (in number of days per week) among respondents that participated in all three data collections



#### Travel Behavior before and during the COVID-19 Pandemic

Travel behaviors have drastically changed since the pandemic started. As reviewed above, more and more people got used to remote work and have started to refrain from outdoor activities. Consequently, as shown in Figure 6 to Figure 8, the usage of private vehicles, public bus, and ridehailing have all decreased among workers, in particular in the first phase of the pandemic.

However, when it comes to the comparison between the usage of those modes for leisure (non-work) purposes, major differences can be observed in the changes in the use of different travel modes. The difference between the usage of private vehicles for work purposes and leisure purposes is much smaller than that between the usage of public buses or ridehailing services. While private vehicles have observed a moderate decrease in usage for leisure purposes, public bus and ridehailing services experienced a drastic decrease for such purposes. This could be due to the anxiety of individuals about the risk of being exposed to pathogens, and their interest in avoiding contact with strangers in a vehicle, so people chose to use private vehicles relatively more often.

Figure 12 to Figure 17 illustrates the changes by extending the comparison to the Fall 2020 iteration. Although there are not a lot of observations from those that were workers at all three survey iterations, it is implied that 1) the use of private vehicles for work purposes was almost back to pre-pandemic levels in the later phase of the pandemic, 2) ridehailing services might have attracted some workers from public bus or other public transit services as they were perceived to expose passengers to a lower risk of pathogens. For leisure purposes, private vehicles seemed to have recovered their level of usage almost to the pre-pandemic level. On the other hand, public buses and ridehailing services were still considered to be an *unsafe* option in Fall 2020 as most of the people who stopped using those services kept themselves away from resuming travel by those modes. Note that, however, the trends presented here uniquely focus on the self-reported frequencies with which respondents used the various available travel modes, which are likely the results of a sum of factors affecting the formation of travel behaviors during the pandemic, and do not necessarily imply a shift from certain modes to others during the pandemic.



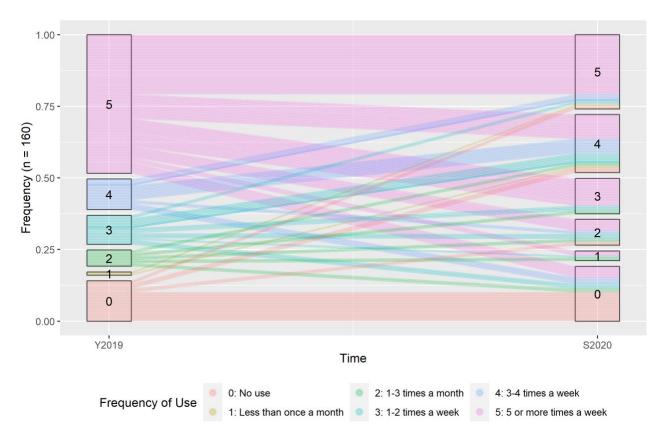


Figure 6. Change in the frequency of use of private vehicle for work purposes

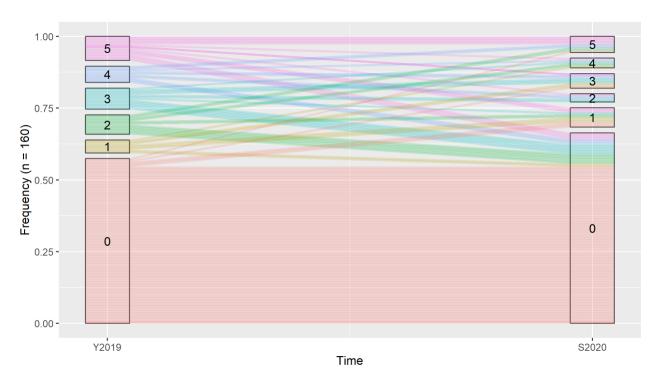


Figure 7. Change in the frequency of use of public bus for work purposes



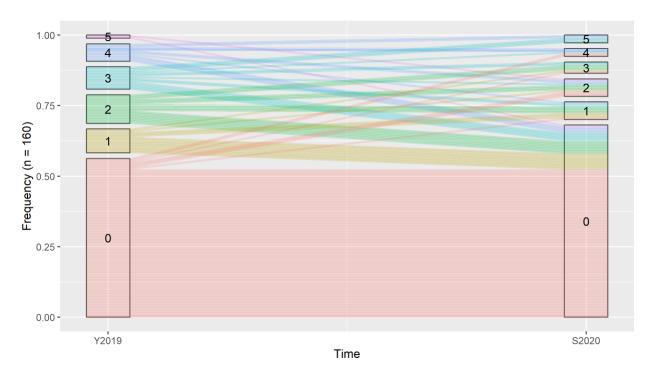


Figure 8. Change in the frequency of use of ridehailing services for work purposes

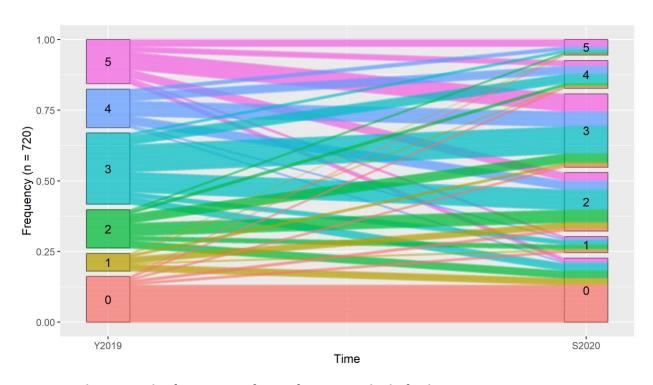


Figure 9. Change in the frequency of use of private vehicle for leisure purposes



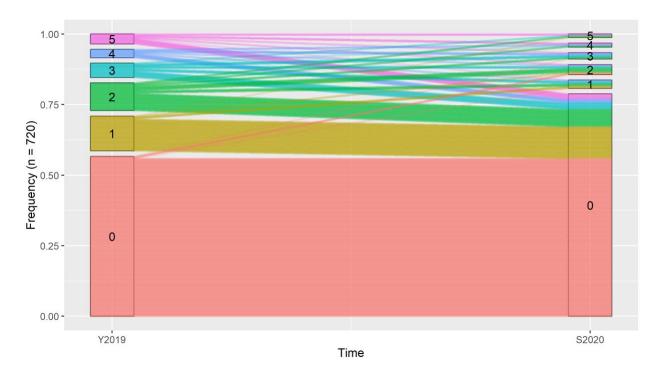


Figure 10. Change in the frequency of use of public bus for non-work purposes

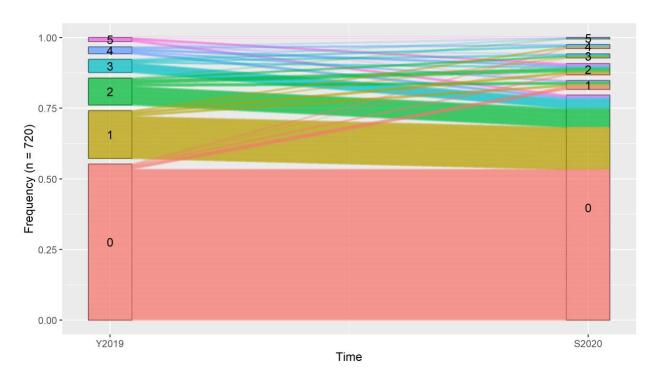


Figure 11. Change in the frequency of use of ridehailing services for non-work purposes



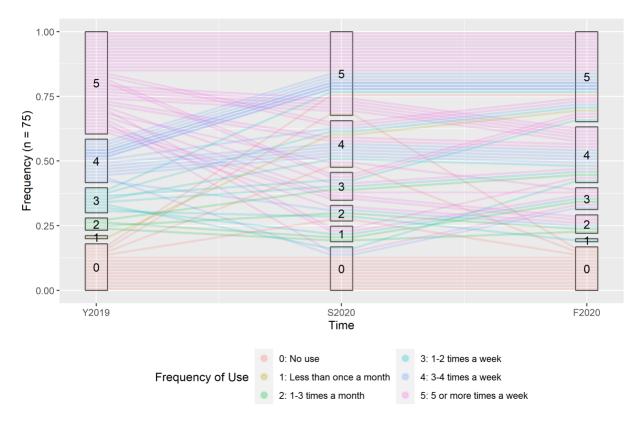


Figure 12. Change in the frequency of use of private vehicle for work purposes among respondents that participated in all three survey waves

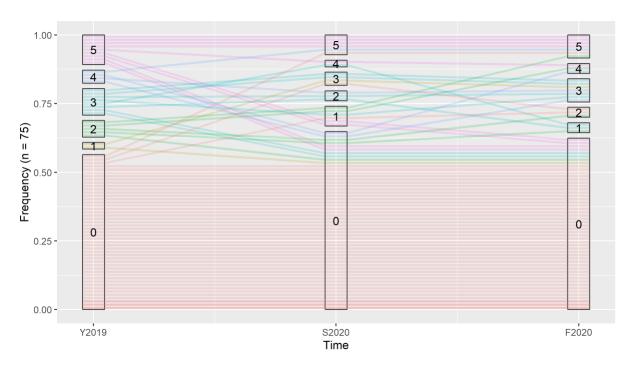


Figure 13. Change in the frequency of use of public bus for work purposes among respondents that participated in all three survey waves



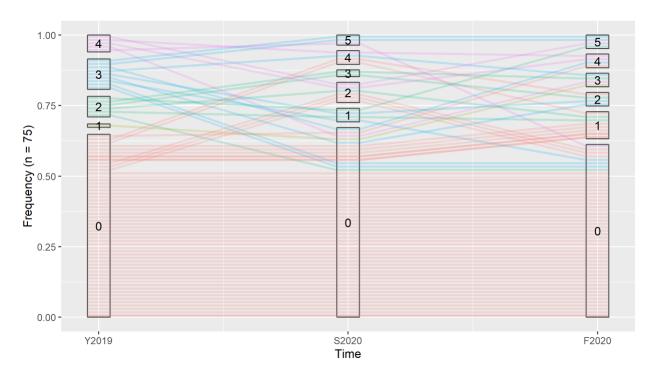


Figure 14. Change in the frequency of use of ridehailing services for work purposes among respondents that participated in all three survey waves

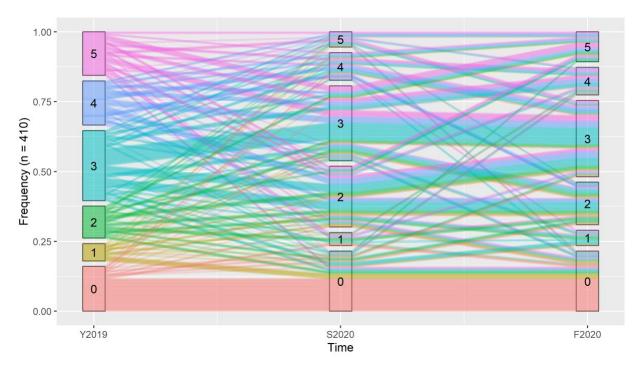


Figure 15. Change in the frequency of use of private vehicle for leisure purposes among respondents that participated in all three survey waves



