FINAL REPORT

Analysis of teleworkers' experiences, adoption evolution and activity patterns through the pandemic

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16. Abstract

The COVID-19 pandemic significantly altered the remote work landscape in the U.S. and there is growing evidence that at leastsome portion of the remote work trends will stick beyond the pandemic. However, there are many unanswered questionsregarding the individual experiences with telework through the pandemic, the evolution of remote work through the pandemicand the potential interaction of remote work with the activity participation behavior, which will have implications for future urbanand transportation planning decisions. In this report, we present three studies focused on gaining a deeper understanding ofteleworkers' experiences, adoption evolution through and beyond the pandemic, and their activity participation behavior. In thefirst study, using data from a U.S. representative sample of 318 working adults, we use a Multiple Indicator Multiple Cause Model(MIMIC) to understand employee satisfaction with telework, which will potentially shape telework adoption decisions beyond thepandemic. In the second study, we undertake a trajectory clustering analysis to reveal and characterize clusters of teleworktrajectories through and beyond the pandemic. Using agglomerative hierarchical clustering we identify four clusters of teleworktrajectories with distinct adoption of telework patterns and then used cluster membership modeling to understand occupationaland socio-demographic factors associated with these trajectories. We also present a set of binary and ordered probit models toproject telework patterns in April 2024, four years since the beginning of the pandemic. Lastly, we study the effect of telework of747 working adults on their activity participation behavior. The three main questions of interest include: What is the effect oftelework on the duration spent on out-of-home non-work activities? Does telework increase or decrease the average distancetraveled from home to reach out-of-home non-work activities? Is there a telework effect on the time of day chosen to engage inout-of-home non-work activities?

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Contents

Executive Summary

The COVID-19 pandemic significantly altered the remote work landscape in the U.S. and there is growing evidence that at least some portion of the remote work trends will stick beyond the pandemic. However, there are many unanswered questions regarding the individual experiences with telework through the pandemic, the evolution of remote work through the pandemic and the potential interaction of remote work with the activity participation behavior, which will have implications for future urban and transportation planning decisions. In this report, we present three studies focused on gaining a deeper understanding of teleworkers' experiences, adoption evolution through and beyond the pandemic and the activity participation behavior.

The first study recognizes that the pandemic experience offers a unique opportunity to examine employees' experiences and perceptions of telework given the broad participation, duration and extent, and as such could provide an understanding of the future trajectory of telework adoption. While employer strategies will play a major role in defining the future forms and adoption of telework, employee preferences and constraints, such as access to appropriate technology to work from home or the home environment, are also going to be important factors. Using data from a U.S. representative sample of 318 working adults, in this study we use a Multiple Indicator Multiple Cause Model (MIMIC) to understand employee satisfaction with telework. The presented model links telework satisfaction with experienced and perceived benefits and barriers related to telework, and hence provide a causal structure to our understanding of telework satisfaction. Also presented is an ordered probit model without latent variables that helps understand the systematic heterogeneity in telework satisfaction across various socio-demographic groups.

Three important take-aways emerged from the presented analysis. First, benefits and barriers to telework are disproportionately distributed across age groups. Specifically, the results suggest that telework satisfaction was higher for middle aged individuals compared to younger and older individuals. For younger individuals, this may be related to loss of networking opportunities that they need to advance in their careers or maybe related to the younger individuals mostly being employed in jobs that are not suitable for telework. For older individuals, the issue might be related to workplace anchoring, difficulty of managing their teams in more senior positions, and possible technology limitations in performing usual work activities. A second important finding is the evidence for inequity along the lines of racial/ethnic identity. Third, the presence of children attending online school is a consistently important factor impacting telework satisfaction.

From a policy standpoint, the findings suggest several implications for employers and policy makers in planning for the pandemic and post-pandemic periods. For employers who plan to adopt a hybrid or remote workplace in the long run, our study highlights several core factors that shape barriers and benefits of telework that can be used for communication and promotion of future efforts (e.g., the benefits of commute time savings). Furthermore, the causal structure of the model reveals the diverse experiences of different employer segments with regard to barriers and benefits. These insights can be

used to design worker support strategies (e.g., on-site school/day-care pods assisting with challenges of inconsistent schooling access). If remote work were to become a norm at least for positions or tasks where physical presence is not necessary, employers must ensure support that is mindful of the diverse experiences and circumstances of workers, including the more complex non-linear effects such as those related to worker age. For younger employees. employers could alleviate these by creating an environment to facilitate networking opportunities like organizing mandatory on-site days at regular intervals or hosting online networking hours. For older individuals who might perceive high barriers and lower benefits to teleworking potentially due to difficulty with technology, employers must invest in providing technology support. Concerns about social isolation, especially for workers for whom work provides an important environment for social interaction may also need to be addressed.

On the other end, if employers opt to have an in-person/office-centric plan for the future, creating a safe working environment will be important to phase in the return to the office since our results indicates a positive relationship between telework satisfaction and COVID-19 related worry. This could potentially be achieved by clear policies on social distancing, masking, and vaccination. As employers seek to determine the appropriate mix of telework and in-person presence, the factors identified in this study could assist in bringing out the positive features of each mode while mitigating some of the negative aspects. As a broader implication for public agencies planning for transportation and other infrastructure, it is important to thoroughly gauge the extent to teleworking in the post pandemic era, since basing future policies solely on trends during the pandemic could be erroneous.

In the second study, a trajectory clustering analysis is undertaken to reveal and characterize clusters of telework trajectories through and beyond the pandemic. Specifically, using agglomerative hierarchical clustering, four clusters of telework trajectories with distinct adoption of telework patterns are identified. Cluster membership modeling is then used to understand occupational and socio-demographic factors associated with these trajectories. A set of binary and ordered probit models are also presented to project telework patterns in April 2024, four years since the beginning of the pandemic. This analysis improves understanding of the factors that will likely govern the future remote work trajectory and the potential impact these emerging patterns will have on urban mobility.

A few key insights emerged from the cluster membership model. First, trajectories of telework through the pandemic are highly associated with nature of the job in which one is employed. For instance, those in transportation/warehousing sector were more likely to have higher in-person work compared to much higher at-home work for those in the information sector. The results also suggested lower telework adoption amongst those who are younger and those who are students and higher remote work for those without a vehicle. Further, those in urban households were more likely to present in clusters 2 or 3 where some form of hybrid work arrangement is expected going forward. From the April 2024 work location models, key insights include presence of higher uncertainty amongst female respondents, students and those who were in cluster 4 (high telework through the pandemic) and lower uncertainty amongst those with a graduate degree. Finally, the ordered probit model for April 2024 work location for those who are certain suggests higher in-person work for transportation, healthcare and education sectors and lower in-person work for information, finance/insurance and professional services sectors. Further, the model also suggests higher in- person work for students and younger individuals, and those with higher education degrees but lower for those without a vehicle, those in lower income groups or those with age greater than 65 years.

There are several important policy takeaways from these results. There is strong evidence for telework to stay beyond the pandemic and this might have several implications for urban cities. The results from the clustering analysis suggest that some form of telework is expected to persist in the future for about 75% of the individuals and it is likely to be more amongst those without a vehicle and those living in urban areas and those working in information or related sectors. Given that most transit users are in urban areas and less likely to have access to a vehicle, telework trends in the future may significantly impact transit revenue which may further deteriorate service quality in the longer term, especially for those who really need it. Reduced demand due to telework might also hurt local businesses like coffee shops in downtown areas and business districts and policy makers need to plan how to alleviate the adverse impact of these changing trends on cities. Lastly, given that the information sector is likely to be more remote going forward, these trends will likely have high impact on cities with higher share of information sector jobs like San Francisco.

Lastly, the third study investigates the effect of telework on the activity participation behavior using activity diary data from 747 working adults in the U.S. The three main questions asked are: What is the effect of telework on the duration spent on out-of-home non-work activities? Does telework increase or decrease the average distance traveled from home to reach out-of-home non-work activities? Is there a telework effect on the time of day chosen to engage in out-of-home non-work activities?

A Tobit regression model is used to study the effect of telework on the total duration spent on out-of-home activities and the effect of average distance between home and out-of-home non-work activity locations. A binary logit model examines the effect of telework on the decision to participate in out-of-home activities. A multinomial logit model is developed to study the effect of telework on choice of time of day to engage in out-of-home non-work activities.

Main findings for this study include significantly shorter out-of-home non-work trips (in terms of trip distance) and shorter out-of-home activity duration by teleworkers compared to those who do not telework. Furthermore, those who telework were less likely to perform out-of-home non-work activities and those who do so were performing these at more during 9 AM to 3 PM or 6-9 PM, compared to other times of the day. These results have important implications for future urban and transport planning decisions since it is expected that a significantly larger share of population will have the ability to telework in the future compared to the -pandemic.

Chapter 1

For Whom Did Telework Not Work During the Pandemic? Understanding the Factors Impacting Telework Satisfaction in the US Using a Multiple Indicator Multiple Cause (MIMIC) Model

Introduction

One of the most impactful transformations triggered by the COVID-19 pandemic is the massive transition of employees and businesses to work from home. According to a U.S. survey conducted by Pew Research in October 2020 (Parker et al., 2020), while only 20% of working adults reported working from home before the pandemic, the number of working adults that reported working from home during the pandemic had grown significantly to 71%. A key finding from this study is that workers were highly divided: only 54% of working adults would like to work from home once the pandemic is over. This finding is significant; while several studies (Ollo-López et al., 2020; Tavares, 2017) have shown positive impact of the option to telework and of actual telework, the experience from the pandemic has been mixed for many. Thus, the extent of continued future adoption of telework when it is an available option remains an open question for employers and policy makers in a post-pandemic world. On the positive side of the argument, we note that the resources that corporations have spent during the pandemic to make teleworking easier, increased schedule flexibility, and inclusion aspects of telework may permanently change the way Americans expect to work, and this may lead to maintaining high levels of telecommuting (Bjursell et al., 2021; Igeltjørn and Habib, 2020). On the other hand, the current level of adoption may not be sustained in the wake of growing evidence related to decline in innovation and productivity (Miglioretti et al., 2021; Song and Gao, 2020) and lack of clearly defined boundaries between work and private life (Lewis, 2017; Pluut and Wonders, 2020). This is further complicated by the fact that the pandemic forced organizations to suddenly adopt remote work, sometimes without providing employees with the necessary skills and support to thrive in the remote work environment (Errichiello and Pianese, 2021).

While we note that employer strategies will play a major role in defining the future forms and adoption of telework, employee preferences and constraints, such as access to appropriate technology or environment to work from home, are also going to be extremely important factors. Overall, there is consensus that different remote work models will persist and that hybrid forms of work will be sustained post COVID-19 pandemic (Gurchiek, 2021). Yet, there is a need for further research to understand employee perceptions, barriers and assets related to remote work, as well as the variation among different employee groups. The resulting behavioral insight will be an important input to establishing the forms and strategies to maintain productivity, worker well-being and company culture in a remote work world.

The broad and durable nature of telework adoption during the pandemic across sectors and user-groups presents a rare and unique opportunity to study telework. Most studies prior to the pandemic treated teleworking as a choice, part of an intentional telework program from the employer's end. Instead, analysis of remote work in the COVID-19 era needs to account for the fact that the pandemic broadly forced employers and workers to adopt telework for an extended period except for individuals for whom onsite presence was essential.

In past research, telework has been considered as a means to reduce congestion and the environmental impact of the transportation sector for several decades (Choo et al., 2005; Gareis and Kordey, 1999; Irwin, 2004; Lari, 2012; Larson and Zhao, 2017; Matthews and Williams, 2005; Mokhtarian et al., 1995). Employee telework adoption has been tied to schedule flexibility (Shabanpour et al., 2018), worker age and educational attainment (Noonan and Glass, 2012; Walls et al., 2007), and interaction with the employer's expectations (Brewer and Hensher, 2000). In terms of attitudes, telework adoption preferences are linked to both constraints (family effects, commuting, job suitability) as well as opportunities (interaction with co-workers) (Mokhtarian and Salomon, 1997; Yen and Mahmassani, 1997)

A comprehensive understanding of the long-term viability of remote work and related spatially and temporally flexible work arrangements is still taking shape (Nayak and Pandit, 2021; Salon et al., 2021b), and many of the earlier findings may need to be revisited in this new context. For example, earlier research suggests that attitudes may be more consistently important than sociodemographic status like presence of children (Mokhtarian and Salomon, 1997). Among the unique features shaping the COVID-19 telework situation is the frequent occurrence of multiple members of the same household teleworking simultaneously, including children attending school online. Overlapping telework arrangements potentially impose resource, time, and space restriction on individuals and increased work-life conflicts.

In light of the above discussion, this study is focused at understanding the systematic heterogeneity and factors associated with telework satisfaction during the COVID-19 pandemic amongst a representative sample of working adults in the United States. We use data regarding self-reported telework satisfaction ratings, responses to several other questions related to benefits of and barriers to teleworking, and socio-demographics and contextual variables from a survey with *318 working adults*. We employ a *multiple indicator multiple cause* (MIMIC) model capable of measuring both the direct and indirect impact (via the latent factors) of socio-demographic information on telework satisfaction, hence providing a causal structure to our understanding of the drivers of telework satisfaction. Our methodology relates telework satisfaction with the perceived/experienced benefits of and barriers to telework and thus helps in identifying factors that may impact telework frequencies in the future. It is known from prior work that satisfaction acts as an antecedent to future behavioral intentions (Allen et al., 2020; Bukhari et al., 2013; de Oña, 2021a, b; Oliver, 1980; Oliver and Linda, 1981; Wang et al., 2020). A common structure in adoption studies is to frame use intentions from the perspective of perceived benefits and barriers, which, in turn, are driven by experiences (Ajzen, 1991; Kadir et al., 2019; Meroño-Cerdán, 2017; Pérez et al., 2002; Van Horn and Storen, 2000; Zunft et al., 1999).

Given the novelty of the setting in which telework is experienced by workers, our chosen approach is to frame the MIMIC modeling around the identification of two latent variables: benefits and barriers. This underpins the three main contributions of this work, namely: defining benefits/barriers of remote work in the unique circumstances of the pandemic, revealing casual structures stemming from the experience during the pandemic, and finally uncovering the systematic differences by respondent features and household status. These findings can help employers determine how to balance employee well-being and aspirations for work flexibility, while maintaining innovation and productivity. More broadly, insights about remote work intentions can aid urban and transport planners in making decisions related to mobility provision and urban design.

The rest of the study is structured as following. Next section presents the data available for this study, details of the conducted survey, and descriptive statistics of socio-demographic and attitudinal variables. This is followed by the mathematical formulation of the ordered probit and MIMIC models. Estimation results are presented next and is followed by summary, policy implications, and limitations of this study.

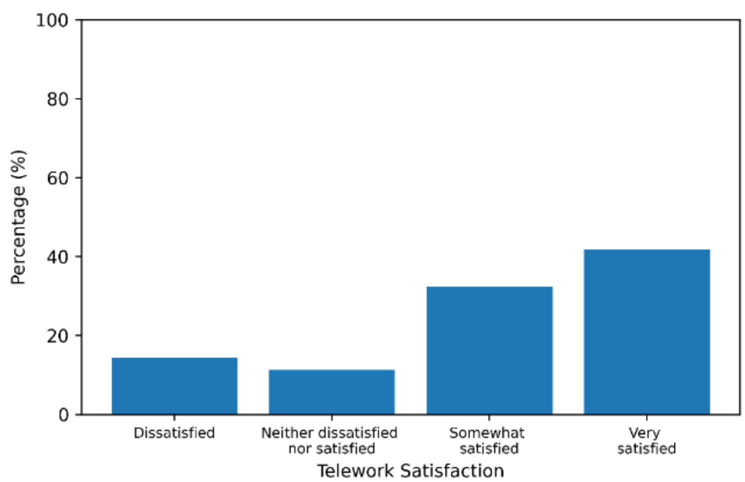

Figure 1 Distribution of reported telework satisfaction in the data

Data

Survey

The data used in this study comes from wave 5 of a 6-wave longitudinal online survey conducted between December 22, 2020 and March 08, 2021 in the United States, using Prolific's panel of individuals aged 18 years or older (Palan and Schitter, 2018). A representative sample in terms of age, gender and ethnicity was recruited using a specialized filter. Although the survey was longitudinal, the data in this survey is extracted from a single wave in the series that focused on telecommuting experiences collected between

February 22 and February 28, 2021. A detailed description of the survey design and response rate of the full longitudinal survey can be found in Tahlyan et al. (2022b). The telework satisfaction and other related experience and perception questions, which are of primary interest to this study, were presented to 318 working adults and students in the survey. These questions were not asked to individuals who were either retired, out of work or unable to work and hence were excluded from this analysis.

Available Variables in the Data

Telework Satisfaction Rating Data

On a 5-point Likert scale (*very dissatisfied* to *very satisfied*), individuals with full-time or part-time employment status and those who have not been working from an office in the past week (i.e. workers with at least some experience of working from home recently) were asked to rate their level of satisfaction with their telework experience using the following question: *"How satisfied are you with your experience of working from home?"* Individuals who are employed but have been working exclusively from an office (i.e., workers with no *recent* experience of working remotely) were instead asked to rate their expected level of satisfaction with teleworking in a hypothetical scenario[1] where telework is a viable option using the following question: *"Imagine you were asked to work from home. How satisfied do you think you would have been working from home?"* Similar questions were asked to students with recent or no experience of working from home in the context of *"attending classes from home"*. In the telework satisfaction rating data, merely 2.52% (8 respondents) of the 318 individuals responded that they were or would have been *very dissatisfied* with teleworking. Hence, we converted the 5-point response scale to a 4-point scale by combining the "very dissatisfied" and "somewhat dissatisfied" response categories. Figure 1 shows the distribution of reported telework satisfaction with about 74.21% individuals reporting they were or would have been somewhat or very satisfied with telework. This 4-point satisfaction response item is eventually used in the presented models as a dependent variable.

