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Quantifying the impact of COVID-19 on travel behavior in different socio-economic segments

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ABSTRACT

This paper investigates the impact of COVID-19 on travel behavior in different socio-economic segments in the USA using integrated mobile device location data over the period 1 Jan 2020 ~ 20 Apr 2021. A fixed-effect panel regression model is estimated to statistically identify the relationship between COVID monitoring measures and travel behavior such as nonwork/work trips, travel miles, out-of-state trips, and the incidence of WFH in different socio-economic segments. We find that as exposure to COVID increases, the number of trips and traveling miles starts to bounce back to pre-COVID levels, while the incidence of WFH remained relatively stable and may never return to pre-COVID level. The findings have implications for understanding the heterogeneous mobility response of individuals in different socio-economic segments to various COVID waves, and thus can provide insights into the recovery of travel behavior.

Key Words: COVID-19, Travel behavior, Socio-economic segments, Mobile device location data, Fixed-effect panel regression model

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1. Introduction

Coronavirus Disease 2019 (COVID-19) has caused the most significant decrease in life expectancy since World War II and greatly impacted on people's daily lives worldwide (Aburto et al., 2022). In the third year of the coronavirus pandemic, global COVID cases continue to rise dramatically due to the recent BA.5 subvariant, and there have been over 599,479,052 COVID cases and 6,468,459 deaths by 20 Aug 2022 worldwide. The World Health Organization has reported that about 4.2 billion people or 54% of the global population were subject to complete or partial lockdowns by 28 April 2020 and nearly all the global population has been affected by some form of containment measures (IEA, 2020). On 12 July 2022, the Australian government, for example, announced that restrictions, lockdowns, and 'stay-at-home' orders would continue to play a part in managing COVID-19. All in all, these measures not only result in changes in people's daily lifestyle and travel behavior but may also have significant long-term implications for future mobility activities.

1.1 Literature context

Given that Coronavirus is transmitted by close contact with infected individuals, public transit usage around the world experienced a dramatic decrease after the initial lockdowns in early 2020. Parker et al. (2021) conducted a survey in the US and reported that 75% of transit riders took less public transit since the COVID pandemic, and less than 10% of transit riders were comfortable taking transit despite the risk of infection and transit service reductions due to the pandemic. There has been a significant decline in demand for taxis and ride-share services such as carpooling and ride-hailing in the US, due to reduced service operations and users' concerns about being exposed to the virus (De Palma et al., 2022). The 'stay-at-home' order enacted in March 2020 in the US reduced the number of taxis operating by 85% and taxi patronages by 95% (Ale-Ahmad, H., Mahmassani, 2022). After three months of COVID-19 restrictions in Australia, annual travel time reductions for car and public transport commuters was estimated as a 'saving' of $5.58 billion in the Greater Sydney Metropolitan Area, representing a 54.02% reduction in the Pre-COVID total time costs (Hensher et al., 2021).

As a result of the significant drop in public transit rideshare, there is a concern that the COVID pandemic could have a substantial negative impact on social equity, decarbonization, and the financial position of transportation providers around the world (Redding et al., 2020). According to a survey in the Hanover Region, local bus and light rail services have been replaced by bike, car, and working from home (WFH), whereas train use has been significantly replaced by bike; females, in particular, have a higher fear of infection than males, which deters them from using public transit (Schaefer et al., 2021). A survey in China (Sun et al. 2022) examined the satisfaction differences of low-income individuals who traveled by bus before and after COVID-19, and found a significant shift in the factors affecting low-income individuals' satisfaction with bus use since the outbreak of COVID-19. Compared to higher-income transit riders, low-income transit riders experienced a significantly smaller reduction in trips and travel distance, indicating that lower-income individuals did not have as much discretion over how many trips they took during the pandemic, particularly if they were in the essential worker category. The demand for public transportation in the 'new normal condition' is still below that of pre-COVID-19 and may never return to that level.

There have been significant changes in people's travel behavior and lifestyle since the outbreak of COVID-19. Physical mobility is being progressively replaced by virtual mobility via the internet, for example, through teleconferences, teleworking, and online shopping. These changes are expected to continue as the pandemic proceeds through its various phases (Mouratidis & Papagiannakis, 2021). Beck & Hensher (2021) conducted a descriptive analysis on the changing dynamics of travel activity associated with public transport, as well as attitudes regarding trip activity, and found that Australians are more comfortable completing day-to-day activities while support for intervention measures remains high. WFH is the most significant transportation policy lever since World War II and is becoming a popular and potentially significant alternative to commuting. Hensher et al. (2022) built the relationship between WFH and commuting by day of the week and time of day during the COVID pandemic into a strategic transport model for two large metropolitan areas in Australia, which identifies the influences on such choices together with a mapping model between the probability of WFH and socio-economic and other contextual influences. Hensher et al. (2021) developed a WFH ordered logit model to assess the incidence of WFH and its impact on the number of weekly one-way commutes by car and public transportation during the COVID pandemic. To gain a better understanding of WFH during and after COVID-19 for train travelers, Ton et al. (2022) conducted a study in the Netherlands among train travelers to examine telework behavior, attitudes, and future intentions regarding teleworking. They also identified six types of teleworkers with varying frequencies of telework, attitudes, intentions, socio-demographics and employer policies based on a latent class analysis. Beck & Hensher (2021b) concluded that there is growing support among employees and employers to continue to support WFH in the future, given evidence of increased productivity. A Dutch nationwide survey study by De Haas et al. (2020) examined the possibility of substantial structural changes after COVID-19 and found that many of those who were able to work from home during the pandemic are expected to work even more from home in the future. Beck & Hensher (2022) suggested that WFH will continue to be supported through a hybrid work model with more flexible working times and locations, associated with improved wellbeing of employees given no reduction in economic productivity; specifically, those who moved to WFH have found the experience positive and would like to continue doing so to a greater extent than they did before. As a result of the COVID-19 pandemic, many stores were closed temporarily or permanently, making online shopping an attractive alternative. Abdullah et al. (2021) investigated the impact of the COVID-19 pandemic on travel patterns in Pakistan and showed that there was a significant shift in primary travel purposes from work and study to shopping during the pandemic. Shamshiripour et al. (2020) in a study in Chicago examined the possible post-pandemic behavior of online shoppers for groceries and meals and concluded that a significant portion of the increased online shopping during the pandemic would continue in the future.

To identify how real-world mobility patterns were impacted by the outbreak of COVID-19, several studies have quantified the changes in human mobility using US mobility location data (Maryland Transportation Institute, 2020; Zhang et al., 2020). For example, Sun et al. (2020) examined the difference between communities in the US responses to mobility interventions, specifically focusing on income levels, and found that the high-income individuals' social distancing behavior could be improved in various situations. Xiong et al. (2020) developed a statistical model to examine the change in mobility inflow across the nation as well as the time-varying relationship between mobility and infection. They used three metrics to quantify human mobility: the daily average number of trips per person, the daily average number of miles traveled per person, and daily percentage of residents staying at home. They found that then the states with 'stay-at-home' orders have reduced average daily mobility by approximately 5% based on the results of several longitudinal models. Lee et al. (2020) identified spatial and temporal heterogeneity, socio-demographic variations, and teleworking trends and indicated the overall mobility heterogeneity between income and density groups.

1.2 Scope and structure of this paper

While a limited number of studies have statistically quantified the extent to which COVID monitoring measures (i.e., new COVID cases, hospital bed utilization, COVID tests done, ICU utilization, ventilator needs, imported COVID cases, COVID exposure, days with decreasing cases, COVID death rate) would impact the travel behavior of individuals in different socio-economic segments, few have identified the travel behavior changes, due to COVID, of different socio-economic segments such as low-employment density *vs.* high-employment density and low-population density *vs.*. high-population density. This paper focuses on travel behavior changes, quantifying the extent of individuals' heterogeneous mobility response to different COVID monitoring measures across socio-economic segments, and estimating a fixed-effect (FE) panel regression model for different socio-economic segments.

The rest of this paper is organized as follows: Section 2 provides a descriptive overview of travel behavior changes in different socio-economic segments in the USA; Section 3 introduces the FE panel regression model for different socio-economic segments and analyzes the results of the model; Section 4 provides a discussion of the findings; Section 5 concludes this paper with suggestions for future planning and future research directions.

2. Descriptive overview of travel behavior during pandemic

In section 2.1, we first conduct a descriptive analysis on the number of daily new COVID cases, nonwork trips/person, the percentage of WFH, and travelling miles during the pre-COVID and COVID pandemic period based on the mobile device location data in the US (Maryland Transportation Institute, 2020; Zhang et al., 2020) and the census data from the US Bureau of Transportation Statistics (Bureau of Transportation Statistics, 2022). In Section 2.2, we analyze the traveler behavior changes, due to the COVID, based on the data from US Census Household Pulse Survey (U.S. Census Bureau, 2022).

