Transportation Research Part F: Psychology and Behaviour 90 (2022) 466–484

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

journal homepage: www.elsevier.com/locate/trf

The Long-Term effects of COVID-19 on travel behavior in the United States: A panel study on work from home, mode choice, online shopping, and air travel

Mohammadjavad Javadinasr [a,*], Tassio Maggasy [b], Motahare Mohammadi [a], Kouros Mohammadain [a], Ehsan Rahimi [a], Deborah Salon [c], Matthew W. Conway [d], Ram Pendyala [b], Sybil Derrible [a]

[a] Department of Civil, Materials, and Environmental Engineering, University of Illinois at Chicago, IL, USA
[b] School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ, USA
[c] School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, USA
[d] Department of City and Regional Planning, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA

A R T I C L E I N F O

Keywords:
Transportation
Telecommute
Online Shopping
Transit
Air Travel
Pandemic

A B S T R A C T

A critical challenge facing transportation planners is to identify the type and the extent of changes in people's activity-travel behavior in the post-Covid-19 pandemic world. In this study, we investigate the travel behavior evolution by analyzing a longitudinal two-wave panel survey data conducted in the United States from April 2020 to May 2021. Encompassing nearly 3,000 respondents across different states, we explored the effects of the pandemic on four major categories of work from home, travel mode choice, online shopping, and air travel. We utilized descriptive and econometric measures, including random effects ordered probit models, to shed light on the pandemic-induced changes and the underlying factors affecting the future of mobility in the post-pandemic world. Upon concrete evidence, our findings substantiate significant observed (i.e., during the pandemic) and expected (i.e., after the pandemic) changes in people's habits and preferences. According to our results, 48% of the respondents anticipate having the option to WFH after the pandemic, which indicates an approximately 30% increase compared to the pre-pandemic period. In the post-pandemic period, auto and transit commuters are expected to be 9% and 31% less than pre-pandemic, respectively. A considerable rise in hybrid work and grocery online shopping is expected. Moreover, 41% of pre-covid business travelers expect to have fewer flights (after the pandemic) while only 8% anticipate more, compared to the pre-pandemic.

1. Introduction

The inextricable link between the spread of the Covid-19 pandemic and transportation systems led to imposing unprecedented restrictions on various types of travel which influenced nearly every aspect of our lives, from daily travel behaviors to long-term residential location choices (Beigi et al., 2022). Online communications drastically substituted various types of travel with remote

* Corresponding author.
E-mail address: mjavad2@uic.edu (M. Javadinasr).

https://doi.org/10.1016/j.trf.2022.09.019
Received 31 January 2022; Received in revised form 12 July 2022; Accepted 21 September 2022
Available online 28 September 2022
1369-8478/© 2022 Elsevier Ltd. All rights reserved.

working, online learning, e-shopping, or even telemedicine becoming the hallmark of the pandemic (Polzin et al., 2021). As most Covid-19 restrictions are being or will be lifted, scholars question the likelihood of which the observed changes will be permanent, and how the pandemic has impacted numerous areas in our society. Given that travel is a demand derived from the need to attend different activities, investigating the changes in people's activity and travel behavior, provides the opportunity to reimagine the big picture of the emerging mobility patterns in the post-covid world. In this regard, the broadness of the changes caused by the Covid-19 crisis necessitates performing multifaceted studies that can shed light on the alterations in different impacted areas of daily activity and travel behavior and assist policymakers and planners in having a better perspective on the future of transportation.

Since the early days of the pandemic, the magnitude and direction of changes, have thrown a spotlight on the United States as one of the major hotspots of the Covid-19 pandemic. Our COVID Future Research Team launched a multi-wave survey to collect U.S. residents' opinions about the pandemic, in addition to socioeconomic characteristics, lifestyle preferences, and mobility (Chauhan et al., 2021). The survey approached pandemic-related behaviors before the pandemic, during the pandemic (capturing information about stay-at-home orders and other social restrictions), and post-pandemic expected behaviors (after all restrictions will be lifted, and the virus is no longer a threat). Exploring evidence from the revealed and the stated behaviors can be especially advantageous to crystalize the levels to which preferences and habits of U.S. adults have changed as well as projecting the stickiness of the changes in the future. We note, however, that respondents here have actually lived the scenario given to them, which we believe, makes their responses more likely to apply than traditional stated-preference surveys.

Furthermore, volatile situations and the rapid pace of occurrences, have caused constant changes in behaviors, perceptions, and mobility patterns of people. Most published studies until now have used data from the early stages of the pandemic. Although important, at this period people were experiencing massive changes without having a clear picture of the future. This period coincides with wave one of our survey. At the end of 2020 and the beginning of 2021, people had a more realistic evaluation of both the pandemic effects and the post-Covid future, especially with the hopes brought by the invention of Covid-19 vaccines. This period coincides with wave two data in our analyses. Moreover, despite the dynamic and ever-changing nature of occurrences and preferences during the pandemic, most studies have used cross-sectional data to investigate changes in people's behaviors and habits. To fill this gap, our panel study provides the opportunity to scrutinize changes and their evolution over time and builds insights upon reliable findings by differentiating between transient and long-lasting changes. Thus, our research provides concrete evidence, rather than just relying on theories, for other researchers and planners and can help to envision the future of transport.

This research is set to explore the dynamics of people's travel behavior before, during, and after the Covid-19 pandemic in the U.S. We investigate the observed changes from the pre-pandemic to wave one, observed transitions from wave one to wave two of data collection, and expected changes after the pandemic. In particular, we seek to address the following research questions: 1) How people's activity and travel behavior regarding the four categories of telecommuting (i.e., work from home), travel mode choice, online shopping, and air travel have evolved from the pre-pandemic period through different waves during the pandemic? 2) What are the expected behavioral preferences and choices regarding the mentioned categories in the post-covid future? 3)What are the underlying factors that can help us understand why individuals are making their decisions in the post covid world? To answer these questions, we performed descriptive and inferential analyses to present the insights from our survey. Moreover, we employed a random effect ordered probit approach to model the expected changes in post-pandemic as a function of attitudinal and socioeconomic variables. The remainder of this article is organized as follows. In section two, we present the literature review. In section three, we describe the survey data. In section four, we introduce the employed methodology. In section five, we present the results and findings of our study. In section six, we present discussion and policy implications. Finally, in section seven, we summarize and mention the limitation of our work.

2. Literature review

The quick and planet-wide spread of Covid-19 across the globe happened mainly due to the virus transmission through air travels which then resulted in massive restrictions that tremendously impacted the demand. According to Transportation Security Administration (TSA), the average daily number of U.S. air travel dropped from 2,555,626 in June 2019 to 491,835 in June 2020 (i.e., 81 % reduction) and it is expected that 3 to 6 years is required for U.S. air transportation to recover (Hotle & Mumbower, 2021). The drop in air travel was not caused by imposed travel restrictions alone, but due to several factors, such as risk perception, shifts to online business meetings, and financial reasons. A line of studies in the literature has attempted to analyze the impacts of Covid-19 on long-distance air travel. Early results of the COVID Future Survey showed that most personal travelers expect future air travel changes due to the perceived risk of sharing close space with others, a concern that should fade away over time as the pandemic gets to an end (Conway et al., 2020). Santos et al., (2021) reported that the pandemic affected business air routes more than leisure ones, and demand for short-distance and low-density routes are among the most impacted airline markets. Serrano & Kazda, (2020) believed that successful airports in the future present a more tech-oriented setting, with biometric and self-service processes, reduced human-to-human interactions, as well as potential diversification in airport activities aiming at non-passenger revenue to compensate for declines in air travel. Among factors that could influence someone's intention to fly during the pandemic, variables such as income level, trip purpose, premium card ownership, airline brand, and sanitation actions could be significant determinants of the willingness to fly internationally (Kim et al., 2022). Polat et al., (2021) explored the attitudinal factors affecting the intention of airline passengers after the Covid-19 pandemic. They used the PLS-SEM approach and showed that trust, habit, social norms, and perceived risk are the significant antecedents of travel intention. Moreover, Jack & Glover, (2021) reported that online conferencing amid Covid-19 remarkably reduced air travel among academics who were frequent travelers, and some of them used to travel more than 150,000 km each year to attend conferences and workshops.

Despite severe restrictions on air travel and screening measures at airports, asymptomatic covid patients and high transmission rates led to the spread of Covid-19 throughout the world (Hendrickson & Rilett, 2020). Given the airborne transmission of the Covid-19 virus, governments attempted to contain the spread by establishing “social-distance” guidelines. Table 1 presents the timeline of the progression of Covid-19 and key government measures taken to curb the virus in the U.S. A combination of social distancing regulations and people’s decisions to avoid the infection risk resulted in an unprecedented change in different parts of the transportation sector as well as mobility styles of individuals (i.e., comprehensive propensity toward mobility and habitual travel behavior) (Prillwitz & Barr, 2011). Accordingly, different types of activities including work, school, and shopping activities witnessed a major shift to online settings, and the total number of travels plummeted. The shift to work-from-home (WFH), was a major change in people’s routines which many believe is long-lasting for certain demographics. For example, Raišiene et al., (2020) found that Millennial females with higher education levels, 4–10 years of experience in the management and administration field, that WFH twice a week are the most satisfied teleworker group. In addition, the authors found that socioeconomic attributes such as gender, age, education background, and work experience influence the efficiency and quality of WFH.

Salon et al., (2021) tried to answer the question of whether these new WFH patterns are temporary, just during the pandemic, or long-lasting, in which employers and workers will adopt the new work modalities? The results showed that 26 % of workers expected to work remotely at least a few times a week after the pandemic, which is double the fraction of the same group before the pandemic. A survey of American adults collected in July and August of 2020 revealed that nearly half of the respondents who did not work from home before and started doing so during the pandemic wanted to continue working from home in the future (Barbour et al., 2021). Barbour et al., (2021) also reported that younger generations (i.e., below 30 years old) and people with graduate education levels, had

Table 1
Timeline of the progression of Covid-19 and key measures taken to curb the virus. (AJMC, 2021; Education Week, 2020; Reis Thebault, 2021).

