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A statistical assessment of work-from-home participation during different stages of the COVID-19 pandemic

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ABSTRACT

Responses to the COVID-19 pandemic have dramatically transformed industry, healthcare, mobility, and education. Many workers have been forced to shift to work-from-home, adjust their commute patterns, and/or adopt new behaviors. Particularly important in the context of mitigating transportation-related emissions is the shift to work-from-home. This paper focuses on two major shifts along different stages of the pandemic. First, it investigates switching to work-from-home during the pandemic, followed by assessing the likelihood of continuing to work-from-home as opposed to returning to the workplace. This second assessment, being conditioned on workers having experienced work-from-home as the result of the pandemic, allows important insights into the factors affecting work-from-home probabilities. Using a survey collected in July and August of 2020, it is found that nearly 50 percent of the respondents who did not work-from-home before but started to work-from-home during the COVID-19 pandemic, indicated the willingness to continue work-from-home. A total of 1,275 observations collected using the survey questionnaire, that was administered through a U.S. nationwide panel (Prime Panels), were used in the model estimation. The methodological approach used to study work-from-home probabilities in this paper captures the complexities of human behavior by considering the effects of unobserved heterogeneity in a multivariate context, which allows for new insights into the effect of explanatory variables on the likelihood of working from home. Random parameters logit model estimations (with heterogeneity in the means and variances of random parameters) revealed additional insights into factors affecting work-from-home probabilities. It was found that gender, age, income, the presence of children, education, residential location, or job sectors including marketing, information technologies, business, or administration/administrative support all played significant roles in explaining these behavioral shifts and post-pandemic preferences.

Introduction

COVID-19 has forced many workers to adapt to new behaviors, norms as well as shifted commute patterns, preferences and mandated many to work-from-home. Despite many abrupt changes to daily routines and commutes that happened mostly in the earlier months of the COVID-19 pandemic, a significant share of workers continued to work-from-home as employers and organizations were constantly encouraging this pattern to combat the spread of infections and ensure the health and safety of the employees. There are several critical elements in understanding work-from-home (also known as teleworking, remote working) probabilities during the pandemic. First, many workers were forced to start working from home with work-from-home probabilities largely influenced by their job types and whether their work could be performed from home. Second, because most workers' typical work schedule was disrupted, it remains to be seen whether they will be willing to continue to work-from-home after the pandemic and which factors will play roles in that probability. Third, gaining more insights into factors influencing shifting towards permanently working from home or returning to workplaces will allow a better understanding of the behavioral complexities and behavioral economics of the post-pandemic world.

Preliminary research in this domain has shown that, although a significant share of the working population is likely to go back to in-person pre-COVID work arrangements, there does remain the possibility that a substantial number of workers would continue to work-from-

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home (Menon et al., 2020). While most workers have shifted to remote work since the onset of the pandemic, the post-pandemic working paradigm is not yet known.

The current study fills an important gap in the literature by investigating the various shifts to work-from-home arrangements along the timeline (stages) of the COVID-19 pandemic. These stages can be conceptually defined as state one being pre-pandemic, state two implying the midst of the pandemic, and state three being post-pandemic period. To study shifts in work-from-home choices, statistical models are estimated using data collected from a web-based stated preference survey of a national panel of the United States adults. As will be shown, the estimated statistical models offer novel information in the context of COVID-19 and travel behavior. The combination of socio-demographic characteristics with job sectors and residential location indicators in the analysis delivers important insights into how explanatory variables have impacted work-from-home choices during different stages of the pandemic. The temporal element of the evolution of behavior is accounted for in the three pandemic stages mentioned above by only considering the responses from people who switched between different work states or were willing to depart from current work arrangements and change their work-from-home status (clear visualization of this framework is presented in detail in Fig. 1). It is important to note that the post-pandemic stage analysis is conditional on having worked from home during the pandemic. Thus, post-pandemic work choices are based on actual work-from-home experiences, a much different paradigm than that where respondents did not have the opportunity to gain such an experience.

Analyzing the factors responsible for the demand, or lack of thereof, of work-from-home is inherently tied to transport system demand. It is particularly important in relation to any future policy targeting behavioral changes to relieve transportation system congestion and lowering emissions from personal mobility. Since transport sector emissions have grown steadily for the last three decades (International Transport Forum, 2021), exploring a viable alternative, and leveraging the disruptions caused by the COVID-19 pandemic by gaining more insights into work-from-home, are relevant in the environmental and travel behavior setting.

The remaining parts of this paper are organized as follows. Section 2 discusses the key findings from the literature on work-from-home, and the impact of the COVID-19 pandemic on travel behavior, activity participation, trip-making, and working from home. Section 3 describes the conceptual framework adopted in this study. Section 4 provides details on the survey design and data collection effort. Section 5 discusses the methods adopted for this study (the random parameters binary logit models with the heterogeneity in means and variances). Section 6 highlights the key results from the model estimations and the paper concludes with Section 7 providing a summary of the key conclusions from this work and its implications in understanding work-from-home in a post-COVID world.