2.1 Descriptive statistics of travel behavior and new cases during the COVID pandemic

We compare the number of new COVID cases with average nonwork trips in the US during three COVID waves from 1 Jan 2020 to 20 Apr 2021. As shown in Figure 1, 1 Jan 2020 ~ 10 Mar 2020 is the pre-COVID period and can be used as the benchmark to compare travel behavior changes due to COVID. During Wave 1, the number of new COVID cases first increased from 188 cases/day to 33,751 cases/day, and the average nonwork trips decreased from 2.9 trips/person to 1.9 trips/person during 10 Mar 2020 ~ 4 Apr 2020 when most states issued 'stay-at-home' orders. During this period, new cases decreased to 19,902 cases/day. Nonwork trips increased to 3.1 trips/person on 15 Jun when the 'stay-at-home' order was ended in the US. During Wave 2, the number of new COVID cases (resp.[1] nonwork trips) first increased (resp. decreased) from 23,796 cases/day (resp. 2.5 trips/person) to 76,077 cases/day (resp. 3.1 trips/person) during 16 June 2020 ~ 16 July 2020, and then decreased to 31,387 cases/day (resp. 2.8 trips/person) on 28 Sep 2020 when global COVID-19 deaths surpassed 1 million. During Wave 3, the number of new COVID cases first experienced a significant increase, reaching the peak of 290,877 cases/day on 2 Jan 2021, and then experienced a dramatic decrease from 208,208 cases/day to 44,197 cases/day during 3 Jan 2021 ~ 8 Mar 2021, and the average nonwork trips/person fluctuated between 2.3 trips/person and 3.6 trips/person. The number of new COVID cases was stable at 60,000 ~ 80, 000 cases/day, while the number of nonwork trips bounced back and even exceeded the pre-COVID levels at 3~5 trips/ person during 11 Mar 2021 ~ 20 Apr 2021.

[1] 'resp.' is the abbreviation of 'respectively'.

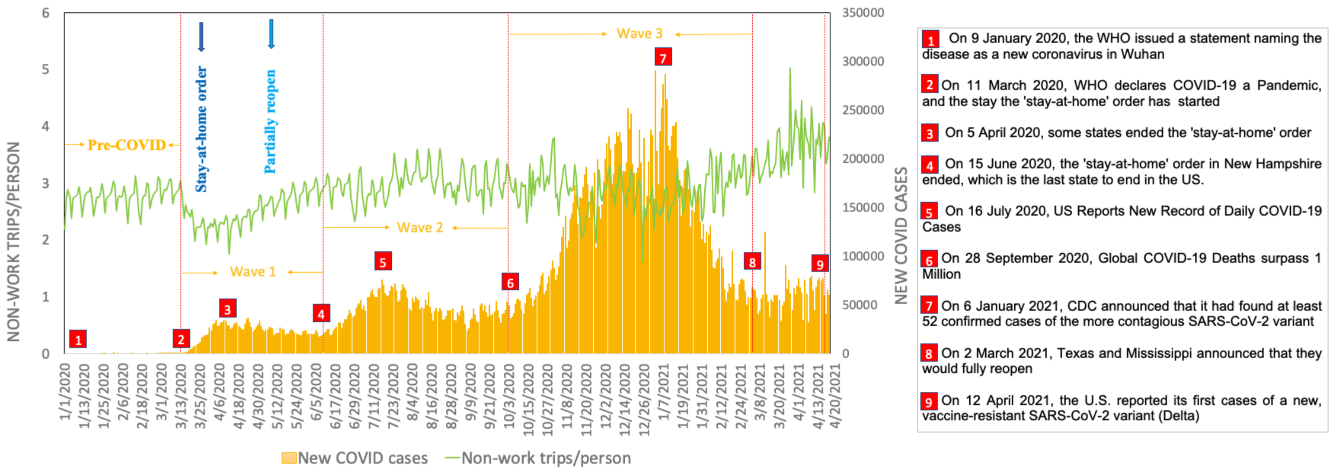


Figure 1. The number of daily new COVID cases and nonwork trips during 1 Jan 2020 ~ 20 Apr 2021, USA

Figure 2. Daily percentage of WFH in different US states during 1 Jan 2020 ~ 20 Apr 2021. State Acronyms are given in the online appendix

We further analyzed the percentage of WFH in all 50 US states from 1 Jan 2020 to 20 Apr 2021. As shown in Figure 2, the %WFH in each state saw a dramatic increase during Wave 1 and then saw a mild decrease during Wave 2 and Wave 3, while bouncing back after the number of new COVID cases peaked. Although the number of new COVID cases during 8 Mar 2021 ~ 20 Apr 2021 experienced a significant decline compared with the peak during Wave 3, the %WFH has only experienced a slight decrease and has not returned to the pre-COVID level. For example, considering the %WFH in the state with the highest employment density (ED) among all 50 states in the US, the %WFH in DC[2] first saw a significant increase from 6.1% to 57.4% during Wave 1 (10 Mar 2020 ~ 15 Jun 2020), then saw a mild decrease afterwards and bounced back to 51.8% during 20 Dec 2020 ~ 2 Jan 2021 before declining to 41.9% on 20 Apr 2021. We find that %WFH in the states with higher ED is higher than in the states with lower ED, and workers in the states with higher ED are more adapted to WFH with the evidence of fewer changes in %WFH during a 14-month COVID pandemic period. For example, %WFH in three states with the highest ED (i.e., DC, NJ, MA) was higher and witnessed less recovery, while %WFH in three states with the lowest ED (i.e., AK, MT, WY) was lower and witnessed more recovery, almost returning to the pre-COVID levels.

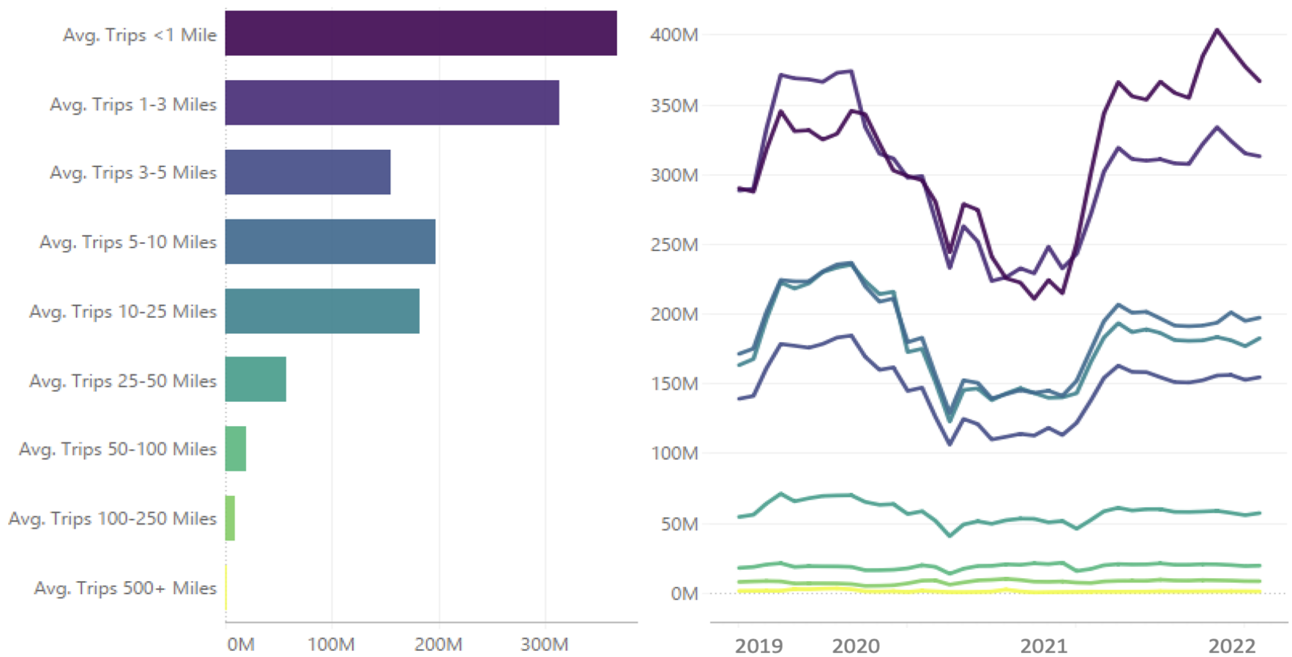


Figure 3. The number of trips taken with different travelling distance during 2019 and 2022 in the US

We next analyze how the number of trips varied by travelling distance from 2019 to 2022 based on US census data (Bureau of Transportation Statistics, 2022). As shown in Figure 3, since the outbreak of COVID-19 (March 2020) in the US, the number of trips with a distance of less than 100 Miles first saw a dramatic decrease during several COVID waves in 2020 (e.g., the US surpassed 20 million infections from SARS-CoV-2 and more than 346,000 deaths and the government issued 'stay-at-home' orders), then saw a significant increase from Jan 2021 to April 2021 (e.g., the US government started the vaccination scheme). By late April 2021, the Center for Disease Control and Prevention (CDC) announced that fully vaccinated individuals do not need to wear masks in most situations, and subsequently the number of trips shorter than 100 miles has recovered to only 20% lower than the pre-COVID level in 2019. Finally, the number of trips in 2022 bounced back and even exceeded the pre-COVID level in 2019. Figure 3 shows that COVID-19 has significantly impacted the number of trips with shorter distances compared to longer distances.

2.2 Descriptive statistics of travel behavior changes due to the COVID-19

In this section, we focus on analysing people's travel behavior change, i.e., the percentage of increased WFH, public transit trips, and in-store trips, due to COVID-19, based on the data collected from US Census

[2] US State Abbreviations List is proved in Online Appendix A.

Household Pulse Survey (U.S. Census Bureau, 2022). This pulse survey is designed to quickly and efficiently deploy data collected on how people's lives have been impacted by the pandemic[3].