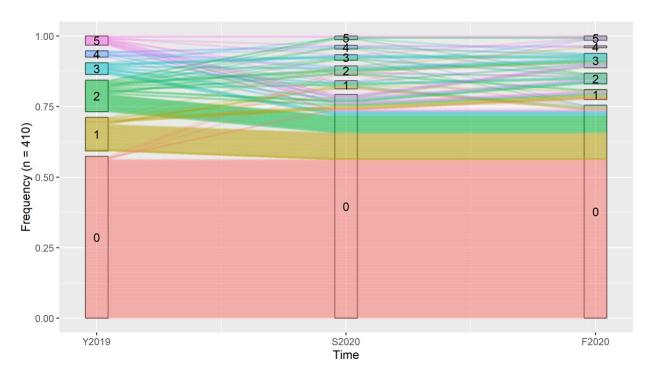


Figure 16. Change in the frequency of use of public bus for leisure purposes among respondents that participated in all three survey waves

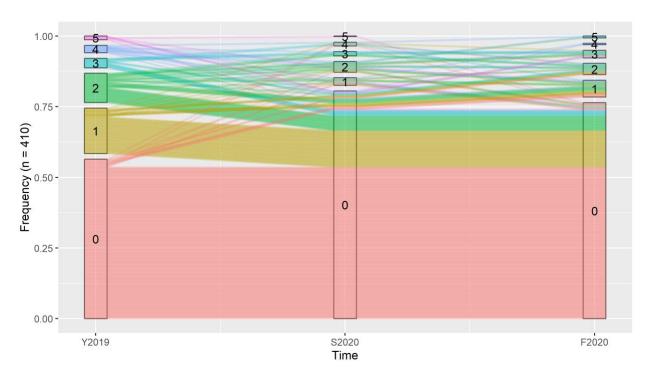


Figure 17. Change in the frequency of use of ridehailing services for leisure purposes among respondents that participated in all three survey waves



# Long-Distance Travel before and during the COVID-19 Pandemic

Another important component of travel that has been highly affected by the COVID-19 pandemic is long-distance travel by private vehicles, flights, buses, or train services. Since the pandemic started, many airlines canceled or reduced their flights due to the risk of spreading the virus, and the falling demand for long-distance travel, especially international travel. In this section of the report, we adopt the definition of "long-distance travel" that was presented to the respondents of all survey waves, as "a trip that takes at least three hours one-way".

The number of long-distance trips made by the longitudinal survey participants significantly dropped for air travel (left column in Figure 18), especially for work purposes. Long-distance travel by car (center column in Figure 18) follows a similar trend for work purposes, though private vehicles were often considered a safer way to travel, and attracted some travelers. This could be because of the global shift to remote work and online meetings, which led to a reduction in *unnecessary* long-distance travel for meetings and conferences. On the other hand, more people made a few leisure (non-work) long-distance trips by car in 2020 than in 2019. This might be caused by a shift from air travel among those who needed a small vacation or getaway during the pandemic.

Meanwhile, it is unclear how the pandemic affected long-distance trips by other modes such as buses or trains (right column in Figure 18) because the majority of survey participants never reported making any long-distance travel with those modes in either 2019 or 2020. This topic could be further investigated in future studies dedicated to the users of those modes.



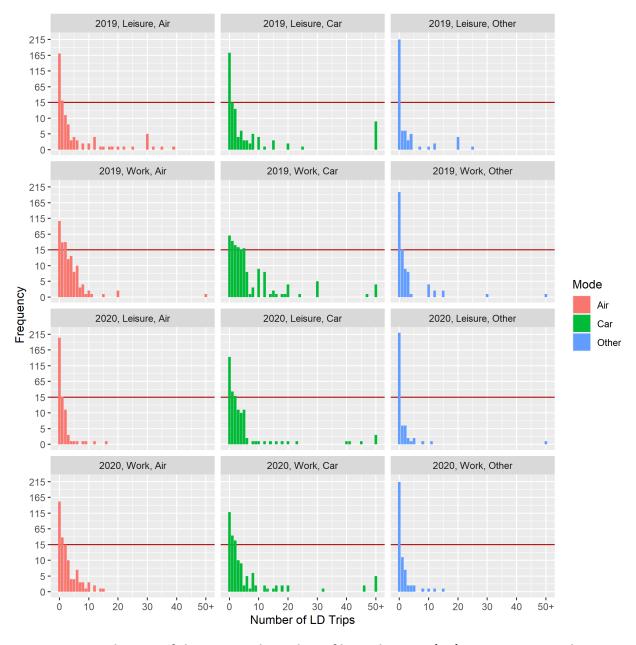


Figure 18. Distribution of the reported number of long-distance (LD) trips in 2019 and 2020, grouped by year, trip purpose, and mode used for the trip. Note that the scale of the y-axis changes at 15 trips.



## **Changes in Active Travel During the COVID-19 Pandemic**

Active travel by walk or bike has been one of the most attractive choices for people who are concern about the global environment, health risks, and/or progressive lifestyles. The COVID-19 pandemic has made a significant impact on every outdoor activity because of the risk of being exposed to pathogens. Does it, however, include the active travel that people had been consistently using for commute and other purposes? If so, how? The remainder of this section is based on the content of the book chapter *Changes in Active Travel during the COVID-19 Pandemic*, which focused on the impacts of the COVID-19 pandemic on active travel by investigating the longitudinal data collected in the 2019 8-cities Mobility Study and the Spring/Fall 2020 COVID-19 surveys.

## Full citation for the book chapter:

McElroy, S., Fitch, D., & Circella, G. (2022). Changes in Active Travel During the COVID-19 Pandemic. Book chapter in Pandemic in the Metropolis: Transportation Impacts and Recovery. Tracts on Transportation and Traffic. Springer.

#### **Abstract**

This chapter examines the impact of the pandemic on walking and bicycling using three longitudinal samples of U.S. adults in the time of COVID-19. We use data from a unique longitudinal panel that was created as a combination of research projects conducted during 2018, 2019 and 2020 at the University of California, Davis. Data was collected in a sequence of four waves of data collection to better understand how active travel mobility changed from early lockdown-orders through lifts in travel restrictions. Bicycling in all three panels showed examples of an increase in the mode share for commuting at the start of the pandemic along with less of a decrease in the absolute number of trips with this mode, compared to other modes. The popularity of walking is observed in our data through our analysis of the broader changes in travel, person level change, changes in mode share (with an increase for the mode share for walking for non-work travel during spring 2020), and daily physical activity. The analyses presented in this chapter show how active travel could be serving as an important source of physical activity for respondents who initially turned to these modes during the early pandemic months.

#### Introduction

Dramatic restrictions to social gatherings and fear of infection have impacted walking and bicycling (active travel) during the COVID-19 pandemic in a wide variety of ways. In addition, the closure or reduced capacity of businesses, schools, and public facilities in response to social distancing guidelines and lockdown measures reduced the demand for out-of-home activities. Changes in activity patterns were accompanied by absolute reductions in travel as well as shifts from public transit to more private and socially-distant modes of transportation such as privately-owned cars, bicycles, and walking [17]–[19]. Large increases in social and recreational travel have been associated with reports of increases in walking and bicycling during the pandemic [20], [21], as well as with surges in the sale of conventional and electric bicycles [22]–



[28]. However, not all increases in active travel were for recreation. While many former commuters sheltered at home, essential workers continued to travel to work, and often did so through active modes [29], [30].

To meet the demand for and promote active travel, many cities throughout the world took the initiative to expand existing or implement new infrastructure to facilitate the use of these modes. Local governments implemented provisional bicycle infrastructure such as "pop-up" bike lanes or made other improvements that included full or partial street closures ("open streets" or "slow streets") allowing local traffic only, decreased speed limits, automated walk signals, and curb space reallocation [31]–[34]. One study that evaluated the impact of new bicycling infrastructure on bicycling rates in 106 European cities using data from bicycle counters found that these projects on average resulted in a 41.6% increase in bicycling volume [35]. Using permanent bike count data, another study found increases in bicycling volume between 5%-20% in major European countries and select regions in the U.S. and Canada with most of the increases occurring on weekends, which is consistent with the narrative of more active recreational trips [36], [37]. Similar results were also reported from passively collected smartphone location-based service and cellular data such as Streetlight Data showing an average increase of 13% in bicycling activity between May 2019 and May 2020 in the U.S.; however, patterns varied by metro area as well as the month chosen for the year-over-year comparison [23], [38].

Despite the many reports and empirical evidence of increases in active travel, there is concern from the public health field that the closure or reduced capacity of out-of-home locations and social distancing have increased sedentary behavior and reduced the capacity for daily physical activity, especially daily activity [39]–[41]. One international online survey found an average decrease of 33.5% in physical activity and a 28.6% increase in daily sitting time [42]. Such observed reductions in physical activity induced by the pandemic could potentially have negative effects on the well-being of many individuals who have become more sedentary at least in part due to COVID-19 changes [43]. Many studies cite the importance of daily physical activity to boost the immune system to reduce the risk and severity of respiratory viral infections [44], [45]. Further, maintaining regular physical activity can prevent the incidence of comorbidities such as obesity, diabetes, hypertension, cardiovascular disease and other serious heart conditions for both adults and children [28], [46], [47]. The reduced physical activity associated with the pandemic is of particular concern for young children. With historically high prevalence of childhood obesity, the closure of schools and the reduced access to physical activity opportunities such as recess, walking to and from school, youth sports programs and physical education (P.E.) are likely to exacerbate the problem [46], [47].

Although previous research has examined the impact of the pandemic during the early months on active travel, limited research exists on the changes in walking and bicycling over the duration of the pandemic. Another gap in the literature is a discussion of the parallel evidence of increasing active travel and increasing sedentary behavior. Considering the observations of increased sedentary behavior (likely from decreases in walking) and increased physical activity



from active travel during the pandemic, this chapter examines the impact of the pandemic on walking and bicycling using three longitudinal samples of U.S. adults in the time of COVID-19.

## Sample Characteristics and Demographics

We use data from a unique longitudinal panel that was created as a combination of research projects conducted during 2018, 2019 and 2020 at the University of California, Davis. Data was collected in a sequence of four waves of data collection, with the first data collection occurring in 2018, the 2018 California Mobility Study<sup>1</sup> (N = 3767), with a statewide sample of residents in California. The second data collection was carried out with the 8-Cities Travel Survey (N = 3410), which collected data from a sample of respondents who live in eight cities across the U.S. in 2019. The third and fourth data collections were carried out as part of a pandemic-specific study, the COVID-19 Mobility Study<sup>2</sup> (N = 13,658 in spring 2020 and N = 8,029 in fall 2020). The surveys administered as part of that project also collected data for 2019 (i.e., "fall 2019" and "before March 2020"), with a set of retrospective travel behavior questions that were included in the 2020 survey instruments.

The geographic scope in the California Mobility Study and 8 Cities Travel Survey is well defined with sampling conducted in the state of California and eight large metropolitan areas across the U.S. (Boston, San Francisco, Sacramento, Seattle, Los Angeles, Kansas, Salt Lake City and the District of Columbia), respectively. Due to the recontact of respondents from pre-pandemic survey rounds as well as two other recruitment methods, both COVID-19 surveys share a more diverse geographic scope with respondents from regions across the U.S.