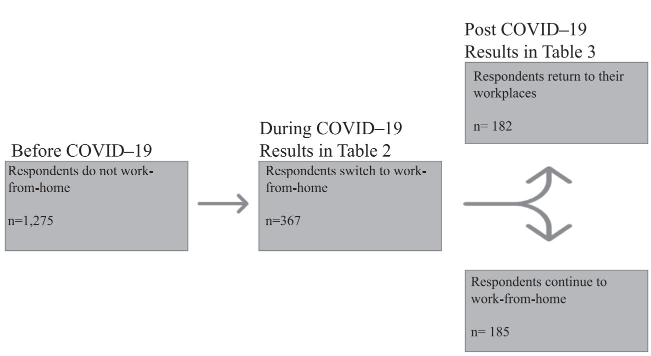

Fig. 1. Conceptual framework of the paper.

Literature review

The COVID-19 pandemic has fundamentally reshaped the way people travel in ways that are not yet fully understood. It is known that early in the pandemic, with the enforcement of "social distancing" measures and employers switching to remote working arrangements, several towns and cities experienced more than a 30 percent reduction in traffic volumes and vehicle miles traveled (Streetlight Data, 2020). Fast forward a year, and American towns and cities have witnessed a significant amount of a reversal, with increasing traffic volumes and a positive rate of percent change in vehicle miles traveled (Streetlight Data, 2021). While walking and biking trips have increased overall in most of the metropolitan areas, transit ridership has dropped considerably across major cities, with some of the major transit agencies reported a drop of more than 80 percent in ridership volume in the immediate aftermath of the pandemic (USDOT Bureau of Transportation Statistics, 2020). Despite an increase in overall traffic volumes and vehicle miles traveled since the initial lock-down era of the pandemic, transit continues to record extremely low ridership levels (USDOT Bureau of Transportation Statistics, 2021).

Research by de Vos (2020) found that the COVID-19 pandemic and its associated social distancing measures affected daily travel patterns, including the frequency and the kinds of out-of-home activities. Wilson (2020) found that people tended to suspend short and unnecessary driving and trips to the store or other locations during the unprecedented crisis. In addition, research has shown that since the onset of COVID-19, several public transportation modes/options have been perceived as "unsafe" due to challenges with social distancing. For instance, the crisis was observed to lead to a 50–90 percent decline in transit riders in major metropolitan areas, based on reports from transportation apps such as Transit App, Moovit, and Google (Taylor and Wasserman, 2020; Tirachini and Cats, 2020). Similarly, the COVID-19 pandemic has also significantly affected transportation network companies, such as Uber, and Lyft with up to an 80 percent decline in ridership in the initial months of the pandemic (Walters, 2020).

A key element in the behavioral response to the pandemic has been to work-from-home that has been enabled largely by web technologies (Sakellariou et al., 2021). Historically, there has been extensive research on work-from-home adoption and frequency from a choice modeling perspective. In general terms, probabilities of working from home were found to be a consequence of multiple factors, including demographic, occupational, and attitudinal (Yen and Mahmassani, 1994; Olszewski and Mokhtarian, 1994), and investigations have been conducted through stated preference (Sullivan et al., 1993; Mokhtarian and Salomon, 1994; Mannering and Mokhtarian, 1995; Drucker and Khattak, 2000) and revealed preference surveys (Popuri and Bhat, 2003). While some past studies have looked at telecommuting purely from a univariate descriptive statistics perspective, most studies employed econometric models to understand the influence of demographics, occupational characteristics, and attitudes (Sullivan et al., 1993; Mannering and Mokhtarian, 1995; Popuri and Bhat, 2003). Results from these efforts have been largely mixed, with several studies showing different indications towards potential influences on this phenomenon (Handy and Mokhtarian, 1996; Bélanger, 1999). While the traditional work-from-home/telecommuting literature has provided valuable insights into underlying behaviors, it is worth noting that the current wave of telecommuting, with the onset of COVID-19, has been motivated by necessity as opposed to the evolution of travel/activity behavior.

During the initial months of the pandemic, the analysis of the sentiments regarding work-from-home found that 73 percent of the tweets had positive sentiments about work-from-home (Dubey and Tripathi, 2020). Interestingly, also during the initial stages, different groups of workers started to adopt different measures to promote well-being and activity and some people have also adopted walking and biking as an approach to relax and fight stress (De Vos, 2020; Dutzik, 2020).

In terms of the changing work paradigm, it was found that 44 percent of workers from the Netherlands Mobility Panel study who switched to work-from-home (teleworking), worked more hours from home, or held 30 percent more meetings online (de Haas et al., 2020). Early studies from the United States also indicated a similarly high percentage of teleworkers and virtual services in response to the COVID-19 pandemic (Menon et al., 2020). When asked about their behavior when COVID-19 would no longer be a threat, approximately 90 percent of respondents from a panel study on the mobility of Dutch workers anticipated an increase in out-of-home activities, whereas 27 percent of workers planned to continue working from home (de Haas et al., 2020). The overall impact of telework on reducing travel demand, decreasing congestion, and increasing the use of active transportation modes has been documented by several early-stage studies (Elldér, 2020).