As shown in Figure 4 - Figure 6, the states marked as green, grey, and cyan denote the states where the reported percentage changes of travel behavior are statistically below, same as, and above the US average, respectively. The values in the round brackets marked in red denote the US average of each travel behavior change during the collection period. Figure 4 shows that the average percentage of American workers moving to WFH, due to COVID, increased from 36.3% to 37.3% during 19 Aug 2020 ~ 9 Nov 2020, and then decreased to 36.9% after experiencing some fluctuations during 11 Nov 2020 ~ 21 Dec 2020, finally increasing to 39.1% during 6 Jan 2021~29 Mar 2021. Figure 5 shows that the average percentage of people in different US states who took fewer trips by public transit (bus, rail, or ride-sharing services) than normal, due to COVID, first saw a decrease from 73.0% to 69.3% during 19 Aug 2020 ~ 9 Nov 2020, and then an increase from 71.1% to 73.4% during 11 Nov 2020 ~ 15 Feb 2021, and finally decreased to 64.0% during 17 Feb 2021 ~ 29 Mar 2021. Similarly, Figure 6 shows that the average percentage of individuals in different US states who took fewer in-store trips, due to COVID-19, first saw a decrease from 70.5% to 65.5% during 19 Aug 2020 ~ 9 Nov 2020, and then an increase from 69.5% to 71.4% during 11 Nov 2020 ~15 Feb 2021, and finally a decrease to 55.7% during 17 Feb 2021 ~ 29 Mar 2021.

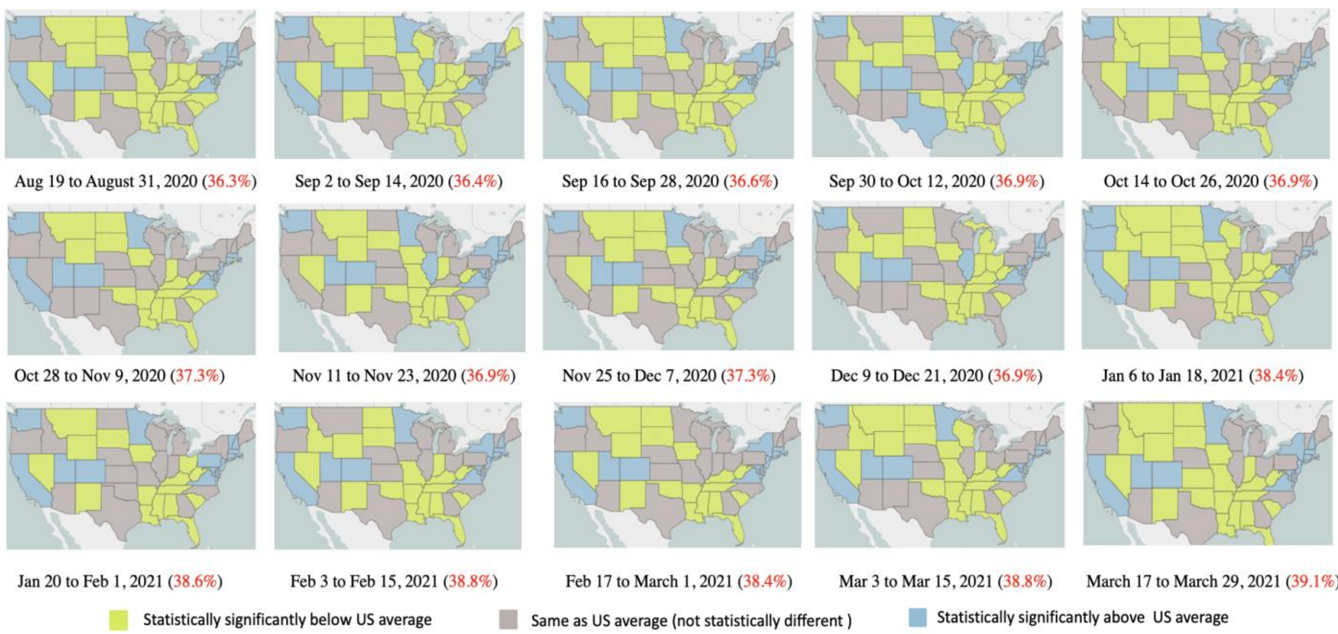


Figure 4. Percentage of increased WFH in different US states due to COVID

Figure 4 – Figure 6 show that the percentages of decreased public transit use and decreased in-store trips varied significantly in different states during different periods; however, the percentage of increased WFH was relatively stable in different states during different periods. For example, the percentage of behavior changes of all 50 US states during two time periods is summarized in Table 1. During 19 Aug 2020 ~ 31 Aug 2020 (resp. 3 Feb 2021 ~ 15 Feb 2021), Figure 4 shows that the percentage of *increased WFH* was statistically below, the same, and above the corresponding US average in 22 (resp. 18) states, 14 (resp. 20) states, and 15 (resp. 13) states, respectively; Figure 5 shows that the percentage of *decreased public transit trips* was statistically below, the same,

[3] The Household Pulse Survey (HPS) continues measuring how the coronavirus pandemic is impacting households across the US from a social and economic perspective. The HPS continues measuring core demographic household characteristics, as well as continuing to ask questions about education, employment, food sufficiency, household spending, household energy expenditures and consumption, housing security, physical and mental health, rental assistance from state and local governments, sexual orientation and gender identity, and transportation.

and above the corresponding US average in 19 (resp. 13) states, 25 (resp. 32) states, and 7 (resp. 6) states, respectively. Figure 6 shows that the percentage of *decreased in-store trips* was statistically below, the same and above the corresponding US average in 21 (resp. 13) states, 21 (resp. 32) states, and 9 (resp. 6) states, respectively.

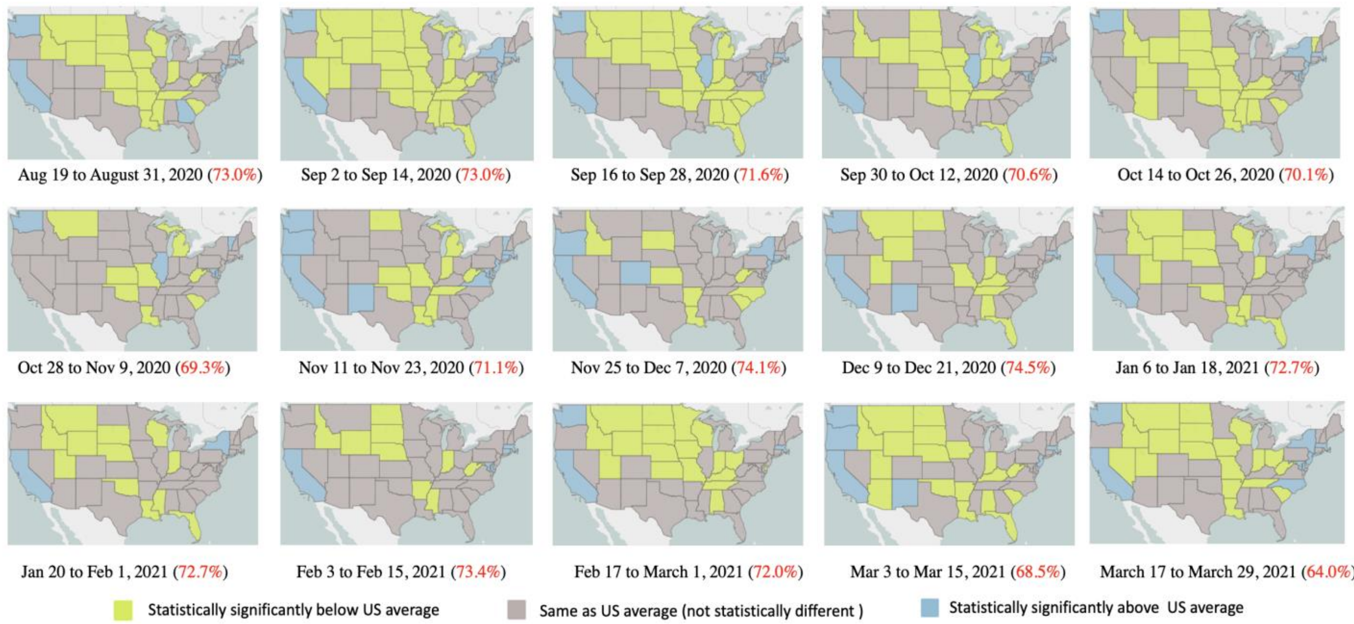


Figure 5. Percentage of decreased public transit trips in different US states due to COVID