Date	Data collection phase	Progression of Covid-19 and the government responses
Jan 21, 2020		The first covid case is confirmed in the U.S.
Feb 2, 2020		Restrictions on international air travel.
March 11, 2020		World health organization (WHO) declares COVID-19 a “pandemic”.
March 12, 2020		Releasing of “telework flexibilities guidance” by Office of Management and Budget.
March 12, 2020		Ohio becomes the first state to announce school closing.
March 13, 2020		Travel restriction on non-U.S. citizens traveling from Europe.
March 25, 2020		Public schools are closed all around the country.
March 16, 2020		The U.S. declares social distancing guidelines to avoid gatherings of more than 10 and to stop eating in restaurants and taking nonessential trips for the next 2 weeks.
March 17, 2020		Centers for Medicare & Medicaid Services (CMS) expands the use of telemedicine.
March 19, 2020		California issues stay-at-home orders.
March 29, 2020		The U.S. extends social distancing guidelines through April 30, 2020.
April 2, 2020	Wave 1	Most Americans are living under stay-at-home orders.
April 30, 2020	Wave 1	The federal government’s social distancing guidelines expire, and most states push ahead with reopening plans.
May 6, 2020	Wave 1	Nearly all states close schools for the academic year.
May 19, 2020	Wave 1	43 states have begun at least some form of reopening to boost their economies.
Sep 3, 2020	Wave 1	The virus surged at U.S. colleges, totaling more than 51,000 cases.
June 8, 2020	Wave 1	In the West and the South, more than a dozen states set records for new infections reported.
June 26, 2020	Wave 1	The governors of Texas and Florida reverse course and shut down bars in their states as infections and hospitalizations soar.
July 2, 2020	Wave 1	States reverse reopening plans as the U.S. new daily cases reach 50,000.
Oct 1, 2020	Wave 1	N.Y.C. was the first major U.S. city to reopen all public schools.
Nov 5, 2020	Wave 2	Coronavirus cases at U.S. colleges hit a quarter million.
Dec 11, 2020	Wave 2	The F.D.A. approved a vaccine by Pfizer.
Jan 8, 2021	Wave 2	The United States records more than 313,000 new cases in a single day.
Jan 29, 2021	Wave 2	The CDC requires the use of face masks in public transit.
Feb. 12, 2021	Wave 2	The CDC released guidance for schools returning to in-person instruction.
Feb 14, 2021	Wave 2	The new daily cases fall below 100,000 for the first time since early November.
March 9, 2021	Wave 2	The CDC says fully vaccinated individuals can gather indoors wearing a mask.
April 2, 2021	Wave 2	The CDC says that fully vaccinated people can travel safely within the US.
May 13, 2021	Wave 2	The CDC says fully vaccinated people do not need to wear masks in most indoor and outdoor public settings.

a higher probability of WFH whereas people in households without a child and low-income population had a lower probability of WFH during the pandemic. Furthermore, Dubey & Tripathi, (2020) analyzed people's sentiments regarding the WFH culture and found that almost three-quarters of people had a positive perception of this modality based on over 100,000 tweets in India.

The shift towards a flexible work modality and increased levels of WFH resulted in reduced commute trips and changes in daily travel patterns (Elldér, 2020). In the U.S., the average commuting volume, based on the total number of commuters within 24 h in a given county, decreased almost by 65 % compared to typical daily values (Klein et al., 2020). A survey conducted in the U.K. showed that nearly half of transit commuters planned to switch their commute mode after the pandemic, while over 80 % of those who commuted by car still desired to use their personal vehicles once travel restrictions were lifted (Harrington and Hadjiconstantinou, 2020). A body of research has been focused on the effects of the pandemic on public transit as the most impacted mode of transportation in urban areas. Thomas et al., (2021) provided evidence that the pandemic adversely has affected shared mobility such as public transit and carpooling in Australia. They also reported that there is a notable intention to decrease transit use and increase private vehicle use after the pandemic, suggesting that Australian public transportation is still far from recovery and returning to the pre-pandemic usage levels. Similarly, Eisenmann et al., (2021) found evidence from Germany that cars became more prevalent while a drop in public transportation was observed during the pandemic. Moreover, Scorrano & Danielis, (2021) studied the determinants of mode choice for trips within medium-sized cities and reported that the Covid-19 pandemic significantly shifted people from bus to private vehicles in Italy. According to their findings, people with higher environmental awareness are more likely to choose transit or active modes while individuals with higher risk aversion toward the pandemic are significantly less likely to use transit.

It is evident that these changes are interconnected in some underexplored ways: a perceived risk of virus infection will impact work modality; as a result, changes in work will lead to changes in routines, travel habits, and economic attributes, which influence purchase power and shopping habits. The fear of infection led people to avoid traveling to stores, reducing in-store purchases while increasing online shopping frequency. For instance, Gerritsen et al., (2021) found that 40 % of household shoppers reduced their in-store grocery shopping frequency in New Zealand. In Finland, a large-scale survey with over 2,500 participants showed that a typical adopter of online grocery shopping due to Covid-19 is under the age of 45, and has health concerns, either their own or regarding a loved one (Eriksson & Stenius, 2022). The stickiness of this habit is still uncertain; however, scholars have been looking at this trend: a survey conducted in Chicago revealed that nearly-three-quarters of online grocery shoppers during the pandemic would rely more on online grocery shopping in the first few months after the pandemic, and 59 % expressed willingness to order their groceries online even far after the pandemic (Shamshiripour et al., 2020).

3. Survey and data collection

In this study, we use the data collected through the first two waves of the COVID Future Panel Survey (Chauhan et al., 2021) in the United States. The first wave included 8723 respondents, out of which, 2973 individuals participated in the second wave as well. Since we aimed to investigate changes in pandemic-related travel behaviors and preferences over time for the same population, we used the respondents who were present in both Wave one (collected from April 2020 to October 2020) and Wave two (collected from November 2020 to May 2021) of our survey. The final dataset is comprised of 2,973 observations.

The COVID Future Panel Survey is a longitudinal survey collecting travel-related behaviors and attitudes, covering various themes, such as lifestyle attitudes, travel patterns, telecommuting, telemedicine, online learning, and shopping. In each category of our analysis (i.e., WFH, Online Shopping, Mode choice, and Air travel), we will present the percentage of people with different levels of engagement from the pre-pandemic period, through waves one and two of data collection and to the post-pandemic future. For this purpose, in addition to the questions regarding the "during pandemic" behaviors and attitudes, there are questions regarding the "pre-pandemic" (asked in wave one) as well as questions about the "post-pandemic" (asked in wave two). It should be noted that the pre-pandemic, wave one, and wave two questions were asked in a *revealed* preference manner while the post-pandemic questions were asked in a *stated* preference manner and people were asked to express their opinion regarding a situation in which Covid-19 is over and there are no restrictions left.

To control for demographic discrepancies and provide more representative results, the panel data were weighted using PopGen 2.0 and were controlled for age, education level, gender, Hispanic status, household income, number of household vehicles, employment status, and white race based on American Community Survey (ACS) 5-year Estimates (U.S. Census Bureau, 2019). To achieve

Table 2
Geographical Distributions of Weighted and Unweighted Panel Samples.

Census Division	Sample Size (N = 2,973)	Unweighted proportion	Weighted sample (N = 2,973)	Weighted proportion	Target Population
Division 1: New England	125	4.2 %	139	4.7 %	4.7 %
Division 2: Middle Atlantic	249	8.4 %	379	12.8 %	12.8 %
Division 3: East North Central	519	17.5 %	426	14.4 %	14.4 %
Division 4: West North Central	177	6.0 %	192	6.5 %	6.5 %
Division 5: South Atlantic	511	17.2 %	603	20.2 %	20.2 %
Divisions 6 and 7: East and West South Central	267	9.0 %	528	17.7 %	17.7 %
Division 8, modified: Mountain, without Arizona	302	10.2 %	156	5.2 %	5.2 %
Division 8, modified: Arizona State	372	12.5 %	66	2.2 %	2.2 %
Division 9: Pacific	451	15.2 %	485	16.3 %	16.3 %

geographic representativeness, the sample was also divided into nine modified census divisions for weighting, and each subsample represents the marginal distribution of the region (Table 2). The reason for the census division modification was due to the large sample of respondents from Arizona, which was large enough to be considered a weighting region by itself. For more details about the weighting process, please refer to Chauhan et al., (2021). It should be noted that all our analyses in this research are based upon the weighted dataset.

After the weighing process, the distributions of the variables used for the weighting scheme match the national distributions (Table 3). Nonetheless, not all possible variables were controlled for the weighted sample, thus some minor differences are observed when comparing some demographic variables and national proportions. Furthermore, in this study, we have used descriptive and econometric analyses which are presented in the Result section. Table 4 includes the name and definition of the explanatory variables that are used and turned out to be significant in our econometric analysis along with their summary statistics.

4. Methodology

In this study, we first utilize descriptive and inferential analyses to shed light on the observed (i.e., during the pandemic) and expected (i.e., after the pandemic) changes in peoples' activity and travel behavior. Our descriptive analysis includes the statistical Z-tests on percentage changes in different classes to examine whether the changes are statistically significant or not. Besides, we performed chi-square tests of independence to investigate whether there is a relationship between the changes in WFH patterns and other explored categories (i.e., Online Shopping, Mode choice, and Air travel) or not.

In addition to descriptive analysis and to account for the panel data, we employed a random effect ordered probit modeling approach to acquire deeper and telling insights from our survey data, especially in terms of computing marginal effects. The ordered probit models are based on the normal distribution assumption for error terms and have been more employed than ordered logit models in the literature (Washington et al., 2020). The random effect models provide an opportunity to capture unobserved heterogeneity given the panel nature of our analysis. The mathematical formulation of the ordered probit model can be characterized as follows (Stata et al., 2014):

$$z_{it} = x_{it}\beta + v_i + \varepsilon_{it} \tag{1}$$

$$p_{itk} = \Pr(y_{it} = k|\boldsymbol{K}, x_{it}, v_i) = \Pr(\ k_{K-1} < x_{it}\beta + v_i + \varepsilon_{it} < \ k_K)$$

$$=.\Pr(k_{K-1} - x_{it}\beta - v_i < \varepsilon_{it} < k_K - x_{it}\beta - v_i)$$
$$=.\phi(k_K - x_{it}\beta - v_i) - \phi(k_{K-1} - x_{it}\beta - v_i)$$

Here, $i = 1, 2, \cdots, n$ represent the panel, and $\boldsymbol{K}$ is a set of cut points from k_1 to k_{K-1}, in which K is the number of possible outcomes. z_{it} is the unobserved continuous latent utility for observation t in period i. β is the vector of coefficients to be estimated corresponding to the explanatory variables x_{it}. The error terms ε_{it} have a standard normal distribution (i.e., mean zero and variance one). Also, $\phi()$ is the standard normal cumulative distribution function. In equation 2, y_{it} are observed ordinal responses that are extracted from the latent continuous expression such that:

Table 3
Socioeconomic distribution of weighted and unweighted panel samples.

		Unweighted sample (N = 2973)	Weighted sample (N = 2973)	Adults in the U.S. (2019)
Age	18–29	8.7 %	21.0 %	21.0 %
	30–44	22.2 %	25.2 %	25.2 %
	45–59	25.8 %	24.4 %	24.4 %
	60 and above	43.3 %	29.4 %	29.4 %
Gender	Female	64.3 %	51.3 %	51.3 %
	Male	35.7 %	48.7 %	48.7 %
Education	High school or less	12 %	39.0 %	39.0 %
	Some college	28.6 %	30.4 %	30.4 %
	Bachelors or higher	59.4 %	30.6 %	30.6 %
Employment	Employed	57.15	62.0 %	62.0 %
	Non-employed	42.9 %	38.0 %	38.0 %
Hispanic status	Hispanic	7.6 %	16.4 %	16.4 %
	Non-Hispanic	92.4 %	83.6 %	83.6 %
Race	Non-white	15 %	26 %	26 %
	white	85 %	74 %	74 %
Household vehicles	0	7.2 %	9.3 %	9.3 %
	1	37.9 %	22.6 %	22.6 %
	2	40.4 %	37.4 %	37.4 %
	3+	14.4 %	30.7 %	30.7 %
Household Income	Less than $49,999	33.6 %	30.3 %	30.3 %
	$50,000 - $99,999	32.3 %	30.7 %	30.7 %
	More than $100,000	34.1 %	39.0 %	39.0 %

Table 4
Definition of explanatory variables used in the random effects ordered probit models.