All surveys were designed for a longitudinal panel analysis (person-level) and to maintain consistent survey language and structure across the questionnaires, to the extent possible. The survey instruments collected information on a variety of topics including the use of active travel modes, regular travel patterns, activity participation, adoption of work from home and telecommuting patterns, shopping behaviors, use of shared mobility and emerging delivery services, as well as individual and household-level characteristics, including household size and composition, presence of children, and vehicle ownership.

We grouped responses to these surveys into the three longitudinal panel datasets (California, 8-Cities, and Nationwide) to examine the person-level change in active travel across time periods (Table 7), using repeated observations for the same respondents. It should be noted that we observe a relatively high mode share for transit use in this study at all times (much higher than the U.S. average) because the data collections mainly focused on large metro areas, which are often served by relatively dense, high-quality public transportation networks.

<sup>&</sup>lt;sup>2</sup> For more information on the COVID-19 Mobility Study please visit the project website [63]



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<sup>&</sup>lt;sup>1</sup> For more information please read the project report for the 2018 California Mobility Study [6]

Table 7. Summary of Longitudinal Panel Datasets in the Study

| Survey Wave |  | California Panel<br>(N = 305) | 8-Cities Panel<br>(N = 404) | Nationwide Panel<br>(N = 2,769) |  |  |
|-------------|--|-------------------------------|-----------------------------|---------------------------------|--|--|
| 0           | <b>2018</b> California Mobility<br>Study (N = 3,767)                         | <b>√</b>                      | ×                           | ×                               |  |  |
| 0           | <b>2019</b> 8 Cities Survey (N = 3,410)                                      | ×                             | ✓                           | ×                               |  |  |
| 0           | <b>2020</b> COVID-19 Mobility<br>Study ( <b>spring 2020</b> ; N =<br>13,658) | 1                             | ✓                           | <b>✓</b>                        |  |  |
| 0           | <b>2020</b> COVID-19 Mobility<br>Study ( <b>fall 2020</b> ; N =<br>8,029)    | ✓                             | ✓                           | <b>✓</b>                        |  |  |

We analyzed demographic characteristics of the entire sample of respondents as well as the demographics of people who bicycle and people who walk to destinations. By comparing the percentage point difference between the sample demographics and the demographics of people who bicycle and people who walk to destination we conclude that our samples seem to represent what has been previously reported about the current demographics of people who bicycle and people who walk to destinations in the U.S. Both people who bicycle and people who walk to destinations in our samples are more likely to live in urban areas. Specific to people who bicycle, they are more likely to be men, be young, and have higher incomes [36]. However, because the data collections include a variety of non-probability sampling techniques, limiting the representativeness of the sample (also in terms of unobserved characteristics of the respondents), we refrain from making strong inferences about the population at large. Instead, we focus on person-level change, the one major advantage of our study design.

## **Findings**

#### **Broad travel changes**

Figure 19 illustrates the changes in the self-reported commuting behavior identifying the groups of commuters who traveled to work or school (or did not) in each panel dataset. The information for commuting and telecommuting behavior was extracted from the self-reported frequencies of telecommuting and commuting trips reported by the respondents in the survey. Respondents were categorized as *Commuters* (only), *Telecommuters* (only), or *Commuters* & *Telecommuters*, based on their commuting behavior in each time period, and the analysis is restricted to only individuals that are workers or students. Members of the latter group (*Commuters* & *Telecommuters*) reported they both physically traveled to work or school and worked remotely at least one day a week. Commuting behavior to a physical work or school location is dominant in each panel in the pre-pandemic time periods. Consistent with the information reported by other studies that have analyzed the impacts of the pandemic on



transportation, a clear shift to a larger adoption of telecommuting is observed during the early pandemic months in spring 2020, which is associated with a decrease in commuting to a physical work or school location.

While commuting declined overall, the decline was not consistent across travel modes. Walking and bicycling for commute purposes (to either work or school) declined between the prepandemic and pandemic time periods in our data, but to a smaller degree than other commute modes. Our data shows that the majority of the early-pandemic commuting respondents traveled to work or school in a private vehicle, which is consistent with the usual commuting patterns in U.S. cities. Mode share of private vehicles for commuting further increased during the early months of the pandemic.

The use of active travel modes accounted for a smaller share of commute trips than private vehicles also in spring 2020. Walking was in general more prevalent than bicycling (personal and shared bikes) in the spring as well as the other four time periods (Table 8). Interestingly, the lack of decline in active travel commute mode share, especially if compared to public transit use, the use of which declined considerably, complements the narrative that active travel modes along with private vehicles experienced an increase in the *share* of commute travel due to their availability as socially-distant travel options.

Walking and bicycling for non-work trips follow a similar trend for both travel modes. When considering non-work trips, mode shares for walking increased for commuters and non-commuters between the pre-pandemic and pandemic time periods, but this increase largely disappeared into the fall for non-commuters (Table 8 and Figure 20). As it can be seen in the table, the larger increase in walking mainly happened for non-work trips, among those that did not commute during the pandemic, which makes sense as this group also includes those that switched to telecommuting, and might have looked at non-work walking trips as a source of physical activity during the days they would otherwise spend at home. Non-commuters ultimately have higher shares of walking for non-work trips and, despite the reduction in mode share between spring and fall 2020, there is some retention of the increased share of walking trips in both groups. The differences in non-work travel mode share between commuters and non-commuters is much smaller for bicycling trips. Nevertheless, changes in bicycling mode share follow similar trajectories to walking for non-work travel.

The prior discussion of the changes in trip frequency for commuting and non-work travel purposes for walking and bicycling provides evidence for a substantial decrease in non-work travel with these modes between spring 2020 and fall 2020. This is an observation that might be explained as a combination of the effect of the reopening of in-person activities, and need to work in person, i.e., a reversal of the early pandemic trends, as well as seasonal effects associated with the colder season, which discourages the use of active modes of travel.



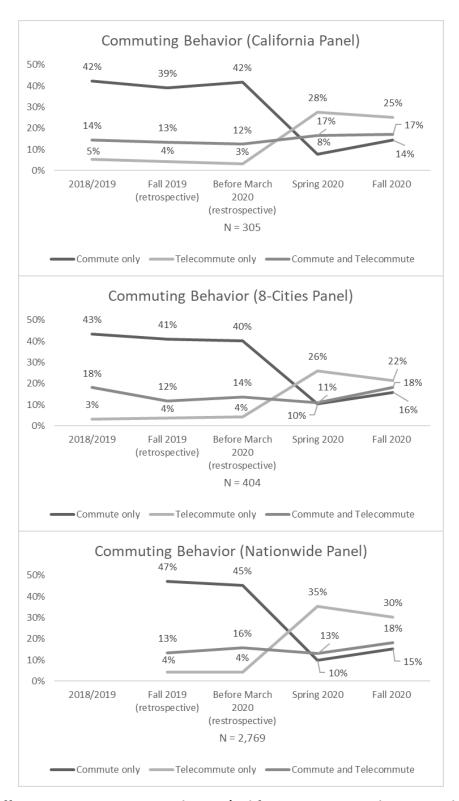


Figure 19. Differences in Commuting Behavior (California, 8-Cities and Nationwide Panels)



Table 8. Changes in Commute and Non-Work Trip Mode Share (California, 8-Cities and Nationwide Panels)

|                |              |                  | Walking   |       |        | Bicycling |           |      |        |      |
|----------------|--------------|------------------|-----------|-------|--------|-----------|-----------|------|--------|------|
|                | Trip Purpose | Commuter         | 2018/2019 | Fall  | Spring | Fall      | 2018/2019 | Fall | Spring | Fall |
|                |              | Status           |           | 2019  | 2020   | 2020      |           | 2019 | 2020   | 2020 |
| California     | Commute      | Commuter         | 6.8%      | 12.1% | 7.9%   | 8.7%      | 2.0%      | 4.6% | 3.7%   | 3.0% |
| Panel          | Non-Work     | Commuter         | 10.0%     | 14.0% | 12.8%  | 15.6%     | 2.9%      | 4.5% | 4.3%   | 4.2% |
|                | Travel       | Non-<br>Commuter | 21.2%     | 25.3% | 44.0%  | 31.2%     | 6.4%      | 4.0% | 6.7%   | 6.1% |
| 8-Cities Panel | Commute      | Commuter         | 13.4%     | 13.7% | 12.5%  | 10.4%     | 3.9%      | 4.3% | 5.2%   | 3.5% |
|                | Non-Work     | Commuter         | 13.8%     | 17.8% | 16.0%  | 18.2%     | 5.7%      | 5.5% | 4.2%   | 3.9% |
|                | Travel       | Non-<br>Commuter | 24.8%     | 25.9% | 43.0%  | 32.3%     | 3.3%      | 2.8% | 6.2%   | 3.8% |
| Nationwide     | Commute      | Commuter         |           | 14.2% | 11.5%  | 11.6%     |           | 4.1% | 4.1%   | 4.0% |
| Panel          | Non-Work     | Commuter         |           | 18.5% | 17.3%  | 17.5%     |           | 4.5% | 5.0%   | 4.5% |
|                | Travel       | Non-<br>Commuter |           | 25.2% | 42.9%  | 33.1%     |           | 3.2% | 6.5%   | 4.2% |





Figure 20. Comparison between changes in Commute and Non-Work Trip Mode Share (California, 8-Cities and Nationwide Panels)

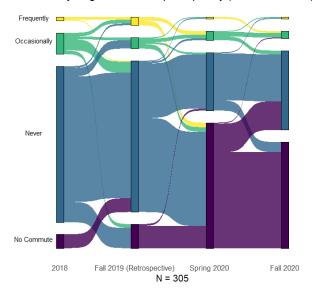


## **Group-level Changes in Active Travel**

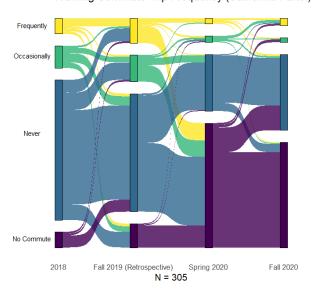
When merged at the dataset level, changes in walking and bicycling trip frequency reiterate the person-level change profiles that are observed when following the travel behavior change of each individual respondent. The largest change profile was a decrease in walking for commute purposes which is apparent in the substantial increase in respondents who either stopped commuting or switched to working from home in spring 2020 (Figure 21). This profile was common in all three datasets, especially the increase in respondents who stopped commuting. The less prominent change profile included increases in trip frequency, particularly among workers returning to commuting to a physical work or school location. Individual change profiles for this group included respondents who returned to their previous reported trip frequency along with others who reported a similar frequency to before the pandemic. Grouplevel changes in walking for non-work travel were more common than commute travel. Among those who increased their walking for non-work purposes during the pandemic, and differently from bicycling, many maintained or at least did not completely revert to their prior level (or lack) of walking by Fall 2020, suggesting the pandemic may have caused some more lasting effects on walking behavior (Figure 22). This does not translate into saying that all people who increased their walking early during the pandemic maintained their walking into Fall 2020, though. The most common walking change profile experienced an increase in walking for nonwork travel during Spring 2020, at the peak of the pandemic and in-person work restrictions, but then slightly reduced their walking by Fall 2020. Still, they continued to walk more than in their pre-pandemic life. This profile is most apparent in the California and Nationwide panel and appear to complement the many news reports of increases in the use of active modes for non-work travel [48].