Regarding socio-demographic characteristics, past work has identified that gender, income, education, and children presence all had an impact on work-from-home related behaviors and that highly educated, high-income, and white workers were more likely to shift to working from home and maintain employment following the pandemic (Bick et al., 2020). The same authors also found a relatively greater job loss for women during the pandemic. Budnitz et al. (2020) also used socio-demographic variables along with residential location characteristics to study mobility and telework shifts during COVID-19 pandemic. Yasenov (2020) concluded that lower-wage workers were up to three times less likely to be able to work-from-home than higher-wage workers. Those with lower levels of education, younger adults, ethnic minorities, and immigrants were also concentrated in occupations with tasks that are less likely to be performed from home. Delventhal et al. (2021) studied benefits of work-from-home and found that workers who were able to switch to telework enjoyed large welfare gains by saving commute time and moving to more affordable neighborhoods whereas workers who continued to work on-site experienced modest welfare gains due to lower commute times, improved access to jobs, and the fall in average real estate prices.

Kramer and Kramer (2020), on the other hand, explored the occupational status in context of work-from-home and concluded that challenges for each job sector may be different and each sector can experience varying impacts resulting from the COVID-19 pandemic. The topic of work-from-home and the factors influencing that probability has been explored from various perspectives including, economic, behavioral, mobility, and equity. Although some researchers have studied this topic considering productivity, outcomes, or overall well-being (Wang et al., 2021), the scope of the current paper is to use a mobility perspective to investigate factors influencing commuting trends regarding work-from-home.

Conceptual framework

In the current study, the starting point is the pre-pandemic stage and particularly the workers who did not work-from-home. Next, the switch to work-from-home is investigatedTable 1 and Table 2 (Table 3). Once the workers have switched to work-from-home either willingly or by necessity, a conditional model on the willingness to continue to work-from-home after the pandemic is estimated (Table 4). The main objective is to study factors determining the individuals' willingness to continue to work-from-home and/or return to the workplace after they experience work-from-home during the pandemic (please see Fig. 1 for conceptual diagram of the study).

Exploring the initial state is important to understanding the reality of the pandemic and the fact that every subsequent work arrangement could be dependent on the initial state. Furthermore, the initial state will establish a baseline for potential anchoring effects that will affect final probabilities on the likelihood of adoption of working from home. The framework of accounting for initial states and developing subsequent models that were consequences of prior states was also employed by Sheela and Mannering (2020). The proposed approach will account for how people commuted before the pandemic, investigate the factors determining the switch to work-from-home, and assess the probabilities of remaining in a work-from-home arrangement.

Table 1
Summary statistics for variables included in the final binary random parameters logit model with heterogeneity in the mean of random parameters on switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home.

Variable Description	Mean	Standard Deviation
Socio-demographic characteristics and residential location		
Older respondents (1 if respondent is above 50 years old, 0 otherwise)	0.05	0.22
Young respondents (1 if respondent is below 30 years old, 0 otherwise)	0.67	0.47
Graduate education level (1 if respondent completed graduate education, 0 otherwise)	0.23	0.42
College education level (1 if respondent holds at least bachelors degree, 0 otherwise)	0.53	0.50
Children present in household (1 if children are present in respondent's household, 0 otherwise)	0.42	0.49
Low household income indicator (1 if annual household income is below $25 k, 0 otherwise)	0.15	0.36
Male respondents (1 if respondent is male, 0 otherwise)	0.38	0.49
Rural area indicator (1 if respondent lives in rural area, 0 otherwise)	0.12	0.32
Large city indicator (1 if respondent lives in large city, 0 otherwise)	0.32	0.46
Job types and sectors		
Information technologies (1 if respondent works in information technologies/technical service sector, 0 otherwise)	0.15	0.36
Administration (1 if respondent works in administrative support, 0 otherwise)	0.08	0.27
Marketing (1 if respondent works in marketing/sales, 0 otherwise)	0.04	0.20

Table 2
Summary statistics for variables included in the final binary random parameters logit model with heterogeneity in the mean of random parameters on continuing to work-from-home after COVID-19 pandemic for people who worked from home during COVID-19 pandemic.

Variable Description	Mean	Standard Deviation
Socio-demographic characteristics and residential location		
Young respondents (1 if respondent is below 30 years old, 0 otherwise)	0.53	0.50
Graduate education level (1 if respondent completed graduate education, 0 otherwise)	0.38	0.49
Children present in household (1 if children are present in respondent's household, 0 otherwise)	0.46	0.50
Low household income indicator (1 if annual household income is below $25 k, 0 otherwise)	0.07	0.25
Non-U.S. born respondents (1 if respondent was not born in the U.S. 0 otherwise)	0.06	0.24
Small town indicator (1 if respondent lives in small town, 0 otherwise)	0.17	0.37
Large city indicator (1 if respondent lives in large city, 0 otherwise)	0.34	0.47
Job types and sectors		
Information technologies (1 if respondent works in information technologies/technical service sector, 0 otherwise)	0.26	0.44
Administration (1 if respondent works in administrative support, 0 otherwise)	0.11	0.32

Data

To understand the factors that may influence shifting to work-from-

Table 3
Binary random parameters logit model with heterogeneity in the mean of random parameters on switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home.