Variables	Definition	Mean	Std. Dev.
Sociodemographic			
Gen Z	Whether the person belongs to Gen Z generation or not (Binary).	0.043	0.203
Elderly	Whether the person is older than 65 years old or not (Binary).	0.294	0.452
Zero vehicle	Whether the person lives in a household with zero vehicles or not (Binary).	0.093	0.257
Income less than 50 K	Whether the household income is less than $50 k or not (Binary).	0.303	0.470
Income more than 150 K	Whether the household income is more than $150 k or not (Binary).	0.146	0.352
Graduate degree	Whether the person holds a graduate degree or not (binary).	0.260	0.438
Income loss	Whether the income was negatively affected by the pandemic or not (Binary).	0.146	0.352
Household Size one	Whether the person lives alone in the household or not (Binary).	0.167	0.418
Attitudes			
More online meetings	If the respondent agrees with “I liked the experience of more online meetings during the pandemic and wish to continue it after COVID-19”, 1, otherwise 0.	0.117	0.260
Commute less	If the respondent agrees with “I liked the experience of less commuting during the pandemic and wish to continue it after COVID-19”, 1, otherwise 0.	0.274	0.334
Pro-environment	If the respondent agrees with “I am committed to an environmentally friendly lifestyle”, 1, otherwise 0.	0.162	0.289
Less motivation at home	If the respondent agrees with “It is hard to get motivated to work away from the main office”, 1, otherwise 0.	0.172	0.355
In-person shopping chore	If the respondent agrees with “In-person shopping is usually a chore for me”, 1, otherwise 0.	0.321	0.431
Technology frustration	If the respondent agrees with “Learning how to use new technologies is often frustrating” 1, otherwise 0.	0.281	0.42
Transit risk	If the respondent agrees with “There is a high risk to catch the COVID-19 virus from riding public transportation”, 1, otherwise 0.	0.55	0.58

$$y_{it} = \begin{cases} 1 & if \quad z_{it} < k_1 \\ 2 & if \quad k_1 < z_{it} < k_2 \\ . & . \quad\quad . \\ . & . \quad\quad . \\ K & if \quad k_{K-1} < z_{it} \end{cases} \tag{3}$$

Equation 2 expresses the probability of observing the outcome k for response y_{it}. In this equation, k_0 is considered as $-\infty$ and k_k is taken as $+\infty$. Moreover, x_{it} does not include a constant term, for its effect has been considered in the cut points. Taking a set of panel-level random effects v_i, which is identically and independently distributed, the conditional distribution for the response y_{it} can be expressed as:

Table 5
Share of responses in different categories of activities (i.e., WFH, Commute mode, and Online shopping) from pre-pandemic to post-pandemic. The numbers inside parentheses indicate the change in percentages in each category compared to the previous period.

Activity category	Level of engagement	Pre-pandemic	Wave 1 (*Pre-pandemic to Wave 1*)	Wave 2 (*Wave 1 to Wave 2*)	Post-pandemic (*Wave 2 to post-pandemic*)
WFH	No option	**63 %**	**36 %** (-0.43 %)***	**42 %** (+0.16 %)***	**52 %** (+0.24 %)***
	Infrequent (once/week or less)	**21 %**	**5 %** (-76 %)***	**4 %** (-20 %)**	**14 %** (+250 %)***
	Frequent (more than once/week)	**16 %**	**46 %** (+187 %)***	**45 %** (-2%)	**34 %** (-24 %)***
Work trip commute mode [1]	Private vehicle	**71.9 %**	**40.4 %** (-44 %)***	**45.8 %** (+13 %)	**65.5 %** (+43 %)***
	Transit	**10.9 %**	**3.5 %** (-68 %)***	**4.6 %** (+31 %)***	**7.5 %** (+63 %)***
Online grocery shopping	Frequent (more than once/week)	**3.2 %**	**6.5 %** (+103 %)***	**5.6 %** (-15 %)	**4.3 %** (–23 %)***
	Infrequent (between once/week and once/month)	**6.9 %**	**12.3 %** (+78 %)***	**12.9 %** (-5%)	**12.9 %** (0 %)
	Rare (less than once/month or never)	**89.9 %**	**81.2 %** (-10 %)***	**81.6 %** (+0.5 %)	**82.8 %** (+1.5 %)

1) Please note that in this table, we only have reported the share of private vehicles and transit commute modes and not the other modes (e.g., walking), which is the reason that summation of percentages in the commute mode category is less than 100%. A more detailed elaboration of commute modes can be found in Fig. 3.
*** Indicates a significance level of 99%, and ** indicates a significance level of 95%.

$$f(y_{it}, k, x_{it}\beta + v_i) = \prod_{k=1}^{K} p_{itk}{}^{I_k(y_{it})} = exp \sum_{k=1}^{K} \{I_k(y_{it})\log(p_{itk})\} \tag{4}$$

We considered four dependent variables corresponding to each category (i.e., WFH, transit mode use, online grocery shopping, and business air travel). The dependent variable in each of these categories had an ordinal nature with three levels to indicate the level of engagement in each activity. Considering the importance of having insights into the long-term effects of the Covid-19 pandemic, we used the stated post-covid answers for the econometric part of our analysis. In this regard, for the WFH category, there are three ordered classes of response including 1) No WFH after the pandemic, 2) Infrequent WFH (i.e., once/week or less) after the pandemic, and 3) Frequent WFH (i.e., more than once/week) after the pandemic. Please note that these response variables are extracted from two waves of survey data which is the reason for selecting the random effect modeling approach to account for the panel effect. Similarly, in the transit mode use category, we have three ordered classes of response including 1) Using transit mode in the post-pandemic less than before pandemic, 2) Using transit mode in the post-pandemic the same as before pandemic, and 3) Using transit mode in the post-pandemic more than before pandemic. Moreover, in the online grocery shopping category, we have three ordered classes of response including 1) Rarely online grocery shopping (i.e., less than once/month or never) after the pandemic, 2) Infrequent online grocery shopping (i.e., between once/week and once/month) after the pandemic, and 3) Frequent online grocery shopping (i.e., more than once/week) after the pandemic. Finally, in the business air travel category, we have three ordered classes of response including 1) Taking business air travel less than before the pandemic, 2) Taking business air travel the same as before the pandemic, and 3) Taking business air travel more than before pandemic.

5. Results

In this section, we present and discuss the important findings of the COVID Future Panel Survey, regarding the following categories: work from home, mode choice, online shopping, and air travel in two parts: Descriptive analysis and Econometric analysis. Before starting a detailed discussion on the findings, tables 5 and 6 summarize some key findings of the survey. These two tables can help the readers easily grasp the results they are more interested in rather than going through the text to find them.

In this regard, Table 5 presents the share and the change of responses in three different categories of activities including WFH, Commute mode, and Online shopping, from pre-pandemic to waves one and two, and to post-pandemic. For example, in the WFH category, 16 % of respondents were frequent telecommuters (i.e., WFH more than once a week) in pre-pandemic. Then, the share of frequent telecommuters increased to 46 % in the first wave of our survey which means 187 % (i.e., ((46–16)Ã· 16)× 100) growth in this class of WFH from before the pandemic to wave one. The values in parentheses in Table 5 present the result of the statistical Z-tests on percentage changes to see whether a change from one period to the next one is significant or not. Moreover, Table 6 presents the expected levels of using private vehicles and transit, as well as the expected levels of taking business and personal air travel in the post-pandemic future. For instance, the first number in this table shows that 12 % of respondents expect to use private vehicles (for all purposes and not just commute), in the post-pandemic future, less than before-pandemic. In the remaining of this section, we elaborate on these tables and each of the four categories of WFH, mode choice, online shopping, and air travel to shed light on the pandemic-induced changes during the data collection times as well as the expectation for the future.

Table 6
The expected levels of using private vehicles and transit, as well as business and personal air travel in the post-pandemic future. Please note that these findings are based on the stated opinion of our respondents.

Activity category	Classes of stated response	Share of responses in each class of use in post-pandemic
Using private vehicles in post-pandemic (All purposes and not just commute)	Less than before the pandemic	12 %
	Same as before the pandemic	71 %
	More than before the pandemic	17 %
Using transit in post-pandemic (All purposes and not just commute)	Less than before the pandemic	13 %
	Same as before the pandemic	76 %
	More than before the pandemic	10 %
Using business air travel in post-pandemic	Less than before the pandemic	41 %
	Same as before the pandemic	51 %
	More than before the pandemic	8 %
Using leisure/personal air travel in post-pandemic	Less than before the pandemic	24 %
	Same as before the pandemic	59 %
	More than before the pandemic	17 %

5.1. Descriptive analysis

5.1.1. Telecommute and productivity

We explored the dynamics of working from home by accounting for different levels of adoption. Based on the collected data, different workers are categorized into three classes: “frequent” (i.e., WFH more than once a week), “infrequent” (i.e., WFH once a week or less), and “no option”. Fig. 1 illustrates the proportions and transitions of respondents who were employed before the pandemic and fall into one of these three classes. The first three columns correspond to the *observed* WFH behavior in the pre-pandemic, wave one, and wave two periods, respectively, whereas the last column refers to the *expected* WFH behavior after the pandemic. Moreover, as mentioned before, Table 5 presents the result of the statistical Z-tests on percentage changes in different classes of WFH. The results show that the fraction of employees without an option to WFH has decreased from 63 % (pre-pandemic) to 36 % and 42 % in wave one and wave two, respectively. The proportion of frequent telecommuters has substantially expanded from 16 % (pre-pandemic) to 46 % (i.e., 187 % rise) in wave one which is also sustained through wave two.

Regarding the post-covid situation, 48 % (i.e., 34 % + 14 %) of the respondents expect to have the opportunity to WFH. The equivalent percentage in the pre-pandemic was 37 % (i.e., 21 % + 16 %) which indicates an approximately 30 % increase in having the opportunity to WFH. The most considerable change can be seen in the frequent commuters by increasing from 16 % in pre-pandemic to 34 % in post-pandemic (i.e., 112 % growth).

We also asked telecommuters in waves one and two to assess their productivity compared to the pre-pandemic period. Our results suggest that around 30 % of the respondents in both waves expressed higher productivity whereas the percentages of the individuals with lower perceived productivity were 24 % in Wave one, and then declined to 20 % in wave two. In general, the proportion of the respondents who believed their productivity has been “higher or the same as the pre-pandemic period” was 60 % in wave one which increased to 71 % in wave two.

To shed light on the underlying factors affecting the perceived productivity of employees during the WFH period, we asked respondents to select among a set of provided reasons with the ability to choose more than just one item. Fig. 2 (a), and (b) show the proportions of the selected components corresponding to lower and higher productivities, respectively. As can be seen, “more distractions at home” is the number one negative factor in both waves causing lower productivity (selected by 59 % and 57 % in waves one and two, respectively) followed by “feeling sad, depressed, or burned out” that was only asked in wave two (selected by 42 %). On the other hand, the first selected positive factor associated with being more productive in both waves is “no commute” (selected by 69 % and 45 % in waves one and two, respectively) followed by “more comfortable workspace at home” (selected by 48 %) in wave one and “flexible hours” (selected by 35 %) in wave two.