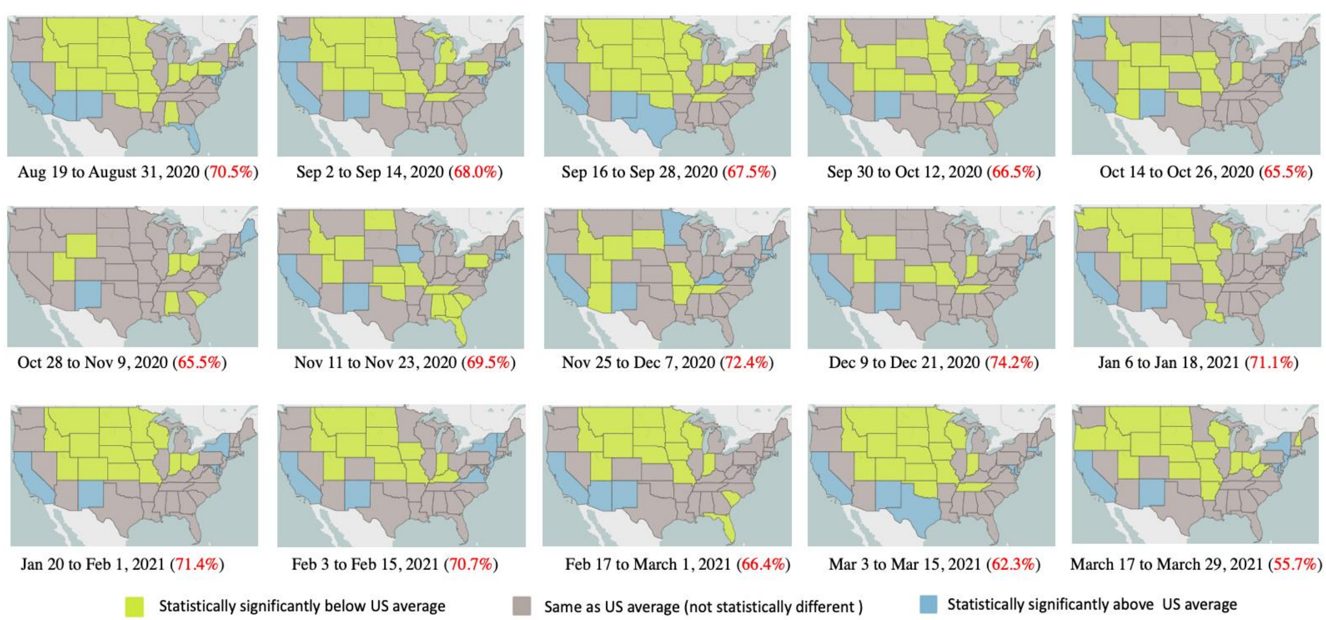


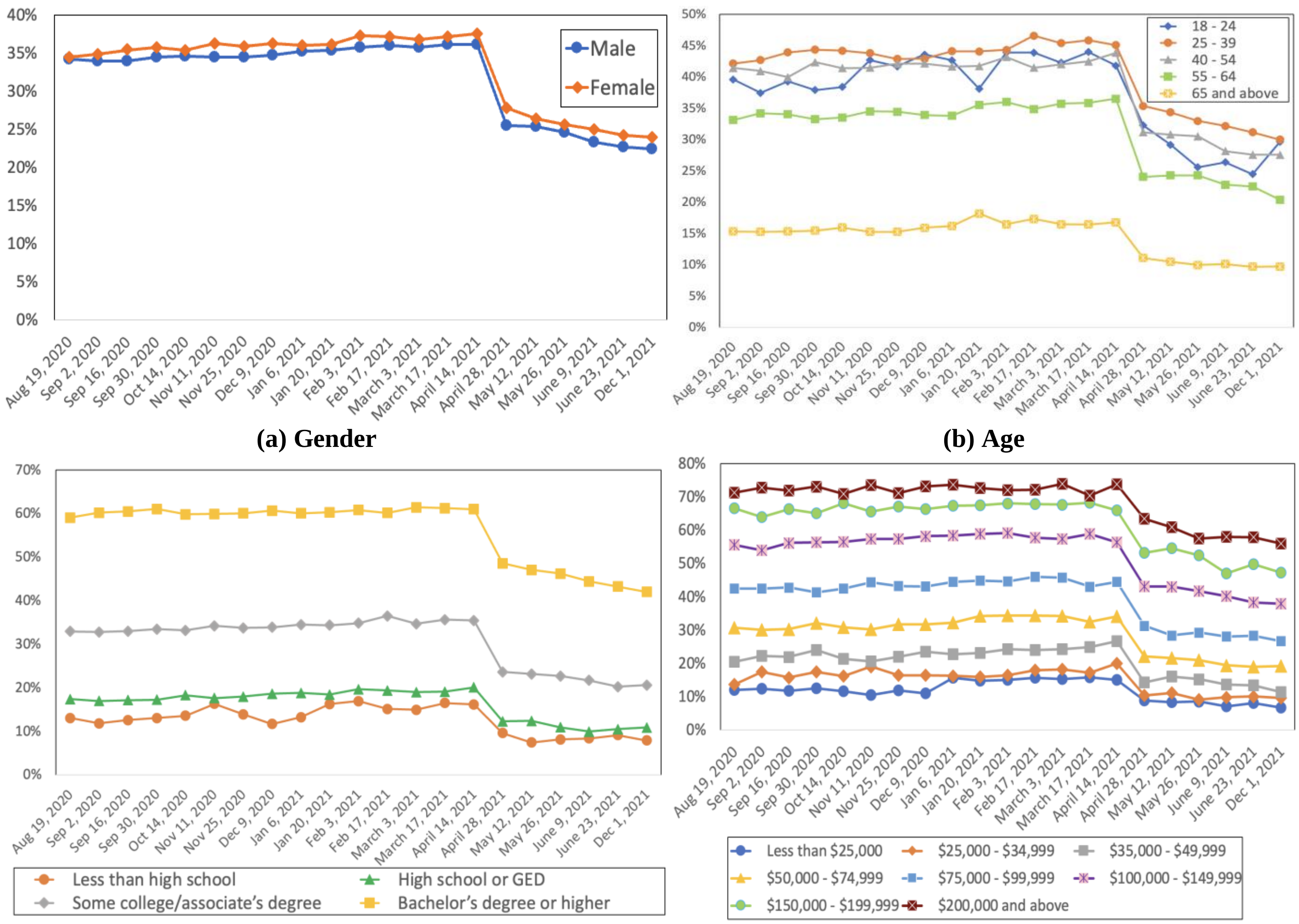
Figure 6. Percentage of decreased in-store trips in different US states due to COVID

Table 1. Travel behavior changes of all US states during 19 Aug 2020 ~ 31 Aug 2020 and 3 Feb 2021 ~ 15 Feb 2021

Period	Percentage of behavior changes	Statistically below US average	Statistically same as US average	Statistically above US average
19 Aug 2020 ~ 31 Aug 2020	% Increased WFH	MV, MS, AL, WY, LA, AR, MT, OK, SC, IA, TN, SD, NV, FL, IN, KY, OH, ND, MO, NC, AK, NM	ID, WI, AZ, NE, DE, TX, KS, MF, OR, IL, PA, GA, MI, HI	CA, VA, NH, RI, CO, NY, VT, WA, NJ, MN, CT, UT, MD, MA, DC
	% Decreased public transit trips	MT, SD, ND, AR, LA, WV, TN, OK, IN, WI, MS, NE, AK, WY, SC, ID, KS, IA, MO	AL, UT, KY, TX, MN, FL, NV, OH, NC, MI, VT, DE, CO, CT, AZ, ME, NM, NH, PA, NY, VA, RI, OR, MD, IL	CA, GA, WA, NJ, HI, MA, DC
	% Decreased in-store trips	WY, ND, MT, SD, IN, UT, ID, IA, NE, AR, AK, MO, KS, AL, VT, PA, OH, OK, MN, CO	SC, TN, GA, NH, MV, MI, ME, WI, WA, IL, MS, OR, NE, DE, NC, KY, LA, NY, CT, VA, MA, TX	AZ, MD, NM, NJ, RI, FL, CA, DC, HI
3 Feb 2021 ~ 15 Feb 2021	% Increased WFH	KY, WY, MS, AL, WV, NE, AR, IN, LA, ND, SD, SC, OK, FL, TN, MO, ID, NM	MT, IA, AK, GA, AZ, MI, DE, NC, TX, NE, OH, WI, RI, PA, ME, HI, KS, OR, IL, VT	CT, CA, MN, WA, VA, NY, CO, NH, NJ, MA, UT, MD, DC
	% Decreased public transit trips	MT, SD, ID, AR, LA, NE, AK, WV, MO, KS, KY, UT, NV	LA, IN, SC, AZ, IA, DE, OH, OK, NH, FL, MS, NM, TN, NC, TX, WI, CT, MI, GA, MT, PA, MN, RI, IL, HI, VA, CO, MA, CA, MD, DC	WA, OR, NJ, NY, VT, ME
	% Decreased in-store trips	ND, ID, SD, KS, UT, IA, AK, MT, IN, WY, MO, KY, NF	NH, MN, WI, CO, GA, OH, PA, LA, IL, AR, NC, AL, RI, FL, AZ, MI, OK, NV, TN, WV, DF, SC, WA, HI, CT, MA, DC, TX, OR, MD, MS, MF	VA, NY, NJ, VT, CA, NM

Compared with the travel behavior changes during 19 Aug 2020 ~ 31 Aug 2020, the number of states with percentages of behavior changes statistically below/above the US average decreased while the number of states with percentages statistically the same as the US average increased during 3 Feb 2021 ~ 15 Feb 2021. We divide all states into low- and high- employment density (ED) segments based on the median of ED (see in Online Appendix B) and find that the states where percentages of behavior changes were statistically below the US average belong to the low-ED segment, while the states where percentages of travel behavior changes were statistically above the US average belong to the high-ED segment. For example, the percentage of travel behavior changes in AK, which has the lowest ED in the US, was statistically below the US average; the percentage of behavior changes in DC, which has the highest ED in the US, was statistically above the US average.

We then investigated the travel behavior changes, due to COVID, in different socio-economic segments, such as gender, age, education, and annual household income, based on US Census Household Pulse Survey (U.S. Census Bureau, 2022). Figure 7 shows the percentage of people in different socio-demographic segments who moved to WFH, to some extent, due to COVID. The percentage of increased WFH across different socio-economic segments first saw a slight increase from 19 Aug 2020 to 14 Apr 2021, and then saw a significant drop before reaching a small decrease from 26 May 2021 to 1 Dec 202; however, the percentage of increased WFH differs a lot between the socio-economic segments with the exception of gender. Figure 7 (a) shows that the percentage of increased WFH of females are slightly higher than males. Figure 7 (b) shows that the 25-39 age group has the highest incidence of WFH due to COVID, followed by 18-24, 40-54, and 55-64 age group, respectively; and the elderly (65 and above) have the lowest incidence of WFH, possibly because many are retired. Figure 7 (c) shows that the increased incidence of WFH varies among different education-level segments, specifically, the higher the education-level, the greater likelihood of WFH, since the higher-level education workers usually do not have to be physically present at work (linked strongly to occupation). Figure 7 (d) shows that there is a positive relationship between WFH and income, implying that the occupations that support greater incidence of WFH are typically higher-income ones.