Telework related experience, perception, and contextual data

The study included questions on telework perceptions, experiences and other contextual variables related to household factors and COVID-19 concerns. This data was also collected for cases where telework was not an available option, such as essential workers. Questions asked to the respondents and the response distribution is presented in Table 1. Although the variables shown in Table 1 were measured on a 4- or 5-point scale, they were recoded to binary variables to reduce the complexity of estimated models, given

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[1] From the data available to us, it is difficult to say whether this was truly a hypothetical scenario or not since the question specifically asked about work location in the "recent" weeks and no particular time frame was provided. It is possible that the respondent did telework in the early period of the pandemic or may have telework experience prior to the pandemic. Further, the hypothetical scenario version of the question was presented to 78 out of 318 respondent and almost all of them were working exclusively on-site due to employer mandates (i.e., working from home was not an available option). Lastly, 59 of 78 individuals were essential workers.

the relatively small sample size[2]. As observed, a significant proportion of individuals did not agree with potential benefits related to telework like productivity gains or quality of life improvements. These findings are in line with the findings by the survey conducted by PwC (2021) in December 2020 in the U.S., however, it contrasts with the research by Baert et al. (2020) in Belgium where respondents mainly attribute positive characteristics to telework. These differences likely reflect the dynamic nature of telework experiences during the pandemic where while early experiences with telework were largely positive but more recent studies suggest a mixed experience. Furthermore, only about 15% of individuals reported lack of technology being a hindrance to telework given that the required technologies like a laptop or a webcam or access to internet have a significantly high market penetration in the U.S.

TABLE 1 Distribution of telework related experience, perception, and contextual data

Indicator/Statement	Abbreviated Variable Name	Disagree	Agree
*I have been / would be more productive working from home.	Work productivity gains	55.0%	45.0%
Not needing to commute to work has improved / would improve my ability to work from home.	Time savings due to not needing to commute	28.6%	71.4%
The option to work from home has improved / would improve my quality of life.	Quality of life improvements	36.2%	63.8%
Lack of technology like a laptop or a webcam has / would hinder my ability to work from home.	Lack of appropriate technology	85.2%	14.8%
Distractions from other household members have / would hinder my ability to work from home.	Distraction from other household members	61.6%	38.4%
Indicate who determines their work location: the employer; there is partial flexibility in the determination of work location; or if there is complete flexibility.	Work location flexibility	57.8%	42.2%
Indicate level of suitability of the respondent's job to remote work: not suitable at all; somewhat suitable; mostly suitable; very suitable.	Job's remote work suitability	45.0%	55.0%
Indicate level of worry (on a 4-point scale of not at all to very worried) about potentially contracting the COVID-19 virus.	Worried regarding contracting COVID-19	61.6%	38.4%

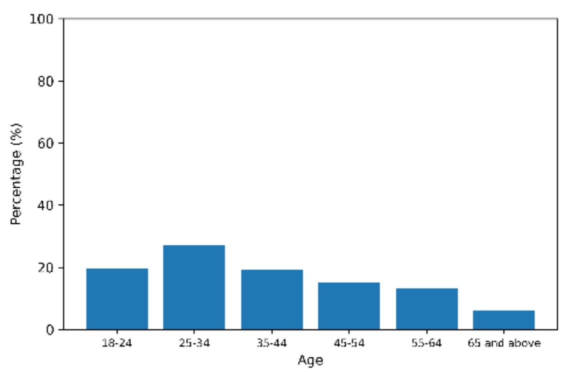
*First five statements measured on a 5-point Likert scale (strongly disagree to strongly agree)

[2] The 5 statements on a 5-point Likert scale were recoded to 1 if the respondent somewhat or strongly agreed with the statements or 0 otherwise. The statement on work location flexibility was recoded as 1 if there was partial or complete flexibility to choose work location and 0 otherwise. The statement on the job's remote work suitability was recoded to 1 if the job was mostly or very suitable to remote work and 0 otherwise. Lastly, the COVID-19 related worry variable was recoded as 1 if the respondent reported being worried or very worried about potentially contracting the virus and 0 otherwise.

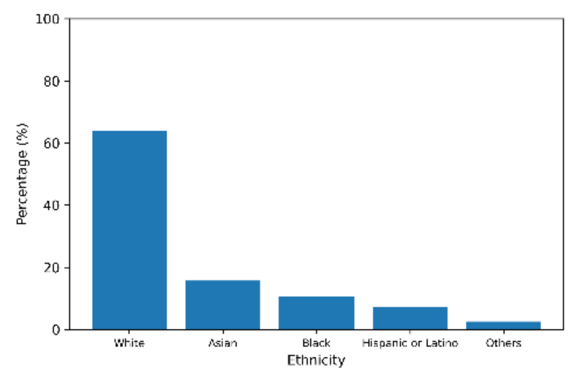
The data from these questions were used to first conduct an exploratory factor analysis, used as foundation to identify factors related to perceived benefit and barriers to telework incorporated into the final MIMIC model. The identification of these latent variables is anchored upon several existing studies on telework before and during the COVID-19 pandemic (Baruch, 2000; Morgan, 2004; Pérez et al., 2002; Tremblay and Thomsin, 2012; Vayre, 2021).

Socio-demographic Data

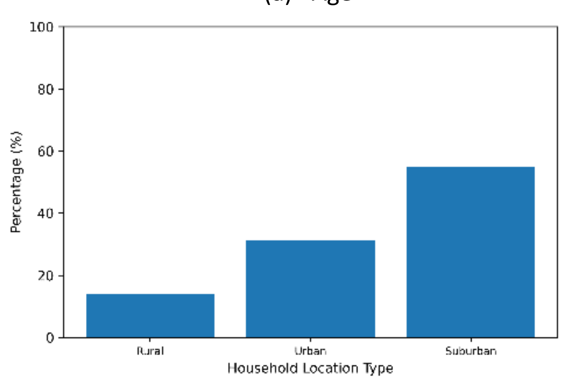
The survey also collected socio-demographic variables that are relevant to study variation in experiences and satisfaction with remote work. Figure 2 presents the descriptive statistics of the socio-demographics used in this study. The variables include age, ethnicity, household location type (urban, rural, suburban), highest level of education, household setup type (living alone or with others), vehicle ownership status etc. Another important variable that we include in our analysis is whether or not an individual works in one of the following four remote work suitable industries: communications and information technology, educational services, media and communications, and professional and business services.



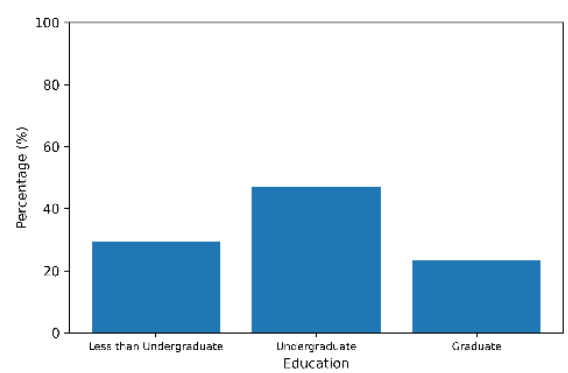
(a) Age



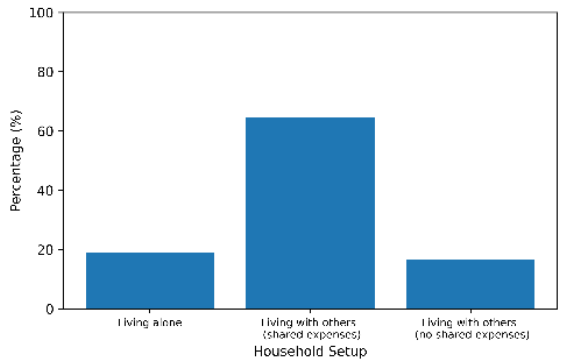
(b) Ethnicity



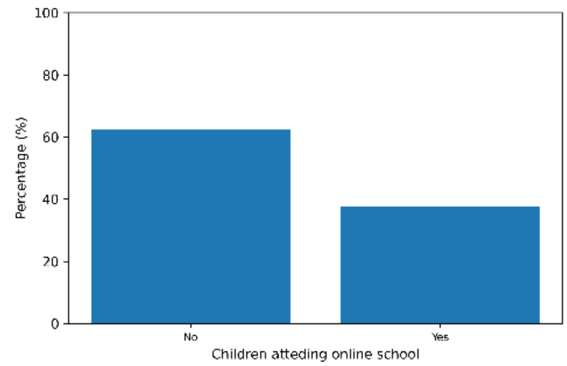
(c) House location type



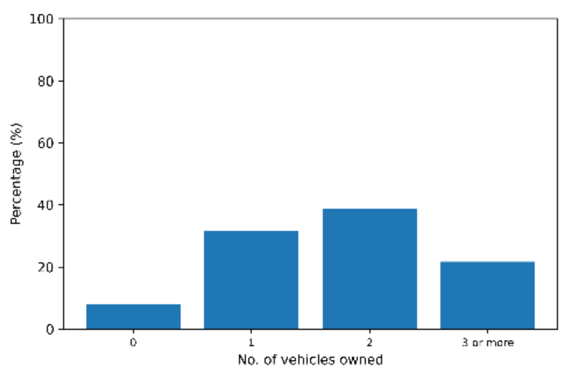
(d) Education level



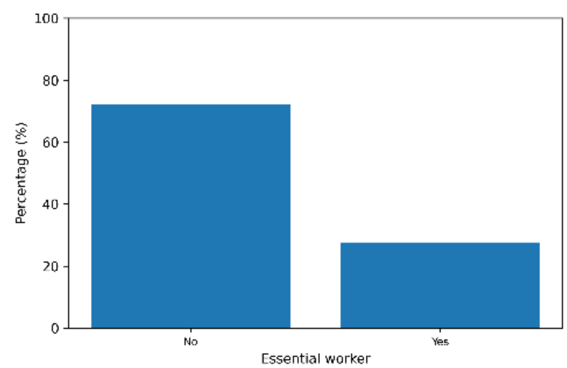
(e) Household setup



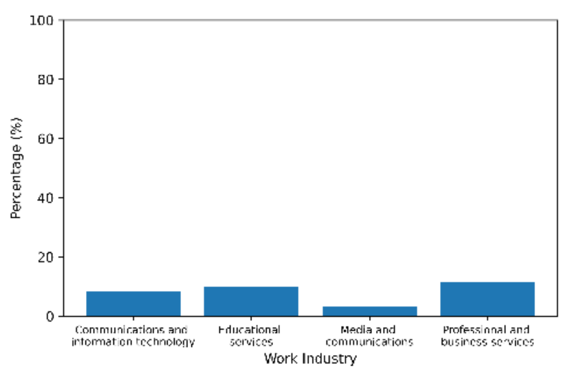
(f) Presence of children attending online school



(g) Number of vehicles in the household



(h) Essential workers or on-site work required



(i) Work Industry

Figure 2 Descriptive Statistics of socio-demographic variables available in the data

Methodology

To understand the drivers of satisfaction and heterogeneity in the self-reported telework satisfaction, we present two models based on the available data. The reference model is an *ordered probit* model controlling for socio-demographic variable effects on telework satisfaction levels. This model is useful to understand the heterogeneity in telework satisfaction across various socio-demographic groups. The second model is a MIMIC model with an ordered probit component relating socio-demographic information as well as latent variables with self-reported telework satisfaction. The model provides a causal structure to our analysis for understanding telework satisfaction. Mathematical details related to both models are presented in the following sections.

<u>Ordered Probit Model</u>

An ordered probit model (Washington et al., 2020) consists of a latent variable (sometimes also referred to as a latent propensity) y^* such that:

$$y^* = z\gamma + u \tag{1}$$

where z is a vector of exogenous variables, γ is a vector of estimable parameters and u is standard normally distributed error term. The latent propensity function y^* is related to the reported $J - point$ response item y (4-point scale satisfaction rating this case) in the following manner:

$$y = \begin{cases} 1 & \text{if} \quad y^* \leq \psi_1 \\ j & \text{if} \quad \tau_{j-1} < y^* \leq \tau_j \ \forall\, j \in (2, \dots, J-1) \\ J & \text{if} \quad \tau_{J-1} \leq y^* \end{cases} \tag{2}$$

where τ_j $(j = 1, 2, \dots, J-1)$ are estimable thresholds dividing the propensity function. Note here that to ensure model identification, either τ_1 or a constant in y^* can be estimated and the other parameter should be fixed to zero. Given the above equations, probability $P(y)$ of observing the self-reported satisfaction rating y is written as:

$$P(y) = \begin{cases} \Phi(\tau_1 - z'\gamma) \\ \Phi(\tau_j - z'\gamma) - \Phi(\tau_{j-1} - z'\gamma) \ \forall\, j \in (2, \dots, J-1) \\ 1 - \Phi(\tau_{J-1} - z'\gamma) \end{cases} \tag{3}$$

where $\Phi(\cdot)$ is standard normal cumulative distribution.

<u>MIMIC Model</u>

The MIMIC model used in this study falls in the category of a generalized structural equation model with categorical data as it takes into account the binary nature of the indicators used for measuring the latent variables. (Muthén, 1984). The MIMIC model consists of an ordered probit component and relates socio-demographic information to perceived / experienced[3] benefits of and barriers to telework satisfaction and to telework satisfaction itself. Similar to other structural equation models, the presented model consists of two components: 1) *a structural model*, capturing the inter-relationship between different latent variables and the relationship between socio-demographic information and latent variables; 2) *a measurement model*, capturing the relationship between continuous latent variables and their observed indicators (all of which are categorical in this study) (Skrondal and Rabe-Hesketh, 2005).

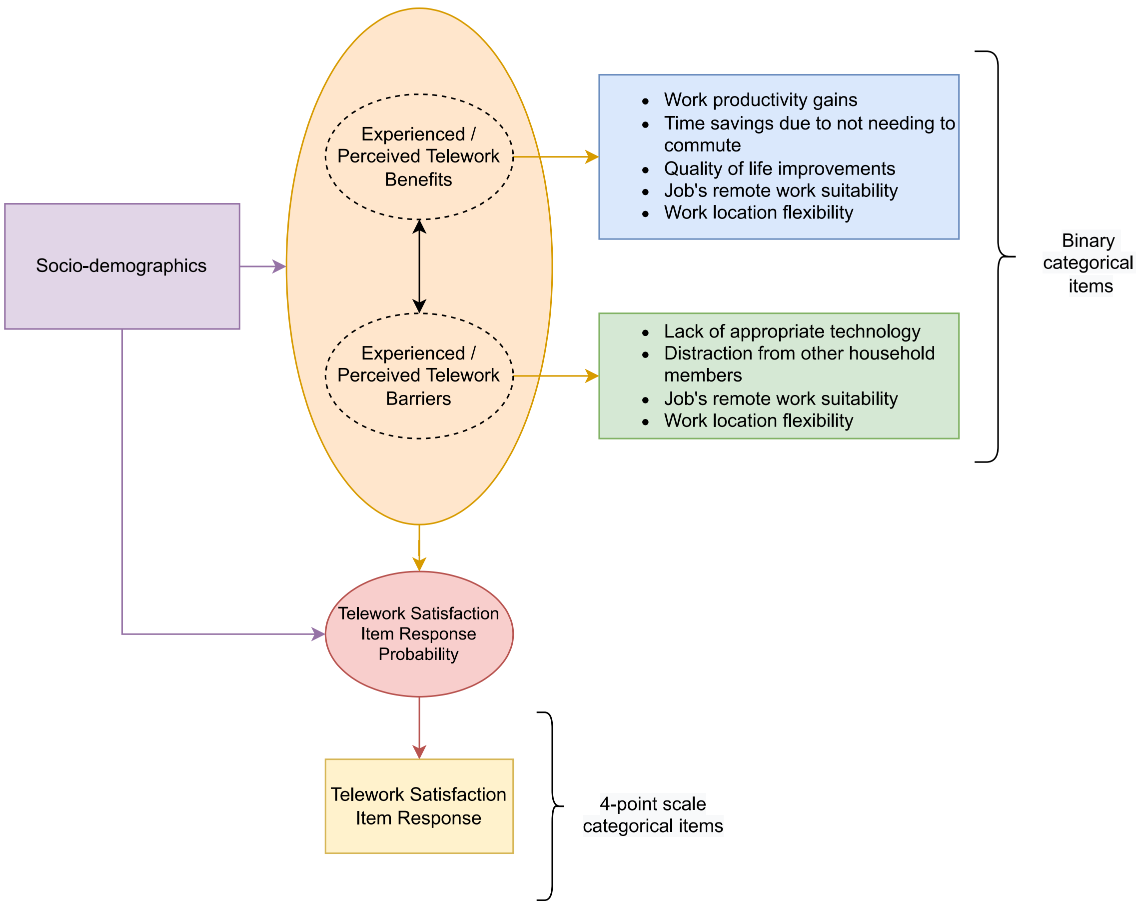


Figure 3 Structure of the MIMIC Model

[3] Note here that we use to perceived / experienced terminology here instead of just experienced due to presence of individuals in the data with no telework experience, for example, essential workers. While using the experienced benefits or barriers is more relevant for individuals who had at least some telework experience during the pandemic, for individuals with no experience of telework during the pandemic, our data only reflects their perception of telework which may not be formed by personal experiences.

Structural model

The structural model defines the inter-relationships between continuous latent variables and the relationship between the latent variables and observed socio-demographic information. In its general form, the structural model can be written as:

$$\eta = \alpha + \mathrm{B}\eta + \Gamma\mathrm{X} + \epsilon \quad (4)$$

where η is a vector of latent variables, α is a vector of intercepts, B is matrix of parameters governing the relationship between latent variables, Γ is a matrix of regression parameters representing the relationship between observed socio-demographic information and latent variables and ϵ is a vector of error terms.

Measurement Model

The measurement model specifies the relationship between the latent variables and its indicators using the following equation:

$$y^{*} = \nu + \Lambda\eta + KX + \mu \quad (5)$$

where y^{*} is a vector of continuous latent variables (assuming that the indicators are categorical), ν is a vector of intercepts, Λ is a factor loading matrix and μ is a vector of measurement errors, and K is the regression parameter matrix defining the relationship between y^{*} and X. The relationship between y^{*} and the observed response to the indicator can be defined as in equation 2 since the indicators are assumed to be ordered categorical in nature.

Table 2 Results from the exploratory factor analysis

Indicator	Factor Loadings	
	Factor 1 (Telework Benefits)	Factor 2 (Barriers to Telework)
Work productivity gains	0.816	--
Job's remote work suitability	0.576	-0.815
Time savings due to not needing to commute	0.680	--
Quality of life improvements	0.852	--
Lack of appropriate technology	--	0.454
Distraction from other household members	--	0.267
Work location flexibility	0.319	-0.649
ω total	0.77	0.58

% of common variance explained by two factors = 52.7%
rotation = varimax

Figure 3 presents the structure of the MIMIC model used in this study. The indicators for each of the latent variables were determined following an exploratory factor analysis that allowed for polychoric correlations (Holgado–Tello et al., 2010). In the MIMIC model, the structural equation relates the socio-demographic information with the identified latent variables (i.e., benefits of and barriers to telework), the measurement equations relate each latent variable with their indicators, and the telework satisfaction response propensity is related with the latent variables and the socio-demographic information using an ordered probit type model. All models in this study are estimated using the R programming package *lavaan* (Rosseel, 2012), which uses mean and variance adjusted weighted least square (WLSMV) procedure (Suh, 2015). WLSMV estimator is the most appropriate estimator for non-normal data and makes minimum assumptions about the distribution of the observed variables (Allen et al., 2020; Bollen, 1989).