5.1.2. Commute trips and mode choice

As a part of the survey, we asked pre-covid workers to specify their main travel mode to work and the findings are presented in Fig. 3 and Table 5. Before the pandemic, around 72 % of the workers relied on private vehicles, and the following most frequently used modes were transit and walking, accounting for transporting around 11 % and 3 % of the commuters, respectively. In wave one, the share of private vehicle commuters plummeted to around 40 % (i.e., 44 % reduction) primarily due to shifting to telecommuting and partly for becoming unemployed. From wave one through wave two, the percentage of private vehicle commuters increased by 13 %, whereas the non-commuter category decreased by 7 %. Regarding the post-covid expectation, around 66 % of the respondents anticipate using a private vehicle for commuting, indicating a 9 % reduction compared to the pre-pandemic period.

Experiencing a 68 % reduction, transit commuters’ share went through the most massive drop from pre-pandemic to wave one. Passing the height of the pandemic restrictions, the percentage of transit commute increased by 31 % from wave one to wave two. Regarding the post-pandemic, our results indicate that although the transit share will continue to grow, it will still be significantly lower than the pre-pandemic period. In other words, the percentage of transit commuters will still be 31 % (i.e., ((7.5–10.9)Ã· 10.9)×

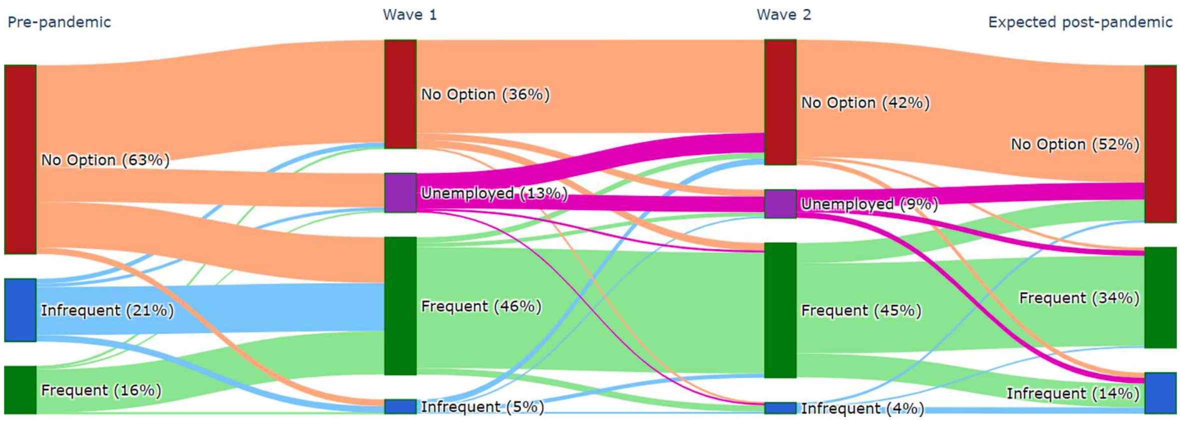

Fig. 1. Proportions and transitions of different levels of work from home adoption from pre-pandemic to post-pandemic. Please note that “Frequent” refers to WFH more than once/week, and “Infrequent” refers to WFH once/week or less.

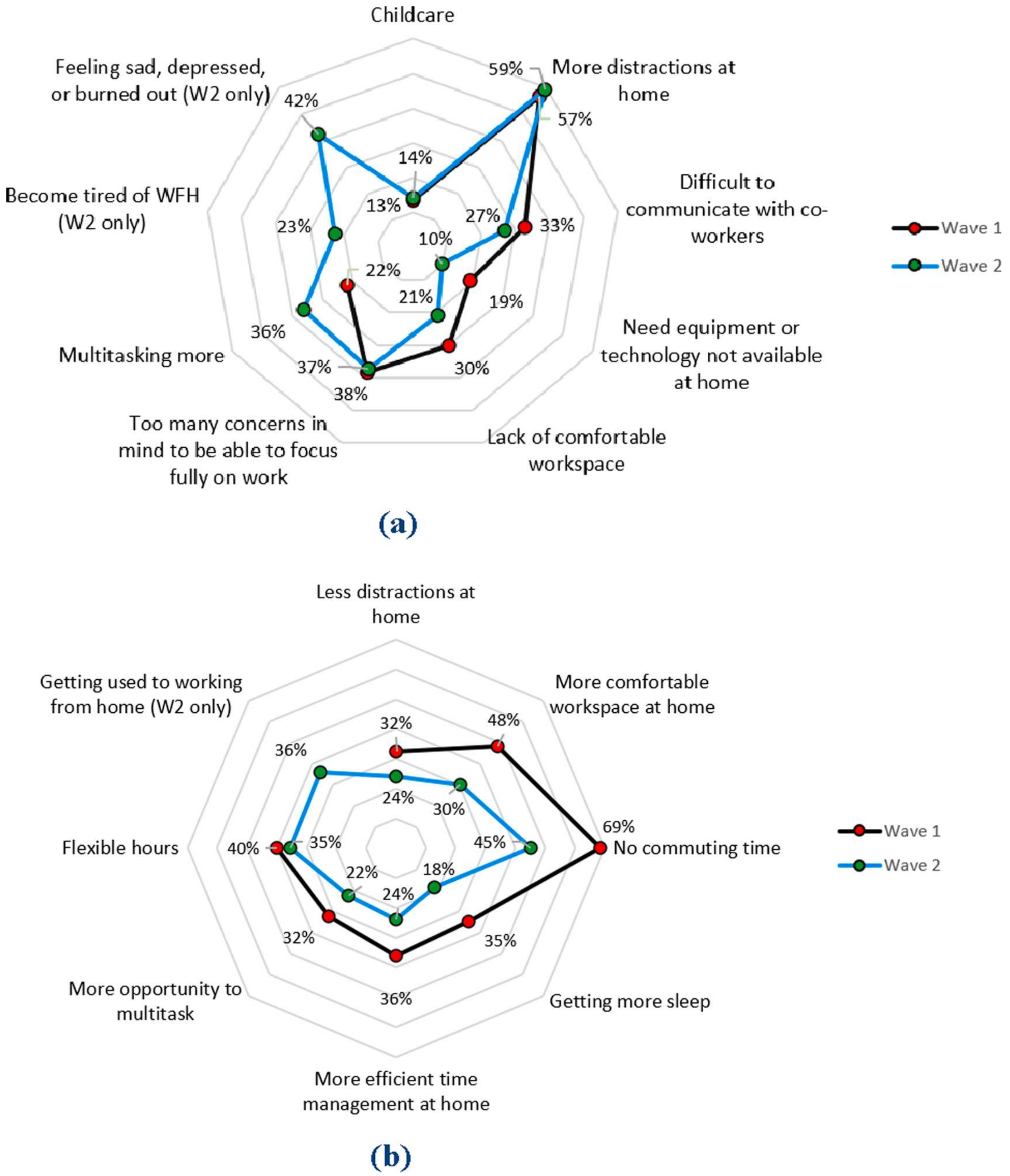

Fig. 2. Different factors affecting WFH productivity for respondents who reported (a) lower and (b) higher perceived productivity (compared to the pre-pandemic situation) reported in wave one and wave two.

100) less than before the COVID-19 outbreak. Furthermore, the percentage of walking commuters sharply declined by 48 % from pre-pandemic to wave one. The fraction of this category then grew by 13 % from wave one to wave two; however, this change is not significant.

The share of commute modes in Fig. 3 should be considered in tandem with the frequency of commuting to account for future changes across days of a week. For example, two individuals might report their main commute modes as transit and private vehicle, respectively. However, the former person commutes twice, whereas the latter commute five times per week. Since Fig. 3 is insufficient to capture this heterogeneity, we asked our respondents to report the number of commute days to work. According to the results depicted in Fig. 4, before the pandemic, the average number of commute days was 4.1 days per week, which then plummeted to 1.75 and 1.87 days per week in wave one and wave two, respectively. Regarding the after-pandemic period, it is expected that, on average, people commute 3.42 days per week (i.e., 17 % decline compared to the pre-pandemic). Scrutinizing the four periods presented in

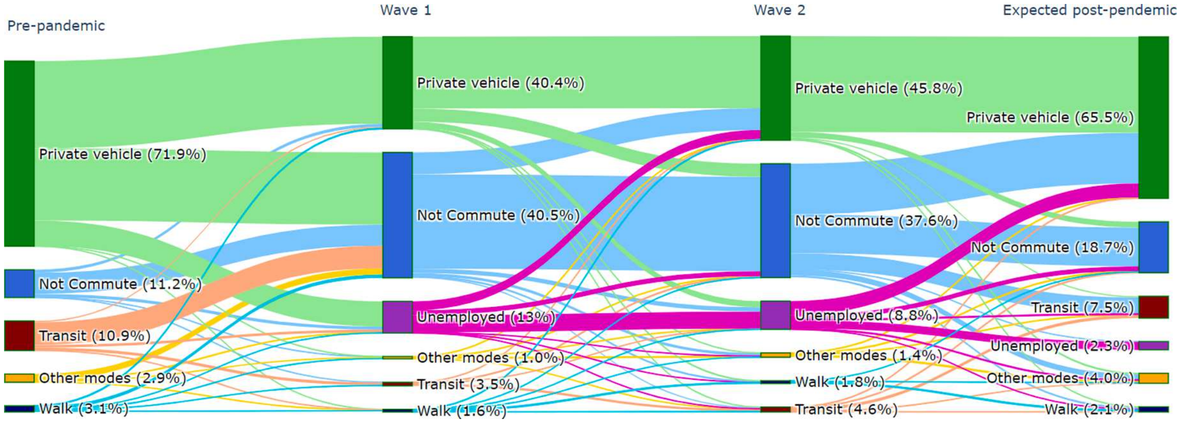

Fig. 3. Proportions and transitions of different categories of workers based on main travel mode to work from pre-pandemic to post-pandemic.

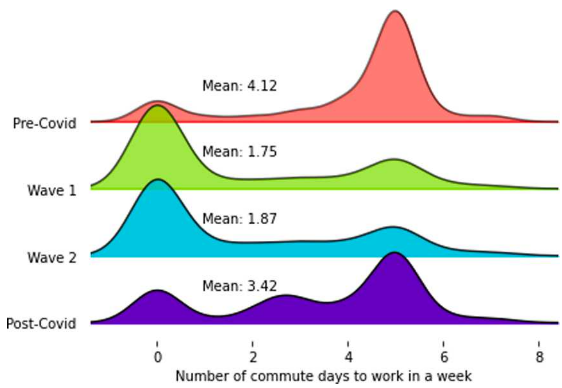

Fig. 4. The number of commute days to work in pre-pandemic, wave one, wave two, and post-pandemic periods.