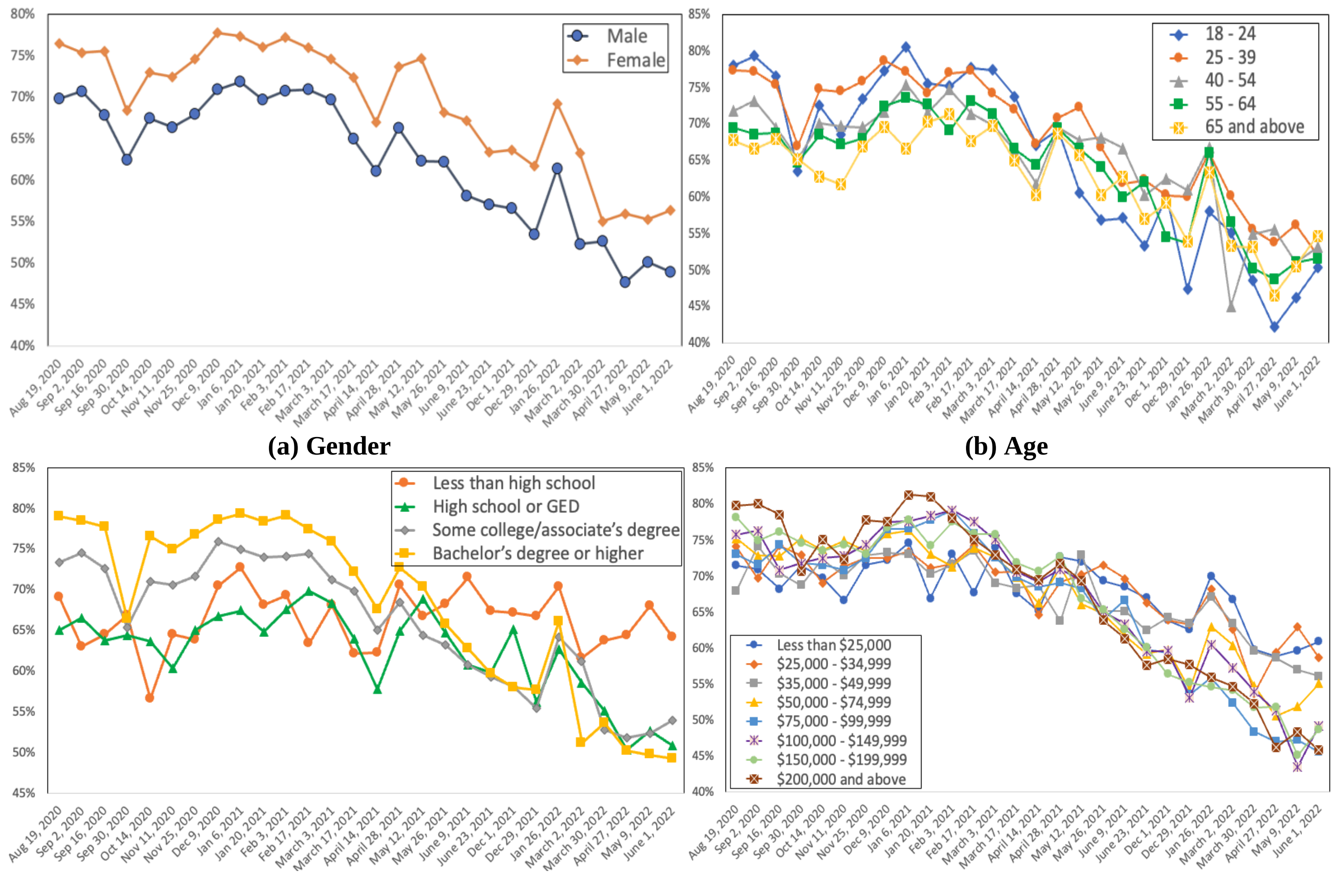


(a) Gender **(b) Age**

(c) Education level **(d) Annual household income**

Figure 7. Percentage of increased WFH in different socio-economic segments due to COVID

Figure 8 shows the percentage of people in different socio-economic segments who undertook fewer trips by public transit (bus, rail, or ride-sharing services) due to COVID-19. Figure 8 (a) shows that females took fewer public transit trips than males during 19 Aug 2020 ~ 1 June 2022. Figure 8 (b) shows that the youngest segment (age 18-24) and middle segment (age 26-39) took fewer trips by public transit than the older segments (age 55-64, 65 and above) during 19 Aug 2020 ~ 14 Apr 2021, and then the youngest segment took more trips by public transit than other segments during 14 Apr 2021 ~ 1 June 2022. Figure 8 (c) shows that the segment with the highest education level had fewer trips by public transit than the other segments during 19 Aug 2020 ~ 14 Apr 2021, and then took more trips by public transit than the other segments during 9 June 2021 ~ 1 June 2022. Figure 8 (d) shows that individuals in the highest-income segment ($200,000 and above) took fewer trips than other segments during 19 Aug 2020 ~ 14 Apr 2021, and then the segment with the lowest household income (less than $25,000) took fewer trips by public transit than other segments during 23 June 2021 ~ 1 June 2022. Figure 8 shows that public transit usage decreased least amongst lower-income and lower-education individuals before 14 Apr 2021, implying that many of these workers are public transit 'captive users' as they still needed to use public transit during the height of the COVID pandemic.



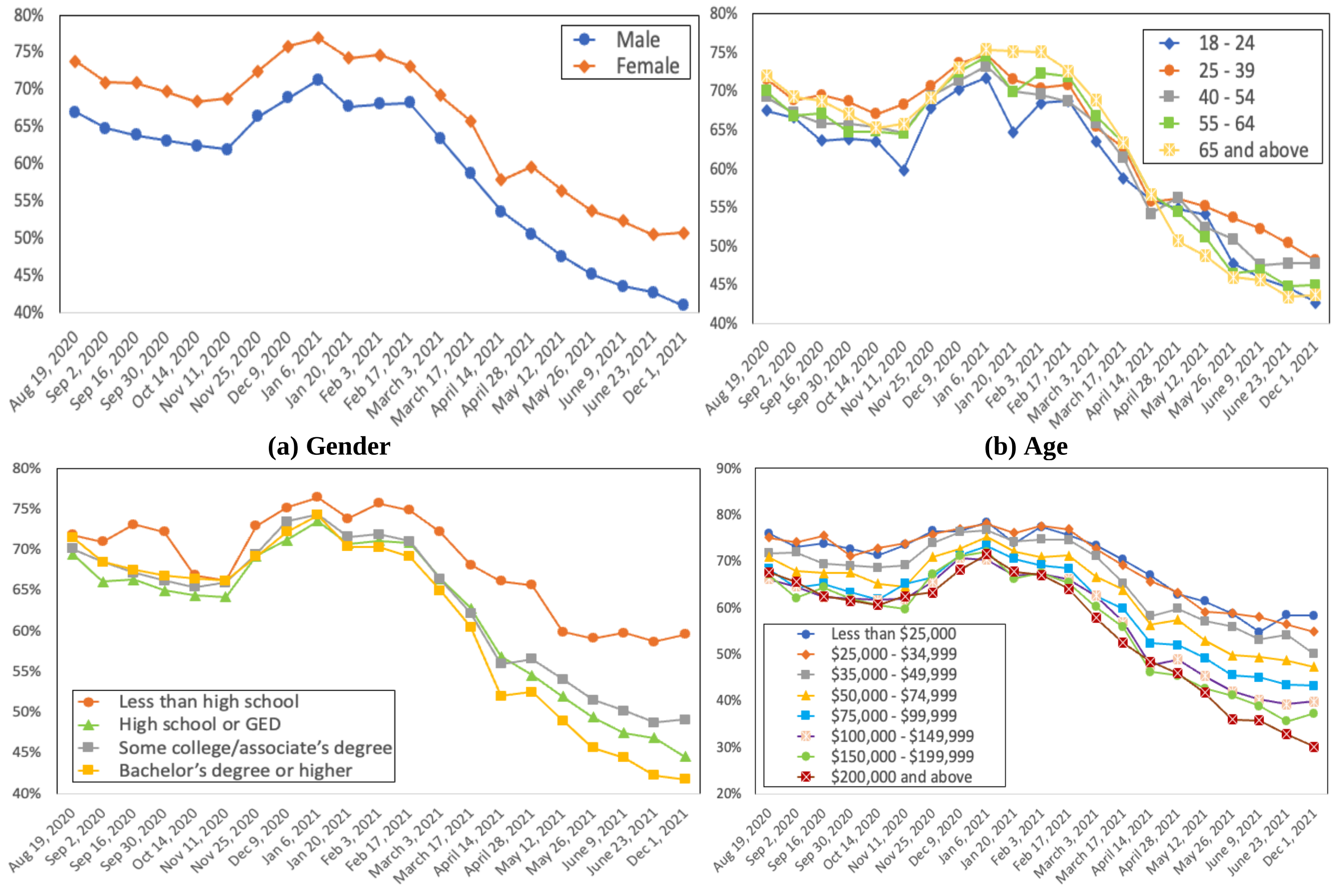
(a) Gender **(b) Age**

(c) Education level **(d) Annual household income**

Figure 8. Percentage of decreased trips by public transit in different socio-economic segments due to COVID

Figure 9 shows that the percentage of people who took fewer in-store trips saw a mild drop during 19 Aug 2020 ~ 1 Nov 2020, and then saw a slight fluctuation during 9 Dec 2020 ~ 17 Feb 2021 before experiencing a dramatic decrease during 17 Feb 2021 ~ 1 Dec 2021. Figure 9 (a) shows that females made fewer in-store shopping trips than males. Figure 9 (b) shows that the youngest segment (age 18-24) took more in-store trips than the other segments during 19 Aug 2020 ~ 14 Apr 2021, and then the older segment (age 65 and above) took more in-store trips than the other segments during 14 Apr 2021 ~ 1 Dec 2021. Figure 9 (c) shows that people with the lowest education level had fewer in-store shopping trips than the other segments, and the highest education-level segment had more in-store trips. Figure 9 (d) shows that people in the higher-income segment undertook more in-store shopping trips than those in the lower-income segments.