Estimation Results

Exploratory Factor Analysis

We began the exploratory factor analysis with the Kaiser – Meyer – Olkin (KMO) test (Kaiser, 1970; Kaiser and Rice, 1974) of sample adequacy and the Bartlett's test of sphericity (Bartlett, 1937) using the 8 indicator variables. A KMO value of 0.66 (minimum acceptable value 0.6) and Bartlett's K squared value of 50.371 (degrees of freedom = 7 and p-value = 1.22×10^{-8}) showed that the data is appropriate for a factor analysis. Table 2 presents the results from a 2-factor solution with *varimax* rotation from an exploratory factor analysis (EFA) conducted using the available telework related experience, perception, and contextual variables. The COVID-19 related concern variable has been excluded from the presented solution since it had a small loading value on the 2-factor and 3-factor solutions attempted. Hence, we include the COVID-19 worry related variable directly into the ordered probit part of the model[4]. Admittedly, some loadings are lower than the generally accepted cutoff values, but we decided to keep the corresponding indicators given that they were extremely important aspects (Hoffman, 2021; Landon-Murray and Anderson, 2021). The two identified latent variables were named as 1) Telework Benefits and 2) Barriers to Telework. Overall, the 2-factor solution explains 52.7% of the common variance in the 7 indicators with 2 cross-loadings across the factors. Given that cross-loadings are reasonably high, we decided to keep these to explicitly account for cross-correlations in the final MIMIC model while defining the latent variables. Given the increasing concerns regarding the use of Cronbach's α for measuring internal consistency reliability in non-continuous data (McNeish, 2018), we use ω total measure of composite reliability proposed by McDonald (1970, 1999). The ω are estimated using the *psych* R programing package (Revelle, 2013) and were found to be 0.77 and 0.58 for factor 1 and factor 2, respectively, which showcases reasonable reliability for the identified factors.

[4] Despite the risk of endogeneity, since we do not have the longitudinal measures of both satisfaction and COVID-19 concerns to resolve the complexity of simultaneous effects, we determined that this variable is a relevant factor during the time of the pandemic where individuals with higher COVID-19 concern might feel more satisfied with telework. Notably, removing this variable from the presented models did not change the remaining parameter estimates or their statistical significance. Capturing COVID-19 concerns and related risk-avoidance or tolerance behaviors remains an important avenue for further research.

Estimation Results

Model of socio-demographic determinants of telework satisfaction

Table 3 presents the results from the ordered probit model with socio-demographic information but without latent variables. This model helps to gain a fundamental understanding of the distribution of satisfaction across the respondents in the data. According to the R^2 value (Hair et al., 2011; Hair et al., 2012), the presented model explains 21.9% of the variance in the *latent propensity function* of the telework satisfaction equation. Note that the typically reported log-likelihood based fit measures are not available here since the model has been estimated using the WLSMV estimator instead of maximum likelihood estimator.

Table 3 Ordered probit model of telework satisfaction with only socio-demographic information

Variable	Parameter Estimate	t-statistic
Age (in years)	0.091	3.800
Age^2 (in years squared)	-0.001	-3.128
Hispanic or Latino indicator	0.653	1.991
Suburban household indicator	0.324	2.462
At least an undergrad degree indicator	-0.334	-2.215
Graduate degree indicator	0.214	1.185
Presence of at least one child attending school from home indicator	-0.594	-3.812
Worried about contracting COVID indicator	0.291	2.059
Thresholds		
$\tau_1 \mid \tau_2$	0.990	1.881
$\tau_2 \mid \tau_3$	1.454	2.747
$\tau_3 \mid \tau_4$	2.429	4.458
Fit Measures		
No. of estimated parameters	11	
No. of observations	318	
R^2 (for ordered probit component)	0.219	

As seen in Figure 4, there is a parabolic relationship between telework satisfaction and age. Specifically, results indicate that while middle aged individuals were more satisfied with teleworking, the satisfaction was lower for younger and older individuals. As reported by some news articles (Atlantic, 2020), this might be related to either loss of networking and mentoring opportunities that younger individuals benefit from in the early stages of their careers or to lack of proper remote working conditions at their homes as many younger individuals often live in shared apartment. For older individuals, the lower satisfaction may be related to higher position ranks, echoing findings in Carillo et al. (2021) where managers adjusted less well to telework than non-managers, related to the difficulty of managing teams in the uncertain environment. Lower satisfaction of older workers may also be associated with challenges to use technology as a primary work tool. Results also suggest that the satisfaction was lower for individuals with at least an undergraduate degree and for households with children attending school virtually from home. A likely reason for presence of children attending school from home impacting satisfaction is that it may strain individual's attention span (Alexander et al., 2021; DeFilippis et al., 2020). Furthermore, telework satisfaction for individuals with a graduate degree was marginally higher than for individuals with just an undergraduate degree, but the corresponding parameter was not highly significant. However, we decided to retain this parameter to control for the effect of having a graduate education, given the consistent importance of this variable in past research.

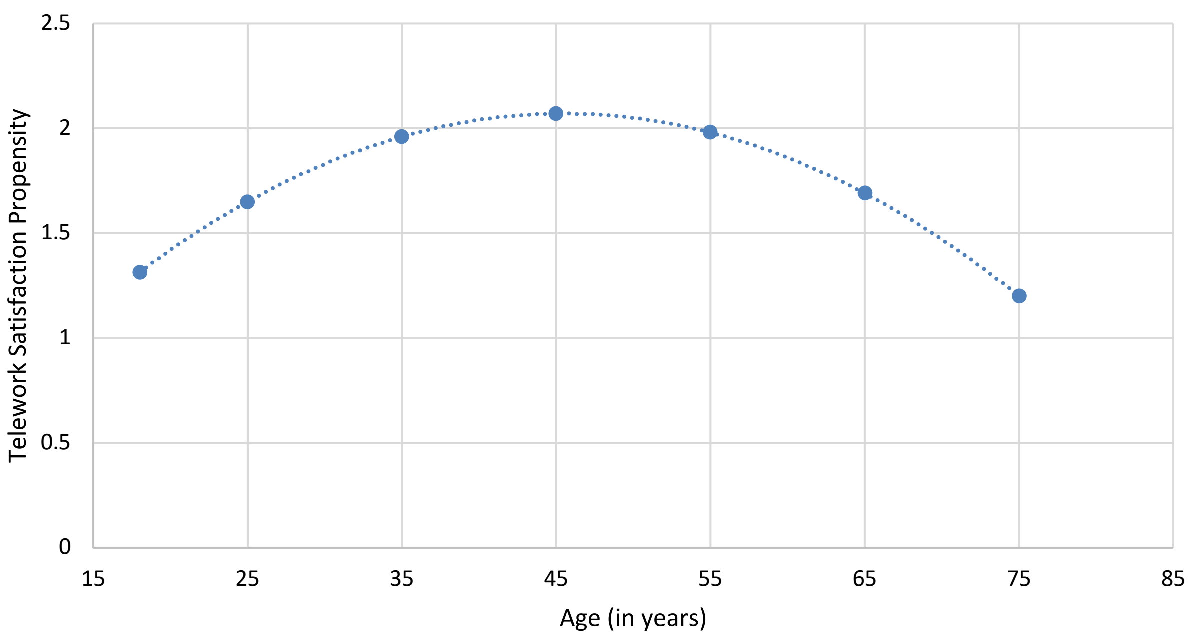
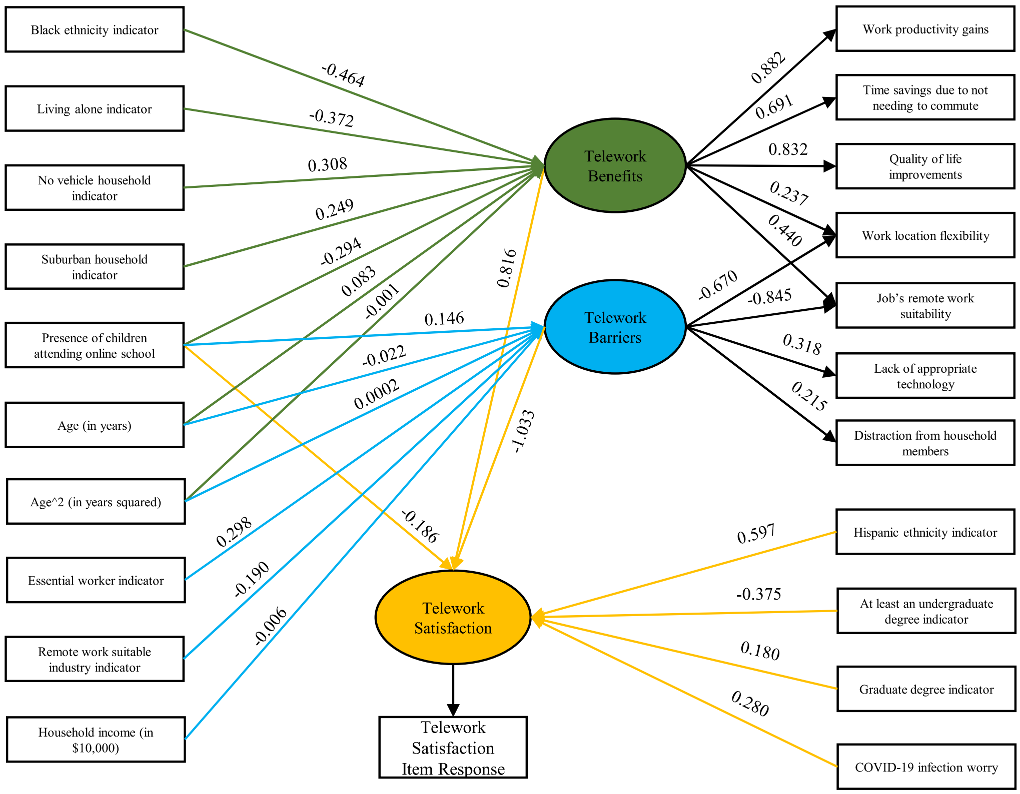


Figure 4 Variation of telework satisfaction as a function of respondent's age

Hispanic or Latino respondents reported higher satisfaction with teleworking compared to other ethnic groups. A conjecture is that Hispanic or Latino respondents tend to be overrepresented in work requiring in-person activities, which are less telework friendly, even before the pandemic (Cerullo, 2020). Hence, their reported satisfaction is higher when they were given a hypothetical situation of teleworking being an available option or when their employers were forced to give telework as an option. Individuals living in suburban areas also reported higher satisfaction with teleworking compared to both rural and urban residents, potentially related to several factors including relocating to suburban areas since telework was possible[5] or to not needing to commute to work anymore (Bowman, 2020; Sheffey, 2021; Wu and Melgar,

[5] Several independent data sources point out to a significant relocation across regions in the U.S. during the pandemic. For example, a study by Zillow, which is a major online real estate marketplace company in the U.S., reported about 11% of American moved during the pandemic of which about 75% did so due to reasons like moving closer to family. Another two studies that use data from United States Postal Service (USPS) found a significant

2021). Lastly, the model also suggests higher satisfaction amongst individuals who were more worried about contracting the COVID-19 virus. This result suggests that satisfaction with remote work can also be driven by factors external to the nature of the work and household environment, to encompass concerns about viral exposure.



FIT INDICES (robust values)

chi-squared test statistic = 138.952
degrees of freedom = 111
relative chi-squared = 1.252

comparative fit index (CFI) = 0.955
Tucker-Lewis index (TLI) = 0.989
root mean square error of approximation (RMSEA)
90 % confidence interval = 0.043

standardized root mean square residual (SRMR) = 0.084

Figure 5 Path diagram for the MIMIC model

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increase movement for individuals from big cities to suburban areas. The studies also found a 27% increase in temporary movers in 2020 compared to the same time-period in 2019. Even in our own data where we asked some of the respondents whether they moved since the beginning of the pandemic, 69 out of 418 (~16.5%) reported doing so.

MIMIC Model

Table 4 presents the ordered probit component of the MIMIC model, which is an extension of the model presented in the previous subsection. This model now includes latent variables which were not included in the previous model. To provide a more causal structure to the model and capture heterogeneity in the latent variables, socio-demographic information was included in both the ordered probit component as well as the structural model where significant, as presented in Table 5. However, preference was given to include socio-demographic information in the structural model when a parameter was significant in only one model components. Hence some of the socio-demographic variables – like age – do not appear in the ordered probit component of the MIMIC model but rather have an indirect impact on satisfaction via the latent variables. Table 5 presents the results from the structural model and Table 6 presents the results from the measurement model. Furthermore, Figure 5 presents a path diagram with all statistically significant paths, as well as various model fit measures typically reported in the structural equation models.

Table 4 Ordered Probit Component of the MIMIC Model

Variable	Parameter Estimate	t-statistic
Hispanic or Latino indicator	0.597	1.926
At least an undergraduate degree indicator	-0.375	-2.300
Graduate education indicator	0.180	0.960
Presence of at least one child attending school from home indicator	-0.186	-1.338
Worried about contracting COVID indicator	0.280	1.924
Latent Variables		
Experienced/perceived telework benefits	0.816	10.958
Experienced/perceived barriers to telework	-1.033	-2.023
Thresholds		
τ_1	0.721	1.278
τ_2	1.205	2.118
τ_3	2.202	3.766
Fit Measures		
No. of estimated parameters in entire model	39	
No. of observations	308	
R^2 (for ordered probit component)	0.648	

Note: Income information was missing for 10 individuals in the data, hence the number of observations dropped to 308 instead of 318 in this model. However, this did not alter the results significantly

Model Fit

As can be seen from Table 4, the R^2 value of the ordered probit model with latent variables is 0.648, which is a significant improvement from the value of 0.219 reported earlier in the model without latent variables. Moreover, the typically reported structural equation based fit measures (see Figure 5) are within the acceptable ranges except SRMR. For example, the acceptable range for TLI and CFI is of greater than 0.95 and both satisfy this criterion. The model is acceptable if the upper bound of 90% confidence interval of RMSEA is below 0.08, which is satisfied in our model as well. While SRMR is slightly above the acceptable threshold of 0.08, SRMR tends to be higher in models with smaller sample sizes and with greater complexity (Kenny, 2015). Given that the inclusion of latent variables significantly improves the R^2 in the ordered probit component and that the typically reported structural equation model fit measures are all within the acceptable ranges, the presented model's results are believed to be trustworthy.

Ordered Probit Model of Telework Satisfaction

As can be seen from Table 4, there is an intuitive link between satisfaction and the latent variables. Namely, individuals which rank higher on telework benefits also report higher satisfaction, and vice versa for barriers. Furthermore, the results related to COVID-19 related worry, level of education and Hispanic or Latino ethnicity remained the same as in the earlier model. It is noted that a few of the variables, like age, which were earlier present in the ordered probit model, are now more appropriately included in the structural component of the overall model, suggesting an indirect effect on telework satisfaction. This indicates that age was structurally correlated with benefits of and barriers to telework variables rather than being a direct causal factor driving telework satisfaction.

Table 5 Structural component of the MIMIC model

Variable	Parameter Estimate	t-statistic
Experienced / perceived telework benefits		
Black ethnicity	-0.464	-2.429
Living alone	-0.372	-2.049
Presence of at least one child attending school from home	-0.294	-1.918
No vehicle household	0.308	1.370
Age (in years)	0.083	3.397
Age^2 (in years squared)	-0.001	-3.191
Suburban household	0.249	1.961
Experienced / perceived telework barriers		
Essential worker	0.298	2.225
Remote work suitable industry	-0.190	-2.048
Presence of at least one child attending school from home	0.146	1.811
Age (in years)	-0.022	-1.734
Age^2 (in years squared)	0.0002	1.396
Household Income (in $10,000)	-0.006	-1.171

Structural Model

Table 5 presents the estimation results from the structural model that captures the heterogeneity in the latent variables included in the ordered probit component. For the *telework benefits*, we found that these were higher for individuals living in suburban areas and individuals without access to a vehicle. Further, the experienced/perceived benefits were lower for Black individuals, individuals living alone, and individuals with children attending school from home. Lastly, age had a non-linear impact on the experienced/perceived benefits as shown for the satisfaction probit model. Regarding households without a vehicle, higher telework satisfaction is expected since many of these individuals are potentially transit users, pedestrians, bicyclists, carpoolers etc. for whom telework potentially is a way to save commute time and to reduce COVID-19 exposure by not using transit or other shared modes (Barbieri et al., 2021). Furthermore, lower satisfaction for individuals living alone is likely associated with the issue of social isolation and emotional well-being (Fingerman et al., 2021). Interestingly, we found that individuals with Black ethnicity perceived/experienced lower benefits of telework. This is potentially due to several factors including individuals with Black ethnicity being disproportionately employed in less telework friendly job sectors (Cerullo, 2020), or not experiencing much productivity gains or quality of life improvements as a results of the telework due to lack of access to necessary resources and environment at home.

Table 6 Measurement component of the MIMIC model (standardized parameters)

Variable	Parameter Estimate	t-statistic
Experienced / perceived telework benefits		
Work productivity gains	0.882	---
Time savings due to not needing to commute	0.691	8.905
Quality of life improvements	0.832	11.537
Job's remote work suitability	0.440	7.416
Work location flexibility	0.237	3.155
Experienced / perceived barriers to telework		
Lack of appropriate technology	0.318	---
Distraction from other household members	0.215	1.550
Job's remote work suitability	-0.845	-2.301
Work location flexibility	-0.670	-2.214
Thresholds		
Work productivity gains | τ_1	1.636	2.675
Time savings due to not needing to commute | τ_1	0.879	1.342
Quality of life improvements | τ_1	1.298	2.109
Job's remote work suitability | τ_1	3.306	4.197
Work location flexibility | τ_1	1.842	2.558
Lack of appropriate technology | τ_1	0.552	0.639
Distraction from other household members | τ_1	-0.195	-0.271

--- t-statistic not available since the parameter was fixed for identification

τ_1 : first thresholds for the binary indicator measurement model

For the barriers to telework[6], we found that the barriers were higher for essential workers and lower for individuals in remote work friendly industries. This highlights that the nature of the work tasks/telework friendliness of the job is a highly important factor driving barriers to telework. Additionally, the barriers were higher for individuals with presence of a child attending school from home and were lower for higher income households (who potentially are in higher ranks in their jobs). Lastly, perceived/experienced telework barriers varied parabolically with age, with higher barriers for younger and older individuals and lower barriers for middle-aged individuals.