Variable description	Parameter estimate*	t-Statistic	Marginal effects
Constant	1.84	11.38	
Socio-demographic characteristics and residential location			
Older respondents (1if respondent is above 50 years old, 0 otherwise)	−1.58	−2.15	−0.004
Graduate education level (1 if respondent completed graduate education, 0 otherwise) (*Standard deviation of parameter distribution*)	1.32(*2.10*)	2.48 (*1.42*)	0.027
Children present in household (1 if children are present in respondent's household, 0 otherwise) (*Standard deviation of parameter distribution*)	−3.68(*4.32*)	−1.71 (*2.41*)	0.020
Low household income indicator (1 if annual household income is below $25 k, 0 otherwise)	−1.42	−3.14	−0.007
Rural area indicator (1 if respondent lives in rural area, 0 otherwise)	−1.21	−2.38	−0.006
Job types and sectors			
Marketing (1 if respondent works in marketing/sales,0 otherwise)	−2.25	−1.86	−0.002
Information technologies (1 if respondent works in information technologies/technical service sector, 0 otherwise)	0.99	3.20	0.017
Administrative/administrative support (1 if respondent works in administrative/administrative support, 0 otherwise)	1.13	3.29	0.012
Heterogeneity in the mean of the random parameters			
Graduate education level: large city (1 if respondent lives in large city, 0 otherwise)	−1.37	−1.99	
Children present in household: college education (1 if respondent has a college education, 0 otherwise)	3.06	1.98	
Children present in household: male gender (1 if respondent is male, 0 otherwise)	−1.33	−1.73	
Number of observations	1275		
Log likelihood at zero, LL(0)	−883.76		
Log likelihood at convergence, LL (β)	−520.13		
$\rho^2 = 1–LL(\beta)/LL(0)$	0.411		

*Parameters defined for work-from-home.

Table 4
Binary random parameters logit model with heterogeneity in the mean of random parameters on continuing to work-from-home after COVID-19 pandemic for people who worked from home during COVID-19 pandemic.

Variable description	Parameter estimate	t-Statistic	Marginal effects
Constant	−0.75	−2.49	
Socio-demographic characteristics and residential location			
Young respondents (1if respondent is below 30 years old, 0 otherwise) (*Standard deviation of parameter distribution*)	−2.04(*1.83*)	−2.75 (*1.44*)	0.034
Graduate education level (1 if respondent completed graduate education, 0 otherwise)	−0.77	−2.35	−0.047
Children present in household (1 if children are present in respondent's household, 0 otherwise)	−0.96	−2.65	−0.070
Low household income indicator (1 if annual household income is below $25 k, 0 otherwise)	2.36	2.68	0.017
Small town indicator (1 if respondent is lives in small town, 0 otherwise)	−0.79	−1.84	−0.019
Large city indicator (1 if respondent lives in large city, 0 otherwise)	0.71	2.09	0.041
Job types and sectors			
Information technologies (1 if respondent works in information technologies/technical service sector, 0 otherwise)	−0.64	−1.85	−0.028
Administrative/administrative support (1 if respondent works in administrative/administrative support, 0 otherwise)	−0.70	−1.53	−0.014
Business (1 if respondent works in business/financial sector, 0 otherwise)	−0.78	−1.52	−0.012
Heterogeneity in the mean of the random parameters			
Young respondents: non-U.S. born respondent indicator (1 if respondent was not born in the U. S., 0 otherwise)	3.12	1.97	
Young respondents: children present in household (1 if children are present in respondent's household, 0 otherwise)	1.57	2.40	
Number of observations	367		
Log likelihood at zero, LL(0)	−254.39		
Log likelihood at convergence, LL (β)	−216.02		
$\rho^2 = 1–LL(\beta)/LL(0)$	0.151		

*Parameters defined for going to continue work-from-home

home during different stages of the COVID-19 pandemic, a web-based stated preference survey was designed, developed, and disseminated to a national panel of United States adults. The initial phase of this study involved a comprehensive review of topics of interest to the data collection effort. While it was important to capture the impact of the COVID-19 pandemic on trip making, activity participation, and travel behavior, it was also important to build the foundation from which these impacts could be best determined. The research team deemed it imperative to understand the public perceptions, opinions, and attitudes to travel, trip-making, and activity engagement in the pre-COVID era to effectively gauge the array of changes that would occur after the onset of the pandemic. Therefore, the web-based survey focused on identifying how people's travel patterns (and needs), residential choices, vehicle ownership, mode choice, use of shared mobility systems, and trip-making/activity engagement, and use of information and communications technology would change considering the global pandemic (see Menon et al., 2020 for more details on the survey and its contents).

The University of South Florida Office of Research Integrity and Compliance processed this study and awarded it "Exempt" from the Institutional Review Board (IRB) review (IRB#: STUDY001076). Upon developing the nationwide survey through Qualtrics, pilot deployments were conducted internally before a final version of the survey questionnaire was administered through a nationwide panel (Prime Panels) in July-August 2020. Prime Panels (also known as Turk Prime) was chosen after a careful review among peer data collection platforms (Amazon Mechanical Turk, Facebook ads, Qualtrics Panels, Prolific Panel). Prime Panels platform has been found to be an effective method for collecting survey data in academic research and has been employed by several studies in the field of transportation engineering and urban planning.

Prime Panels is a web-based survey participant pool that aggregates dozens of market research platforms to give researchers access to survey participants across the United States. With over 50 million Americans in its database, this platform was used to recruit participants for the study.