Figure 8 and Figure 9 suggest that the decreased public transit trips and in-store trips, due to COVID, started to recover after 14 Apr 2021 when the B.1.1.7 variant had dominated COVID-19 in the US and started to significantly recover after 13 May 2021 when the CDC said that fully vaccinated individuals do not need to wear masks in most situations. In contrast, Figure 7 suggests that the increased incidence of WFH, due to COVID, kept relatively stable after experiencing a mild decrease, and it tend not to return to the pre-COVID level.



(a) Gender **(b) Age**

(c) Education level **(d) Annual household income**

Figure 9. Percentage of decreased in-store trips in different socio-economic segments due to COVID

3. Fixed-effect panel regression model

This section estimates a fixed-effect (FE) panel regression model to establish the presence or otherwise of any systematic relationship between the COVID monitoring measures (see Table 2) and travel behavior in different socio-economic segments.

3.1 Data description

We use the mobile device location data of 50 US states with over 150 million monthly active samples provided by the University of Maryland COVID-19 Impact Analysis Platform (Maryland Transportation Institute, 2020; Zhang et al., 2020), which incorporates the daily movements of about 20 million anonymous individuals from 1 Jan 2020 to 20 Apr 2020. The aggregated location data are then integrated with COVID-19 case data from Johns Hopkins University and the census population database. We arrange the data as a panel data set which accounts for time series and state-level variables based on different segment classification criteria. The formatted panel data set has 24,276 observations (N) for each variable by setting different cross sections and following the observed variables from time to time. The panel data is robust to several types of violations of the Gauss Markov assumptions, i.e., heteroskedasticity and normality (Wooldridge, 2010). Table 2 summarizes the US state-level descriptive statistics for the variables used in the statistical regression model. A detailed explanation on the data and variables are provided in Online Appendix C.

Table 2. Descriptive statistics of the variables

	Variables	Notation	N	Mean	Std.	Min	Max
COVID monitoring measures (Independent variables)	New cases/1000 people	*NewCov*	24,276	0.19	0.26	0	3.60
	Hospital bed utilization	*Hos*	24,276	55.17	12.76	28	124.80
	COVID Tests done/1000 people	*Test*	24,276	405.20	490.70	0	2,954
	ICU utilization	*ICU*	24,276	10.63	11.94	0	121.50
	Ventilator needs	*VS*	24,276	194.60	408.30	0	5,887
	Imported COVID cases	*ImCov*	24,276	3,051	4,382	0	30,960
	COVID exposure/1000 people	*CovE*	24,276	7.10	8.41	0	34.79
	Days with decreasing cases	*DC*	24,276	3.47	4.37	0.10	38.50
	COVID death rate	*DCov*	24,276	11.17	11.80	0	83.97
Travel behavior (Dependent variables)	Nonwork trips/person	*NWT*	24,276	2.95	0.51	1.15	6.29
	Work trips/person	*WT*	24,276	0.45	0.15	0.14	1.49
	Miles/person	*MPP*	24,276	40.07	14.29	9.70	1,648
	% Out-of-state trips	*OOS*	24,276	6.90	6.76	0	52.30
	% Working from home	*WFH*	24,276	28.08	12.01	2.30	60.50

3.2 Fixed-effect panel regression model description

We divided the 50 US states into three low- and three high- segments based on the median of the following three classification criteria: 1) income, 2) employment density (ED), and 3) population density (PD). To estimate the impact of COVID monitoring measures on heterogeneous mobility behavior, we propose a state-level fixed-effect (FE) panel regression model for different socio-economic segments as follows:

$$NWT_{it}^{j} = \alpha_1^j NewCov_{it} + \alpha_2^j Hos_{it} + \alpha_3^j Test_{it} + \alpha_4^j ICU_{it} + \alpha_5^j VS_{it} + \alpha_6^j ImCov_{it} + \alpha_7^j CovE_{it} + \alpha_8^j DC_{it} + \alpha_9^j DCov_{it} + z_i^j + \varepsilon_i^j \tag{1}$$

$$WT_{it}^{j} = \beta_1^j NewCov_{it} + \beta_2^j Hos_{it} + \beta_3^j Test_{it} + \beta_4^j ICU_{it} + \beta_5^j VS_{it} + \beta_6^j ImCov_{it} + \beta_7^j CovE_{it} + \beta_8^j DC_{it} + \beta_9^j DCov_{it} + z_i^j + \varepsilon_i^j \tag{2}$$

$$MPP_{it}^{j} = \gamma_1^j NewCov_{it} + \gamma_2^j Hos_{it} + \gamma_3^j Test_{it} + \gamma_4^j ICU_{it} + \gamma_5^j VS_{it} + \gamma_6^j ImCov_{it} + \gamma_7^j CovE_{it} + \gamma_8^j DC_{it} + \gamma_9^j DCov_{it} + z_i^j + \varepsilon_i^j \tag{3}$$

$$OOS_{it}^{j} = \kappa_1^j NewCov_{it} + \kappa_2^j Hos_{it} + \kappa_3^j Test_{it} + \kappa_4^j ICU_{it} + \kappa_5^j VS_{it} + \kappa_6^j ImCov_{it} + \kappa_7^j CovE_{it} + \kappa_8^j DC_{it} + \kappa_9^j DCov_{it} + z_i^j + \varepsilon_i^j \tag{4}$$

$$WFH_{it}^{j} = \eta_1^j NewCov_{it} + \eta_2^j Hos_{it} + \eta_3^j Test_{it} + \eta_4^j ICU_{it} + \eta_5^j VS_{it} + \eta_6^j ImCov_{it} + \eta_7^j CovE_{it} + \eta_8^j DC_{it} + \eta_9^j DCov_{it} + z_i^j + \varepsilon_i^j \tag{5}$$

where the notation for the variables is given in Table 2; the subscript j denotes the index of segment classification criteria, $\forall j \in \{1,2,3\}$, i denotes an individual US state, $\forall i \in \{1,2,\cdots,50\}$, and t denotes a specific date within 1 Jan 2020 ~20 Apr 2021 (476 days), $\forall t \in \{1,2,\cdots,476\}$, $\alpha_1^j \sim \alpha_9^j$, $\beta_1^j \sim \beta_9^j$, $\gamma_1^j \sim \gamma_9^j$, $\kappa_1^j \sim \kappa_9^j$, $\eta_1^j \sim \eta_9^j$ denote the generalized least square (GLS) coefficients of the FE panel regression model to be estimated, z_i^j denotes the unknown intercept of state i under segment classification j, and ε_i^j denote the random terms varying with individual state and segment classifications.

Table 3. Coefficients of the panel regression model for low-income and high- income segment

Coefficients	Dependent variables									
	Nonwork trips/person		Work trips/person		Miles/person		Out-of-state trips		%Working from home	
	Low-income	High-income	Low-income	High-income	Low-income	High-income	Low-income	High-income	Low-income	High-income
New cases/1000 people	1.7e-4	-0.26***	-0.03***	-0.03	-0.24	-3.53**	-0.15**	-0.34***	4.18**	9.78***
Hospital bed utilization	-0.3***	-0.01***	9.8e-4	7.4e-4	-0.47***	-0.19**	-0.02**	-3.6e-4	-0.26*	-0.06
COVID Tests done/1000 people	4.3e-4***	5.4e-5	-2.1e-5	-6.4e-6	3.0e-3*	-8.1e-4	-5.8e-4***	-6.4e-4***	4.1e-3	7.4e-4
ICU utilization	-3.7e-3*	-0.01***	-1.8e-3***	-1.0e-3**	0.07	-0.09**	0.01***	-0.01*	0.44***	0.15**
Ventilator needs	8.1e-5*	5.5e-6	3.2e-5**	2.2e-5	1.7e-4	-1.7e-4	-5.1e-6	1.0e-4	-4.8e-3**	-3.9e-3
Imported COVID cases	1.0e-5**	1.2e-5***	-4.1e-6***	-3.4e-6***	3.9e-4***	3.1e-4***	3.8e-5***	3.7e-5***	8.3e-4***	5.4e-4***
COVID exposure/1000 people	0.01***	0.03***	2.4e-3***	8.6e-4	0.27***	0.51***	0.01	0.01	-0.35**	-0.12
Days with decreasing cases	7.5e-4***	8.3e-4***	-1.4e-4***	-1.6e-4***	0.02***	0.02***	6.9e-4*	1.0e-3**	0.04***	0.04***
COVID death rate	-9.7e-4	1.4e-3	-2.9e-3***	-3.9e-3***	-0.19***	-0.15***	-0.02***	-0.02***	0.48***	0.57***
Constant	4.08***	3.35***	0.44***	0.49***	59.82***	46.98***	6.68***	8.64***	26.13***	17.59***
R-squared	0.3039	0.3111	0.1095	0.1567	0.3701	0.4123	0.0522	0.0689	0.5037	0.5457
observations	12,376	11,900	12,376	11,900	12,376	11,900	12,376	11,900	12,376	11,900