Fig. 4, clear distinctions between the distributions of the number of commute days in pre-covid versus post-covid can be observed. Accordingly, the before-pandemic distribution was comprised of mostly workers commuting five days per week with a significantly smaller portion who did not commute. In comparison, the post-covid distribution is different in two ways. First, the share of five days per week commuters has decreased while the share of non-commuters has increased. Second, although even after the pandemic most workers expect to commute around five days per week, there is a lump in the post-covid distribution around three days per week,

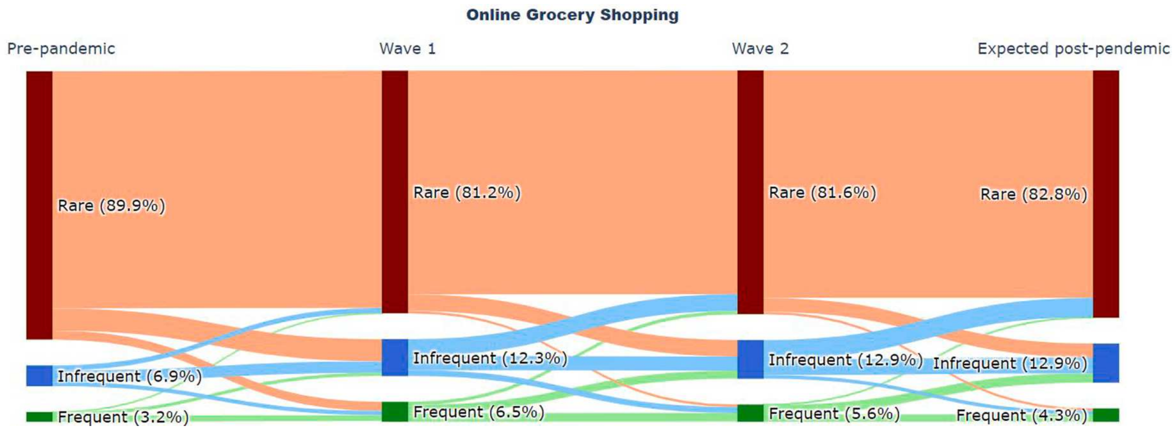

Fig. 5. Proportions and transitions of different categories of online grocery shoppers from pre-pandemic to post-pandemic. The "Frequent" refers to doing online shopping more than once/week, "Infrequent" refers to between once/week and once/month, and "Rare" refers to less than once/month or never.

which is unprecedented in the other three distributions. This signifies that in the post-covid period, it is expected that a considerable portion of workers will switch to a hybrid work model with a few days working from home and a few days commuting to an office.

To have a more comprehensive projection toward the future, we asked all respondents (i.e., not just commuters) to specify their anticipated post-covid use of private vehicle and transit modes (for all purposes and not limited to just commute) by drawing a comparison with the pre-covid period. The reported results are reported in Table 6, indicating that 12 % of the people expect to use private vehicles less than before, whereas 17 % expect to use them more. This finding supports the idea that although the proportion of private vehicle *commute* trips is expected to decrease, the total use of private vehicles including for *other purposes* might increase. This can be attributed to the flexibility provided by working from home and assigning the saved commute time to other activities. Regarding the transit mode, 13 % of the respondent expect to use it less than before whereas 10 % expect to use it more. Shedding light on the underlying components that negatively influence the use of transit mode, we asked the people who want to use this mode less than before, to select among a set of provided factors. The number one concern manifested to be the "I no longer feel safe and comfortable sharing space with strangers" by being selected by 73 % and 63 % of the respondents in wave one and wave two, respectively. Moreover, WFH was the second most reported reason negatively affecting transit use, which has interestingly increased from 30 % in wave one to 45 % in wave two.

5.1.3. Online shopping

As part of the survey, we asked our respondents to indicate the frequency of using online grocery shopping before, during (i.e., in waves one and two), and after the pandemic (i.e., expected). The results are plotted in Fig. 5 and Table 5, encompassing three categories: "frequent" (i.e., more than once/week), "infrequent" (i.e., between once/week and once/month), and "rare" (i.e., less than once/month or never) shoppers. As can be seen, only around 10 % of individuals had utilized online services at least once per month before the pandemic. This proportion then increased to around 19 % in wave one, indicating 90 % growth which is also sustained in wave two. Furthermore, the frequent online grocery shoppers have almost doubled in wave one, and although they have decreased in wave two, this decline is not significant. We also witnessed 78 % growth in "infrequent" online grocery shoppers from pre-pandemic to wave one. The last column in Fig. 5 presents the respondents' expectations toward their future shopping choices in the post-pandemic situation. The biggest expansion is expected to occur in infrequent buyers (i.e., 87 %) followed by frequent buyers (i.e., 34 %), compared to the pre-pandemic.

5.1.4. Air travel

To better understand the impacts of the pandemic on long-distance air travel, we designed a set of questions in our survey by distinguishing between leisure/personal and business travel purposes. As reported in Table 6, compared to the pre-pandemic, 24 % of respondents expect less while 17 % expect more leisure/personal air travels in the post-pandemic period. Correspondingly, 41.% of respondents expect less while only 8 % anticipate more business air travels in the post-pandemic period.

To investigate underlying factors affecting peoples' preference to take less air travel, respondents were asked to select among a set of potential contributing reasons. Regarding leisure/personal travel, the first negative factor turned out to be "being uncomfortable sharing a close space with a stranger" (selected by 69 % and 53 % in waves one and two, respectively). On the other hand, the most influential factors in business air travel were reported as "I expect reduced budget for travel" (selected by 47 %) and "I realized I could conduct my meetings by conference call/video conference" (selected by 47 %) in wave one. However, in wave two, the budget concern becomes less important (selected by 27 %), whereas the ability to conduct meetings through videoconference became the number one factor (selected by 44 %) encouraging people to take less business air travel.

5.1.5. Relationships between WFH and travel Mode, online shopping and air travel

The previous sections demonstrate remarkable shifts in expected behaviors in different aspects of daily lifestyle, including working, commuting, shopping, and long-distance travel in the post-covid world. These categories are all pieces of a puzzle that altogether help us to shed light on the emerging mobility styles of individuals. The critical question here is whether there is any significant relationship between the explored categories or are these expected changes independent from each other? To answer this question, we performed a chi-square independence test to examine the links between the different discussed areas, and the results are presented in Table 7. This

Table 7
Results of chi-square independence test to examine the links between WFH and travel mode, online shopping, and air travel in the post-covid future.

Variable	Break down based on	χ^2	$p-value$
Work from home (Categories: Frequent, Infrequent, No option)	***Private vehicles use*** (Categories: Less than before, Same as before, More than before)	48.615	0.000 (***)
Work from home (Categories: Frequent, Infrequent, No option)	***Transit use*** (Categories: Less than before, Same as before, More than before)	69.896	0.000 (***)
Work from home (Categories: Frequent, Infrequent, No option)	***Online Grocery Shopping*** (Frequent, Infrequent, Rare)	28.065	0.000 (***)
Work from home (Categories: Frequent, Infrequent, No option)	***Personal Air Travel*** (Categories: Less than before, Same as before, More than before)	8.4216	0.0773
Work from home (Categories: Frequent, Infrequent, No option)	***Business Air Travel*** (Categories: Less than before, Same as before, More than before)	14.745	0.005(***)

*** Indicates a significance level of 99%.

table unfolds significant relations between WFH behavior and private vehicle use, transit use, online grocery shopping, and business air travel after the pandemic. However, there is no significant association between WFH and personal air travel.

To further scrutinize the actual implications of these relationships, the residuals for the chi-square tests are illustrated in Fig. 6, in which positive residuals (i.e., blue cells) show a positive association between the corresponding row and column variables, whereas the red color in cells indicates a negative association between the corresponding row and column variables. The WFH and private vehicle residual plot shows that frequent WFH workers, expect to use their automobiles more than before. This finding is interesting knowing that although frequent WFH workers do not commute to their offices every day, they expect to have more travel by their private vehicle after the pandemic. A potential reason is that, since WFH can provide people with time flexibility and save commute times, they might attend other activities (i.e., generate more travel) by using private vehicles. This plot also shows that people who do not have the option to WFH are associated with the same number of private car trips as pre-pandemic. WFH and transit use were also found to have a significant relationship since "frequent WFH" is positively associated with less transit use and "no option to WFH" is negatively associated with less transit use.

Moreover, "Frequent WFH" is positively associated with "Frequent Shopper" implying that individuals who expect to frequently telecommute, are also more inclined to do their grocery shopping using online platforms. This might occur due to the increased experience of online shopping during the pandemic and the provided advantages such as spending less time going to the store, or not having to carry purchased items. Frequent WFH is also positively associated with less business air travel after the pandemic, while "No option to WFH" is positively associated with the same number of travels as before. From a holistic perspective, the pandemic is changing the travel behavior and mobility style of a considerable portion of the population who are going to frequently WFH (i.e., 34 % of workers, from Fig. 1) in a way that they want to use their cars more than before, use transit less than before, do online shopping more than before and go on business air travels less than before.

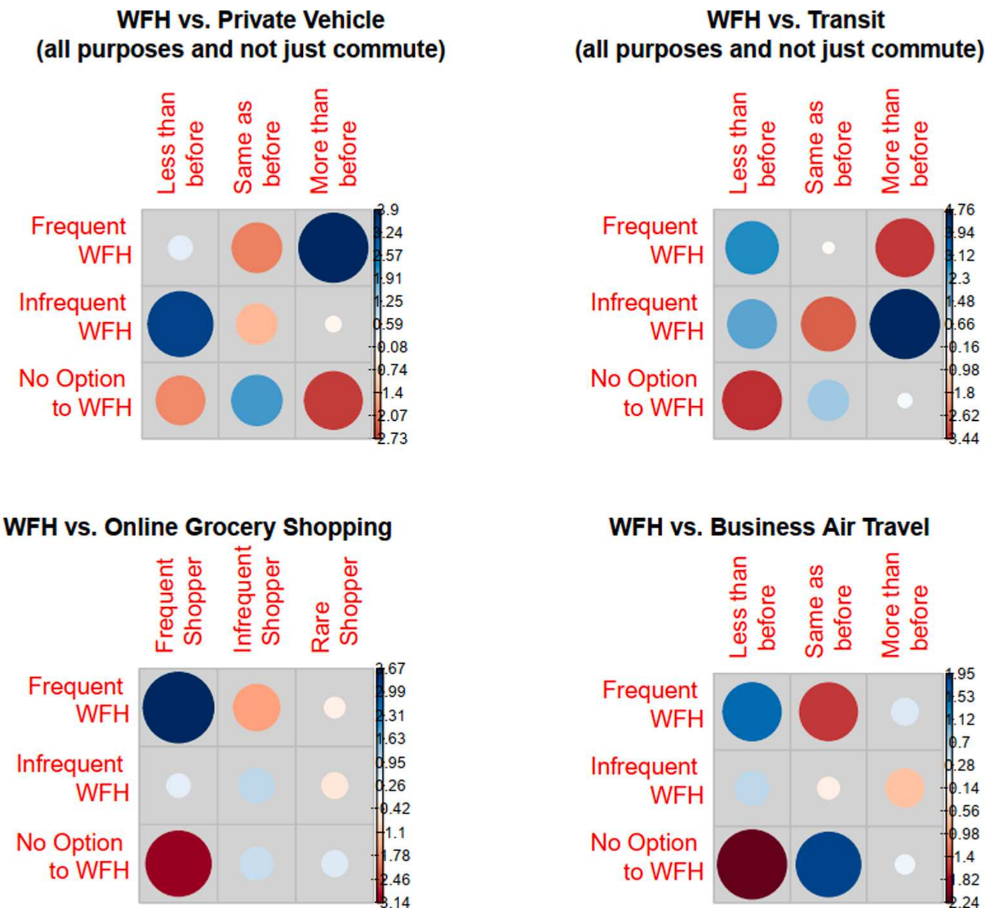

Fig. 6. The residuals for the chi-square tests between WFH and travel modes, online shopping, and air travel. Here, positive residuals (i.e., blue cells) show a positive association between the corresponding row and column variables, whereas the red color in cells indicates a negative association between the corresponding row and column variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 8
The estimation results for four random effects ordered probit models on 1)WFH, 2) Transit mode use, 3) Online grocery shopping, and 4) business air travel in the post-Covid future.