For the purpose of this project, the authors were interested in a sample that encompassed U.S. adults from all 50 states and Washington D.C. A pilot test of the survey was conducted among the research team's networks with the main purpose of soliciting feedback on the survey questions, and investigating for any textual bias, clarity, and succinctness of the queried aspects. Once the results of the pilot testing were obtained, the research team further modified the survey questionnaire to reflect the feedback obtained and the finalized version was submitted for data collection through Prime Panels. A final usable sample size of 2,432 responses was used for the project. The responses from students living on and off campus were rejected as well as responses from participants whose modal shifts did not fall into the scope of the paper. Additional quality control and assurance procedures were also employed to extract good quality data for further analyses and investigations. Quality control and assurance procedures checks ranged from investigating for premature completion of responses and removing responses that were completed in 8 min or less (the average response time for completing the survey was 16 min). Then, missing entries were analyzed, and where missing entries corresponded to more than one-fifth of the total number of questions, they were removed from the analysis as well. Straight-lining of responses were monitored, and if detected, these erroneous responses were removed from the final sample size. Lastly, any missing entries in any of the variables of interest were also investigated and removed from the survey database leaving the final clean sample size of 1,275 observations.

At the time the survey was conducted, and even today, the exact specifications and characteristics of a post-COVID world are not yet fully known or understood. Therefore, a stated preference survey about hypothetical scenarios would be saddled with a hypothetical bias as has been found in previous literature (Chang et al., 2009; Carlsson, 2010). However, the approach adopted (one with stated preferences and the additional details of a post-COVID travel environment) still provides important initial insights into respondents' intentions for shifting to work-from-home along different stages of the COVID-19 pandemic.

Out of 1,275 respondents, 28.8 percent started work-from-home once the pandemic has begun. Out of these 367 respondents, 50.4 percent indicated the willingness to continue work-from-home, whereas the remaining 49.6 percent of individuals stated that they were planning to return to their workplaces.

provide summary statistics for some key variables of interest in both models. The data from the entire sample (Table 1) overrepresent female respondents (61 percent) relative to their male counterparts. Table 1 also shows that roughly two-thirds (67 percent) of those surveyed were young (below the age of 30), and that 5 percent of the respondents were over the age of 50 years. Close to one-fourth (23 percent) of the respondents possessed a graduate degree, while 28 percent of the respondents lived in households with an annual income of more than \$100,000. Nearly one-third of the respondents (32 percent) owned their homes, and a similar share of respondents (32 percent) lived in a large city and possessed a graduate degree. Lastly, close to 15 percent of the respondents worked in the information technology sector, while marketing and service industry workers each comprised 4 percent.

Methodology

In the current study, random parameters binary logit models with heterogeneity in means and variances were estimated. This approach allows the mean and variance of random parameters to be functions of explanatory variables and thus provides additional flexibility in capturing unobserved heterogeneity. Although this technique is not yet widely applied to travel behavior studies, it has been widely used in studies addressing travel safety and traffic crash outcomes (Mannering et al., 2016; Behnood and Mannering, 2017b; Seraneeprakarn et al., 2017). This method differs from the more frequently used random parameters models that assume the same random parameter mean and variance for all observations. By relaxing this constraint and considering the effects of unobserved heterogeneity in a multivariate context, new insights into the effect of explanatory variables and their impact on the likelihood of working from home can be gained. This way the unobserved heterogeneity in the data can be more effectively captured and deliver findings that would have not been identified otherwise (Mannering et al., 2016). Furthermore, allowing for the heterogeneity in the means and variances of random parameters helps to increase the depth of the analysis and advance the standard approach in the field. In comparing traditional fixed parameters models and random parameters, a likelihood ratio test can be applied with the null hypothesis being fixed and random parameters models fit the data the same. In all of the forthcoming model estimations this likelihood ratio test rejects this null hypothesis with over 99 percent confidence indicating that random parameters models are statistically superior.

Two binary logit models with heterogeneity in means and variances were estimated. The first model investigated the likelihoods of switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home, and the second model estimated the probabilities of the willingness to continue work-from-home after COVID-19 for people who switched to work-from-home during COVID-19 pandemic.

To arrive at an estimable statistical model for the research questions, a function that determines the probability of either switching to work-from-home for respondents who did not previously work-from-home or the willingness to continue to work-from-home for respondents who started working from home during COVID-19 pandemic is defined as,

$$\mathrm{F}_n = \beta \mathbf{X}_n + \varepsilon_n \tag{1}$$

where $\mathbf{X}_n$ is a vector of explanatory variables that affect the probability of observation n being a respondent who switched to work-from-home or is planning to work-from-home after the pandemic, β is a vector of estimable parameters, and ε_n is a disturbance term. If the disturbance term is assumed to be generalized extreme-valued distributed, a binary logit model results as (McFadden, 1981),

$$\mathrm{P}_n(\mathrm{w}) = [1 + EXP(-\beta \mathbf{X}_n)]^{-1} \tag{2}$$

where $\mathrm{P}_n(\mathrm{w})$is the probability of the respondent n switching to work-from-home during COVID-19 pandemic when they did who did not previously work-from-home or probability of the willingness to work-from-home after COVID-19 pandemic if they worked from home during the pandemic.