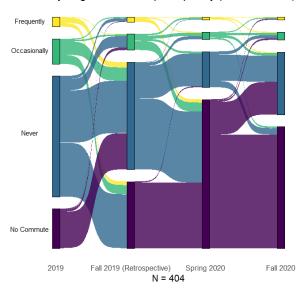
## Bicycling Commute Trip Frequency (California Panel)



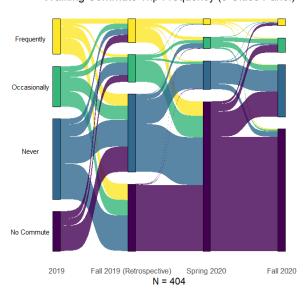
## Walking Commute Trip Frequency (California Panel)



Bicycling Commute Trip Frequency (8-Cities Panel)



Walking Commute Trip Frequency (8-Cities Panel)





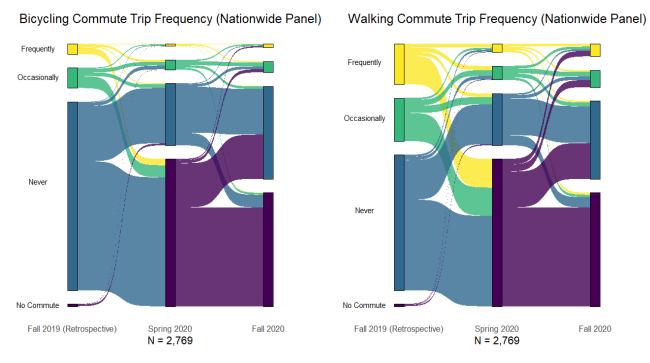


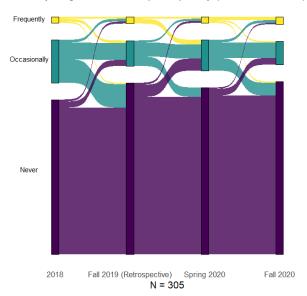
Figure 21. Walking and Bicycling Frequency for Commute Travel Purposes (California, 8-Cities and Nationwide Panels). The aggregate categories (Occasionally and Frequently) are created using the original trip frequencies from each survey questionnaire. "Less than once a month", "1-3 times a month", and "1-2 times a week" are combined into the "Occasionally" category (roughly equating to less than 3 times a week) and "3-4 times a week" and "5 or more times a week" are combined into the "Frequently" category (roughly equating to 3 or more times a week). The white shading indicates no data point.



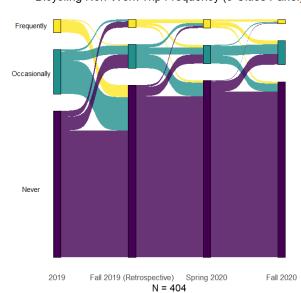
Walking trip frequency showed more behavior changes at the dataset level than bicycling for commute and non-work travel. The group of people who showed no behavior change was considerably smaller for walking than for bicycling. This suggests that the barriers to change walking behavior were less strong compared to bicycling. This is not surprising, given the overwhelming evidence that traffic safety is still a dominant barrier to bicycling in the United States [49]–[52]. The most common change in behavior was "no change at all", i.e., people who never rode a bike continued to not ride a bike. This was apparent in all three datasets, particularly for non-work travel (Figure 22). The second most common change profile was a marked reduction in bicycling. This profile was more common in the 8-cities dataset for both commute and non-work travel and was also present to a small degree in the Nationwide panel, but not so much in the California panel. The third profile showed an increase in bicycling, particularly for non-work travel (Figure 22). This profile accounts for only a small share of respondents but shows up in all three datasets. This group included individuals who reported never bicycling prior to the pandemic but showed regular bicycling activity during the pandemic. This profile is the one consistent with the media reports of bicycling as a booming mode of transportation during the pandemic [24], and an important one for policy implications, as encouraging these individuals to continue to ride their bicycle after the pandemic would lead to environmental and societal benefits. However, the profile of people who increased bicycling for non-work travel already shows some attenuation by the Fall 2020 (Figure 22). The substantial return to pre-pandemic bicycling levels for many members of this group is particularly evident in the Nationwide panel. This suggests that much of the behavioral change that occurred during the early stage of the pandemic already reversed by fall 2020, most likely for the combination of reasons mentioned previously.



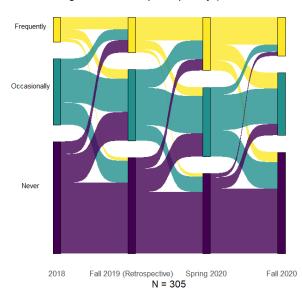
## Bicycling Non-Work Trip Frequency (California Panel)



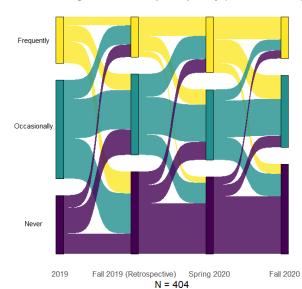
## Bicycling Non-Work Trip Frequency (8-Cities Panel)



## Walking Non-Work Trip Frequency (California Panel)



Walking Non-Work Trip Frequency (8-Cities Panel)





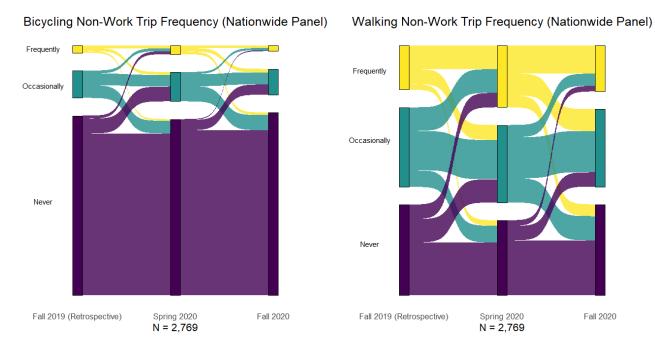


Figure 22. Walking and Bicycling Frequency for Non-Work Travel Purposes (California, 8-Cities and Nationwide Panels). The aggregate categories (Occasionally and Frequently) are created using the original trip frequencies from each survey questionnaire. "Less than once a month", "1-3 times a month", and "1-2 times a week" are combined into the "Occasionally" category (roughly equating to less than 3 times a week) and "3-4 times a week" and "5 or more times a week" are combined into the "Frequently" category (roughly equating to 3 or more times a week). The white shading indicates no data point.



While these group-level profiles suggest potential segments of the population that changed travel behavior, due to the small number of individuals who bicycle (especially for commute purposes), we caution against extrapolating more subtle change profiles at the dataset level to the population. For example, a closer look at a less common profile of increased bike commuting during the pandemic in the 8-Cities panel reveals that only ten respondents increased bicycling in spring 2020, six of whom continued using that mode in the fall. This retention of bicycling as a commute travel mode suggests that for some people, the pandemic is likely a primary cause of changing bicycling behavior. However, the evidence remains largely anecdotical, and the degree to which this happens just cannot be fully ascertained with the analyses of the data from our study.

Also, it should be noted that in most regions of the U.S., active travel tends to be more popular during the warmer months of the year, in particular during spring and summer, than in the colder months during fall and winter. Accordingly, the seasonal differences in the time periods in which the surveys were administered, and the accompanying weather patterns in the select cities represented in each longitudinal sample, at least in part might explain the observed changes in non-work trips during the pandemic months.

#### Person-level mode substitution

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

## Changes in Daily Physical Activity

Our Nationwide surveys also tracked active travel, not only in terms of numbers of trips, but also in terms of days and minutes of activity. We first asked respondents to report the number of days that they participated in a physical activity in a week during the pandemic as well as the number of minutes they spent performing each activity for the days in which they participated in that activity. The various activities presented in the questionnaire are summarized in Table 9. "Total Active Travel" is an aggregate category built using responses from both walking and bicycling activities. Using the measures of days and minutes spent performing each activity, we calculated average daily activity minutes for each activity in spring 2020 and fall 2020 for the



Nationwide Panel<sup>3</sup>. With this measure we calculated individual change in physically active travel between pring 2020 and fall 2020 for each activity.

Table 9 displays the population-level averages along with the standard deviations, confidence intervals, and the mean person-level differences<sup>4</sup> between the two time periods. Results for the average minutes spent per day participating in each activity indicate an average increase in most forms of physical activity across the two time periods. This suggests that people were increasing their physical activity (on average) well into the pandemic. However, the magnitude of change appears small (less than 2 minutes) for most activities, except for exercise at a non-home location. While the magnitude of change is small, even small increases in physical activity can have large effects on public health [28].

<sup>&</sup>lt;sup>4</sup> A paired sample t-test was computed to determine the statistical significance of the mean difference between fall and spring.



<sup>&</sup>lt;sup>3</sup> The measure of average daily minutes was calculated by multiplying the reported number of days in a week the respondent reported doing that activity by the self-reported minutes per day, and dividing the total by 7.

Table 9. Average minutes spent per day on each activity, Spring 2020-Fall 2020

|   |                | Spring 2020 |                       | )         | Fall 2020 |                       |               | Mean<br>Difference | Standard<br>Error of Mean<br>Difference |  |
|---|----------------|-------------|-----------------------|-----------|-----------|-----------------------|---------------|--------------------|---|--|
|   | Sample<br>Size | Mean        | Standard<br>Deviation | 95% CI    | Mean      | Standard<br>Deviation | 95% CI        | Fall-Spring        |   |  |
| Walk to get to and from places                                | N = 1,044      | 13.3        | 21.9                  | 11.9-14.6 | 14.6      | 18.0                  | 13.5-<br>15.7 | +1.3               | 0.73                                    |  |
| Walk for leisure/exercise                                     | N = 1,980      | 27.6        | 31.8                  | 26.2-29.0 | 26.0      | 33.3                  | 24.6-<br>27.5 | -1.5               | 0.69                                    |  |
| Bicycle to get to and from places                             | N = 232        | 10.8        | 17.2                  | 8.6-13.0  | 10.5      | 13.7                  | 8.7-12.2      | -0.4               | 1.22                                    |  |
| Bicycle for leisure/exercise                                  | N = 435        | 17.4        | 24.6                  | 15.1-19.7 | 17.5      | 27.9                  | 14.8-<br>20.1 | +0.1               | 1.24                                    |  |
| Total Active Travel   | N = 1,980      | 39.7        | 41.1                  | 37.9-41.5 | 35.0      | 39.1                  | 33.2-<br>36.7 | -4.7               | 0.94                                    |  |
| Exercise at home  | N = 1,620      | 21.8        | 28.5                  | 20.4-23.2 | 20.1      | 25.8                  | 18.8-<br>21.4 | -1.7               | 0.73                                    |  |
| Exercise at non-<br>home location (e.g.,<br>park, beach, gym) | N = 257        | 15.9        | 18.6                  | 13.6-18.2 | 21.0      | 28.7                  | 17.5-<br>24.5 | +5.1*              | 1.72                                    |  |

<sup>\*</sup>P < 0.05



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

We also examined these changes in physical activity by region (West, Midwest, South and Northeast) to examine the impact of seasonal change. While total active travel (walking plus bicycling) slightly increased on average for the entire sample, this trend was not observed among respondents living in the West or South. Examining the mean differences in total active travel, we see that the South has the largest average decrease (-4.9 mins), while the Northeast has the largest and only increase (2.5 mins). Specific to walking for leisure/exercise, the West and South had the highest seasonal averages but both regions also had the largest average decrease whereas only the Midwest experienced a small increase (0.7 mins). The only mean difference that was calculated to be statistically significant was walking to and from places in the Northeast. Incidentally, this activity saw an increase on average (4.3 mins). Lastly, the South appeared to be the most popular region for bicycling, i.e., the highest seasonal averages for bicycling to and from places and bicycling for leisure/exercise, in the spring; however, the mean differences showed decreases for bicycling, walking, and total active travel suggesting that any large increases in the spring were only temporary. These differences by region suggest that some of the changes in walking and bicycling during the various stages of the COVID-19 pandemic might be at least partially explained by travel behavior changes due to weather patterns, but they were also affected by the changes in the COVID-19 related policies. This is particularly evident in the increases in total active travel between spring and fall 2020 in the Northeast region, one of the coldest regions of the country in the fall, but also a region that experienced stay-at-home orders and strong restrictions to movement during the spring of 2020.