Three levels of the ordered response (For after the pandemic period)	Model 1: Work from home 1) No WFH2) Infrequent WFH (once/week or less)3) Frequent WFH (more than once/week).		Model 2: Transit mode use 1) Using transit less than before the pandemic. 2) Using transit the same as before the pandemic. 3) Using transit more than before the pandemic.		Model 3: Online grocery shopping 1) Rarely (less than once/month or never)2) Infrequent (between once/week and once/month)3) Frequent (more than once/week) .		Model 4: Business air travel 1) Taking business air travel less than before the pandemic. 2) Taking business air travel the same as before the pandemic. 3) Taking business air travel more than before the pandemic.	
Sociodemographic variables	Coeff	ME[1]	Coeff	ME	Coeff	ME	Coeff	ME
Gen Z	1.007***	−0.146 0.006 0.140			0.784***	−0.076 0.046 0.030		
Elderly			0.175**	−0.026 0.006 0.020	−0.831**	0.081 −0.049 −0.032		
Zero vehicle			0.233***	−0.041 0.009 0.032	1.041***	−0.101 0.061 0.040		
Income less than 50 K	−1.06***	0.154 −0.005 −0.149						
Income more than 150 K	0.600**	−0.09 0.01 0.08	−0.235***	0.037 −0.008 −0.028	0.414**	−0.040 0.024 0.016	−0.542**	0.081 −0.045 −0.036
Household Size one	0.889**	−0.129 0.005 0.124	−0.209***	0.038 −0.008 −0.029				
Graduate degree	0.488**	−0.071 0.006 0.065	−0151**	0.027 −0.006 −0.021			−0.366**	0.055 −0.031 −0.024
Income loss	−0.350**	0.051 −0.002 −0.049						

Three levels *of the ordered response (after the pandemic.)*	Model 1: Work from home 1) No WFH2) Infrequent WFH (once/week or less) 3) Frequent WFH (more than once/week)		Model 2: Transit mode use 1) Using transit less than before the pandemic. 2) Using transit the same as before the pandemic. 3) Using transit more than before the pandemic.		Model 3: Online grocery shopping 1) Rarely (less than once/month or never) 2) Infrequent (between once/week and once/month)3) Frequent (more than once/week) .		Model 4: Business air travel 1) Taking business air travel less than before the pandemic. 2) Taking business air travel the same as before the pandemic. 3) Taking business air travel more than before the pandemic.	
Attitudes	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
More online meetings	0.894***	−0.129 0.004 0.125					−0.443***	0.067 −0.037 −0.029
Commute less	1.479***	−0.215 0.008 0.207	−0.484***	0.082 −0.018 −0.064				
Pro environment	0.831***	−0.121 0.006 0.115			0.198**	−0.019 0.012 0.008	−0.064*	0.009 −0.005 −0.004
Less motivation at home	−0.402**	0.058 −0.002 −0.056					0.141***	−0.021 0.012 0.009
In-person shopping chore					0.148**	−0.014 0.009 0.006		
Technology frustration							0.076**	

(*continued on next page*)

Table 8 (*continued*)

Three levels *of the ordered response (after the pandemic.)*	Model 1: Work from home 1) No WFH2) Infrequent WFH (once/week or less) 3) Frequent WFH (more than once/week)		Model 2: Transit mode use 1) Using transit less than before the pandemic. 2) Using transit the same as before the pandemic. 3) Using transit more than before the pandemic.		Model 3: Online grocery shopping 1) Rarely (less than once/month or never) 2) Infrequent (between once/week and once/month)3) Frequent (more than once/week) .		Model 4: Business air travel 1) Taking business air travel less than before the pandemic. 2) Taking business air travel the same as before the pandemic. 3) Taking business air travel more than before the pandemic.	
Attitudes	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
								−0.011 0.006 0.005
Transit risk			−0.258****	0.020 −0.004 −0.016				
Panel-level variance								
Sigma	5.838		0.439		−0.831		0.958	
Model Statistics								
Cut point 1	0.889**		−1.651***		6.840***		−1.392	
Cut point 2	2.052***		1.383***		8.750***		2.662	
Pseudo R-squared	0.23		0.14		0.21		0.16	

Note: * Significant at 90%, ** Significant at 95%, *** Significant at 99%.

5.2. Econometric analysis

In this section, we present the estimation results of four random effect ordered probit models on the WFH, transit mode use, online grocery shopping, and business air travel. We use sociodemographic and attitudinal features as explanatory variables to shed light on the underlying factors influencing the activity and travel behavior of individuals in the “post-pandemic” era. Table 8 presents the estimation results including the variables that turned out to be significant in each model, their corresponding coefficient, and significance level. Moreover, this table reports the marginal effects for each variable which indicates the average change in the outcome probabilities because of one unit increase in the corresponding explanatory variable. For all four models, the cut points are statistically significant suggesting that the consideration of three levels of the outcome variable in all cases has been an appropriate approach.

Starting with model 1 (i.e., the WFH model) in Table 8, there are three levels of WFH in the post-pandemic period: 1) No WFH, 2) Infrequent WFH (once/week or less), and 3) Frequent WFH (more than once/week). According to the results Gen Z age group, people with an annual household income of more than $150 k, individuals who live alone (i.e., household size equals one), and those with a graduate degree are significantly and positively correlated with higher levels of WFH in the post-pandemic future. On the other hand, people with an annual household income of less than $50 k, and individuals who went through income loss during the pandemic are significantly and negatively correlated with lower levels of WFH. These findings are supported by the existing literature. For example, Bick et al., (2020) found that having higher education or higher income facilitates working from home. Moreover, people who live alone in a household are more likely to have less distractions which make their home environment conducive to telecommuting. In this regard, Mohammadi et al., (2022) also highlighted that fewer distractions at home play a significant role in having higher productivity while working from home. This issue can be more critical in the presence of children in a household as Barbour et al., (2021) found that having children makes it less likely to continue to WFH after the pandemic. Regarding the effect of age on WFH, Barbour et al., (2021) reported that younger generations (i.e., below 30 years old) show a higher probability of WFH after the pandemic. This could be attributable to the fact that younger generations in general are more familiar with the online world and feel more comfortable using technology to communicate. Also, people who lost income during the pandemic were likely to be working in job categories that were negatively affected the most by the pandemic (e.g., working in restaurants and bars or service taxi drivers that require physical presence) which makes them more likely to not WFH after the pandemic compared to other industries.

Marginal effect values provide informative insights on the contribution of each explanatory variable to the probability that a respondent falls into a certain level of the dependent variable (in model 1, each of three levels of WFH in post-pandemic). For example, as indicated by the three marginal effect values, Gen Z respondents were found to have 0.146 less probability of not WFH (i.e., belonging to class one of the WFH), 0.006 higher probability of WFH “Infrequently” (i.e., belonging to the class two of the WFH), and 0.140 higher probability to WFH “Frequently” (i.e., belonging to the class three of the WFH), compared to people who are not in the Gen Z age group.

Moreover, four attitudinal variables affect WFH in model 1. People who liked and wish to continue the experience of online meetings during the pandemic, people who liked and wish to continue the experience of less commuting during the pandemic, and those who stated that are committed to an environmentally friendly lifestyle were revealed to be positively and significantly correlated with more levels of WFH, whereas people who found it hard to remain motivated away from their main office turned out to be negatively correlated with more levels of WFH in the post-pandemic future. Among all the variables with a positive coefficient, the variable “Commute less” has the highest marginal effect (i.e., 0.207) in the third level of the WFH dependent variable. This means that the desire to commute less among people increases the probability of WFH after the pandemic more than any other predictor in our model. This finding is compatible with our descriptive analysis in which “less commuting” was ranked the number one factor that positively affected the productivity of WFH (i.e., Fig. 2. b). Furthermore, among the variable with negative coefficients, “Income less than 50 K” has the highest marginal effect (i.e., 0.154) in the first level of the WFH dependent variable. This means that being low-income increases the probability that the respondents do not WFH after the pandemic more than any other variable in our model.

The second model in Table 8 presents the estimation results for public transit use. There are three levels of transit use in the post-pandemic period: 1) Using transit less than before the pandemic, 2) Using transit the same as before the pandemic, and 3) Using transit more than before the pandemic. Regarding the sociodemographic characteristics, elderly people, and those with zero vehicles in their household are significantly and positively correlated with using public transit more than before the pandemic. On the other hand, respondents in households with an income of more than $150 K, individuals who live alone (i.e., household size equals one), and people with a graduate degree are significantly and negatively correlated with using public transit more in the future. The finding regarding the elderly people in this model is thought-provoking. Elderly people experienced the highest rates of casualties due to their vulnerability to the Covid-19 virus, which made them reduce their use of public transit more than younger individuals *during* the pandemic (Park & Cho, 2021). Nonetheless, our model suggests that *after* the pandemic, elderly people expect to rely more on transit to meet their transportation needs. This area requires further research to accurately scrutinize the potential reasons for this phenomenon. For example, do the unprecedented inflation rates and high gas prices in the U.S. hinder elderlies from affording and maintaining private cars and leaves them with other options such as public transit? However, our study does not have enough information to answer this question.

5.2.1. *Marginal effect*

An interesting finding here is that the three sociodemographic variables that are negative in the public transit use model, are all positive in the WFH model. In other words, people with graduate degrees, people in households with income of more than $150 K, and people who live alone are all positively correlated with more WFH in the future, and also negatively correlated with more use of transit in the post-covid period. This finding is compatible with our descriptive analysis in section 5.1.5 where we showed that “frequent WFH” is positively associated with less transit use. Therefore, it can be concluded that, to some extent, WFH among certain population groups accounts for decreasing the transit ridership after the pandemic era. Two attitudinal variables affect transit use in model 2. First, individuals who liked and wish to continue the experience of less commuting during the pandemic are negatively correlated with more transit use in the future. Second, respondents who perceived high risk of exposure to the COVID-19 virus from riding public transportation are less likely to use public transit more frequently in the post-pandemic period. The marginal effect values indicate that the “Zero vehicles” variable has the highest positive effect (i.e., 0.032) in the third level of transit mode use (i.e., using transit more than before) suggesting that living in a household without a private car increases the probability of using transit more than any other variables in the model. This is plausible given that those people have fewer transportation choices and even if transit mode does not fully satisfy their expectations, they probably still are bound to use it.

The third model in Table 8 presents the estimation results for online grocery shopping. There are three levels of online grocery shopping in the post-pandemic period: 1) Rarely (less than once/month or never), 2) Infrequent (between once/week and once/month), and 3) Frequent (more than once/week). As can be seen in Table 8, the Gen Z age group, people who live in zero vehicle households, and people with a household annual income of more than $150 k are positively correlated while being in the elderly age group is negatively correlated with higher levels of online grocery shopping in post-pandemic. The finding that age is a major factor in determining online shopping behavior is consistent with prior research (Koch et al., 2020). A potential explanation could be a lack of familiarity with using technology and different shopping apps which might make older people prefer to go to the store. In addition, Koch et al., (2020) confirmed that compared to high-income households, low-income groups are less likely to do online shopping after the pandemic, possibly to avoid the additional costs such as delivery or service fees. Moreover, not having a car, in the context of U.S. cities, makes it notably inconvenient to do in-person grocery shopping. Furthermore, two attitudinal variables positively influence online grocery shopping in our model. Accordingly, people who are committed to an environmentally friendly lifestyle, and individuals who think in-person shopping is usually a chore are more likely to engage in higher levels of online grocery shopping after the pandemic. Previous studies also have underscored the significance of attitudinal determinants of online shopping after the pandemic (Koch et al., 2020).