To account for the possibility that one or more parameter estimates in the vector β may vary across respondents due to unobserved heterogeneity, a distribution of these parameters can be assumed, and Equation (2) can be rewritten as (see Washington et al., 2020)

$$\mathrm{P}_n(\mathrm{w}) = [1 + EXP(-\beta \mathbf{X}_n)]^{-1} f(\beta|\varphi) d\beta \tag{3}$$

where $f(\beta|\varphi)$is the density function of β, φ is a vector of parameters describing the density function (mean and variance), and all other terms are as previously defined. With this definition random parameters logit model is defined (see Mannering et al., 2016, for a description of alternate methods of accounting for unobserved heterogeneity).

To account for the possibility of the mean and variance of individual parameters to be a function of explanatory variables where β_n is defined as Equation (4), (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017a)

$$\beta_n = \beta + \theta_n \mathbf{Z}_n + \sigma_n EXP(\omega_n \mathbf{W}_n) \varphi_n \tag{4}$$

where β is the mean parameter estimate, $\mathbf{Z}_n$ is a vector of explanatory variables that influence the mean of β_n, $\theta_n$is a vector of estimable parameters, $\mathbf{W}_n$ is a vector of explanatory variables that captures heterogeneity in the standard deviation σ_n, $\omega_n$is the corresponding parameter vector, and φ_n is a randomly distributed term that captures unobserved heterogeneity across respondents.

Both models were undertaken by simulated maximum likelihood approaches using 1,000 Halton draws as they can deliver more efficient distribution of simulation draws than purely random draws (McFadden and Ruud, 1994; Bhat, 2003). Just like in other studies in travel behavior to achieve the most superior estimation, the normal distribution was assumed for random parameters (Menon et al., 2019; Barbour et al., 2020). Marginal effects were calculated (averaged over all observations) to determine the effect that individual explanatory variables have on response probabilities. The marginal effect of an explanatory variable gives the effect that a one-unit increase in an explanatory variable has on the response probabilities. For indicator variables (that assume values of zero or one), marginal effects will give the effect of the explanatory variable going from zero to one (Washington et al., 2020).

Estimation results

Table 3 presents the results of binary random parameters logit model with heterogeneity in the means of random parameters on switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home, and Table 4 presents the results of a binary random parameters logit model with heterogeneity in the means of random parameters for continuing to work-from-home after the COVID-19 pandemic for people who started working from home during COVID-19 pandemic. In the estimation of both models, heterogeneity in the variances was not found to be statistically significant, so both models only include heterogeneity in the means. Also, during model estimation, consideration was given to the possibility of correlated random parameters (Washington et al, 2020), but allowing for possible correlation did not significantly improve the log-likelihood function at convergence, so both model estimations have the commonly used uncorrelated random parameters. Tables 3 and 4 indicate that the overall statistical fit of the models is good as indicated by the ρ^2 statistic.

A total of 1,275 observations were used in estimating the first model (Table 3) and 367 observations (the 28.8 percent of the 1,275 people who were observed to switch to work-from-home during the pandemic) were used in estimating the second model (Table 4). Only variables that significantly improved the likelihood function at convergence (with over 90% confidence using a likelihood ratio test) were included in the model. All random parameters were found to be normally distributed since other tested distributions did not produce significantly better results.

The variables in each model were divided into two categories; first category included the socio-demographic and residential location variables while the second one indicated job types and sectors of respondents' employment. A wide variety of variables was found significant in all models namely age, education, gender, education level, income, residential location type, and job types, among others.

Socio-demographic characteristics and residential location

Starting with socio-demographic characteristics, it was found that age played a significant role in making shifts to work-from-home during the pandemic. Respondents who were above 50 years old and did not previously work-from-home were found to have a 0.004 lower probability of starting to work-from-home during the pandemic compared to their younger counterparts (Table 3), perhaps reflecting some hesitancy among older people or being uncomfortable with remote technologies due to adjustments required in displaying and consuming information (Brem et al., 2021). Once working from home during the pandemic, age had a more complex effect on the likelihood of continuing to work-from-home after the pandemic. For this, Table 4 shows that younger respondents (below 30 years old) were more likely to continue to work at home (an average marginal effect of 0.034) but that this effect varies across the population of younger respondents (as indicated by the statistically significant random parameter). This suggests considerable heterogeneity in this group that is influenced by country of origin (respondents who indicated that they were not born in the United States) and the presence of children in the household, both of which increased the mean of the young respondents' random parameter and thus their likelihood of continuing to work-from-home (the effect of children will also be accounted for in other variables in the model as well).

For the probability of working from home during the pandemic, respondents who indicated having a graduate-level education had a higher likelihood of shifting to work-from-home during the pandemic (an average marginal effect of 0.027), but there was significant heterogeneity in this group as indicated by the statistically significant random parameter (Table 3). This finding is consistent with prior studies that found that higher education level plays a role in being able to easier accommodate work-from-home (Bick et al., 2020). However, the variation across respondents for this education variable is also influenced by location with respondents living in large cities having a lower mean making them less likely to shift to work-to-home during the pandemic (Table 3).

Regarding continuing to work-from-home post-pandemic (Table 4), respondents who had a graduate education and switched to work-from-home during the pandemic had 0.047 lower probability to continue to work-from-home (Table 4). Although as Bick et al. (2020) have concluded that higher education makes it easier to work from home, it was found that respondents with graduate degrees, who moved to work-from-home during the pandemic, will be less likely to continue work-from-home after the pandemic than their non-graduate degree counterparts.