## **Transportation Planning and Policy Implications**

Results from our present analysis provide evidence for widespread increases in walking and more sparing increases in bicycling during the early months of the pandemic. However, much of the increase reported during the early months of the pandemic were erased or considerably eroded by the fall of 2020. Findings from this analysis suggest that relying on "natural" changes in travel behavior due to COVID-19 to increase active travel is not likely to succeed unless specific policies to promote (and/or maintain) certain behavioral changes are implemented. In particular, our results highlight how the pandemic affected mode choice and the use of various modes. However, many of the temporary changes observed during the pandemic might have been short-lived. There might be need for continued or renewed efforts to facilitate the use of active travel modes, if planners and policy makers want to promote the use of these modes in the longer term. Popular strategies that were implemented at the start of the pandemic included full or partial street closures from cities such as Oakland, California that closed 74



miles of city streets to vehicle through traffic [48]. Similar traffic calming projects in other cities that were often framed as "open streets" or "slow streets" could become permanent features of the built environment to encourage and facilitate the use of walking and bicycling. Traditional traffic calming strategies such as road diets, lowering speed limits and restricting streets to local traffic are also available as preexisting tools for transportation planners to make the built environment more accessible for pedestrians and bicyclists.

Improving accessibility can also come in the form of increasing pedestrian and bicycling infrastructure through new bike lanes, multi-use trails and other amenities such as pocket parks or urban plazas. Despite what seemed like a renewed commitment from cities to make streets safer for pedestrians and cyclists, the slow streets pilot programs often remained temporary programs as many cities such as San Diego and Washington D.C., at the time of writing, were planning to or were in the process of removing their pilot programs [53]. This potentially hurts many of the communities that could benefit the most from these programs which tend to be low-income neighborhoods that have traditionally been underserved from transportation investments. A proper evaluation of these pilot programs is warranted to ensure that successful experiments are not disregarded. In addition to transportation planning solutions, an additional avenue for encouraging the use of active travel modes is through more direct incentives such as the Electric Bicycle Incentive Kickstart for the Environment Act (E-Bike Act) and the Bicycling Commuter Act of 2019 [54], [55]. Rebates, tax incentives, and other monetary incentives may help encourage more active travel, though none of these were explicitly studied as part of this research. Similarly, disincentives for car use such as pricing parking, reducing parking minimums, congestion pricing, car-free zones, etc. are likely to support active travel. Policy measures of this type may encourage people to change their auto-centered travel and may also help support more widespread policies like increasing transportation funding for active travel.

## **Conclusions**

The present chapter presents findings from the analysis of three longitudinal datasets on the use of active travel modes for commuting, non-work travel and daily physical activity. An overall decrease in the share of commuters is observed between the pre-pandemic survey waves in 2018 and 2019 and the early months of the pandemic in spring 2020. Consistent with other studies, all travel modes including walking and bicycling experienced a decrease in the number of trips for commuting to work and school at the start of the pandemic. Bicycling in all three panels showed examples of an increase in the mode share for commuting at the start of the pandemic along with less of a decrease in the absolute number of trips with this mode, compared to other modes. The popularity of walking is observed in our data through our analysis of the broader changes in travel, person level change, changes in mode share (with an increase for the mode share for walking for non-work travel during spring 2020), and daily physical activity. However, because of seasonal differences in our two "during" COVID-19 waves, and the confounding impacts of COVID-19 travel limitations that in certain regions acted in the opposite direction of the seasonal variation, it is difficult to determine the lasting change in active travel from the analysis of these data.



The analyses presented in this chapter show how active travel could be serving as an important source of physical activity for respondents who initially turned to these modes during the early pandemic months. However, this phenomenon could also be complemented by increases in sedentary behavior associated with work-from-home and increased indoor activities, which were not measured in this study (we did not measure all types of physical activity).

The increase in non-work travel during the early pandemic months was a result of the new adoption of active travel during the pandemic months for pre-pandemic "non-users" combined with small increases in trips from pre-pandemic "users". Whether this added active travel overcame the potential increase in sedentary behavior brought on by the pandemic remains to be seen. Our analysis stops short of providing a post-pandemic effect, but the trends in declining active travel during 2020 are worrying and suggest that this component of travel behavior change from the pandemic may be fleeting. While the present analysis only presents broader trends in the use of active travel modes, further analysis of these data—as well as the analysis of additional waves of data collected during the following stages of the pandemic, and beyond—can reveal the unique factors that affect changes in active travel use. Further, the inclusion of spatial variables in future analyses can provide objective measures of the impacts of the built environment on these behavior changes.



# **Changes in Activity Organization and Travel Behavior Choices in the United States**

The COVID-19 pandemic has made a significant impact on how people travel around and the mode choice when they travel. Further, the way people work has changed with the pandemic to avoid commuting and being exposed to pathogens. Individual lifestyles and the way of thinking about their personal life, such as owning a car, preference on places to live, and environmental friendliness could change because of the disruption. But how? The following is an extract from the book chapter *Change in life and travel behavior, which* examines the longitudinal change of people's attitude toward various factors in their life, mode choice, telecommuting habits and so on, using the three-time datasets (2019 8-cities Mobility Study and Spring/Fall 2020 COVID-19 Mobility Study).

Full citation to the book chapter:

Soza-Parra, J., Circella, G., & Sperling, D. (2021). Change in life and travel behavior. Transportation during the COVID-19 Pandemic: Practices and Policies. Elsevier.

#### **Abstract**

The COVID-19 pandemic has brought disruptive changes to society. In this chapter, we discuss how participation in activities and travel behavior choices have changed during the various stages of the pandemic through the analysis of data collected through multiple waves of surveys administered in 2020 in various regions of the United States. We present insights regarding how different aspects of life and mobility have reshaped during this period, and discuss the potential temporary vs. longer-term nature of the changes. We observe how some phenomena that presented a steep increase during the first stage of the pandemic started to decline, to some extent, in late 2020, whereas others, such as the adoption of remote work and increased reliance on personal vehicles, persisted also in the later stage of the pandemic at rates that are considerably higher than the pre-pandemic patterns. We discuss the different impacts that the pandemic has had on different segments of the population, and the importance for public policies to react to these new circumstances not only to account for the modified mobility and travel behavior landscape, but also considering the socio-economic and equity implications underneath these impacts.

## Introduction

The COVID-19 pandemic has impacted almost every aspect of our daily lives. The urban mobility sector has been no exception to this trend. The impacts that the pandemic has had on transportation over the past year have received widespread attention in the academic and planning sphere. These studies have focused on many impacts of the pandemic, including shifting preferences for and perceptions of travel modes, public transportation operations and ridership, changes in vehicle use, traffic congestion, pollutant emissions, and equity impacts, among others [56]–[60]. Limiting physical interaction, and thus mobility, has been considered among the most critical actions to contain the spread of the virus. Certainly, there is a strong



relationship among the disruption brought by the pandemic, the changes in individual lifestyles and the use of transportation.

Remote work, one of the most distinctive impacts of the pandemic, has become more frequent during the pandemic, though its adoption has not been uniformly distributed across groups. Higher-income white-collar office workers are most likely to work remotely [61]. While the increased adoption of remote work and frequency of telecommuting will likely extend, to some extent, into the future, it is not clear which groups of individuals, and with what frequency, will continue to work remotely, and what the impacts will be on the time, place and quantity of travel. Other travel-related impacts of COVID-19 include changes in residence, workplace, and activities, as well as vehicle ownership. The nature and magnitude of all these changes are uncertain, and it is also uncertain how long they might persist. Knowledge and foresight of these many effects have huge implications for climate change, local air pollution, transportation infrastructure investments, urban planning, equity impacts, vehicle sales, workplace dynamics, and much more.

This chapter discusses lifestyle and mobility changes through the analysis of multiple waves of survey data collected in the United States. These longitudinal data come from an array of surveys conducted before and during various stages of the pandemic. The pre-pandemic data were collected with the 2018 California Mobility Survey and the 2019 "8 Cities" Travel Survey, while the during-pandemic data were collected in Spring and Fall 2020 with modified versions of the surveys that incorporated COVID-19-related questions. The 2020 data collections were carried out in the same geographic regions of the pre-pandemic surveys (respectively, the state of California for the 2018 data collection, and eight large metro regions of the U.S.—Boston, Kansas City, Los Angeles, Sacramento, Salt Lake City, San Francisco, Seattle and Washington DC—in 2019) with the addition of a few additional locations. In total, the 2020 surveys were administered in 17 large metro regions in the United States and Canada. These surveys were designed in a consistent way and administered to the extent possible among the same respondents over time, while also refreshing each sample with new respondents at each round of data collection.

In this chapter, we present results from the analysis of the survey data from U.S. living in the U.S. who participated in at least two survey waves, of which at least one during the pandemic. We focus on three different time periods: "before the pandemic" (from the 2018 or 2019 studies, in addition to the retrospective behaviors from 2019 as reported by respondents in the Fall 2020 survey), "early stage of the pandemic" (Spring 2020 survey wave), and "late stage of the pandemic" (Fall 2020 survey wave).

The structure and wording of the questions in the surveys make them valid to conduct a longitudinal analysis. The nature of the questions asked in the surveys is diverse and goes beyond regular travel characterization, vehicle ownership and household demographic variables, including attitudinal questions, adoption of telecommuting and e-shopping

<sup>&</sup>lt;sup>5</sup> Additional information on the data collection is available at https://postcovid19mobility.ucdavis.edu/



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behaviors, use of emerging delivery services, and preferences toward active transportation, shared mobility and other modes of travel. The timeline of the data collection is represented in Figure 23, together with the trend in the number of new COVID-19 cases in the United States during the same period.