Measurement model

Table 6 presents the results from the measurement model with standardized parameters estimated to measure the two latent variables. The signs of all the parameters are intuitively correct, providing more confidence in the results. For *benefits* our results echo the importance of saving commute time, which was a leading factor supporting remote work productivity in Shamshiripour et al. (2020). Considering barriers, the importance of remote work suitability reflects earlier telework research (Mokhtarian and Salomon, 1997) while location flexibility is likely a new feature shaped by the notable professional and personal uncertainty surrounding the pandemic work policies (Carillo et al., 2021). As previously discussed, although some loadings are smaller in magnitude than the generally acceptable values, they were retained in the model because they captured important information and had intuitively plausible signs.

Summary, Policy Implications, and Limitations

Using data from a U.S. representative sample (based on gender, age and ethnicity variables) of 318 working adults, this study uses a multiple indicator multiple cause model (MIMIC) to understand individual's satisfaction with telework. The study also presents an ordered probit model without the latent variables, which reveals systematic heterogeneity in telework satisfaction. The MIMIC model consists of an ordered probit component relating socio-demographic information and perceived/experienced telework benefits and barriers to telework satisfaction. Additionally, we anchor the modeling on personal, work, and household environment factors that help disentangle structural differences in how people experienced remote work.

[6] In earlier drafts of this study, it was suggested to us to incorporate a dummy or interaction variable representing whether an individual was given a potentially hypothetical situation on telework or not so that differences in satisfaction levels or benefits and/or barrier latent variables or the two groups can be captures. However, since almost all individuals in the hypothetical group were working on-site due to employer set mandates (i.e. had no work location flexibility) and large portion of them were essential workers or from non-telework friendly industries, this variable was highly correlated the variables already present in the barriers structural model and hence was dropped from presented model. However, our analysis suggests that the respondents who were given a hypothetical situation regarding telework perceived/experienced higher barriers, which makes sense since they didn't have work location flexibility.

The results from the ordered probit model without latent variables suggests that the telework satisfaction was higher for middle aged individuals compared to younger and older individuals, Hispanic or Latino respondents, respondents with less than an undergraduate degree, and respondents with higher levels of concern about contracting the COVID-19 virus. On the other hand, satisfaction was found to be lower for individuals with children attending school virtually from home. The results from the MIMIC model confirms the ordered probit reference findings, namely that Hispanic or Latino ethnicity, education level, presence of an online-schooling child and worry related to contracting the COVID-19 virus are the main factors to drive satisfaction. Age, however, is now included in the structural component of the MIMIC model, revealing instead an indirect impact on satisfaction. The model also suggests a positive impact of telework related benefits and negative impact of barriers to telework. Epidemic-induced telework *benefits* can be associated with several demographic and household factors, namely: it is lower for individuals with Black ethnicity, those living alone or with presence of at least one child attending online school from home. The benefits were found to be higher for individuals without a vehicle and those who are suburban dwellers. Lastly, the barriers to telework were found to be most pronounced for essential workers and those with a remote-schooled child in the household. On the other hand, barriers were found to be lower for individuals employed in remote work suitable jobs and those with higher household income. A non-linear impact of age was also found to be a significant factor for both benefits and barriers latent variables.

Overall, three important take-aways emerged from the presented analysis. First, benefits and barriers to telework are disproportionately distributed across age groups. For younger individuals, this may be related to loss of networking opportunities that they need to advance in their careers or maybe related to the younger individuals mostly being employed in jobs that are not suitable for telework. For older individuals, the issue might be related to workplace anchoring, difficulty of managing their teams in more senior positions, and possible technology limitations in performing usual work activities. A second important finding is the evidence for inequity along the lines of racial/ethnic identity. Our findings are in line with other reports that Black and Hispanic or Latino individuals are disproportionately impacted in term of not being able to telework (Cerullo, 2020). Third, the presence of children attending online school is a consistently important factor impacting telework satisfaction. This is not surprising since several recent studies have pointed to negative impact of the pandemic on working parents with younger children (Feinberg et al., 2021; Patrick et al., 2020).

From a policy standpoint, our results suggest several implications for employers and policy makers in planning for the pandemic and post-pandemic periods. For employers who plan to adopt a hybrid or remote workplace in the long run, our study highlights several core factors that shape barriers and benefits of telework that can be used for communication and promotion of future efforts (e.g., the benefits of commute time savings). Furthermore, the causal structure of the model reveals the diverse experiences of different employer segments with regard to barriers and benefits. These insights can be used to design worker support strategies (e.g., on-site school/day-care pods assisting with challenges of inconsistent schooling access). If remote work were to become a norm at least for positions or tasks where physical presence is not necessary, employers must ensure support that is mindful of the diverse experiences and circumstances of workers, including the more complex non-linear effects such as those related to worker age. For younger employees, a hypothesis is that higher barriers or lower benefits are perceived due to lack of networking opportunities that they need to excel and advance in their careers. Employers could alleviate these by creating an environment to facilitate networking opportunities like organizing mandatory on-site days at regular intervals or hosting online networking hours. For older individuals who might perceive high barriers and lower benefits to teleworking potentially due to difficulty with technology, employers must invest in providing technology support. Concerns about social isolation, especially for workers for whom work provides an important environment for social interaction may also need to be addressed.

On the other end, if employers opt to have an in-person/office-centric plan for the future, creating a safe working environment will be important to phase in the return to the office since our results indicates a positive relationship between telework satisfaction and COVID-19 related worry. This could potentially be achieved by clear policies on social distancing, masking, and vaccination. As employers seek to determine the appropriate mix of telework and in-person presence, the factors identified in this study could assist in bringing out the positive features of each mode while mitigating some of the negative aspects. As a broader implication for public agencies planning for transportation and other infrastructure, it is important to thoroughly gauge the extent to teleworking in the post pandemic era, since basing future policies solely on trends during the pandemic could be erroneous (Hensher et al., 2021).

Some limitations of this study are worth mentioning here. First, for at least for some of the respondents, the satisfaction data was related to a hypothetical scenario of teleworking, and results could potentially be impact by the hypothetical bias (Hensher, 2010). Second, our study uses a relatively small sample size and additional insights could potentially be derived from a larger sample. Third, our study provides only a snapshot in time in an otherwise dynamic process; it would be important to examine the longer-term impacts of telework on both employees and employers, particularly with regard to factors such as productivity, creativity and worker retention, as well as personal satisfaction, work-life balance and happiness. The results presented in this study highlight important factors impacting telework satisfaction and provide insights for employers and policy makers to help design future telework policies.

Chapter 2

Trajectories of Telework Through the Pandemic: Outlook and Implications for Cities

Introduction

The altered work landscape in the US as a result of the COVID-19 pandemic is still evolving and its true nature in the post pandemic world is unknown. Several earlier studies have shown that is it likely that at least some of the pandemic accelerated telework trends will stick long beyond the pandemic (Javadinasr et al., 2021; Mohammadi et al., 2022; Parker et al., 2022; Salon et al., 2021a), and if true, this will have strong implications for the future of cities (Althoff et al., 2022; Barth, 2021; Conway et al., 2020). For example, data from Seattle (Kroman, 2022) shows that while about 50% of downtown workers commuted to work via transit pre-pandemic, that number dropped to just 18% by the end of 2021, partly attributable to more than 46% downtown workers working remote in 2021 compared to only 6% pre-pandemic. Another data from Washington D.C. in June 2022 points out that the commuter metrorail ridership was only about 38% of pre-pandemic levels, a slower than expected rebound, likely due to both private and federal workers being offered the option to work remotely. At the national level, a study by Pew Research Center (Parker et al., 2022) in early 2022 found that about 61% of workers with telework friendly jobs are continuing to work from their homes even when their workplace is open, with increasing numbers of workers citing personal preference as their top reason for doing so instead of the COVID-19 related risks.

While the recent increase in telework might have significant benefits at an individual level including it being better for productivity, creativity, and inclusiveness (Co-operation and Development, 2020; Schur et al., 2020), its potentially devastating impact on transit ridership and potential inability to reduce VMT cannot be ignored (FHWA, 2022; Tappe, 2021)[7]. If current telework trends are to continue, it becomes imperative for cities (especially for major metropolitans where the local economy largely relies on presence of a lot of people at the same time and place) to re-orient themselves to cater to these changing trends.

Under the current evolving telework and hybrid work landscape, this study has three underlying goals: 1) to understand the evolution of telework through the pandemic using a trajectory analysis framework; 2) to gain an understanding of the telework outlook in April 2024, about 2 years into the future; 3) to provide insights into what these changing telework trends might mean for the future of our cities. Using data from

[7] Based on the traffic volume trends data published monthly by the office of highway policy information of Federal Highway Administration (FHWA), vehicle miles traveled (VMT) in the US in March 2022 were higher than in March 2019 and only ~4% and ~1% lower than April and May 2019, respectively.

a U.S representative sample of 905 working adults, we accomplish the above goals using following three sets of analyses:

- First, using individual level trajectories of work location at different time points (7 time point between 2019 (pre-pandemic) to March 2022 (2 years since the pandemic began)), we present an *agglomerative clustering-based sequence analysis* focused at identifying clusters of telework trajectories through the pandemic. With this analysis, we identify *four* clusters of trajectories with differing levels of telework adoption, ranging from a group that maintained significantly high in person work participation even at the height of the pandemic, to a group that worked exclusively from home for an extended period in the pandemic and shows little sign of rebounding back to their pre- pandemic behavior.
- Next, with the identified clusters, we estimate a *multinomial logit-based cluster membership model* focused at understanding the systematic heterogeneity in clusters of telework trajectories. Specifically, we identify how different occupational sectors, and individuals in different age, gender, ethnic, educational, or other socio-economic groups followed distinct trajectories.
- Lastly, we present a set of comprehensive predictive models to understand how telework landscape might look like in *April 2024*, about four years since the beginning of the pandemic, when we expect any COVID-19 related concerns to be resolved. Specifically, we present predictive models for two different outcome variables: 1) a *binary logit* model for predicting who is still unsure about their April 2024 work location; and 2) a set of *ordered logit* models to understand who is more likely to work in person in April 2024. We present three different versions for the second model; a) a model with only socio-demographic information focused at understanding the distribution of telework across the population going forward; b) a model with socio-demographic information as well clusters identified in the previous step as indicator variables, which captures a combined effect of individual inertia to change as well as potential employer side decisions requiring workers to return back to the office; and c) a model that builds upon the previous two models by adding individual attitudes towards the impact of telework on various aspects of work like productively, creativity, and mentorship.

We use the above analysis to identify what these trends could mean for the future of cities (specifically, transit and local economy) and how cities could re-orient themselves for long term sustainability. The outline of rest of the study is as follows.

Data

The data used in study comes from Wave 7 of a 7-wave *longitudinal* tracking survey focused at capturing and understanding changes to tele-mobility patterns in the U.S. as the result of the COVID-19 pandemic (Said et al., 2022; Tahlyan et al., 2022a, b). The data were collected between April and May 2022, where

972 individuals who participated at least once in the previous 6 waves of the survey were re-invited to participate in this wave and an additional U.S. population representative sample (by gender, age, and ethnicity) of 905 individuals was also collected. In total, 1291 complete responses were available for this study (386 respondents from the re-invitations, ~40% return rate).

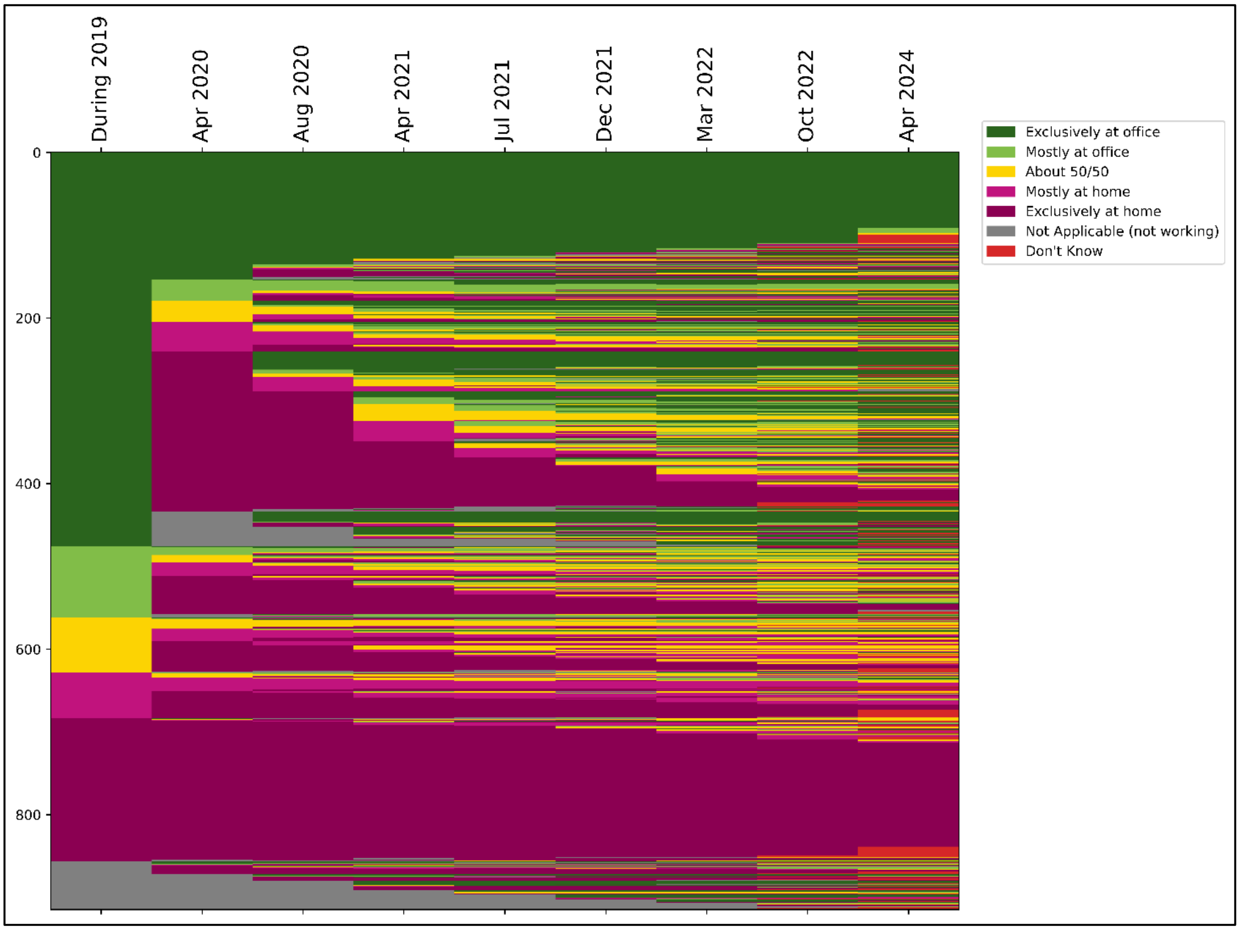


FIGURE 1: Telework trajectories of 905 respondents in the survey

In this wave of the survey, respondents were asked several questions related to their frequency and spending patterns related to grocery, cooked food, and non-grocery items via different acquisitions channels; their work location (if employed); their trip making patterns and mode usage; socio-demographics and their attitudes, perceptions, and experiences regarding technology, environment, and remote work. To characterize the trajectories of telework through the pandemic and to understand the future of (remote) work, each respondent working full time, part time or a student (905 out of 1291) was asked to report their work location during the following time points:

- During 2019 (before the COVID-19 pandemic)

- April 2020 (start of lockdown period, 1st peak in COVID-19 cases)
- August 2020 (2nd peak in COVID-19 cases)
- April 2021 (vaccine available for all adults)
- July 2021 (COVID-19 cases at an all-time low)
- December 2021 (surge in cases due to Omicron variant)
- March 2022 (month prior the survey was conducted)

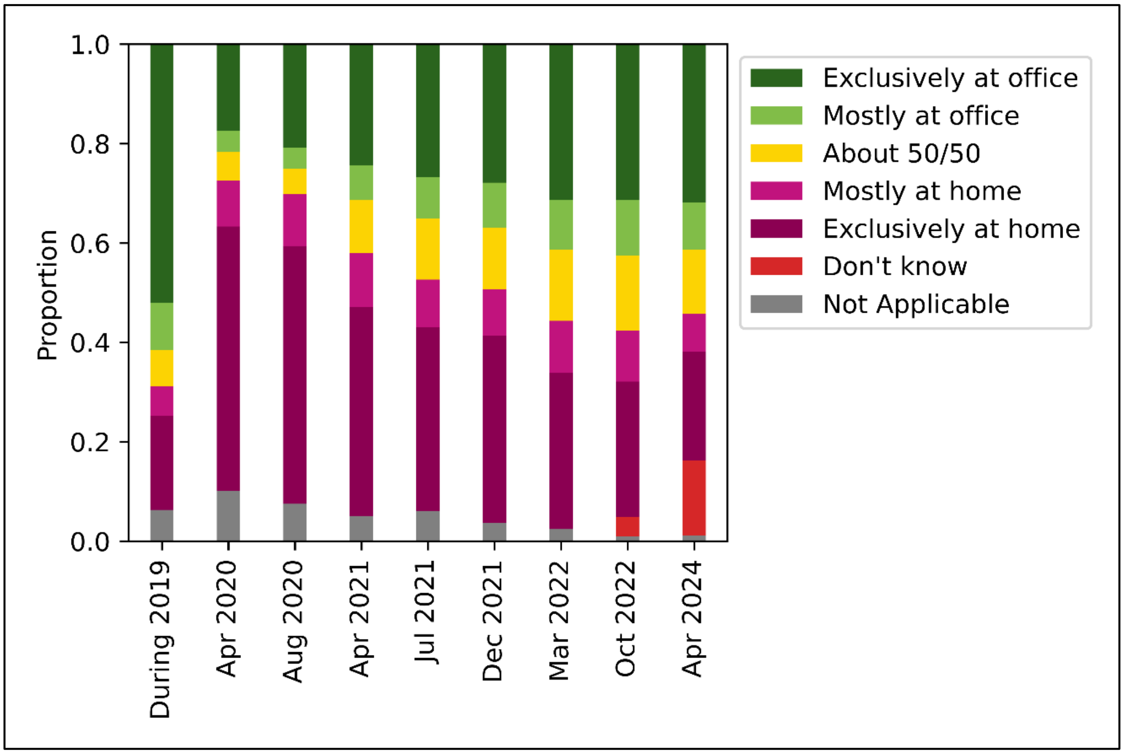


FIGURE 2: Work location proportions before, during and post pandemic

The possible responses included: Exclusively on-site/at the office, Mostly on-site/at the office, Sometimes at home and sometimes on-site/at the office (or About 50/50), Mostly at home, Exclusively at home and Not applicable. The "Not Applicable" would be chosen if the respondent (who was employed at the time of the survey) was not employed at a particular time point (either by choice or due to layoffs). Further, data for two additional future time points were also collected to understand the expected future work location behavior: *October 2022 and April 2024*. For these two time points, the respondents were also given an option of "Don't Know" to indicate work location *uncertainty* during the future time points, i.e. the respondent does not know where they will work from in the future. Other information that we used in this study include respondents' socio-demographic information. Further, we also collected and used respondents' attitudes regarding the impact (positive, neutral, negative, or not applicable) of a *2-days a* *week remote work program* on 12 different response items including their productivity, creativity, ability to innovate, effectiveness to get the job done etc. The available work location trajectory data, socio-demographic information, and attitudes data were later used for trajectory clustering analysis, estimating cluster membership model and for estimating a predictive model for April 2024 work location.