Finally, the fourth model in Table 8 presents the estimated results for the business air travel model. There are three levels of business air travel in the post-pandemic period: 1) Business air travel less than before the pandemic, 2) Business air travel the same as before the pandemic, and 3) Business air travel more than before the pandemic. According to the results, people with a household annual income of more than $150 k and respondents with a graduate degree are negatively correlated with higher levels of business air travel post-pandemic. Moreover, four attitudinal variables are significant in model 4. People who found it hard to remain motivated away from their main office and individuals who think learning how to use new technologies is often frustrating are positively correlated with more levels of business air travel in the future. Conversely, people who liked and wish to continue the experience of online meetings during the pandemic, and individuals who are committed to an environmentally friendly lifestyle are less likely to take more business air travel in the post-pandemic period. These findings are well in line with our descriptive analysis in section 5.1.4. where we showed that the most influential factor in decreasing business air travel was reported as “the ability to conduct meetings through videoconference” by the respondents during the pandemic. This finding also can be supported by the previous research (Jack

& Glover, 2021), and not surprisingly, our model suggests the effect of adopting virtual meetings is likely to transcend the pandemic era.

6. Discussion

Work from home: One of the most conspicuous changes in our data is the substantial expansion of frequent (i.e., more than once/week) telecommuters. From the individuals' perspective, WFH can be beneficial by saving hours of commuting and assigning that time to increase the work-life balance or enhance productivity (Zwanka & Buff, 2020). Moreover, WFH can lead to decreased peak hour congestion, lower emissions, and saved office costs (Guyot & Sawhill, 2020). However, WFH brings up management challenges for employers to ensure the productivity of their employees since some management styles simply are not feasible. In our data, the most stated negative factor affecting teleworkers' productivity is "More distractions at home". To ensure the productivity of telecommuters, considering the critical role of home environments that are reasonably free of distractions is a must. Employers can improve productivity by investing in providing their employees with suitable and comfortable home offices. Given that WFH potentially saves office and transportation expenses, employers can assign a budget to design efficient home offices for their employees, or even to move to new places with more "workable" home environments. Moreover, long-lasting periods of social isolation can lead to sadness, depression, and anxiety, and jeopardize the productivity of WFH. Greenwood and Krol, (2020) reported that a lack of proper communication between employees and their managers can increase the likelihood of having mental health issues by 23 %. In this regard, managers can improve workers' mental health through more communication as well as providing support by investing in training that can educate employees on the necessary skills to maintain mental health (Greenwood & Krol, 2020). Nonetheless, WFH will remain undesirable for some employees who prefer to go to their office. Even people with homes conducive to WFH might prefer to go to the office a few days a week and benefit from the social interactions in the traditional office culture (Bloom, 2021). Accordingly, a flexible and hybrid telecommuting approach, rather than a compulsory policy, can optimize the benefits while mitigating the disadvantages of WFH across different individuals.

Travel mode: The remarkable shift to WFH will also significantly alter the commute travel patterns. Altogether, our findings indicate that the future of urban mobility includes a lower number of commute trips, higher car dependency, significant transit ridership lost, new and additional generated trips, and different traffic patterns rather than just the conventional morning/afternoon peak. To mitigate the decline in transit ridership, implementing additional health measures such as providing a sufficient number of sanitizers, screening the temperature of boarding patrons, and avoiding crowdedness can help to rebuild the trust in the transit system. Another important factor is the reliance of certain population groups such as elderlies and people without private cars on public transit. Planning to provide a safe and reliable service for these groups can improve transit equity and, to a certain extent, reclaim the lost ridership or even attract new patrons. Promoting active and micro-mobility modes is another strategy to move toward a sustainable, resilient, and environment-friendly transportation system with low virus exposure risk (Pourfalatoun & Miller, 2022). As one measure, more road space or exclusive lanes can be allocated to active modes to encourage and facilitate their adoption. Furthermore, preparing for traffic management and transportation planning in the emerging post-pandemic world necessitates a more in-depth focus on occurring changes in people's travel diaries. More reliance on private vehicles and increased time flexibility of telecommuters can create different peak hours throughout the day or even exacerbate congestions in unexpected hours. Further data collection and modeling are crucial since pre-pandemic models and simulations cannot simply predict emerging traffic patterns. Collecting data on people's daily travel patterns provides valuable insights that assist transportation planners in many ways, like manipulating the demand by spreading the demand throughout the day or even between days of a week. For instance, encouraging alternate workdays (e.g., traveling to the office only three days a week) can be consistent with the hybrid work model. Accordingly, all workers are not compelled to commute every day and the commute traffic can be spread over different days (Thombre & Agarwal, 2021).

Online shopping: According to our survey, a wide range of policies can be implemented to improve the quality of the online shopping experience for customers. For example, enhancing the reliability of purchases so the customers can be sure that they get exactly what they have ordered, designing user-friendly online platforms for all population groups, making sure that customer reviews are accurate and not based on paid reviews, and providing fast and affordable services to deliver fresh grocery items can help to sustain the growth of the online market. Regardless of the remarkable surge in online grocery shopping, most of the respondents remained "rare" shoppers (i.e., do online shopping less than once a month) during the pandemic and do not plan to use online shopping more in the future. This statistic highlights the vital role of retail grocery stores in providing for people's daily needs after the pandemic. Thus, authorities should take implementing health safety measures such as sanitizing, ventilation, and air cleaning in grocery establishments seriously to lower the exposure risks. They also need to have contingency plans in case the Covid-19 variants aggravate the situation and social distancing becomes more imperative again.

Air travel: Although the demand for leisure/personal air travel is also expected to decline, the decline seems marginal, and recovery seems likely to happen quicker. The significant changes in the air travel patterns would make pricing policies in the after-pandemic world a challenge since the business and pricing models that are based on the pre-pandemic data can not accurately understand the passengers' behavior in future situations. Airlines can take several actions to mitigate pandemic-induced financial difficulties. In short term, airlines should guarantee the safety of airports and airplanes and ensure passengers that air travel does not imperil their health. Also, with lower business-class trips demand, airlines can focus on reconfiguring airplane cabins by assigning more space to leisure trips. Moreover, to account for the drastic changes in demand, airlines need to reconsider their demand and long-term business models based on new data sources rather than relying on historic data (Gallego & Font, 2020). Another important factor that is affecting the airline industry is the massive rise in online shopping, which means giant online companies such as Amazon demand more air travel for transporting their cargo to different cities. Thus, airlines can utilize this opportunity by reallocating their fleet to cargo and freight transportation to compensate for their lost revenue (Bouwer et al., 2021). Another critical point is that moving toward a resilient airline industry is of vital importance after the experience of the Covid-19 outbreak and its catastrophic repercussions. For example, designing airplanes and airports in such a manner that makes implementing social distancing easier, can boost the resiliency of the airline industry.

7. Summary and limitations

7.1. Summary

In this study, we investigated the impacts of the Covid-19 pandemic on activity-travel behaviors and attitudes in the United States. We designed and implemented a nationwide survey in two waves, from April 2020 to May 2021, and collected 2973 observations. We first employed descriptive analysis to gain insights from the survey data into the evolution of changes in people's activity-travel behavior from before the pandemic to during the pandemic (i.e., waves one and two of the survey), and to the expected post-covid future. Our results confirm significant changes during and after the pandemic in telecommuting, mode choice, online shopping, and air travel habits and preferences. Most likely, the resulting impacts will stick and transcend the pandemic era by shaping different dynamics and patterns in the workplace, shopping market, and transportation sector. According to our results, 48 % of the respondents anticipate having the option to WFH after the pandemic, which indicates an approximately 30 % increase compared to the pre-pandemic period. In the post-pandemic period, auto and transit commuters are expected to be 9 % and 31 % less than pre-pandemic, respectively. A considerable rise in hybrid work and grocery online shopping is expected. Regarding the after-pandemic period, it is expected that, on average, people commute 3.42 days per week (i.e., 17 % decline compared to the pre-pandemic). Moreover, 41 % of pre-covid business travelers expect to have fewer flights (after the pandemic) while only 8 % anticipate more, compared to the pre-pandemic. Furthermore, we utilized random effects ordered probit approach to shed light on the factors affecting the level of engagement in each of the four categories of WFH, transit use, online grocery shopping, and business air travel in the post covid world. The results corroborated the significance of sociodemographic as well as attitudinal variables in forming the travel behavior of respondents in the future. In general, younger people, people with higher education or higher income, and individuals who are concerned about the environment are more likely to embrace the changes such as adopting more WFH, and less business air travel after the pandemic.

8. Limitations

In this study, we used a weighted sample to perform both descriptive and econometric analyses. Although geographic areas in our study all have reasonably large samples, it should be noted that due to the survey recruitment strategy, some areas were over-represented (e.g., Arizona), while some areas were underrepresented (e.g., East and West South Central). In fact, the issues on the representativeness of our sample, regarding both geographical and Socioeconomic representativeness, motivated us to develop a set of weights and include them in our analysis. We attempted to develop the weight values such that it is consistent with other studies and avoid causing instability in our data. The ratio of the 95th percentile weight to the 5th percentile weight in our sample is 115. This is in line with other surveys. For instance, the equivalent ratio for individual weights in the 2017 US National Household Travel Survey is 135, and 40 in the 2019 Panel Study of Income Dynamics. Nonetheless, readers should keep in mind that the presented analyses are based upon a sample that has been weighted and our results are inevitably influenced by it.

CRediT authorship contribution statement

Mohammadjavad Javadinasr: Conceptualization, Investigation, Data curation, Methodology, Software, Visualization, Formal analysis, Writing – original draft, Writing – review & editing. **Tassio Maggasy:** Investigation, Data curation, Writing – original draft, Writing – review & editing. **Motahare Mohammadi:** Investigation, Data curation, Writing – review & editing. **Abolfazl Kouros Mohammadain:** Conceptualization, Investigation, Data curation, Writing – review & editing, Supervision. **Ehsan Rahimi:** Investigation, Data curation, Writing – review & editing. **Deborah Salon:** Conceptualization, Investigation, Data curation, Supervision. **Matthew Wigginton Conway:** Conceptualization, Investigation, Data curation, Writing – review & editing. **Ram Pendyala:** Conceptualization, Investigation, Data curation, Supervision. **Sybil Derrible:** Conceptualization, Investigation, Data curation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data for wave one of our survey is available at https://covidfuture.org/data/. The wave two data also will be available in the future.

Acknowledgments

"This research was supported in part by the National Science Foundation (NSF) RAPID program under grants no. 2030156 and 2029962, awarded to the University of Illinois at Chicago and Arizona State University. Also, this study was supported by the Center for Teaching Old Models New Tricks (TOMNET), a University Transportation Center sponsored by the U.S. Department of Transportation through grant no. 69A3551747116, as well as from the Knowledge Exchange for Resilience at Arizona State University. This COVID-19 Working Group effort was also supported by the NSF-funded Social Science Extreme Events Research (SSEER) network and the CONVERGE facility at the Natural Hazards Center at the University of Colorado Boulder (NSF Award #1841338) and the NSF CAREER award under grant no. 155173. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funders."

All authors reviewed the results and approved the final version of the manuscript. The authors do not have any conflicts of interest to declare.