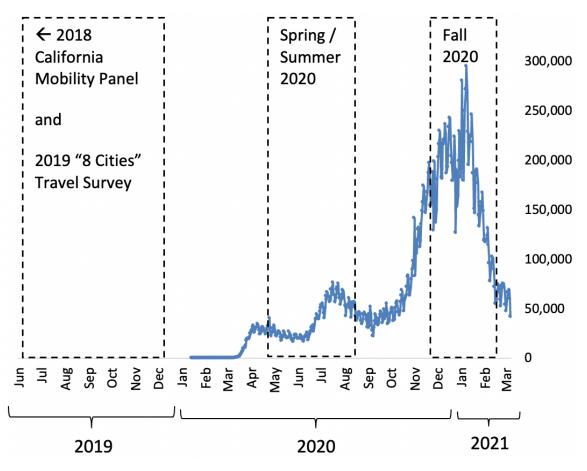


Figure 23. Number of new COVID-19 cases in the United States and timing of surveys

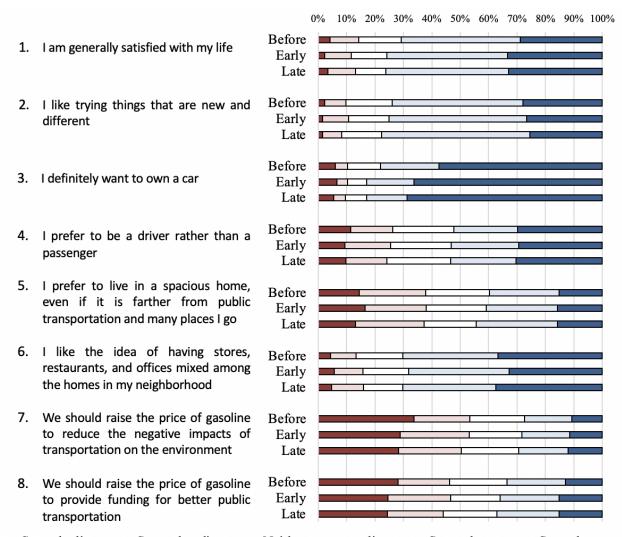
The remainder of the chapter is structured as follows. First, we present insights into the reported changes in lifestyles and activity organization during the pandemic. We then discuss changes in mobility. Finally, we discuss potential long-term consequences of these impacts, planning and equity implications, and policy recommendations.

## Changes in lifestyles

The pandemic has affected the life of individuals in the U.S. and other parts of the world in many ways. First, we focus on changes in individual attitudes along several dimensions, including life satisfaction, interest in trying and using new technologies, car dependence, and the acceptance of increases in gas taxes to protect the environment. All attitudinal variables were measured through the self-reported level of agreement with a batch of statements, measured on a 5-level Likert-type scale from "Strongly disagree" to "Strongly agree". In Figure 24, we present the distribution of a set of selected statements that were common to all



versions of the survey, drawn from a group of 719 respondents that participated in at least one of the surveys before the pandemic and in both Spring and Fall 2020 versions of the survey.



■ Strongly disagree □ Somewhat disagree □ Neither agree nor disagree □ Somewhat agree ■ Strongly agree

Figure 24. Agreement with various attitudinal statements before and during the two stages of the pandemic. Sample size: 719 respondents that participated in either the 2018 or 2019 surveys and in both 2020 COVID-19 surveys

At first sight, there are no major differences in individual attitudes on most dimensions across the different time periods, with only a few exceptions. This is expected as the time frame between the different data collections is relatively short, and attitudes are usually fairly consistent over time, changing only gradually during the life stages of the individuals. However, it is reasonable to expect that a major disruption such as the COVID-19 pandemic might cause some impacts on individual attitudes and preferences, in particular those related to certain topics.



It seems that, interestingly, self-reported life satisfaction remained rather constant over the past two years, and it has even slightly increased, on average, whereas more respondents during the pandemic report a somewhat positive attitude on their interest in trying new things, with strong opinions on both ends (for both agreeing and disagreeing) being less common during the pandemic. Average life satisfaction seems to have been increasing in the U.S. society over the past few years, during times of positive economic growth, and it seems that not even the disruption brought by the pandemic interrupted this trend. This is likely a hint that many individuals were not affected too severely (in their finances, health or wellbeing) during the pandemic, with a minority of the society bearing most of the negative impacts during this time.

Perhaps the most meaningful change in attitude and preferences for transportation relates to vehicle ownership and use. The desire to own a car largely increased during the pandemic, whereas the desire of driving (versus being a passenger) remained somewhat constant. This change in attitudes is consistent with actual observed changes in the use of transportation modes, and with increased concerns about the use of shared modes of travel during the pandemic. Spending more time at home due to the remote work and increased e-shopping, as well as the reluctance to share travel modes with strangers because of the fear of getting infected, might be reasons to an increased willingness to acquire a new vehicle. This signals a further increase in the reliance of individuals on personal vehicles (in the already very cardependent society in the United States), which could lead to potentially negative longer-term consequences in terms of continued personal habits and vehicle use even after the pandemic is over.

The statements related to land use and household residential location are also potentially instrumental. A growing number of respondents in 2020 reported an interest in living in a spacious home, even if it is farther from public transportation and many desired destinations. This trend continued during the various stages of the pandemic, even after the initial lockdowns were lifted in the country, showing that the continuation of the pandemic somewhat cemented these residential location preferences towards more spacious homes, even if further away in suburban locations. Quantifying exactly how much these changes in land use preferences will translate into actual changes in residential locations remains an active research question, and is difficult to know at the time of writing, in part because in many cases households that moved during the pandemic predominantly included renters and members of those population segments that are rather "mobile" (e.g., they have no children, have flexible jobs, etc.). These households could more easily reverse their decisions towards residential location if the situation changes again in the future, and in particular if remote work arrangements with employers are not supported in the future. This residential location preference remains an important research topic with large implications for the future of cities. For example, one somewhat counteracting finding, compared to what has just been discussed, relates to the interest in mixed land use. While there was a somewhat sizable decrease in the interest in living in central, more mixed land use neighborhoods during the early stages of the pandemic, this seemed somehow to recede during the later stage of the pandemic in late 2020.



Another noted attitudinal change was the increasing support for rising gasoline taxes, both to reduce the negative impacts of transportation on the environment and to provide funding for better public transportation. This positive increase is still marginal compared to the current absolute support for these measures, with over 25% of the respondents who are in strong disagreement with increasing gasoline taxes—this number reaches more than 45% when also considering respondents that somewhat disagree with such policy—but shows a somewhat promising process, with more sensitivity towards these topics. Still, this change is probably not a direct consequence of the disruption brought by the pandemic, but rather an effect of the growing evidence of climate change and of the harm caused by transportation in the U.S. society, a growing awareness that did not stop even during the pandemic.

Another interesting phenomenon that has disrupted individuals' lives during the different stages of the pandemic is the change in using mobility services and vehicles for conducting various activities. While in the next section of this chapter we focus on the adoption of telecommuting and remote work, here we first discuss the use of online shopping, both for grocery and non-grocery items. In all survey waves, respondents were asked to report the number of times that each respondent had been buying items online. For the purposes of this analysis, answers were categorized in five different categories, namely "never", "less than once a month", "at least once a month but less than once a week", "once a week", and "more than once a week". The relative proportions as well as the changes in online shopping frequency before and during the pandemic are presented in Figure 25.a for grocery items and Figure 25.b for non-grocery items.



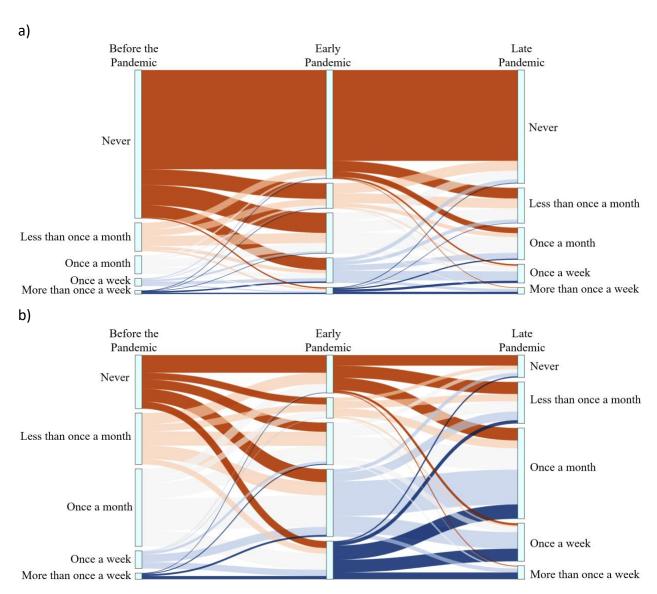


Figure 25. Frequency of shopping online before and during the two stages of the pandemic for a) grocery items b) non-grocery items. Sample size: 1,723 respondents that participated in both 2020 COVID survey waves.

The impact of the initial stage of the pandemic is evident. In early 2020, a substantial increase is observed in the frequency of e-shopping for groceries, especially when considering the number of respondents that reported they were shopping online at least once a month during the early stage of the pandemic. This increase in frequency somewhat bounced back during the later stage of the pandemic as activities restarted and many stores and shops reopened. It should be noted, though, that the number of respondents who shopped online with low frequency (less than once a month or less often) remained somewhat larger than in the pre-pandemic era, while the number of frequent e-shoppers declined. This highlights how there was an initial increase in the use of these services, which expanded the user base for e-shoppers and generated an overall adoption of them over time, though the average frequency of use slightly



declined in the later stage of the pandemic compared to the early pandemic stage. Similarly, in terms of buying non-grocery items online, we observe an initial increase in the frequency of doing this activity. The increase in online shopping for non-grocery items, in terms of average frequency, was significantly higher than the uptick for grocery items, and thus the bounce back was also larger in magnitude. Overall, the proportion of people who never buy non-grocery items online has declined during the pandemic. The overall net effect, when comparing the before and late pandemic patterns, is a significant increase in online shopping: the pandemic somehow accelerated the growth in the use of e-shopping that was already happening in the pre-pandemic years.

## Changes in work habit and mobility

In this section, we will focus on the changes in the adoption of remote work and physical commuting. To that end, we first present (in Figure 26) the change in the distribution of weekly working hours during the three different times analyzed in this study among those who were working in the three time periods. This way, it is possible to do the analysis isolating the changes in work and commuting patterns from the effect of people that became students, retired from work, and/or lost their job due to the pandemic (or other concurring reasons during the same timeframe). During the early stages of the pandemic, there was a sizable decrease in the number of working hours per week, even among those that still had a job during the pandemic, as shown by the decrease of people working 40 or more hours per week and the considerable increase of people working less than 20 hours a week. This trend some reverted during the later stage of the pandemic, suggesting a positive rebound in the number of working hours, as the distribution gets closer to the one from before the pandemic.



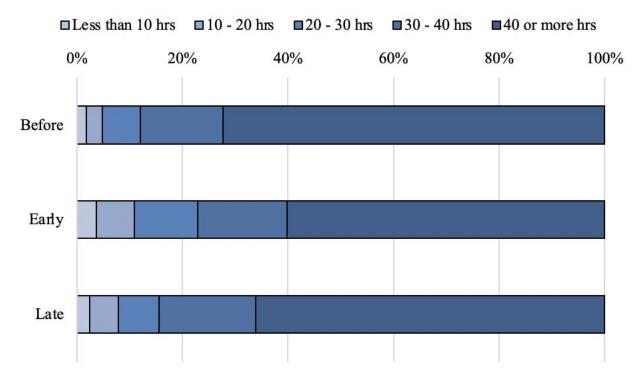


Figure 26. Number of weekly working hours before and during the two stages of the pandemic. Sample size: 1,540 respondents that participated in both 2020 COVID survey waves.