As anticipated, household composition, and particularly the presence of children, played a role in COVID-19 related work-from-home probabilities. Children in households have been shown to impact travel behavior and mode choice in studies before the pandemic (Dias et al., 2017; Barbour et al., 2019), and the presence of children during and after the pandemic will clearly affect work-from-home probabilities. The estimation results in Table 3 show that the presence of children increased the likelihood of working from home during the pandemic (with an average net marginal effect of 0.020), but that there was significant heterogeneity in this effect across the population as indicated by the statistically significant random parameter. The mean of the random parameter was found to be influenced by college education (with college education increasing the mean and thus the likelihood of working from home during the pandemic when children are present) and by the male indicator (with men having a lower mean and thus decreasing the likelihood of working from home during the pandemic relative to females when children are present). The parameter indicating children present in the household was also significant in the probability of continuing to work-from-home after the pandemic, as shown in Table 4. Here, having children make respondents less likely to continue to work-from-home during the pandemic (the marginal effect is −0.070). This finding likely reflects the expectation that children will return to school post-pandemic and resume normal out-of-home activities which would make participating in work activities at the workplace less onerous.

Respondents with low annual household income (below $25,000) who did not work-from-home before were found to have a significantly lower probability to begin work-from-home after the pandemic started (Table 3) as well as a higher probability to continue work-from-home (by 0.017 as indicated by marginal effects in Table 4). This indicates that more permanent work-from-home could be an appealing proposition for lower-wage respondents who experienced work-from-home during the pandemic, either by choice or necessity. As prior studies suggest, the trend is that most of the surveyed people intended to return to work (de Haas et al., 2020), however when accounting for unobserved heterogeneity in a multivariate context as was done in this study, the actual effect attributable to income is mitigated by other statistically significant factors.

Interestingly, gender was found to have no direct impact on the dependent variables in either estimation. However, it is worth emphasizing that the male indicator produced a statistically significant effect on the mean in one random parameter in the probability of working from home during the pandemic, which is children present in the household (Table 3). As discussed above, male respondents with children present in their household had a decrease in their mean, meaning they were less likely to start working from home during the pandemic (relative to females). Prior studies on this topic have also found that there are substantial differences in how different genders experience the shift to work-from-home (Kaur and Sharma, 2020).

All residential location data was self-reported by respondents with choices being a large city, suburb near a large city, small city or town, and rural area. Work-from-home in geographic contexts relating to cities and neighborhoods has been also considered by prior studies. Zenkteler et al. (2019) found strong evidence of home-based workers' preferences for neighborhoods that integrate residential amenities with place-making initiatives to enhance economic performance, networking, and collaboration, while Mokhtarian et al., (2004) concluded that telework is an important factor in locational decisions (in a study of workers from California, U.S.).

Current work confirms this relationship. As indicated by the marginal effects, respondents who indicated living in rural areas and did not work-from-home before COVID-19 pandemic, were found to have 0.006 lower probability to work-from-home during the pandemic (Table 3). As shown in Table 4, respondents who lived in large cities were found to have a 0.041 higher probability of continuing to work-from-home post-pandemic whereas respondents from small towns had a 0.019 lower probability as indicated by the marginal effects. It could be speculated that these findings reflect heterogeneity in traffic patterns and mobility options in large and small cities as well as rural areas, which could be a contributing factor to the varied behavior among the respondents. Furthermore, because public transit is available in large cities, fear or infection could be the leading argument used by the workers who were found to prefer to continue to work-from-home.

The impacts of job sectors

As identified in prior studies (before and during COVID-19 pandemic) working in a particular job sector has a substantial impact on the possibility and willingness to work-from-home (Popuri and Bhat, 2003; Kramer and Kramer, 2020). Understandably there is an inherent tendency in all sectors to return to workplaces, even after switching to work-from-home during the pandemic, as firms and workers seek to return to well-established and known methods and productivity assessments. Even workers from information technology and administrative sectors who had a higher probability of starting to work-from-home during the pandemic were found to also have a higher probability of being willing to return to their workplaces after the pandemic.

Looking at the influence of job sectors on working from home during and after the pandemic, Table 3 shows that respondents who indicated working in marketing or sales sectors and did not work-from-home before the pandemic were found to have a lower probability to start working from home, likely reflecting the nature of this specific job sector and the effectiveness in working traditionally.

Workers in the information technology sector who did not work-from-home before the pandemic were found more likely to switch to work-from-home during the pandemic as indicated by marginal effect of 0.017 (Table 3). However, as shown by the marginal effects in Table 4, information technology workers who also worked from home during the pandemic were found to have a lower probability of continuing work-from-home after the pandemic. This finding likely reflects the difference between the necessity and preference of workers from this sector.

Administrative/administrative support workers who did not work-from-home before the pandemic were found more likely to switch to work-from-home during the pandemic as indicated by marginal effect in Table 3. And, like the behavior of respondents from the information technology sector, they also had a lower probability of continuing to work-from-home after the COVID-19 pandemic (as indicated by the 0.014 marginal effect in Table 4).

Finally, as the estimation in Table 4 shows, the respondents from the business/financial sector who started working from home during the pandemic were less likely to be willing to continue with that arrangement. As indicated by the marginal effects, they were found to have 0.012 lower probability of working from home in the post-pandemic world.