References

AJMC. (2021). *A Timeline of COVID-19 Developments in 2020*. https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020.

Barbour, N., Menon, N., & Mannering, F. (2021). A statistical assessment of work-from-home participation during different stages of the COVID-19 pandemic. *Transportation Research Interdisciplinary Perspectives, 11*, Article 100441. https://doi.org/10.1016/J.TRIP.2021.100441

Beigi, P., Haque, M., Rajabi, M. S., & Hamdar, S. (2022). *Bike Share's Impact on COVID-19 Transmission and Bike Share's Responses to COVID-19: A case study of Washington DC*. https://doi.org/10.48550/arxiv.2205.05011.

Bick, A., Blandin, A., & Mertens, K. (2020). *Work from Home After the COVID-19 Outbreak Work from Home After the COVID-19 Outbreak* *. https://doi.org/10.24149/wp2017.

Bloom, N. (2021). Hybrid is the future of work. *Stanford Institute for Economic Policy Research (SIEPR)*, 1–5.

Chauhan, R. S., Conway, M. W., da Silva, D. C., Salon, D., Shamshiripour, A., Rahimi, E., Khoeini, S., Mohammadian, A., Derrible, S., & Pendyala, R. (2021). *A database of travel-related behaviors and attitudes before, during, and after COVID-19 in the United States*. https://arxiv.org/abs/2103.16012v2.

Conway, M. W., Salon, D., Silva, D. C. da, & Mirtich, L. (2020). How Will the COVID-19 Pandemic Affect the Future of Urban Life? Early Evidence from Highly-Educated Respondents in the United States. *Urban Science 2020, Vol. 4, Page 50*, *4*(4), 50. https://doi.org/10.3390/URBANSCI4040050.

Dubey, A. D., & Tripathi, S. (2020). Analysing the Sentiments towards Work-From-Home Experience during COVID-19 Pandemic. *Journal of Innovation Management, 8*(1), 13–19. https://doi.org/10.24840/2183-0606_008.001_0003.

Education Week. (2020). *The Coronavirus Spring: The Historic Closing of U.S. Schools (A Timeline)*. https://www.edweek.org/leadership/the-coronavirus-spring-the-historic-closing-of-u-s-schools-a-timeline/2020/07.

Eisenmann, C., Nobis, C., Kolarova, V., Lenz, B., & Winkler, C. (2021). Transport mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. *Transport Policy, 103*, 60–67. https://doi.org/10.1016/J.TRANPOL.2021.01.012

Elldér, E. (2020). Telework and daily travel: New evidence from Sweden. *Journal of Transport Geography, 86*, Article 102777. https://doi.org/10.1016/J.JTRANGEO.2020.102777

Eriksson, N., & Stenius, M. (2022). Online grocery shoppers due to the Covid-19 pandemic - An analysis of demographic and household characteristics. *Procedia Computer Science, 196*, 93–100. https://doi.org/10.1016/J.PROCS.2021.11.077

Gallego, I., & Font, X. (2020). Changes in air passenger demand as a result of the COVID-19 crisis: Using Big Data to inform tourism policy. *Https://Doi.Org/10.1080/09669582.2020.1773476, 29*(9), 1470–1489. https://doi.org/10.1080/09669582.2020.1773476

Gerritsen, S., Egli, V., Roy, R., Haszard, J., De Backer, C., Teunissen, L., Cuykx, I., Decorte, P., Pabian Pabian, S., Van Royen, K., Te Morenga Ngapuhi, L., Whātua, N., Uri Hua, T., Rarawa, T., & Te Morenga, L. (2021). *Seven weeks of home-cooked meals: changes to New Zealanders' grocery shopping, cooking and eating during the COVID-19 lockdown*. https://doi.org/10.1080/03036758.2020.1841010.

Greenwood, K., & Krol, N. (2020). 8 Ways Managers Can Support Employees' Mental Health. *Harvard Business School Cases, 1*. http://ezproxy.library.ubc.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=bsu&AN=145569924&site=ehost-live&scope=site%0Ahttp://hbr.org/product/a/an/H05RRN-PDF-ENG.

Guyot, K., & Sawhill, I. V. (2020). Telecommuting will likely continue long after the pandemic. *Brookings*. https://www.brookings.edu/blog/up-front/2020/04/06/telecommuting-will-likely-continue-long-after-the-pandemic.

Harrington, D. M., & Hadjiconstantinou, M. (2020). *Commuting behaviours and COVID-19*. https://osf.io/46hzd/.

Hendrickson, C., & Rilett, L. R. (2020). The COVID-19 Pandemic and Transportation Engineering. *Journal of Transportation Engineering, Part A: Systems, 146*(7), 01820001. https://doi.org/10.1061/JTEPBS.0000418

Hotle, S., & Mumbower, S. (2021). The impact of COVID-19 on domestic U.S. air travel operations and commercial airport service. *Transportation Research Interdisciplinary*. *Perspectives, 9*, Article 100277. https://doi.org/10.1016/J.TRIP.2020.100277

Jaap Bouwer, Steve Saxon, Nina Wittkamp. (2021). *The Future of the Airline Industry After COVID-19 | McKinsey*. https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/back-to-the-future-airline-sector-poised-for-change-post-covid-19.

Jack, T., & Glover, A. (2021). Online conferencing in the midst of COVID-19: An "already existing experiment" in academic internationalization without air travel. *Https://Doi.Org/10.1080/15487733.2021.1946297, 17*(1), 293–307. https://doi.org/10.1080/15487733.2021.1946297

Kim, S. (Sam), Kim, J., Choi, Y., Shin, J., & Morrison, A. M. (2022). Can communication messages affect promotion of international air travel in preparation for the post COVID-19 pandemic era? *Journal of Hospitality and Tourism Management*, *51*, 252–267. https://doi.org/10.1016/J.JHTM.2022.03.019.

Klein, B., Larock, T., Mccabe, S., Torres, L., Friedland, L., Privitera, F., Lake, B., Kraemer, M. U. G., Brownstein, J. S., Lazer, D., Eliassi-Rad, T., Scarpino, S. V, Vespignani, A., & Chinazzi, M. (2020). *Reshaping a nation: Mobility, commuting, and contact patterns during the COVID-19 outbreak*.

Koch, J., Frommeyer, B., & Schewe, G. (2020). Online Shopping Motives during the COVID-19 Pandemic—Lessons from the Crisis. *Sustainability 2020, Vol. 12, Page 10247*, *12*(24), 10247. https://doi.org/10.3390/SU122410247.

Mohammadi, M. (Yalda), Rahimi, E., Davatgari, A., Javadinasr, M., Mohammadian, A. (Kouros), Bhagat-Conway, M. W., Salon, D., Derrible, S., Pendyala, R. M., & Khoeini, S. (2022). Examining the persistence of telecommuting after the COVID-19 pandemic. *Transportation Letters*, 1–14. https://doi.org/10.1080/19427867.2022.2077582.

Park, B., & Cho, J. (2021). Older Adults' Avoidance of Public Transportation after the Outbreak of COVID-19: Korean Subway Evidence. *Healthcare 2021, Vol. 9, Page 448*, *9*(4), 448. https://doi.org/10.3390/HEALTHCARE9040448.

POLAT, İ., ERDOGAN, D., & SESLIOKUYUCU, O. S. (2021). *THE IMPACT OF ATTITUDE AND SUBJECTIVE NORM ON AIRLINE PASSENGERS' TRAVEL INTENTION IN THE COVID-19 ERA: MEDIATING ROLE OF PERCEIVED RISK*. https://doi.org/10.5281/ZENODO.5770983.

Polzin, S., Choi, T., & Technology, U. S. D. of T. O. of the A. S. for R. and. (2021). *COVID-19's Effects on The Future of Transportation*. https://doi.org/10.21949/1520705.

Pourfalatoun, S., & Miller, E. E. (2022). Effects of Covid-19 Pandemic on Use and Perception of Micro-Mobility. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.4113031

Prillwitz, J., & Barr, S. (2011). Moving towards sustainability? Mobility styles, attitudes and individual travel behaviour. *Journal of Transport Geography, 19*(6), 1590–1600. https://doi.org/10.1016/J.JTRANGEO.2011.06.011

Raišiene, A. G., Rapuano, V., Varkulevičiute, K., & Stachová, K. (2020). Working from Home—Who Is Happy? A Survey of Lithuania's Employees during the COVID-19 Quarantine Period. *Sustainability 2020, Vol. 12, Page 5332*, *12*(13), 5332. https://doi.org/10.3390/SU12135332.

Reis Thebault, T. M. and J. A. (2021). *A year of covid-19: Timeline of the pandemic in America - Washington Post*. https://www.washingtonpost.com/nation/interactive/2021/coronavirus-timeline/.

Salon, D., Conway, M. W., Silva, D. C. da, Chauhan, R. S., Derrible, S., Mohammadian, A. (Kouros), Khoeini, S., Parker, N., Mirtich, L., Shamshiripour, A., Rahimi, E., & Pendyala, R. M. (2021). The potential stickiness of pandemic-induced behavior changes in the United States. *Proceedings of the National Academy of Sciences*, *118* (27), e2106499118. https://www.pnas.org/content/118/27/e2106499118.

Santos, L. J., Oliveira, A. V. M., & Aldrighi, D. M. (2021). Testing the differentiated impact of the COVID-19 pandemic on air travel demand considering social inclusion. *Journal of Air Transport Management, 94*, Article 102082. https://doi.org/10.1016/J.JAIRTRAMAN.2021.102082

Scorrano, M., & Danielis, R. (2021). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. *Research in Transportation Economics, 86*, Article 101031. https://doi.org/10.1016/J.RETREC.2021.101031

Serrano, F., & Kazda, A. (2020). The future of airports post COVID-19. *Journal of Air Transport Management, 89*, Article 101900.

Shamshiripour, A., Rahimi, E., Shabanpour, R., & Mohammadian, A. (Kouros). (2020). How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. *Transportation Research Interdisciplinary Perspectives*, *7*.

Stata, A., Stata, A., Publication, P., & Lp, S. (2014). *STATA BASE REFERENCE MANUAL RELEASE 14*. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.637.2432.

Thomas, F. M. F., Charlton, S. G., Lewis, I., & Nandavar, S. (2021). Commuting before and after COVID-19. *Transportation Research Interdisciplinary Perspectives, 11*. https://doi.org/10.1016/J.TRIP.2021.100423

Thombre, A., & Agarwal, A. (2021). A paradigm shift in urban mobility: Policy insights from travel before and after COVID-19 to seize the opportunity. *Transport Policy, 110*, 335–353.

U.S. Census Bureau. (2019). https://data.census.gov/cedsci/table?d=ACS 5-Year Estimates Data Profiles&table=DP05&tid=ACSDP5Y2018.DP05&g=0400000US06.

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). Statistical and Econometric Methods for Transportation Data Analysis Interdisciplinary Statistics. *Chapman & Hall/CRC*. https://www.routledge.com/Statistical-and-Econometric-Methods-for-Transportation-Data-Analysis/Washington-Karlaftis-Mannering-Anastasopoulos/p/book/9780367199029.

Zwanka, R. J., & Buff, C. (2020). COVID-19 Generation: A Conceptual Framework of the Consumer Behavioral Shifts to Be Caused by the COVID-19 Pandemic. *Https://Doi.Org/10.1080/08961530.2020.1771646, 33*(1), 58–67. https://doi.org/10.1080/08961530.2020.1771646