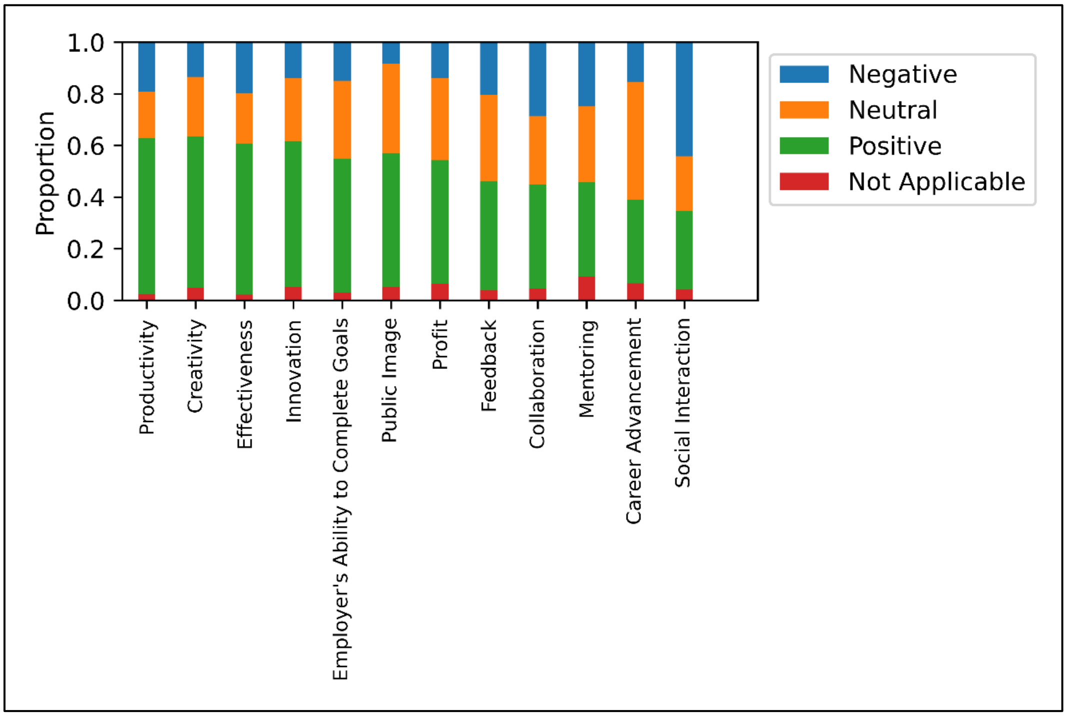


FIGURE 3: Respondents' attitudes regarding the impact of 2-days a week remote work on various aspects of work

Descriptive Statistics

Telework Trajectories

Figure 1 presents a *color-coded* snapshot of work location trajectories of all 905 respondents in the data between 2019 (pre-pandemic) and April 2024. The color coding presented can be used to determine whether a respondent worked exclusively at home **(dark maroon)** or exclusively on site **(dark green)** during a time point. Colors **light green**, **light maroon** and **yellow** represent mostly at office, mostly at home and about 50/50, respectively. The **grey color** represents whether a respondent was not employed during a particular time point either by choice or due to the market conditions. The last two time points (October 2022 and April 2024) also have **red color** representing someone with *uncertainty* about their work location in the future. A different version of this data as *cross-sectional proportions* across different work locations and at different time points is presented in Figure 2. A number of important observations can be made from these two figures, which acts as a sanity check for the quality of the data as well as builds a comprehensive picture regarding the evolution of telework through the pandemic.

TABLE 1: Socio-demographic information

Variable	Percent (%)
Respondent's occupational sector	
Transportation, Warehousing and Manufacturing	8.42
Health Care	8.20
Information	13.01
Educational Services	13.33
Finance and Insurance	6.78
Professional, Scientific, and Technical Services	14.32
Retail Trade	10.05
Arts, Entertainment, and Recreation	10.05
Others	15.85
Respondent is *essential* workers or have been asked to work in-person	27.98
Ethnicity	
White	70.93
Black or African American	11.91
Asian	7.87
Hispanic or Latino	6.23
Others	3.06
Age	
Less than or equal to 44 years	56.50
Between 45 and 64 years	35.52
More than 65 years	7.98
Household location	
Urban	31.04
Rural	15.08
Suburban	53.88
Highest education level	
Less than undergraduate degree	28.09
Undergraduate degree	50.16
Graduate or professional degree	21.75
Household income	
Less than or equal to $49,999	35.41
Between $50,000 and $99,999	38.36
More than or equal to $100,000	26.23
Household with at least one kid under the age of 12 years	17.05
Respondent is female	48.42
Respondent is a student	8.42
Household size	
1	22.73
2	35.52
3	20.11
4	13.66
5	6.23
6 or more	1.75
Household without access to a vehicle	8.42

As can be seen in Figure 1, our data captures the fact that many individuals lost their jobs at the height of the pandemic (**dark green** to **grey** transition betweeen 2019 and April 2020) and that those who did so were working exclusviely in person pre-pandemic. This is in line with other data sources where it was found that majority of jobs lost due to the pandemic were low paying jobs (which generally tend to be exclusively in person jobs) (Food, 2020). The trends of economic recovery over time can also be seen as COVID-19 cases reduced and economy was slowly re-opened. Second, as seen from Figure 2, the number of individuals working exclusively from office reduced from 52% in 2019 to 17.5% in April 2020 and then is slowly increasing since then with 31.4% in March 2022 and 32% (expected) in April 2024. The data also captures the expected trend of higher uncertainty at farther time point than at a time point only a few month away (3.9% **don't know** response in October 2022 and 15.1% in April 2024). Other interesting trends include an increase in exclusively at home work from 18.9% in 2019 to 53.2% in April 2020, 31.4% in March 2022 and 21.9% (expected) in April 2024. Comparing 2019 and April 2024, even if everyone with a don't know response switches to exclusively working from office, there is a clear expected shift toward exclusively at home and hybrid work arrangements going forward.

Socio-demographics

Table 1 presents the descriptive statistics of various socio-demographic information for the available data. This information is later used as exogenous variables in both the cluster membership model as well the April 2024 predictive model to understand how trajectories of telework through the pandemic and telework outlook post pandemic varies by occupational characteristics and socio-economic status.

Attitudes regarding impact of 2-days a week remote work

Figure 3 presents respondents attitudes regarding the impact of 2-days a week remote work program on 12 different aspects of work. Specifically, respondents were asked: *"Imagine that your employer has committed to a future work program allowing a hybrid workforce with an option of remote work for 2 days a week. In your opinion, what effects will such a program have on the following [12 aspects related to work]?"* The respondents were asked to report their response on a 5-point Likert scale varying from Very Negative to Very Positive with "*Not Applicable"* as a possible option to choose from for cases where a particular response item was not relevant for an individual. The 5-point scale was converted to a 3-point scale to reduce complexity. It is not surprising that most respondents agree that a 2-days a week remote work program will have negative effect on social interaction with colleagues, neutral to negative effect on career advancement, mentoring, collaboration and a positive impact on productivity, creativity, and effectiveness to get the job done. Based on the available respondent data on 12 attitude attributes, we conduct a latent class cluster analysis (Collins and Lanza, 2009) using the *'poLCA'* package in R (Linzer and Lewis, 2011), where respondents were clustered in 6 latent clusters ranging from respondents with negative, positive, or mixed opinions about the impact of a 2-days a week remote policy at their workplace, and then these clusters were later used to predict their work location preferences in April 2024. Figure 4 presents the results from the latent class analysis where the top row shows the estimated proportion of respondents belonging to each cluster. All six clusters have been named based on the patterns in estimated conditional response probability values as shown in the collection of twelve bar plots, one for each response item. For example, the first clusters is named as those with *Negative* outlook towards the impact of 2-days a week remote work policy as a majority of respondents in this cluster think that a 2-days a remote work would have a negative impact on various work related aspects. Based on the latent class model, we estimate the class probability of each individual in the data and assign them to a cluster based on modal assignment (i.e., assigning them into cluster with the highest probability) and then use these cluster indicators as independent indicator variables in the April 2024 work location model.

Methodology

<u>Agglomerative Clustering of Trajectories</u>

To identify clusters of telework trajectories between 2019 and March 2022, we use *Agglomerative Hierarchical Clustering* (Abkarian et al., 2022; Hastie et al., 2009; Ward Jr, 1963) with *Levenshtein* or *Edit* distance (Levenshtein, 1966) as a similarity metric (calculated using *TraMineR (Gabadinho et al., 2011)*) and with *agnes (Kaufman and Rousseeuw, 2009)* package in R programming language. Agglomerative hierarchical clustering is a bottom-up clustering approach with the benefit of not needing to pre-specify a set number of clusters (unlike k-means). It uses a pairwise similarity measure to combine observations into clusters in a hierarchical framework beginning with each data point as a unique cluster and then merging closer points into a single cluster until the entire dataset is one big cluster. Determination of number of clusters is done using *dendrogram,* which is a graphical representation of the hierarchical structure of clustering process. Given the sequential nature of the trajectories, Levenshtein distance metric is used as a similarity measure instead of other distance metrics that do not recognize sequential nature of the data. Levenshtein distance determines the similarity between trajectories based on the minimum number of insertions, deletions or substitutions required to make two trajectories similar and is a popular metrics with origins in protein/DNA sequence alignment and bioinformatics. Note here that we only use data up to March 2022 for the clustering and April 2024 data is used as the prediction time point. The clustering analysis reveals 4 distinct trajectory clusters with differing telework adoption levels through the pandemic.

Class Labels	Negative	Neutral	Positive to Neutral	Mixed	Positive	NA
Proportions	20.29%	10.17%	6.15%	24.53%	28.12%	10.82%
Productivity						
Not Applicable	0.02	0.00	0.09	0.00	0.00	0.98
Positive	0.09	0.09	0.50	0.90	0.98	0.00
Neutral	0.18	0.75	0.31	0.07	0.02	0.01
Negative	0.70	0.17	0.10	0.03	0.01	0.01
Creativity						
Not Applicable	0.05	0.03	0.25	0.01	0.02	1.00
Positive	0.20	0.01	0.43	0.84	0.95	0.00
Neutral	0.23	0.85	0.21	0.15	0.03	0.00
Negative	0.51	0.11	0.11	0.01	0.00	0.00
Ability to innovate						
Not Applicable	0.03	0.01	0.28	0.00	0.02	1.00
Positive	0.19	0.00	0.40	0.79	0.95	0.00
Neutral	0.24	0.89	0.19	0.19	0.03	0.00
Negative	0.54	0.10	0.13	0.02	0.00	0.00
Effectiveness to get the job done						
Not Applicable	0.02	0.01	0.08	0.01	0.00	0.95
Positive	0.05	0.00	0.57	0.85	0.97	0.00
Neutral	0.15	0.87	0.32	0.11	0.02	0.01
Negative	0.79	0.12	0.03	0.03	0.00	0.04
Receiving / delivering mentoring						
Not Applicable	0.03	0.04	0.49	0.03	0.04	1.00
Positive	0.08	0.06	0.45	0.13	0.90	0.00
Neutral	0.17	0.90	0.07	0.51	0.05	0.00
Negative	0.72	0.01	0.00	0.33	0.00	0.00
Receiving / delivering feedback						
Not Applicable	0.01	0.00	0.23	0.00	0.00	0.98
Positive	0.09	0.07	0.58	0.18	0.96	0.00
Neutral	0.23	0.93	0.18	0.57	0.04	0.02
Negative	0.67	0.00	0.00	0.25	0.00	0.00

	Negative	Neutral	Positive to Neutral	Mixed	Positive	NA
Proportions	20.29%	10.17%	6.15%	24.53%	28.12%	10.82%
Ability to collaborate						
Not Applicable	0.01	0.00	0.28	0.00	0.00	0.95
Positive	0.09	0.16	0.48	0.20	0.90	0.00
Neutral	0.11	0.74	0.22	0.42	0.08	0.00
Negative	0.78	0.10	0.02	0.38	0.02	0.05
Career Advancement						
Not Applicable	0.01	0.04	0.36	0.00	0.03	0.98
Positive	0.07	0.00	0.32	0.21	0.76	0.00
Neutral	0.42	0.93	0.30	0.67	0.19	0.01
Negative	0.51	0.03	0.02	0.12	0.02	0.01
Social Interaction with collegues						
Not Applicable	0.01	0.00	0.26	0.01	0.01	0.95
Positive	0.13	0.24	0.40	0.08	0.64	0.00
Neutral	0.09	0.54	0.20	0.21	0.22	0.01
Negative	0.77	0.22	0.14	0.70	0.13	0.04
Employer's ability to accomplish goals						
Not Applicable	0.00	0.00	0.17	0.02	0.00	0.95
Positive	0.05	0.07	0.38	0.63	0.98	0.01
Neutral	0.30	0.86	0.45	0.34	0.02	0.02
Negative	0.65	0.07	0.00	0.01	0.00	0.01
Employer's profit						
Not Applicable	0.03	0.02	0.35	0.03	0.03	0.94
Positive	0.13	0.10	0.17	0.59	0.87	0.01
Neutral	0.32	0.79	0.45	0.34	0.09	0.02
Negative	0.52	0.09	0.04	0.04	0.01	0.02
Employer's public image						
Not Applicable	0.01	0.00	0.34	0.02	0.01	0.94
Positive	0.23	0.12	0.23	0.57	0.92	0.02
Neutral	0.41	0.84	0.39	0.39	0.08	0.04
Negative	0.34	0.04	0.04	0.02	0.00	0.00

FIGURE 4: A collection of bar charts showing response probabilities for each response items in each latent class

Cluster Membership model

Based on the four trajectory clusters identified in the previous step, we estimate a multinomial logit (Washington et al., 2020) based cluster membership model to understand the factors associated with various trajectories of telework through the pandemic. In the membership model, the discrete outcome, cluster c, for observation n is associated with a set of covariates using linear-in-parameter function T_{cn} such that:

$$T_{cn} = \beta_c X_{cn} + \epsilon_{cn} \quad (1)$$

$$P_n(c) = P(T_{cn} \geq T_{Cn}) \;\; \forall\, C \neq c \quad (2)$$

$$P_n(c) = P(\beta_c X_{cn} + \epsilon_{cn} \geq \beta_C X_{Cn} + \epsilon_{Cn}) \;\; \forall\; C \neq c \quad (3)$$

$$P_n(c) = P(\beta_c X_{cn} - \beta_C X_{Cn} \geq \epsilon_{Cn} - \epsilon_{ic}) \;\; \forall\; C \neq c \quad (4)$$

where β_c is a vector of estimable parameter for cluster c, X_{cn} is a vector of covariates and ϵ_{cn} is a gumbel distributed error term. The probability of membership into cluster c for observation n, $P_n(c)$, can be written as the following closed form expression:

$$P_n(c) = \frac{e^{\beta_c X_{cn}}}{\sum_{\forall c} e^{\beta_c X_{cn}}} \quad (5)$$

We estimate the above model using maximum likelihood estimation with the *apollo* package in R programming language (Hess and Palma, 2019).

Predicting April 2024 Remote Work Location

As shown in Figure 5, the April 2024 work location response variable consists of 6 possible responses. Since the response scale is partly ordered (for Exclusively at home to Exclusively at office) and partly unordered discrete (for don't know), we estimate two separate models: 1) a binary probit model to understand the factors associated with work location uncertainty in April 2024; 2) an ordered probit model to understand the factors associated with April 2024 work location preferences, only for those who do not have any uncertainly (i.e. they chose one of 5 ordered responses as their future work location). For both the binary and ordered model, we also include trajectory clusters as an indicator variable to capture impact of inertia as well as potential employer side decisions.

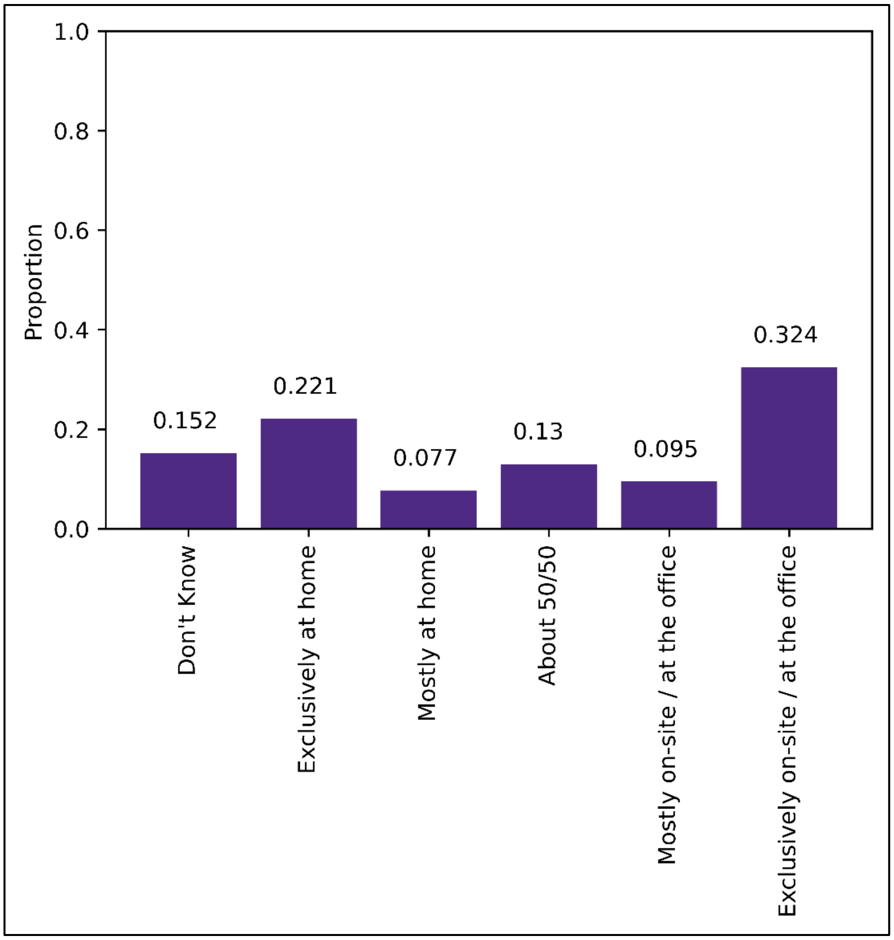


Figure 5 Distribution of April 2024 work location response variable

Binary Logit Model Predicting Work Location Uncertainty

The binary logit setup in our study is similar to the cluster membership model presented earlier but with only 2 possible discrete outcomes (don't know and know). We estimate this model using maximum likelihood estimation and include socio-demographic information and trajectory cluster indicators as covariates.