Next, we analyzed the proportion of workers that adopted forms or remote work during the pandemic. In terms of transportation, working from home is probably one of the most disruptive phenomena that emerged with high strength during the COVID-19 pandemic. In Figure 27, we present the average number of days per week respondents physically commuted to their workplace (commuting) and vs. worked remotely (telecommuting). The trend is clear, with a steep decline in the number of physical commutes during the pandemic, and a significant increase in its remote work counterpart. Further, physical commuting bounced back, to some extent, in the later stage of the pandemic. This is in line with the changes in policies from companies and institution aiming to move to what has been called a "limited" normal operation during late 2020, during the process of reopening of the economy and of work activities in the country.



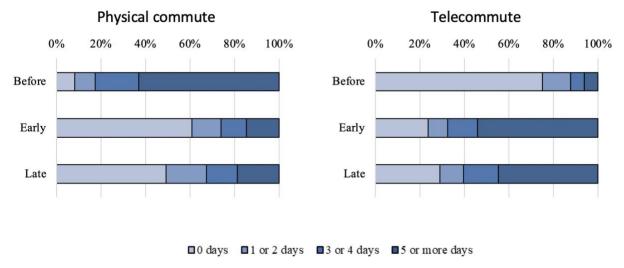


Figure 27. Number of days a) physically commuting and b) telecommuting before and during the two stages of the pandemic. Sample size: 1,540 workers that participated in both 2020 COVID survey waves.

Telecommuting still persisted with rather high penetration among the U.S. workforce in the later stage of the pandemic. It is still not clear to which extent it will persist over time, after the remaining impacts of the pandemic continue to fade away, as it might become part of a "new normal" characterized by hybrid work and partial remote work schedules even after the pandemic. In addition, the analysis of the sociodemographic profiles of the respondents shows that a higher proportion of predominantly white-collar, highly educated and higher-income workers were still telecommuting in the late stage of the pandemic. This suggests that any persistence of (even partial forms of) telecommuting will be likely strongly correlated with certain sociodemographic and employment characteristics of the individuals.

Finally, we calculated the average days in a month that commuting respondents used each mode of travel and the relative differences in the "before vs. during the pandemic" time periods (as shown in Figure 28). Somewhat not surprisingly, the relative ranking in the use of various travel modes for commuting purposes remains similar to the pre-pandemic levels: most Americans used to commute to work by private car, and this trend further expanded during the pandemic. In terms of the relative differences in the use of various modes in the three time periods, a steep decline in the use of both private vehicles and public transportation was observed during the early stages of the pandemic, with a more pronounced rebound for the use of private vehicles in the late stage of the pandemic in late 2020, characterized by the increased dependence on private car use. The decline was significantly higher for public transportation users, with a reduction up to 49.2% in train use among the respondents in the sample during the early stage of the pandemic. This can be explained by the restrictions in mobility, adoption of full-time or part-time telecommuting, and the fear of getting the disease because of sharing the same vehicle with others. The decrease in the use of public buses was less extreme than the one for rail-based public transportation, a finding that is largely explained by the different demographics of the users that travel with these public transportation services: white-collar



workers that are better able to replace their physical commutes with forms of remote work are more likely to be using rail-based public transportation, while a larger proportion of bus users comprises captive riders that were more often considered essential workers (and had to report to work also during the pandemic) and had reduced ability to switch to other travel modes. It should be noted that the observed ridership data in large U.S. metro areas point to an even larger decline in the use of public transportation during the early stage of the pandemic, a difference that might be attributable to the sampling of respondents and possible measurement errors in the way the frequency of using various travel modes is measured in this study.

The trend is slightly different for ridehailing, as the initial decrease during Spring 2020 did not recover significantly during Fall 2020. The reliance on both using a personal bike or e-scooter and walking shows a continuous decrease over time, though (a) the reduction is proportionally smaller than the one observed for public transportation and ridehailing, and (b) the lower adoption of bicycling and walking in Fall 2020 might be somewhat due to weather and seasonal effects, as colder weather conditions in many of the studied U.S. metro areas might discourage the use of active modes of travel during the colder parts of the year. Interestingly, forms of shared micromobility services, including shared e-scooters or shared e-bikes, experienced an increase in their use during the early stage of the pandemic, followed by a decline after that. The increase in the early stage of the pandemic might be explained by both the smaller baseline use of these services in the pre-pandemic conditions, which makes even small changes appear as sizable percentage increases in the use of these services, as well as the potential mode shift from public transportation, as many users chose to avoid public transportation in particular during the early stage of the pandemic and micromobility options represented a potential "safe" alternative to the use of public transportation.



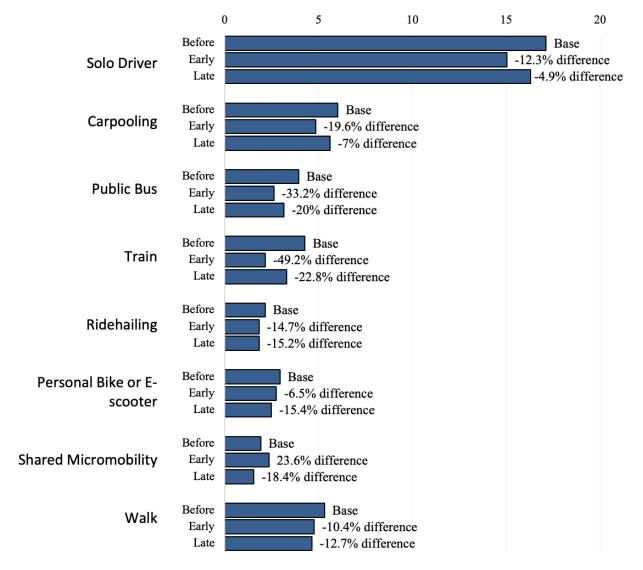


Figure 28. Change in the average number of trips per month by travel mode among those commuting before and during the two stages of the pandemic. Sample size: 549 commuters that participated in both 2020 COVID survey waves.

# Long-term consequences, planning and equity implications, and policy recommendations

The COVID-19 pandemic has disrupted society in many ways. Among the most dramatic changes, the pandemic prompted a large increase in the adoption of remote work, a portion of which might also extend beyond the end of the pandemic. While we expect that remote work adoption levels will gradually decline from the current pandemic levels in the upcoming years, as society transitions to a new normal and most workers return to their in-person work activities, in the medium terms it will likely cause important impacts, and continue to replace a sizable proportion of commuting trips. Considering the composition of the U.S. workforce, and the service-oriented economy of the country, it is estimated that approximately one third of U.S. workers can work remotely effectively. Even if only a limited portion of these workers



continued to work remotely, and only on a part-time basis, the resulting impacts on transportation would be substantial, and the magnitude of the impacts on commuting travel could be, for example, larger than the entire volume of public transportation trips in the country (as public transportation only accounts for less than 2% of trips, nationwide).

The fact that more people might work from home after the pandemic than in the pre-pandemic society might have huge impacts on the use of various travel modes as well as the spatiotemporal distribution of trips in the country. On one end, the increased adoption of telecommuting might promote a more extensive use of the car for shorter non-work-related home-based trips that are difficult to serve with non-auto modes. This is not exclusive to people that usually commute by car: for example, those that used to commute to work by public transportation before the pandemic, if they switched to remote work in the longer term, would have increased access to their own cars at home, while car access would have not been available to them if they spent most of the day at work, traveling by public transportation to reach their workplace. While the total amount of commute travel for these workers might decrease as an effect of the reduced commuting trips, discretionary home-based travel might limit the total reduction in travel (or even cause an increase in total travel, in some cases) and modify the average split across travel modes and times of day. Overall travel during peak hours will likely remain below pre-pandemic levels, especially during the morning peak, due to the reduction in commutes. However, an increase in the off-peak periods is likely, producing a more levelled usage of the transportation network over time, and a potential rebalancing of trips across local roads vs. major highway system.

To this equation it is important to add the effect that online shopping might have on total vehicle miles traveled. The pandemic accelerated a pre-existing trend with the increase in the frequency of online shopping. It is still not clear to which extent this trend will continue in the upcoming years and with which strength. Online shopping will likely account for a sizable and growing portion of total sales, but not all shopping trips can be replaced by online shopping. As the pandemic effects recedes, more trips will likely be carried out for social/entertainment purposes, as it has already been seen in the U.S. society in recent years with the evolution of many shopping centers in "entertainment centers" with a mix of restaurants, cafés, bars, centers for social and recreational activities mixed with physical and experiential stores [62]. These trips will be accompanied by a continuously-increasing number of trips made by delivery vehicles to bring items purchased online (and/or through on-demand delivery smartphone apps) to their customers' homes.

The potential and very much hoped-for long-term reduction in vehicle miles traveled (VMT) and traffic congestion during peak hours, or even during the entire day, associated with the pandemic will likely prove to be only temporary, and somewhat promote additional shift in travel. This might include new trips by car in the form of induced demand, as the faster travel times might make traveling by car more convenient to many, or shift in travel times, e.g., reducing the advantages of very early commuting before the AM peak in the post-pandemic society. Consequently, trips that did not exist in the past because they were discouraged by heavy traffic congestion might be generated (or brought back to peak time) in this new context.



This might also be encouraged by the increase in the interest in owning vehicles that has been observed in this study, together with the decision of a significant portion of zero-vehicle-owning households to purchase their first vehicle. All these patterns are confirmed by the robust and increasing vehicle sales observed in the past year in the United States—even if the official numbers on vehicle sales have been affected by major supply chain issues, which affected both supply and demand through reduced inventories and increases in prices, so the overall impact of the pandemic on vehicle sales is more difficult to decipher—and seem to point to the risk of an increase in car dependence in the future U.S. society. Thus, in the absence of policies to discourage increased car travel, the potential benefits from the reduced use of the transportation network because of telecommuting might eventually vanish, giving way to even more widespread and frequent use of private vehicles.

## Planning and equity implications, and policy recommendations

As discussed in this chapter, the adoption and frequency of telecommuting strongly correlate with certain sociodemographic characteristics. Specifically, white-collar, highly-educated, and higher-income workers are more likely to be able to continue to telecommute to some extent after the end of the pandemic. Accordingly, it is key that public policies also consider the socioeconomic distributional effects of the potential benefits associated with remote work. Current data have already shown how lower-income individuals and members of minorities have been more affected by the pandemic (in their employment and financial conditions), and they have continued to use public transportation for commuting (among those who did not lose their job) during the pandemic. Making sure public transportation service is maintained and its quality preserved (or even improved) in spite of the lower ridership and declining revenues would be a high-priority policy goal, to make sure that the population groups that have already suffered the consequences of the pandemic the most are not further damaged in the post-pandemic recovery.

The reduction in public transportation ridership is not the best ground to control the transportation externalities and sustainability impacts of the increased use of private vehicles. It is not rare that a decreased public transportation ridership is used as an argument against public transportation subsidies and investments in new public transportation infrastructure, which goes in the opposite direction of what would be needed for the upcoming years. Instead, the U.S. transportation sector is in much need of a shift toward policies that disincentivize the use of single-occupancy vehicles (SOVs) and single-passenger services (e.g., non-pooled ridehailing services) and incentivize everything else. This would create more choice, moving away from car dependence through breaking the link between personal trips and vehicle trips, and allowing an increase in individual mobility without necessarily and increase in vehicle miles traveled.