Conclusions

The current paper sought to identify significant variables during shifting to work-from-home and the willingness to go back to the workplaces during different stages of the pandemic. From a methodological perspective, the data were analyzed with a focus on different state changes during the COVID-19 pandemic. In the estimated random parameters logit models, many variables were found to be statistically significant, and some were found to exhibit heterogeneous effects across observations, with the means of the random parameters also being a function of explanatory variables.

The overall findings are mostly consistent with prior studies and have confirmed that the permanent switch to work-from-home may be challenging (Menon et al., 2020). Two classes of variables were found significant: socio-demographic/residential location variables and job-sector variables. Each class delivered insights and allowed a better understanding of how different factors impacted work-related behaviors and teleworking. Although older respondents (above 50 years old) had a lower probability of starting to work-from-home during the pandemic, younger respondents (below 30 years old) exhibited a heterogeneous behavior when stating their willingness to continue work-from-home. This willingness was found to be impacted by their nationality (U.S. born individuals) and their household composition (children present). Respondents with a graduate education who did not work-from-home before the pandemic were found to have a heterogenous behavior that was impacted by living in a large city. Interestingly, while low-income respondents (under $25,000 annually per household) were likely to have a lower probability of starting to work-from-home, they were found to have a higher probability to continue to work-from-home after the pandemic (a finding revealed by the conditional nature of the results in Table 4 and the heterogeneity accounted for in the methodology). This finding could reflect an opportunity for lower-wage sectors to consider remote work for their employees. Lastly, a variable capturing children present in the household was found to be statistically significant in two models (Tables 3 and 4) and exhibited heterogeneous behavior across the population regarding the likelihoods of starting to work-from-home during the pandemic by producing statistically significant heterogeneity in the mean which was influenced by gender and education.

The results were able to uncover some complexities in work-from-home relating behaviors and could be used for policy formation and further research. Regarding policy, a few key findings relating to job sectors are worthy of note. Although workers from job sectors such as administration/administrative support, business, and information technology could, in theory, work remotely, they all had a higher probability of returning to their workplaces after working from home during the pandemic. This suggests that encouraging permanent shifts to work-from-home is not an easy proposition, and multiple incentives may be needed to successfully encourage continuing to work-from-home. Based on the model estimation results contained herein, policies to encourage or discourage work-from-home should be made with consideration to residential location and should be location-specific. The results shown in Table 4 concluded that respondents who lived in large cities were found to have a higher probability of continuing to work-from-home post-pandemic while respondents from small towns had lower probability to do so. The above findings suggest that recognizing these differences in behavior and preference is essential for policy formation and planning.

Model estimation results also show that the variable reflecting children present in the household has rather complex heterogeneous effects across the population. As prior studies have confirmed (Dias et al., 2017; Barbour et al., 2019), accounting for children in travel behavior studies as well as policy formation is essential. Although, to some degree, aligned with prior research (Bick et al., 2020) that has indicated the switch for lower income workers to work-from-home being more difficult, the conditional findings (conditioned on shifting to work-from-home during the pandemic) show these workers being more willing to continue work-from-home which consequently could mean an opportunity for creating lower income jobs that are remote. Lastly, it is found that about 50 percent of the respondents who undertook work-from-home during the pandemic indicated the willingness to continue work-from-home. In the extant literature, there is considerable uncertainty about transitioning from work-from-home post-pandemic, with de Haas et al. (2020) concluding that only 27 percent of their respondents indicated their willingness to work-from-home past the pandemic and Abdullah et al. (2020) indicating that most of the employees prefer working from home even though they could go back to their workplaces. The discrepancies in these numbers could be particularly significant in the context of estimation methods and accounting for experiences the work-from-home arrangements. The current paper broadens this analysis by accounting for the fact that once an individual experiences certain phenomenon, their perception towards it may change.

Although the study has incorporated advanced statistical methods and a detailed and comprehensive data collection process, the work has some limitations. The data were collected a few months after the pandemic began; therefore the responses could have changed since then and the respondents could shift their preferences towards the willingness to work-from-home resulting in a reality that may not be reflected in their stated preferences (the temporal instability of preferences and behaviors has been well established in many fields, see Mannering, 2018). Furthermore, the literature from other disciplines suggests that whether an individual decides to work-from-home depends on multiple factors such as perceived productivity, output, or overall well-being (Wang et al., 2021), but the current paper does not address these factors directly due to the difficulty in gathering such information, and instead accounts for them as unobserved heterogeneity in the context of observable factors relating to socio-demographics, residential location, and job-sector variables. Explicitly including these tadeonal factors would improve the precision of model estimates.

CRediT authorship contribution statement

Natalia Barbour: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Nikhil Menon:** Project administration, Funding acquisition, Data curation, Writing - original draft, Writing - review & editing. **Fred Mannering:** Conceptualization, Methodology, Funding acquisition, Data curation, Writing - original draft, Writing - review & editing.

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.

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Author contribution

Natalia Barbour contributed to designing research question, data analysis, and interpretation of the results. Nikhil Menon designed the survey, collected the data, and assisted with organization and development of this manuscript. Fred Mannering contributed to designing the conceptual framework and statistical and econometric analysis. All authors took an active role in writing and preparation of this manuscript.

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