Ordered Probit for April 2024 Work for Those Without Uncertainty in Work Location

An ordered probit model (Washington et al., 2020) consists of a latent variable (sometimes also referred to as a latent propensity) y^* such that:

$$y^* = z\gamma + u \tag{6}$$

where z is a vector of exogenous variables (covariates), γ is a vector of estimable parameters and u is standard normally distributed error term. The latent propensity function y^* is related to the reported $J - point$ response item y in the following manner:

$$y = \begin{cases} 1 & \text{if} \quad y^* \leq \psi_1 \\ j & \text{if} \quad \psi_{j-1} < y^* \leq \psi_j \ \forall \, j \, \epsilon \, (2, \dots, J-1) \\ J & \text{if} \quad \psi_{J-1} \leq y^* \end{cases} \tag{7}$$

where ψ_j $(j = 1, 2, \dots, J-1)$ are estimable thresholds dividing the propensity equation. Note here that to ensure model identification, either ψ_1 or a constant in y^* can be estimated and the other parameter should be fixed to zero. Given the above equations, probability $P(y)$ of observing the self-reported satisfaction rating y is written as:

$$P(y) = \begin{cases} \Phi(\psi_1 - z'\gamma) \\ \Phi(\psi_j - z'\gamma) - \Phi(\psi_{j-1} - z'\gamma) \ \forall \, j \, \epsilon \, (2, \dots, J-1) \\ 1 - \Phi(\psi_{J-1} - z'\gamma) \end{cases} \tag{8}$$

where $\Phi(\cdot)$ is standard normal cumulative distribution. We estimate three versions of this model: 1) a model with just socio-demographic information; 2) a model with both socio-demographic information and trajectory clusters; 3) a model with socio-demographic information, trajectory clusters and attitude clusters.

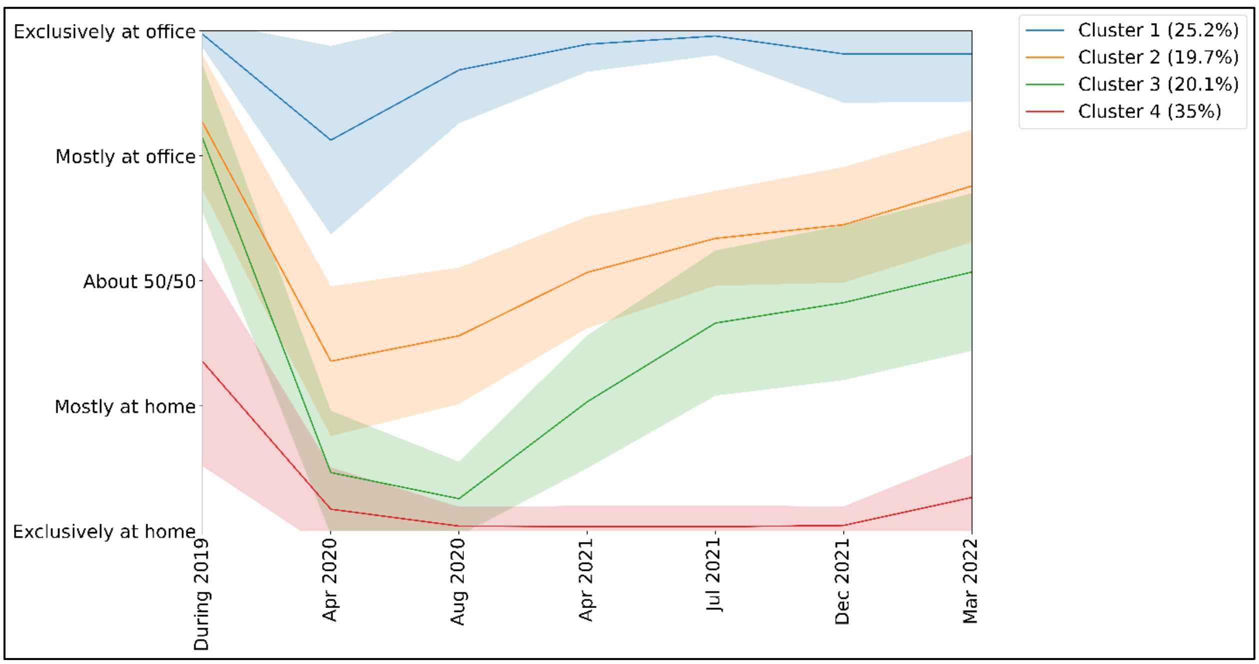


Figure 6: Mean telework trajectories for each cluster

Results

<u>Clusters of Telework Trajectories</u>

Figure 6 presents the mean trajectories for 4 identified telework trajectory clusters with error bars corresponding to the standard deviation from the mean trajectory in each cluster. To generate Figure 6, individual response regarding work location was assigned a value between 1 to 5 (1 = exclusively at home, 5 = exclusively at office, excluding *not applicable* cases). Figure 7 presents a color-coded trajectory plot as in Figure 1 but now for each cluster separately. In Figure 7, note that data for October 2022 and April 2024 was not used for clustering but is shown to describe how individuals in different clusters expect to work in the future. Several interesting insights can be derived from each cluster as presented below:

- **In-person workers (Cluster 1, 25.2%)** – Most respondents in this cluster worked exclusively at office pre-pandemic and continued doing so at the height of pandemic. Even for cases where a set of respondents were able to shift to full or partial remote work, there was a significant rebound back to exclusively at office work in later stages of the pandemic. Most of the respondents in this cluster expect to work in person in April 2024, with some uncertainty for a small number of respondents. We name this cluster as the *in-person workers* cluster given the high prevalence of exclusively at office work throughout the pandemic and similar expected behavior in April 2024.
- **Level 1 hybrid workers (Cluster 2, 19.7%) –** Most respondents in this cluster worked either exclusively at office or mostly at office pre-pandemic but a majority of them moved to some form of telework at the height of the pandemic in April 2020 (exclusively at home and mostly at home being more common). However, as the pandemic progressed, most respondents rebounded back to higher in-person activity and appears to have settled around mostly at office or about 50/50 at office / at home work. We name this cluster as *Level 1 hybrid workers* given their potential for at least some telework but perhaps also an employer side requirement for higher in person presence.
- **Level 2 hybrid workers (Cluster 3, 20.1%) –** Most respondents in this cluster worked either exclusively at office or mostly at office pre-pandemic (similar to as in cluster 2) but made a drastic shift to exclusively at home work at the height of the pandemic. This cluster showed slower rebound back to workplace and also showed much higher levels of telework adoption compared to cluster 2. In April 2024, the respondents in this cluster are expected to showcase higher at home work adoption compared to cluster 2. Given that this cluster showed higher at home presence compared to cluster 2 (and is also expected to maintain this behavior going forward), we name this cluster as *Level 2 hybrid workers*.
- **At home workers (Cluster 4, 35%) –** A majority of respondents in this cluster worked exclusively or mostly at home pre-pandemic and continued doing so for a long time during the pandemic. For those who were working hybrid or exclusively at office, they too shifted to exclusively at home worker with a minor rebound to some in person work in 2022. This cluster shows higher uncertainty in April 2024 work location preferences but still is expected to maintain a much higher at home work arrangement compared to other clusters. We name this cluster as *at home workers* due to high prevalence of remote work throughout the pandemic and a similar expected behavior going forward.

Cluster Membership Model

Table 2 presents the cluster membership model aimed at understanding the factors associated with the identified telework trajectory clusters. Note that the clusters show an ordered pattern of telework adoption through the pandemic with cluster 1 showcasing most in-person presence at work location, cluster 4 with least in-person presence at work location and clusters 2 and 3 being hybrid work location clusters with increasing level of at home presence. In the presented model, cluster 1 is kept as the reference cluster for most variables, so the estimated parameters are interpreted with reference to cluster 1. Several important insights can be derived from these results. Firstly, job related factors played a strong role in dictating the trajectory of telework through the pandemic. The model suggests essential workers were more likely to be in clusters 1, 2 and 3 (in-person or hybrid clusters) and similarly those in the health care sector were less likely to be in the cluster 4 (remote work cluster). Further, those in transportation and manufacturing were less likely to be in clusters 2, 3 and 4 while those in the information sector were more likely to be in clusters 2, 3 and 4 (hybrid or fully remote). The model also suggests that full time students were less likely to be in cluster 3 or 4 suggesting a return to school for the students going forward. The model also suggested significant variation in telework trajectories by other socio-demographics like ethnicity, level of education, household income, age, household location, and household size. Specifically, the results suggest those with Asian ethnicity were more likely to be in cluster 2, those with black or African American ethnicity were more likely to be in cluster 2, 3 and 4 and those with Hispanic ethnicity were less likely to be in cluster 2 and 4. Those with higher education were more likely to be in clusters 2 and 3 (potentially capturing individuals in jobs that require higher levels of education as well as in-person presence like a lawyer, hardware engineers etc.) and those with higher income were less likely to be in clusters 2 and 4 and those with lower income were less likely to be in cluster 3. We also found that the likelihood of membership in cluster 4 was lower for those with age less than 44 (i.e. less fully at home work for young and mid age group) and higher for those with age 65 years (i.e. higher at home work for older individuals). We also found that those living in urban areas were more likely to be in clusters 2 and 3 (hybrid work), those with a young child were more likely to be in cluster 2, 3 and 4 (at home or hybrid work) and those without a vehicle were more likely to be in cluster 2, 3 or 4 (at home or hybrid work, potentially capturing the impact of ease of transportation to work). The model also suggests that those who are female were less likely to be in hybrid work clusters and those with large household size more likely to be in cluster 2 (level 1 hybrid cluster).

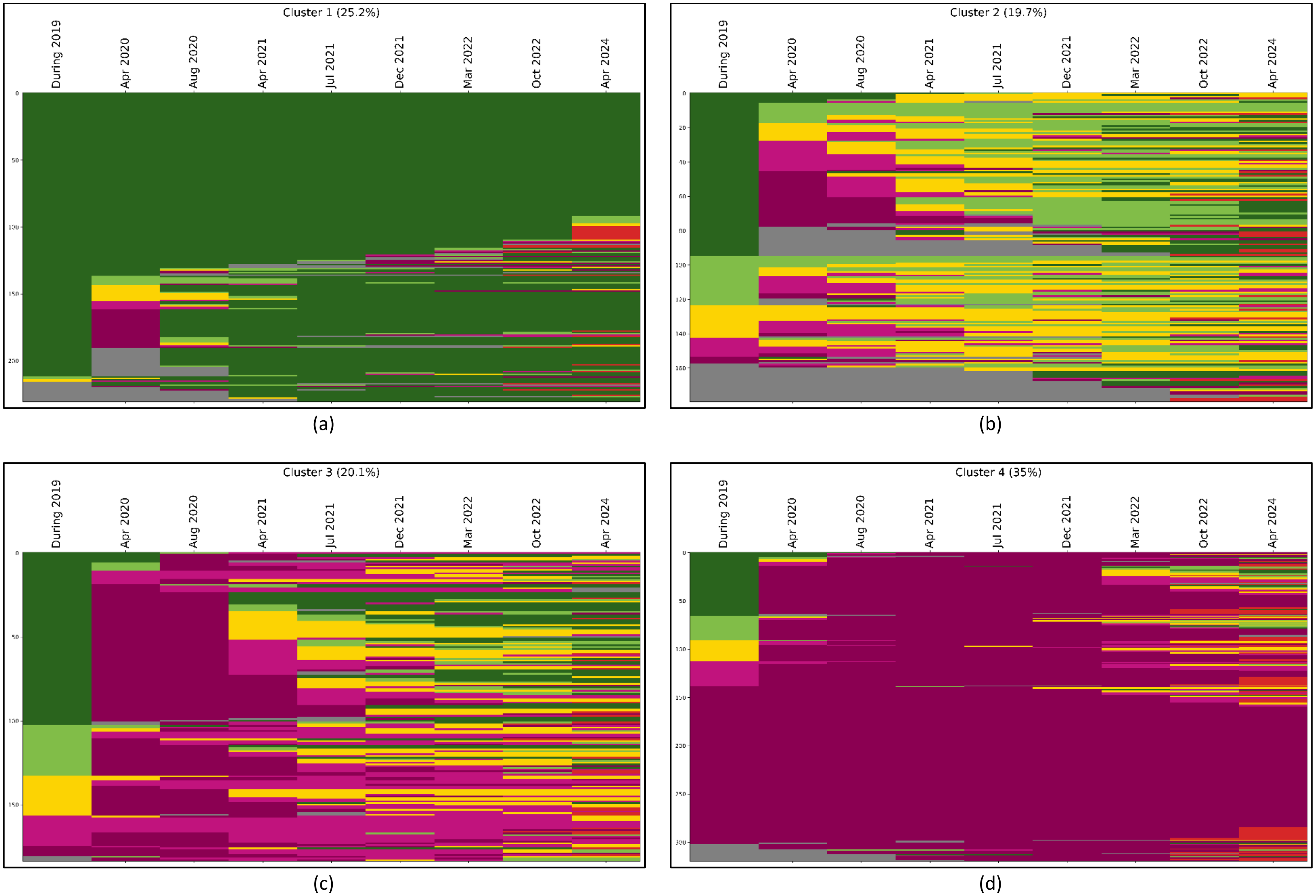


Figure 7: Color coded telework trajectories for each cluster (See figure 1 and figure 2 for legend)

Table 2 Cluster membership model

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Constant	--	-0.5285 (-3.014)	-0.1708 (-1.201)	1.3156 (12.320)
		Socio-Demographics		
Ethnicity				
Asian Ethnicity Indicator	--	0.337 (2.552)	--	--
Black or African American Ethnicity Indicator	--	0.815 (4.787)	0.693 (3.952)	0.483 (2.667)
Hispanic Ethnicity Indicator	--	-0.860 (-4.168)	--	-0.884 (-4.813)
Level of Education				
Highest Degree as Undergraduate Indicator	--	0.608 (5.336)	0.856 (7.132)	--
Highest Degree as Graduate Indicator	--	0.573 (4.034)	0.973 (6.806)	--
Household Income				
Income less than $50k Indicator	--	--	-0.282 (-2.694)	--
Income $50k to $100k Indicator	--	-0.136 (-1.350)	--	-0.144 (-1.513)
Age				
Age less than 44 years Indicator	--	--	--	-0.234 (-2.571)
Age more than 65 years Indicator	--	--	--	0.695 (4.538)
Urban Household Location Indicator	--	0.590 (6.071)	0.189 (1.901)	--
Household with at least one child under age 12 years indicator	--	0.470 (2.988)	0.304 (2.021)	0.445 (2.950)
Female Respondent Indicator	--	-0.511 (-5.417)	-0.294 (-3.176)	--
Full Time Student Respondent Indicator	--	--	-0.291 (-1.903)	-1.422 (-7.941)
Household Size Indicator	--	0.118 (2.883)	--	--
Household without a vehicle Indicator	--	0.654 (2.934)	0.510 (2.173)	0.798 (3.760)
		Job Related Factors		
Essential Worker Indicator	3.194 (23.282)	1.712 (11.965)	1.142 (7.590)	--
Sector of Occupation				
Transportation and Manufacturing	--	-1.019 (-5.449)	-0.717 (-4.036)	-2.379 (-10.090)
Information	--	0.959 (4.208)	0.868 (3.724)	1.566 (7.369)
Health Care	--	--	--	-0.390

				(-2.191)
Educational Services	--	0.460 (2.920)	0.525 (3.358)	-0.393 (-2.317)
Finance and Insurance	--	--	--	0.541 (3.556)
Professional, Scientific and Technical Services	--	0.719 (3.898)	0.801 (4.350)	0.953 (5.358)
Model Fit				
Number of observations	905			
ρ_c^2	0.1743			
Adjusted ρ_c^2	0.1646			

Predictive Model for April 2024 Work Location

Binary Probit Model Characterizing Work Location Uncertainty

Table 3 presents results from a binary probit model for understanding the uncertainty in work location in April 2024. Main findings from these results include presence of higher uncertainly for female respondents, students and those present in cluster 4 (in-person cluster) and lower uncertainly for those with a graduate degree. Note that the coefficient estimate for the information sector occupation indicator is insignificant in the presented model but was significant in the model without the cluster 4 indicator variable potentially due to high correlation between the two variables. Higher uncertainty for student respondents makes sense since they might be unsure about potential job situation 2 years down the line after graduation. For respondents with highest education as a graduate degree, lower uncertainty may be potentially related to either the nature of the work or higher leverage viz. their employers since individuals with a graduate degree are typically in more specialized jobs and hence are able to negotiate their work location. Higher uncertainty for individuals in cluster 4 (which is highly correlated with information sector) is likely associated with employer side uncertainty in reaching a work location policy for the future. Higher uncertainty for female respondents is potentially related to higher job switching rates or potentially higher rate of burnout amongst women during the pandemic (Smith, 2021b).