Interestingly, many of the same policies that today can discourage car dependence and solo driving could be used in the future to create the proper incentives and rules that will direct the future use of autonomous vehicles (AVs) toward pooled mobility services and away from personal vehicle ownership and the use of low- or even zero-occupancy vehicles in a future dominated by AVs. Such policies include but are not limited to pricing of congestion and



parking, encouraging substitution of telecommunications for travel, land use densification around public transportation stations, promoting active modes of travel and pedestrianization of cities, and encouraging partnerships between bus/rail and new mobility services. These policies have additional benefits that align with widely embraced goals, including the use of road user charges (much needed, in times of a declining role for gas taxes due to the shift to alternative fuel vehicles) to generate funding for transportation infrastructure and services, including public transportation investments. And they can be used to improve accessibility/mobility for those marginalized by today's car monoculture, i.e., environmental justice and disadvantaged communities, as well as those with physical or other impairments to travel.

## **Key Messages**

### **Key findings**

- a. The pandemic caused a significant increase in the intention to acquire a new vehicle, together with an increased interest in living in lower-density neighborhoods.
- b. The adoption of e-shopping increased significantly during the first stage of the pandemic, and plateaued in its later stage. This caused an overall increase in the frequency of e-shopping for both grocery and non-grocery items, and an expansion of its user base, accelerating a pre-existing trend in e-shopping growth from before the pandemic.
- c. There was a steep decline in the number of physical commute trips during the pandemic, with a significant increase in their remote work counterpart. Physical commuting bounced back, to some extent, in the later stage of the pandemic, but remote work remains more widely adopted than before the pandemic, pointing to its potential longer-term persistence even if on a part-time basis in future society.
- d. The use of both private vehicles and public transportation decreased and later bounced back during the various stages of the pandemic. However, the public transportation recovery has been significantly slower, in particular for rail-based public transportation.

## **Policy recommendations**

- a. Public policies must consider the socioeconomic distributional effects of the potential benefits associated with remote work, in particular as lower-income individuals and members of minorities show much lower ability to engage in forms of remote work.
- b. It is of the highest importance that public policy strengthens and promotes public transportation service in spite of its ridership reduction.
- c. There is need for a shift towards policies that disincentivize the use of single-occupancy vehicles and single-passenger transportation services. Congestion pricing and parking-related policies are good examples of policy areas that can support these goals.

#### **Research recommendations**

a. Changes in vehicle miles traveled should be studied in detail. Especially, the increase in discretionary travel might vanish any potential reductions in travel associated with



- telecommuting, and might lead to very different spatiotemporal and mode distribution of trips.
- b. Researchers should investigate what circumstances can make passengers return to public transportation, and what would make users of other travel modes consider public transportation for their travel needs.



# III. Conclusions and Policy Implications

This report summarizes the work carried out to collect and analyze data from three surveys that were administered in 2019, Spring 2020, and Fall 2020, to investigate the changes brought to transportation by new transportation patterns and innovative technologies, and the impacts of the COVID-19 pandemic that has disrupted society starting in early 2020. The three data collections were carried out using online opinion panels in eight major U.S. cities in 2019, and they were expanded to cover 15 major cities in the U.S. and two cities in Canada starting in 2020. Additional participants were recruited using convenience sampling, starting in 2020, and all respondents from previous surveys were retained to the extent possible in all following waves of data collection, with the aim of creating a longitudinal dataset with the same respondents participating in more than one survey over time.

The analysis of these datasets can help get a better understanding of how the nationwide transportation patterns and travel choices are affected by the transportation revolutions in digital devices and on-demand services. These changes affect the way individuals make travel choices and approach transportation services, and eventually adopt emerging options such as ridehailing and shared mobility, or alternative-fuel vehicles, among various population cohorts. These perspectives can hardly be obtained with the analysis of datasets from traditional surveys such as the U.S. National Household Travel Survey. Further, the initial objectives of the research project were altered due to the COVID-19 pandemic. For this reason, the various waves of data collection from this project have provided a very useful source of data that can help explain the disruptive impacts of the pandemic on the transportation sector. In particular, the longitudinal portions of the dataset collected in this project (and its follow-up projects that are collecting additional waves of data, following these first waves of surveys) can help investigate the temporary vs. longer-term nature of the various impacts of the COVID-19 pandemic.

Among other aspects, the project highlights how remote work has become very popular in the U.S. society starting in Spring 2020, due to the need for social distancing and for reducing the risk associated with exposure to pathogens. More than 75% of respondents in our surveys, who were employed, were engaged in forms of remote work at least one day per week at that time. Remote work remained a common practice in Fall 2020 as most of the workers who had adopted full-remote work in Spring 2020 continued the work remotely at least to some degree in Fall 2020. Workers seemed to have found some balance among their personal life, on-site work, and flexible work during the pandemic situation, as many of them adjusted to some forms of hybrid work, combining remote work with some days in which they physically commute to work.

The impacts of the pandemic on the use of various modes of transportation are substantial. Public transportation accounts for only a few percent of total miles traveled in the United States. However, the impact of this remote-work habit further depressed the use of public transit, as this is mainly used during peak times for commuting purposes. The transition in remote work has also offered the opportunity to reduce traffic congestion in particular during peak times. Most notably, some blue-collar workers kept commuting by public transit also during the pandemic, and their use of transit already started to recover (faster for the bus than



for rail services) by Fall 2020. Under these circumstances, it is important to maintain and support public transit services for those essential workers even despite a reduction in ridership.

On the other hand, another notable shift associated with the pandemic was the strong increase in e-shopping behaviors. Both grocery and non-grocery items have largely attracted people to e-shopping since the pandemic started in Spring 2020 but it leveled off, to some extent, in the later phase of the pandemic. Still, the overall rate of e-shopping has considerably increased from before the pandemic, accelerating the global trend of e-shopping from the previous years.

Changes in the frequency of travel have shown different patterns across travel modes. While all modes observed a severe reduction in the usage for both work and leisure purposes in Spring 2020, private cars marked the highest degree of recovery in Fall 2020 as people started to prefer traveling by a private vehicle, probably as this was considered the least unsafe option. If this trend continued in the following phases of the pandemic, this would mean that the total vehicle miles traveled would likely continue to increase during the following phases of the pandemic (and in the post-pandemic) period.

A similar tendency has been observed in people's behavior in long-distance (LD) travel. While travelers generally refrained from making LD trips during the peak of the pandemic, many also experienced a shift from flying to other modes and in particular traveling by private cars as the pandemic severely restricted LD trips by air, bus, or train.

Travel behavior by active modes (i.e., walk or bike) highlighted another important component of the disruptions caused by the pandemic. As active modes were considered safer than using public transit or other modes that expose passengers to sharing a vehicle with strangers, active travel mode did not see a major decline in usage in 2020. Interestingly, there was a large increase in walking and bicycling for non-work travel among non-commuters in Spring 2020. This implies that the active modes were used for some recreational and/or physical-activity purposes under the stay-at-home order. Looking at the group-level changes, it seems that walking behavior was less easy to adopt or abandon than bicycling behavior. Also, while walking continued to account for a relatively higher proportion of trips (compared to bicycling), much of the behavioral change for the active modes was already reversed by Fall 2020. When it comes to the physical activity carried out during the pandemic, exercising at non-home locations (e.g., park, beach, gym) has seen a major increase in the total duration during the pandemic period. This could be caused by people seeking distraction and/or fitness under restrictive situations.

Besides travel behavior and telecommuting practice, we also examined how people's attitudes related to various dimensions such as transportation preferences, environmental friendliness, or preference for being a driver vs. a passenger in a vehicle might have changed during the past year. First of all, interestingly, the average life satisfaction maintained a similar level in Spring and Fall 2020. This implies that even if the majority of the population were impacted in some way by the disruptions brought by the pandemic, only a certain limited group felt this had a serious impact on their satisfaction in life. Also, a marked increase in the desire to own a car was observed during the pandemic, which relates to the preference to own and use private vehicles for travel, and could lead to further reliance on private vehicles in the future. While the



usage of public transits for both work and leisure purposes largely decreased during the pandemic, the data collected in this study shows how most individuals did not significantly change their attitudes towards the environment and/or the interest (or lack of interest) in the adoption of eco-friendly modes of transportation. A high agreement with raising gasoline prices to fund more environmentally-friendly transportation options was also observed.

In conclusion, our series of data collection efforts and the analyses of these datasets provide several important insights that help understand the changing patterns in transportation use, remote work habits, e-shopping behavior, individual attitudes, and others, during times of big changes affecting society. Some of the changes brought by the COVID-19 pandemic, such as remote work habits, are expected to remain to some degree after the pandemic is over. However, it is not clear if the combination of the changes and drawbacks will result in a reduction in total miles traveled and/or an improvement in eco-friendly transportation options. Further analyses from the data collected from this project, and the follow-up data collections built on related research in 2021 and beyond, will help disentangle such complex effects in the post-COVID world.



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# V. Data Summary

#### **Products of Research**

As part of this project, the research team carried out several rounds of data collections through survey administered among the general public. All datasets feature a similar structure and contain information on similar topics related to transportation, including personal attitudes and preferences, adoption of mobile devices or social media, household composition, general travel patterns, vehicle ownership, use of new mobility services such as ridehailing (Uber, Lyft), carsharing (Zipcar), or bikesharing, and household and individual socio-demographics.

The first dataset was collected in 2019, targeting residents in 8 metropolitan areas in the United States (California; Los Angeles, Sacramento, and San Francisco, Non-California; Boston, Kansas City, Salt Lake City, Seattle, and Washington D.C.). For this survey, we adopted two distribution channels to recruit survey respondents: an online opinion panel and a longitudinal channel for returning participants. The total number of valid responses was 3,410. All respondents completed the survey online.

The second dataset was collected in Spring 2020, targeting residents in 15 metropolitan areas in the United States and 2 regions in Canada (California: Los Angeles, Sacramento, San Diego, and San Francisco; Non-California: Atlanta, Boston, Chicago, Denver, Detroit, Kansas City, New York City, Salt Lake City, Seattle, Tampa, and Washington D.C.; Canada: Toronto, Vancouver). Also this survey administration did not include the distribution of a (printed) paper questionnaire but also included a convenience sampling method with which we reached out potential participants through online advertisements (e.g., Facebook Ads) in addition to the online opinion panel and the longitudinal channel. Also, as the COVID-19 pandemic severely disrupted society, we accordingly modified some components of the survey. For example, questions about pooled-ridehailing (e.g., UberPOOL and Lyft Share) were omitted since such services were entirely suspended in the study regions during the pandemic. Also, questions asking about participants' attitudes toward health concerns due to the pandemic, using new mobility services (e.g., bikesharing) during the pandemic, and the detailed impact of the pandemic on their job were added. The total number of valid responses for this survey wave was 13,648 (1,440 longitudinal + 10,815 opinion panel + 1,393 convenience sampling).

The third dataset was collected in Fall 2020. In this iteration, we resampled respondents from the previous survey waves, while adding new respondents through the opinion panel and convenience sampling approaches. The survey content was maintained mostly consistent with that of the Spring 2020 survey to measure the longitudinal impacts of the COVID-19 pandemic. The total number of valid responses was 8,029 (3,385 longitudinal + 3,766 opinion panel + 878 convenience sampling).

### **Data Format and Content**

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



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

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

# **Data Access and Sharing**

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

#### **Reuse and Redistribution**

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