Table 4. Coefficients of the panel regression model for low- employment density (ED) and high-ED segment

Coefficients	Dependent variables									
	Nonwork trips/person		Work trips/person		Miles/person		Out-of-state trips		%Working from home	
	Low-ED	High-ED	Low-ED	High-ED	Low-ED	High-ED	Low-ED	High-ED	Low-ED	High-ED
New cases/1000 people	0.03	-0.26***	-0.03***	-0.03	1.85	-3.53**	-0.12***	-0.34***	5.51***	9.78***
Hospital bed utilization	-0.03***	-0.01***	1.4e-3**	7.4e-4	-0.47***	-0.19**	-0.03***	-3.6e-4	-0.28**	-0.06
COVID Tests done/1000 people	2.5e-4**	5.4e-5	-1.7e-5	-6.4e-6	1.6e-3	-8.1e-4	-2.1e-4	-6.4e-4***	3.6e-3	7.4e-4
ICU utilization	-0.01**	-0.01***	-1.8e-3***	-1.0e-3**	0.06	-0.09**	0.01***	-0.01*	0.39***	0.15**
Ventilator needs	1.7e-4***	5.5e-6	2.2e-5**	2.2e-5**	1.4e-3***	-1.7e-4	3.9e-6**	1.0e-4	-3.5e-3*	-3.9e-3**
Imported COVID cases	2.1e-5***	1.2e-5***	-5.0e-6***	-3.4e-6***	3.4e-4*	3.1e-4***	5.1e-5	3.7e-5***	9.8e-4***	5.4e-4***
COVID exposure/1000 people	0.01***	0.03***	2.4e-3***	8.6e-4	0.26***	0.51***	-0.01	0.01	-0.36***	-0.12
Days decreasing cases	1.1e-3***	8.3e-4***	-1.4e-4***	-1.6e-4***	0.02***	0.02***	7.0e-4	1.0e-3**	0.04***	0.04***
COVID death rate	-1.6e-3	1.4e-3	-3.2e-3***	-3.9e-3***	-0.22***	-0.15***	-0.01***	-0.02***	0.51***	0.57***
Constant	4.05***	3.35***	0.44***	0.49***	61.51***	46.98***	6.89***	8.64***	27.04***	17.59***
R-Squared	0.2676	0.3111	0.1035	0.1567	0.0662	0.4123	0.0456	0.0689	0.4811	0.5457
Observations	12,376	11,900	12,376	11,900	12,376	11,900	12,376	11,900	12,376	11,900

Table 5. Coefficients of the FE panel regression model for low- population density (PD) and high-PD segment

Coefficients	Dependent variables									
	Nonwork trips/person		Work trips/person		Miles/person		Out-of-state trips		%Working from home	
	Low-PD	High-PD	Low-PD	High-PD	Low-PD	High-PD	Low-PD	High-PD	Low-PD	High-PD
New cases/1000 people	-2.4e-3	-0.22**	-0.02**	-0.03	0.72	-2.46*	-0.15**	-0.37***	3.21*	10.78***
Hospital bed utilization	-0.3***	-0.01***	1.0e-3	6.7e-4	-0.53***	-0.17**	-0.03***	-7.4e-4	-0.24	-0.06
COVID Tests done/1000 people	2.6e-4***	-1.0e-5	-1.6e-5	-4.5e-6	1.9e-3*	-1.2e-3	-2.1e-4	-6.2e-4***	3.4e-3	2.8e-4*
ICU utilization	-3.8e-3	-0.01***	-2.2e-3***	-9.1e-4**	0.10**	-0.13***	0.02***	-0.01**	0.49***	0.12**
Ventilator needs	3.3e-4	1.4e-5	6.4e-5**	1.9e-5**	3.3e-3	1.9e-4	1.7e-4	1.1e-4	-0.01*	-3.1e-3***
Imported COVID cases	2.1e-5***	7.9e-6**	-5.4e-6***	-3.2e-6***	3.3e-4	3.0e-4***	5.3e-5**	3.7e-5***	1.0e-3***	4.9e-4
COVID exposure/1000 people	1.2e-2***	0.04***	2.4e-3***	6.1e-4	0.24***	0.55***	-0.01	0.01	-0.37***	-0.06***
Days decreasing cases	1.1e-3***	8.7e-4***	-1.4e-4***	-1.7e-4***	0.02***	0.02***	8.3e-4	9.1e-4**	0.03***	3.9e-2***
COVID death rate	-3.0e-3***	-2.2e-3*	-3.3e-3***	-3.8e-3***	-0.27***	-0.11***	-0.02***	-0.01**	0.53***	0.56***
Constant	4.24***	3.29***	0.47***	0.49***	64.46***	45.31***	7.31***	8.43***	24.90***	17.54
R-Squared	0.2593	0.3318	0.0992	0.1639	0.0731	0.4103	0.0496	0.0668	0.4863	0.5525
Observations	12,376	11,900	12,376	11,900	12,376	11,900	12,376	11,900	12,376	11,900

Notes: Statistical significance is indicated by *p* values: **p* < 0.10, ***p* < 0.05, ****p* < 0.01. Standard errors are clustered by states for each socio-economic segment in the robustness test. Each column within the panel reports the generalized least square (GLS) coefficients of the fixed-effect (FE) panel regression model. The dependent variables include: 1) Nonwork trips/person, 2) Work trips/person, 3) Miles/person, 4) Out-of-state trips, and 5) %Working from home. The state-relevant FE is used to control the fixed effects of different states in the US. The detailed results are given in Online Appendix D.

3.3 Results and analysis

The generalized least square (GLS) coefficients of the FE panel regression model for different socio-economic segments are given in Table 2 - Table 4. The detailed results of statistical testing are given in Online Appendix D.

We first analyze the coefficients of the high- and low-income segments in Table 3. Suppose *new COVID cases* increase by 10%, *all else being equal*, we expect to see a 2.6% decrease in *nonwork trips/person* for the high-income segment, a 0.3% decrease in *work trips/person* for the low-income segment, a 35.3% decrease in *Miles/person* for the high-income segment, a 1.5% (resp. 3.4%) decrease in *out-of-state trips*, and a 41.8% (resp. 97.8%) increase in *%WFH* for low-income (resp. high-income) segment. Once *new COVID cases* increase by 10%, the *%WFH* of the high-income segment is predicted to double that of the low-income segment, implying that individuals in the high-income segment have greater flexibility and do not have to be physically present at work, while people in the low-income segment might be more often expected to be physically present at work, in part given the occupation and in-office or elsewhere requirement for face-to-face contact or their role as an essential worker (Ton et al., 2022); thus *work trips* of people in the high-income segment are far less sensitive to the new COVID cases while *work trips* of people in the low-income segment are more sensitive to the *new COVID cases*. Since people in the high-income segment usually spend more time on their work, their *nonwork trips* decrease as the *new cases* increase. Suppose *hospital bed utilization* increases by 10%, all else being equal, we expect to see that *nonwork trip/person* in the high-income segment decrease 30 times more than those in the low-income segment, *miles/person* in the low-income segment (4.7%) decrease by more than twice of the high-income segment (1.9%), and *%WFH* in the low-income segment decrease by 2.6%. This indicates that *hospital bed utilization* has a more significant impact on the travel behavior of people in the low-income segment since they have a lower budget for hospitalization expenditure, and their insurance coverage is often limited.

Suppose *COVID tests done/1000 people* increase by 10%, other things being equal, we expect a light increase in *nonwork trips/person*, *Miles/person* in the low-income segment. Suppose *ICU utilization* increases by 10%, *nonwork trips/person* in the low-income (resp. high-income) segment will see a 0.037% (resp. 0.1%) decrease, *work trips/person* of low (resp. high) income segment will see a 0.018% (resp. 0.02%) decrease, and *%WFH* of low-income (resp. high-income) segment will experience a 4.4% (resp. 1.5%) increase. This implies that more people in the high-income segment will cancel *nonwork trips* and more people in the low-income segment will move to *WFH* as the *ICU utilization* and *Ventilator needs* increase. *Imported COVID cases* have a little positive effect on *nonwork trips/person*, *out-of-state trips*, *%WFH* for both low- and high- income segments, and a little negative effect on *work trips/person* for both low- and high- income segments. Suppose *COVID exposure/1000 people* increases by 10%, *nonwork trips/person* and *miles/person* in the high-income segment will see a higher increase (0.3% and 5.1%) than those in the low-income segment (0.1% and 2.7%), and *%WFH* will see a 3.5% decrease in the low-income segment but no change in the high-income segment. This suggests that as the number of residents who are already exposed to infectious people (*COVID exposure*) increases, the number of trips and travel miles will increase since more and more people are tired of taking coronavirus precautions. As *the number of days with decreasing cases* increases by 10%, *Miles/person* is expected to see a 0.2% increase for both low- and high- income segments. Suppose the *COVID death rate* increases by 10%, *work trips/person* in the low (resp. high) income segment will see a 0.029% (resp. 0.039%) decrease, *miles/person*, and *out-of-state trips* in the low-income (resp. high-income) segment will see a 1.9% (resp. 1.5%) and 0.2% (resp. 0.2%) decrease, and *%WFH* of low-income (resp. high-income) segment will see a 4.8% (resp. 5.7%) increase.