Table 3 Binary probit model of work location uncertainty in April 2024

Variable	**Parameter Estimate**	**t-stat**
Intercept	-2.331	-12.663
Female respondent indicator	0.506	2.634
Information sector occupation	0.185	0.687
Student	1.064	3.742
Highest degree is graduate	-0.439	-1.707
Cluster 4 Indicator	0.707	3.571
Model Fit		
Number of observations	905	
ρ_c^2	0.047	

Table 4: Ordered probit model for work location in April 2024

Variable	Without clustering info	With clustering info	With trajectory info + attitude latent class
	Socio-demographics		
Highest level of education			
Highest degree is Undergraduate	0.347 (2.077)	0.331 (1.732)	0.330 (1.722)
Highest degree is graduate	0.351 (1.721)	0.469 (2.081)	0.447 (1.983)
Income less than $50k	-0.263 (-1.773)	-0.471 (-2.879)	-0.466 (-2.843)
Age			
Age less than 44 years	0.421 (2.843)	0.368 (2.346)	0.353 (2.249)
Age more than 65 years	-0.564 (-2.031)	--	--
Respondent is a student	0.982 (3.378)	1.006 (3.009)	1.004 (2.998)
Zero vehicle household	-0.359 (-1.458)	--	--
Occupational Sector			
Transportation and manufacturing	0.722 (2.831)	--	--
Information	-0.960 (-4.603)	--	--
Health Care	0.545 (2.051)	--	--
Education Sector	0.912 (4.144)	1.296 (5.322)	1.301 (5.322)
Finance and insurance	-0.707 (-2.678)	--	--
Professional, Scientific and Technical Services	-0.301 (-1.559)	--	--
Trajectory Info			
Cluster 2 indicator	--	-2.538 (-9.757)	-2.496 -9.574
Cluster 3 indicator	--	-3.049 (-11.353)	-2.983 (-11.042)
Cluster 4 indicator	--	-5.327 (-18.774)	-5.282 (-18.554)
***Negative* attitude towards remote work class indicator**	--	--	0.406 (2.000)
Thresholds			
1|2	-0.757 (-4.030)	-4.236 (-14.383)	-4.139 (-13.872)
2|3	-0.271 (-1.454)	-3.422 (-12.107)	-3.326 (-1.602)
3|4	0.455	-2.248	-2.145

	(2.436)	(-8.353)	(-7.833)
4|5	0.976 (5.169)	-1.387 (-5.379)	-1.276 (-4.838)
Model Fit			
ℒℒ	-1,063.28	-823.96	-821.95

Ordered Probit Model Characterizing Work Location for Those Without Uncertainty

Table 4 presents results from three different ordered probit models focused at understanding the relationship between April 2024 work location (for those who are certain about it) and socio-economic factor, attitudes regarding remote work and behavioral inertia. A positive parameter estimate represents a higher likelihood for in-person work in April 2024 and a negative parameter represents a lower likelihood for in-person work.

As suggested by the first model with just the socio-demographic information, those in transportation/manufacturing, healthcare and education sector are more likely to work in-person and those in information, finance/insurance and professional/scientific/technical services are less likely to be in person. Further, those with an undergraduate or a graduate degree, those with age less than 44 years and those who are students are more likely to work in-person and those with income less than $50,000, those with age more than 65 years and those without a vehicle are less likely to work in-person.

In the model with clustering information, the results suggest lower in-person work likelihood for clusters 2, 3 and 4 (in increasing order of magnitude), potentially indicating a continuation of the trends captured in the clustering analysis. Note here that some of the occupation sector related variables have been removed from this model since the corresponding parameters are now insignificant due to potential correlation between trajectory clusters and these variables.

Lastly, the model with both the trajectory cluster and attitude latent class variable suggests that those with negative attitudes regarding the impact of remote work on job related factors are more likely to be in-person.

Summary and policy implications

Summary of results

Using data from U.S representative sample of 905 respondents, this study presents a trajectory-based clustering analysis of work location trajectories through the pandemic. We identified 4 distinct clusters of telework trajectories with distinct levels of telework adoption patterns. Following the clustering analysis, the study presented results from a cluster membership model focused at understanding the factors associated with various telework trajectories including sector of occupation and socio-economic factors. This was followed by a two-part model focused at understanding the April 2024 expected work location, four years since the beginning of the pandemic.

A few key insights emerged from the cluster membership model. First, trajectories of telework through the pandemic are highly associated with nature of the job in which one is employed. For example, the model suggested that those in transportation/warehousing sector were more likely to higher in-person work compared to much higher at-home work for those in the information sector. The model also suggested lower telework adoption amongst those who are younger and those who are students and higher remote work for those without a vehicle. Further, those in urban households were more likely to present in clusters 2 or 3 where some form of hybrid work arrangement is expected going forward.

From the April 2024 work location models, key insights include presence of higher uncertainty amongst female respondents, students and those who were in cluster 4 (high telework through the pandemic) and lower uncertainty amongst those with a graduate degree. Finally, the ordered probit model for April 2024 work location for those who are certain suggests higher in-person work for transportation, healthcare and education sectors and lower in-person work for information, finance/insurance and professional services sectors. Further, the model also suggests higher in-person work for students and younger individuals, and those with higher education degrees but lower for those without a vehicle, those in lower income groups or those with age greater than 65 years.

Policy implications

There are several important policy takeaways from these results. There is strong evidence for telework to stay beyond the pandemic and this might have several implications for urban cities. The results from the clustering analysis suggest that some form of telework is expected to persist in the future for about 75% of the individuals (cluster 2, 3, and 4) and it is likely to be more amongst those without a vehicle and those living in urban areas and those working in information or related sectors. Given that most transit users are in urban areas and less likely to have access to a vehicle, telework trends in the future may significantly impact transit revenue which may further deteriorate service quality in the longer term, especially for those who really need it. Reduced demand due to telework might also hurt local businesses like coffee shops in downtown areas and business districts and policy makers need to plan how to alleviate the adverse impact of these changing trends on cities. Lastly, given that the information sector is likely to be more remote going forward, these trends will likely have high impact on cities with higher share of information sector jobs like San Francisco.

Chapter 3

Modeling the Effects of Telework on the Duration, Distance, and Time of Day of Out-of-Home Non-Work Activities

Introduction

The massive pivot to remote work triggered by the COVID-19 pandemic has accelerated trends of remote work. Two years into the pandemic, one of the greatest questions faced by employers, workers, and urban and transport planners centers on the impact of a 'hybrid' way of working. Individuals seeking employment are now having hybrid work as one of their top priorities. A study conducted in October of 2020 found that 54% of individuals want to continue working from home after the pandemic (Parker et al., 2020). The same study was repeated in January of 2022 with the same sample with the main finding that the percentage of individuals working from home because they choose not to work from the office, and not because their workplace is closed, rose from 36% in October 2020 to 61% in January 2022 (Parker et al., 2022).

A study done by Wakefield research in April of 2021 found that 47% of working adults are willing to quit their job if there was no flexibility to work remotely in the post-pandemic world (Smith, 2021a). The interest in remote and hybrid schedules on behalf of individuals is motivated by the fact that it offers a flexible schedule, allows for multi-tasking, allows for home relocation, and decreases time spent commuting to and from the office, which in turn allows for spending less money. As it has become more common for industries to shift to a hybrid work model that allows employees to work remotely as well as in person, it is important to understand the travel patterns and the performance of the multimodal transportation system.

Most studies done in the pre-pandemic era tried to relate the effect of telework to improvements in congestion as well as energy use. A research team in Minnesota, U.S. measured the vehicle miles traveled and cost savings of telework (Lari, 2012). Another study estimated a 1% energy savings if 50% of working adults worked remotely 4 days per week (Matthews and Williams, 2005). Kitamura et al. (1991) found that telecommuting reduces vehicle miles traveled and had no effect on non-work trips.

Several studies examined the change in people's behaviors and activities during the COVID-19 pandemic (De Haas et al., 2020; Irawan et al., 2022; Lee et al., 2020). A research team in Indonesia found that individuals were heavily affected during the beginning of the pandemic evidenced by a decrease in the number of out-of-home activities being made. Furthermore, research from the Netherlands found that individuals were making fewer trips and traveling shorter distances during the beginning of the pandemic when compared to the fall of 2019. Additionally, the research team in Maryland, U.S. found that mobility trends were greatly influenced by the pandemic during its early stages such that there was a nationwide mobility reduction. Another research team found that the activity patterns of individuals are greatly influenced in stability by life events (Hilgert et al., 2018). A research team in North Carolina studied the change in activity-travel behavior due to the COVID-19 pandemic, while relating the change to socioeconomic status (Wang et al., 2022). They found out that individuals living in low- and medium-income areas decreased their visits to retail stores. Another study examined the change in activity-travel behavior and mobility styles in Chicago during the early stages of the pandemic (Shamshiripour et al., 2020). They found an increase in the number of teleworking individuals during and after the pandemic. A research team also studied the behavior change of individuals before, during, and after the pandemic by developing a survey sent between July and October of 2020 (Salon et al., 2021a). The team found that there was a 13% increase before the pandemic to after the pandemic in the individuals who expect to work from home at least a few days each week as well as a 40% decline in transit commute trips. These findings are aligned with earlier pre-pandemic research, one of which showed that individuals who telework decreased their number of trips, as well as the distance traveled (Elldér, 2020).

In sum, ongoing research suggests that remote work in the acute stage of the pandemic has changed commuting patterns, mode choices, residential preferences, and household travel schedules. Yet, there is still limited understanding of the effects of telework during more recent phases of the COVID-19 pandemic, characterized by limited restrictions and where people are accustomed to the pandemic and remote work opportunities. A comprehensive understanding of the effects of telework is greatly needed for transportation planners to prepare for the post-pandemic world through land use and mobility decisions. This study aims to examine 3 main questions about out-of-home travel activities that affect the performance of the multimodal transportation system in the current stage of the pandemic of 'sustained management':

What is the effect of telework on the **duration** spent on out-of-home non-work activities? Does telework increase or decrease the average **distance** traveled from home to reach out-of-home non-work activities? Is there a telework effect on the **time of day** chosen to engage in out-of-home non-work activities? The research questions will be answered along with a descriptive analysis of data we have obtained from a national survey sent between March and April of 2022.

The next section presents the data as well as the deployed survey used to answer the above research questions along with a descriptive analysis of the activity diary, followed by the methodology. The methodology section introduces the conceptualization of models used in the rest of the study. The fourth section presents the estimation results of the models. The fifth section closes off with a discussion of the results as well as policy implications and concluding remarks.

Data

<u>Survey</u>

This study relies on data collected between March and April of 2022 in the United States. The web-based survey was designed using Qualtrics and distributed to individuals of at least 18 years of age using the

Prolific platform (https://www.prolific.co/), which allows for having a representative sample in terms of gender, age, and ethnicity. The study makes up the 7th wave of a longitudinal survey, with earlier analysis focusing on remote work satisfaction (Tahlyan et al., 2022a) and spending patterns (Said et al., 2022)

<u>Activity Diary</u>

The main source for the analysis of out-of-home non-work activities is the activity diary. The diary question was designed to examine the effect of telework status on the duration, distance, and time of day chosen to participate in activities. Specifically, respondents were asked to fill in their previous day's activities starting at 4 AM and ending on 4 AM of the next day. Since respondents had to report the activity diary for one day of the week, the survey invitations were sent out over several days to cover all days of the week. The activity diary included the activity, start and end time, activity location (in-person and online/virtual), the activity's distance from home, and the mode used to reach the activity location if the activity was not at home. Activities had to be reported in one-hour intervals, while also allowing individuals to record more than one activity per hour interval. The 14 activities that respondents could choose from included: caring for others, driving/traveling, eating and drinking, entertainment/leisure, exercise, grocery or other shopping, household chores, other, personal maintenance, preparing meals or snacks, sleeping, socializing, working at the main job, and working at another job. It was necessary to include the last activity type, working at another job, as hybrid work has seen an increase in the number of individuals working remotely for two different employers. A study found that around 50% of respondents were working for two companies at the same time during the pandemic (Kelly, 2021).

As this study heavily relies on the activity diary, respondents who reported their last activity at or before 6 PM were omitted from the sample. After cleaning, the sample went down to 1116 respondents. Various activity diaries were also corrected due to "AM" and "PM" mix-ups.

<u>Employee Subgroups</u>

To determine the group of individuals who telework, the occupations that were considered were: employed full-time, employed part-time, and other. The "other" category mostly included self-employed individuals. Employed individuals represent 66.9% of the total sample as shown in Table 1, which shows the variables that are relevant to the study such as occupation, age, gender, and others.

Out of the employed group of individuals, we had to determine the subgroups of individuals who telework and do not telework. To help with this categorization, a question was asked to the employed respondents on the location they have been working from in recent weeks. The options that respondents could choose from and their distribution are found in Figure 1. Individuals who chose one of the last 3 options were included in the "Telework" group of individuals who do telework. Individuals who chose "mostly on-site/at the office" were not automatically included in this group. Another question was asked about their work location in the past week and had the following options to choose from: home, non-home location, both, or did not work. Individuals who chose "mostly on-site/at the office" to the previous question and "home" or "both" to this question were considered part of the "Telework" group. The individuals who chose otherwise to this question were considered part of the “Do Not Telework” group, which also included individuals who chose the “exclusively on-site/at office” option to the previous question. Out of the 747 individuals who are employed, 67.3% of them were part of the “Telework” group, and 32.7% were part of the “Do Not Telework” group.

Table 1 Sample Statistics

Variable	Sample (frequency)	Sample (%)
Occupation		
Employed full-time	526	47.1
Employed part-time	179	16.0
Full-time student	62	5.6
Full-time homemaker, parent or caretaker	42	3.8
Retired	137	12.3
Unemployed or out of work	88	7.9
Unable to work	40	3.6
Other	42	3.8
Age		
18-24 years old	121	10.8
25-34 years old	232	20.8
35-44 years old	208	18.6
45-54 years old	183	16.4
55-64 years old	218	19.5
65 years or older	154	13.8
Gender		
Man	543	48.7
Woman	560	50.2
Non-binary	13	1.2
Ethnicity		
American Indian or Alaska Native	3	0.3
Asian	76	6.8
Black or African American	124	11.1
Hispanic or Latino	58	5.2
White	833	74.6
Other	22	2.0
Highest degree completed or are completing		
Middle School	9	0.8
High School	227	20.3
Trade/technical/vocational Training	130	11.6
Undergraduate Degree	520	46.6
Graduate or professional Degree	230	20.6
Household size		
HH members = 1	266	23.8
HH members = 2	401	35.9
HH members = 3	237	21.2
HH members = 4	139	12.5
HH members = 5	54	4.8

Variable	Sample (frequency)	Sample (%)
HH members = 6+	19	1.7
Household kids under the age of 12		
HH kids = 0	957	85.8
HH kids = 1	105	9.4
HH kids = 2	43	3.9
HH kids = 3+	11	1.0
Household vehicles		
HH vehicles = 0	98	8.8
HH vehicles = 1	467	41.8
HH vehicles = 2	380	34.1
HH vehicles = 3+	171	15.3
Household location type		
Rural	191	17.1
Suburban	606	54.3
Urban	319	28.6
Household income (annual)		
Less than $24,999	192	17.2
$25,000 to $49,999	286	25.6
$50,000 to $74,999	229	20.5
$75,000 to $99,999	168	15.1
$100,000 to $149,999	148	13.3
$150,000 or more	93	8.3

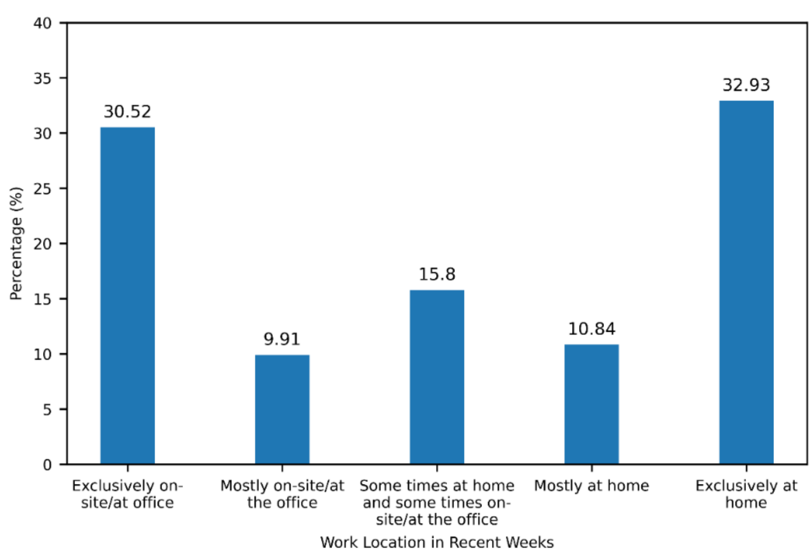
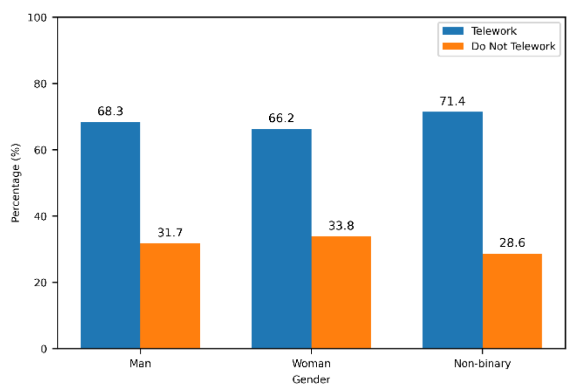


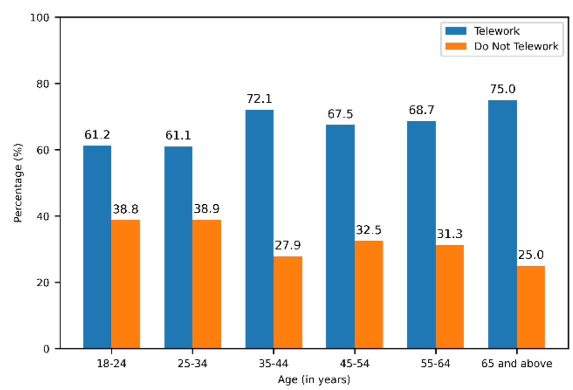
Figure 1 Work location of employed adults in recent weeks

Descriptive Analysis

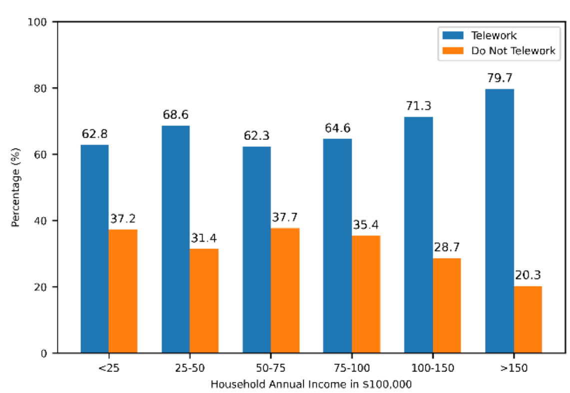
Referring to Figure 2, we can see that men, women, and non-binary individuals are more likely to telework than not telework. As for the highest level of education completed or are completing, we can see that the gap between individuals who telework and individuals who do not increase after high school. Jobs that are suitable for teleworking will most likely require a college degree. Interestingly, as the number of vehicles owned per household increases, individuals are more likely to not telework than telework. Individuals who telework do not necessarily need a vehicle for commuting purposes. The data shows that individuals who live alone have the biggest gap between telework and non-telework. Likely, individuals living with others are not able to work from home due to distractions. When looking at household location type, the biggest gap between telework and non-telework is in urban areas. This is an important finding since individuals who telework, living in urban areas, may not need to live there anymore and may resort to moving to suburban or rural areas. As for household income, we can see that the higher the income, the more likely it is for individuals to telework. This is also in agreement with the findings of Salon et al. who expected that individuals with a household income of $100,000 or above were likely to commute at least a few days after the pandemic (Salon et al., 2021a). As for work from home suitability, results show that individuals with jobs that are very suitable for working from home are more likely to telework. As suitability decreases, it becomes more likely that individuals do not telework.