Comparing the coefficients of Table 3 and Table 4, we find that the COVID monitoring measures have a similar impact on the travel behavior of individuals in the high-ED (resp. low-ED) segment and the high-income (resp. low-income) segment, due to the relevance between income and ED. Namely, an individual state with higher ED will usually have a higher income.

Finally, we comment on the coefficients of low and high population density (PD) segments in Table 5. Suppose *new cases* increase by 10%, other things being equal, *nonwork trips/person* of the high-PD segment will decrease by 2.2%, *work trips/person* of the low-PD segment will decrease by 2%, *miles/person* of the high-PD segment will decrease by 24.6%, *out-of-state trips* of low-PD (resp. high-PD) segment will decrease by 15% (resp. 37%), and *%WFH* of low-PD (resp. high-PD) segment will see a 32.1% (resp.107.8%) increase, respectively. Suppose *hospital bed utilization* has a 10% increase, *nonwork trips/person* and *miles/person* of low-PD (resp.

high-PD) will see a 3% (resp. 0.1%) and 5.2% (resp. 1.7%) decrease, *out-of-state trips* of the low-PD segment will see a 0.3% decrease, and *% WFH* of both segments will not be impacted. *Tests done/1000 people* has a little positive impact on *nonwork trips/person* and *miles/person* in the low-PD segment and a little negative impact on *out-of-state trips* in the *high-PD* segment. Suppose *ICU utilization* increases by 10%, other things being equal, *nonwork trips/person* of the high-PD segment will see a 0.1% decrease, *work trips/person* of both segments will see a slight decrease, *miles/person* of the low and the high-PD segment will see a 1% increase and 1.3% decrease, *out-of-state trips* will see a 0.2% increase and 0.1% decrease for the low and the high-PD segment, and *%WFH* of the low and high-PD segment will see a 4.9% and 1.2% increase. Individuals in the low-PD segment are more sensitive to *imported COVID cases* than those in the high-PD segment. Given the evidence of COVID fatigue and the tendency for many individuals to ignore the risks, when *COVID exposure/1000 people* increases by 10%, *nonwork trips* and *miles/person* of the low (resp. high) PD segment will see an increase of 0.12% (resp.0.4%) and 2.4% (resp. 5.5%), and *% WFH* of the low-PD (resp. high-PD) segment will see a 3.7% (resp. 0.6%) decrease. Suppose *the days with decreasing cases* increase by 10%, *nonwork trips/person*, *miles/person*, and the *%WFH* of low- PD and high-PD segments will experience a light increase, while *work trips/person* of the low- PD and high-PD segments will experience a light decrease. Suppose the *COVID death rate* increases by 10%, *miles/person* and *out-of-state trips* of the low-PD (resp. high-PD) segment will see a decrease of 2.7% (resp. 1.1%) and 0.2% (resp. 0.1%), while *%WFH* of the low-PD (resp. high-PD) segment will see an increase of 5.3% (resp. 5.6%).

4. Summary of findings

From the analyses conducted in this paper we find that the percentage of decreased public transit trips and in-store trips, due to COVID, started to recover after 14 Apr 2021, when the B.1.1.7 variant had become the dominant COVID-19 strain in the US, and started to significantly recover after 13 May 2021 when the CDC announced that fully vaccinated individuals do not need to wear masks in most situations; while the increased incidence of WFH, due to COVID, was relatively stable after experiencing a mild decrease and is unlikely to return to the pre-COVID levels. When we look at different socio-economic segments, lower-education level and lower-income individuals tend to have a lower incidence of WFH and a reduced incidence of a decline in public transit usage. Lower-education level and lower-income workers are more likely to continue using public transit during COVID pandemic since they are more likely to be employed in the occupations which are expected to be physically present at work, in part given the occupation and in-office or elsewhere requirement for face-to-face contact or their role as an essential worker.

The results of the fixed-effect panel regression model in Section 3.3 indicate that *nonwork trips* in three low segments (i.e., low-income, low-ED, and low-PD) and three high segments (i.e., high-income, high-ED, and high-PD) are most sensitive to *hospital bed utilization* and *new COVID cases*, respectively. *Work trips* in three low segments (resp. three high segments) are most sensitive to *new COVID cases* (resp. *ICU utilization*); *miles/person* in three low (resp. high) segments are most sensitive to *hospital bed utilization* (resp. *new COVID cases*); and *out-of-state trips* and *%WFH* are most sensitive to *new COVID cases* in all six segments. Among the nine COVID monitoring measures, *new COVID cases* have the most significant impact on the travel behavior of individuals in the high-income, high-ED, and high-PD segments, while *hospital bed utilization* has the most significant impact on low-income, low-ED, and low-PD segments. We find that when *new COVID cases* increase, the *%WFH* of the high-income segment is predicted to be double that of the low-income segment, implying that people in the high-income segment have greater flexibility and do not have to be physically present at work, while people in the low-income segment might be more often expected to be physically present at work. We find that the increase of *new COVID cases* has significant impact on the number of *work trips* in the low-income, low-ED, and low-PD segments, but has little impact on the number of work trips in the high-income, high-ED and high-PD segments. We find that when the medical resources are limited, i.e., *hospital bed utilization*, *ICU utilization*, and *Ventilator needs* increase, the number of *nonwork trips*, *miles/person*, *out-of-state trips* in the low-income, low-ED and low PD-segments will see a more significant decrease than those in the high-income, high-ED segments, and high-PD segments. This indicates that the less medical resources there are, the fewer mobility behavior individuals in the low-income, low-ED, and low-PD segments will undertake.

As time goes by, although the risk of infection remains, more individuals have adjusted to living with COVID, and as COVID exposure increases, the number of trips and travelling miles starts to increase and bounces back to the pre-COVID levels. However, the incidence of WFH has become relatively stable and has not returned to its pre-COVID levels due to support from employers and the adoption of new workstyle and lifestyle preferences. We find that once *new COVID cases* increase, the incidence of WFH in the high-income (resp. high-ED) segment will increase much more than that in the low-income (resp. low-ED) segment. Workers in the high-income and high ED segments (such as central business districts of cities) care little about how new COVID cases will impact work trips since they can move to greater levels of WFH and have more job opportunities, which suggests that more and more people in the high-income segment and high-employment density locations have already adopted WFH and will continue WFH to an extent in the future.

5. Conclusion

This paper has statistically qualified how COVID-19 impacted individuals' travel behavior in different socio-economic segments through both descriptive analysis and panel regression modelling. A key contribution lies in the descriptive analysis of travel behavior changes (i.e., percentage of increased WFH, decreased public transit usage, and decreased in-store trips) of people in different socio-economic segments (i.e., gender, age, income, education), due to COVID, based on the most recent census data from the US Household Pulse Survey. We have quantified the extent to which the COVID monitoring measures are likely to impact heterogeneous human travel behavior based on the integrated mobile device location data in the US during 1 Jan 2020 ~ 20 Apr 2021. We estimate a fixed-effect panel regression model to identify the relationship between COVID monitoring measures (i.e., new COVID cases, hospital bed utilization, COVID tests done, ICU utilization, ventilator needs, imported COVID cases, COVID exposure, days with decreasing cases, COVID death rate) and travel behavior (i.e., nonwork trips, work trips, travel miles, out-of-state trips, and %WFH) of individuals in different socio-economic segments, i.e., high income *vs.* low income, high employment density (ED) *vs.* low employment density (ED), high population density (PD) *vs.* low population density (PD).

Although the results of the panel regression model are based on US data, the selected segment classification criteria are universal, and thus the insights obtained are also applicable in other western countries. Although we are currently unaware of the travel behavior of different socio-economic segments in a post-COVID era, we observed that the number of trips and travelling miles started to recover after the initial waves of the COVID pandemic, and returned to their pre-COVID levels afterwards, while the incidence of WFH tends not to return to the pre-COVID level. It is not an understatement to argue that WFH is the most significant transportation policy lever since World War II and is becoming a popular and potentially significant alternative to daily commuting. Our findings provide timely evidence for governments and transport planners in gaining a better understanding of the heterogeneous mobility response during successive COVID waves to various COVID monitoring measures and medical resources, to inform revised policies for different socio-economic segments in order to provide benefits and fairness for people in disadvantaged segments. Based on our findings, the travel behavior of individuals in the low-income segment is more sensitive to medical resource availability (i.e., hospital bed utilization, ICU utilization, and ventilator needs); this is important to be aware of when planning for the impact of future virus-driven stresses. Similarly, future planning should recognise that while individuals in the high-income or high-ED segment have greater discretion in their work trips and flexibility in choosing to WFH, people in the low-income and low-ED segments do not have as much discretion over how many work trips they can take. Thus, more attention should be focused on achieving equity in terms of access to public transit by allocating subsidies for the most vulnerable groups of the population who continue to rely on public transit in times of crisis. There are several limitations of the analysis presented. We acknowledge the limitation of the mobile device data where not all the population has access to mobile devices, and accuracy issues may occur under some circumstances. The fixed-effect panel regression model has not been able to capture the impact of time periods. In future research, we will model the time-varying relationship between COVID monitoring measures indicators and travel behavior using a dynamic panel regression model and undertake latent class analysis to obtain insights into other candidate socio-economic segments.

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