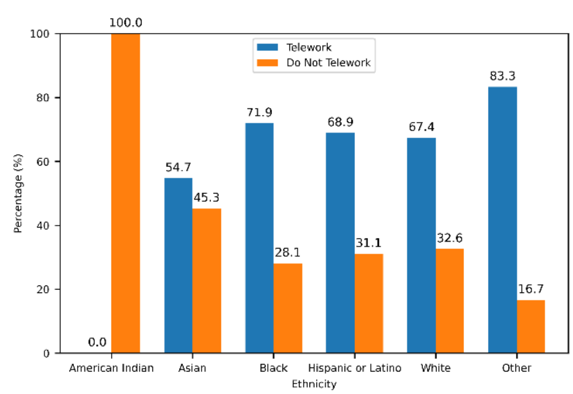


(a) Gender



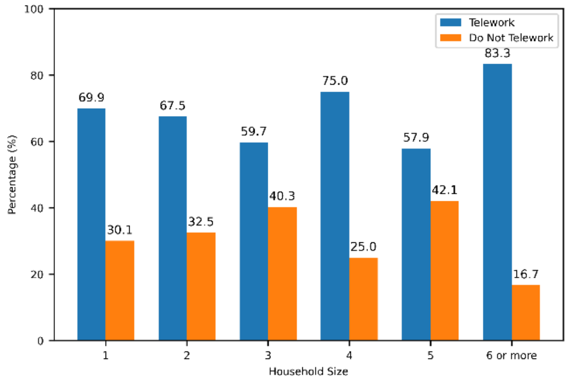
(b) Age

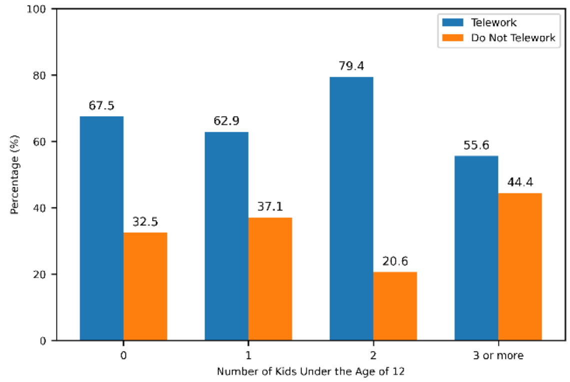




(c) Household annual income

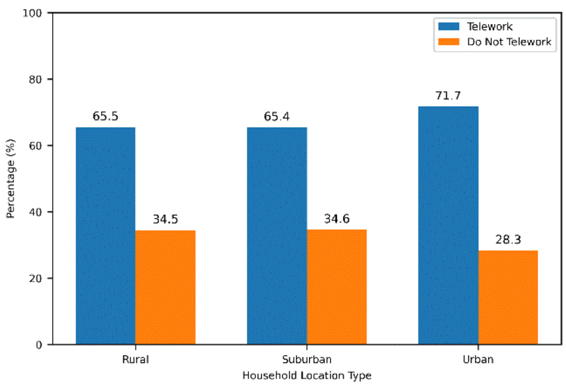
(d) Ethnicity

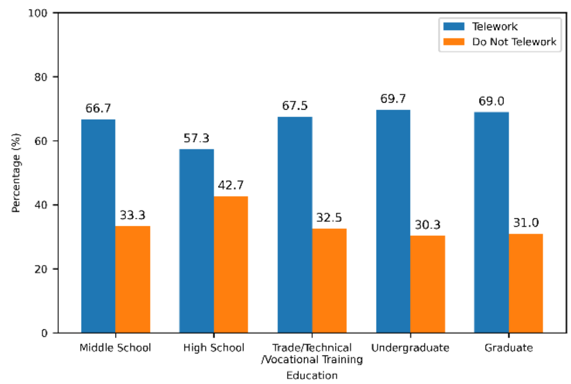




(e) Household size

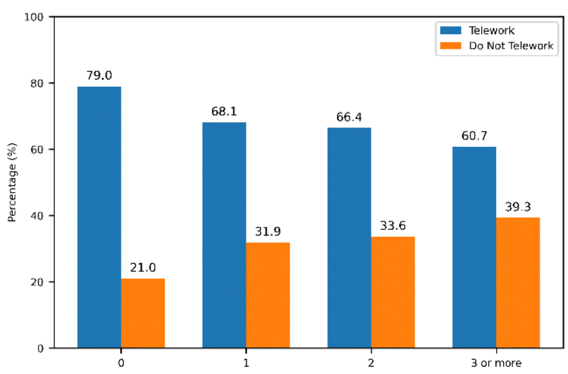
(f) Number of kids under 12 years old

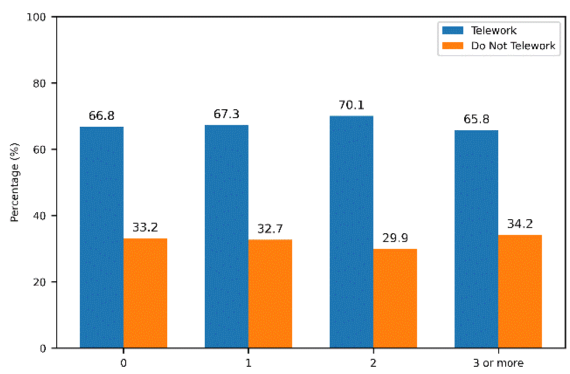




(g) Household location type

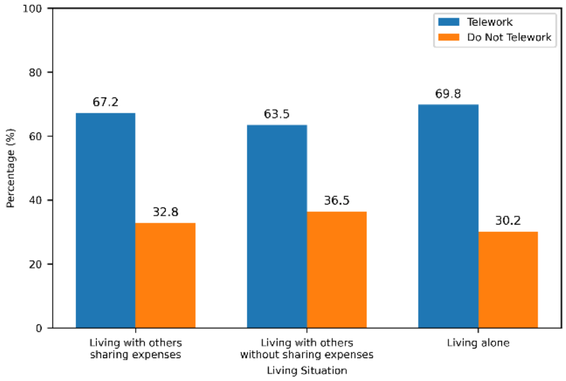
(h) Education level completed or are completing



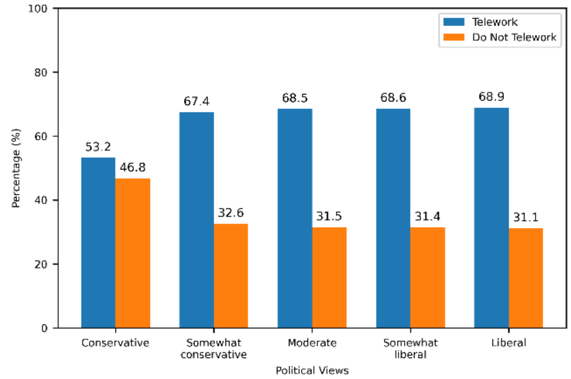


(i) Number of household vehicles

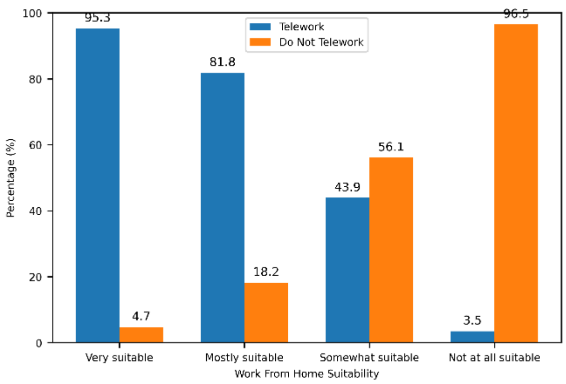
(j) Number of household bicycles



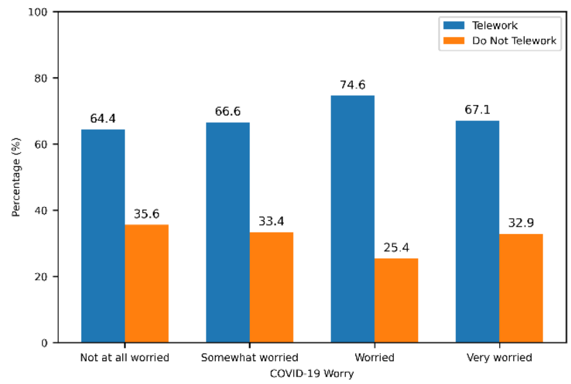
(k) Living situation



(l) Political views



(m) Work from home suitability



(n) COVID-19 worry

Figure 2 Descriptive analysis of variables comparing telework to non-telework status

Activity Duration Comparison

Figure 3 shows the average duration in hours per day spent on the various activities. Activity durations are compared between individuals who telework and those who do not. As duration increases from 0 to 10, the blue and orange bars are filled accordingly. We can see that teleworking individuals spend more time every day than non-teleworking individuals caring for others, except for Friday. This makes sense as telework allows for more time spent at home for caregiving activities. It is evident that individuals who work at the office or on-site spend more time driving or traveling than individuals who work remotely. This is reasonable since working at the office or on-site requires commuting to and back from the office. The data shows that individuals who telework spend more time eating and drinking than those who do not telework on weekdays. Individuals who work from home may be able to spend more time on meals than those who work from the office. Interestingly, we can see that individuals who telework spend less time sleeping from Sunday through Thursday. This makes sense since individuals who work at the office have to sleep at an earlier time so that they can wake up and get ready for work. Non-teleworking individuals appear to compensate by sleeping less on Friday and Saturday as they would be spending time on other activities that they were not able to do during the week. Individuals who telework spend a bit more time working at their main job, which is reasonable as they are more flexible in their daily schedules. Interestingly, individuals who telework were spending more time working at other jobs. This is an intriguing insight that was also observed by a study that found that 50% of respondents who worked for two companies at the same time during the pandemic (Kelly, 2021).

Activity	Duration per Day of Week (hours)						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Caring for others	0.49	0.27	0.42	0.25	0.81	0.79	1.36
	0.22	0.00	0.32	0.50	0.53	0.33	0.25
Driving / traveling	0.45	0.48	0.78	0.42	0.90	0.11	0.54
	0.73	0.60	0.89	1.17	1.29	0.50	0.63
Eating and drinking	1.37	1.41	1.18	1.39	1.40	0.97	1.79
	1.18	1.07	1.25	1.04	0.94	1.75	1.25
Entertainment / leisure	2.69	3.27	2.86	2.50	2.90	4.74	4.43
	2.97	1.80	2.64	2.44	3.00	3.58	4.38
Exercise	0.53	0.18	0.53	0.48	0.38	0.42	0.43
	0.35	0.07	0.36	0.33	0.35	0.25	0.00
Grocery or other shopping	0.37	0.32	0.22	0.24	0.33	0.32	0.71
	0.29	0.53	0.14	0.26	0.56	0.83	0.25
Household chores	0.54	0.91	0.50	0.58	0.86	1.84	1.21
	0.84	0.53	0.41	0.69	0.76	1.17	0.50
Other	0.43	0.18	0.21	0.49	0.10	0.11	0.21
	0.38	0.53	0.09	0.08	0.53	0.83	0.25
Personal laintenance	0.95	0.77	0.67	0.84	0.88	0.84	1.43
	0.76	0.73	1.07	0.91	0.65	0.92	0.50
Preparing meals or snacks	0.56	0.61	0.51	0.65	0.48	0.37	1.07
	0.52	0.73	0.68	0.50	0.82	0.50	0.50
Sleeping	7.28	6.59	6.83	7.18	8.62	8.58	7.79
	7.78	7.07	7.05	7.28	6.59	8.33	9.38
Socializing	0.35	0.36	0.85	0.51	0.67	1.26	1.14
	0.37	1.93	0.45	0.59	0.59	1.33	2.63
Working at main job	6.35	6.89	6.25	6.51	4.43	2.11	0.86
	6.03	5.80	6.82	6.53	4.53	1.33	2.38
Working at other job	0.42	0.41	0.67	0.38	1.10	0.11	0.50
	0.35	0.73	0.09	0.13	0.53	0.17	0.00

Telework　　Do Not Telework

Figure 3 Average duration spent per activity per day of the week

Figure 4 shows the average duration spent per activity on all days in hours. On average, individuals who telework spend more time on caring for others, eating and drinking, exercising, personal maintenance, working at their main job, and working at other jobs. These findings agree with the findings from the above daily durations spent on each activity. Individuals who telework spend less time driving and traveling as they do not need to commute to and from the office. The added flexibility of teleworking appears to mainly translate into time spent caring for others, exercising, and working. Interestingly, those who telework sleep an average of 0.2 hours less than those who do not. It is important to mention that the durations of each group do not add up to 24 hours since some individuals did not fill in their full 24-hour activity diary.

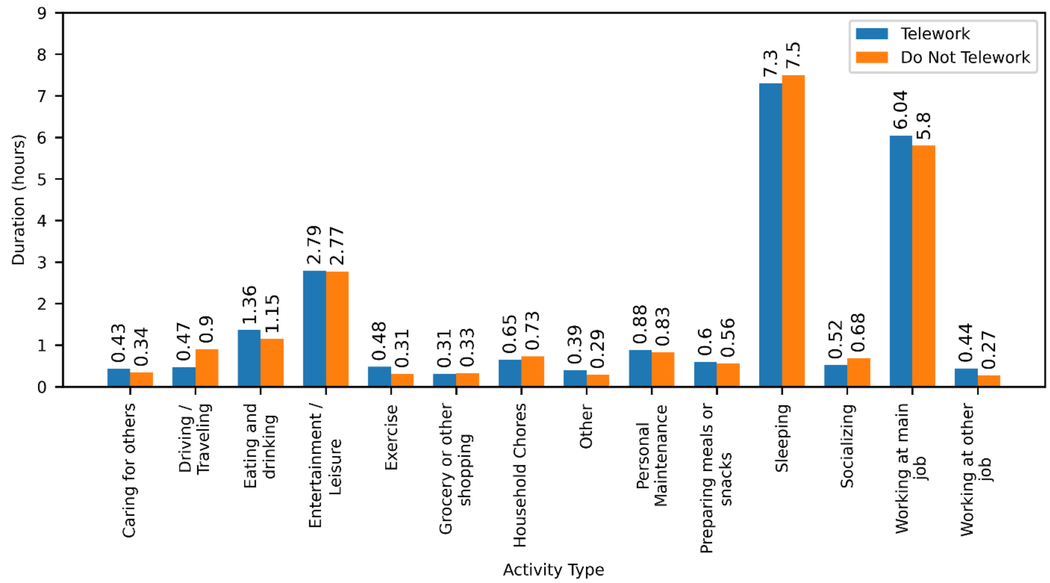


Figure 4 Average duration spent per activity on all days

Methodology

Several models aided in studying the effects of telework on the duration, distance, and time of day of out-of-home non-work trips. A Tobit regression model was utilized to better understand the effect of telework on the total duration and average distance of out-of-home non-work trips. This type of model was used to censor negative datapoints as well as add a ceiling on positive datapoints. A binary logistic regression model was used to better understand the socio-demographics of individuals who had an out-of-home non-work activity during their day. Finally, a multinomial logit model was utilized to understand the variables that help explain the choice to engage in an activity at a certain time of day.

Tobit Regression

A Tobit regression model (Washington et al., 2020) is a type of regression model used to censor the range of the dependent variable. The econometric model was proposed by Tobin (1958). The Tobit regression model can be written as shown in Equation 1.

$$Y_i^* = \beta X_i + \varepsilon_i , \qquad i = 1, 2, \dots, N$$

$$Y_i = Y_i^* \qquad \text{if } Y_i^* > 0 \qquad (1)$$

$$Y_i \quad = 0 \qquad\qquad \text{if } Y_i^* \leq 0$$

where Y_i^* is a latent variable observed when positive, Y_i is the dependent variable, X_i is a vector of explanatory variables, β is a vector of parameters to be estimated, and ε_i is an error term $\sim N(0, \sigma^2)$.

Multinomial Logit

A multinomial logit model (MNL) is a discrete choice model used to analyze a choice of an individual. These types of models are based on random utility theory (Ben-Akiva et al., 1985; McFadden, 2000). The general form of the utility function can be written as shown in Equation 2.

$$U_{in} = V_{in} + \varepsilon_{in} \tag{2}$$

$$V_{in} = \beta_i X_{in}$$

where i is the choice, n is the individual, U_{in} is the random utility, V_{in} is the systematic utility or the observed portion of the utility, X_{in} is a vector of explanatory variables, β_i is a vector of parameters to be estimated, and ε_{in} are Type I extreme value distributed random error terms with mean 1 and variance 0. The MNL model can then be written as shown in Equation 3.

$$P(i) = \frac{e^{V_{in}}}{\sum_{j=1}^{J} e^{V_{jn}}} \tag{3}$$

where $P(i)$ is the probability of choosing alternative i (*23*).

Binary Logistic Regression

A binary logistic regression is a type of logit regression used when the dependent variable to be predicted is binary.

Results

Modeling Duration of Activities

A Tobit regression model was used to study the effect teleworking has on the total duration spent on out-of-home non-work activities, as shown in Table 2. The Tobit regression model was selected to censor data below 0 and above 24 hours since durations cannot be negative and cannot be more than the hours of a day. As such, the model would not predict in ranges that are not viable. Here, a positive coefficient estimate increases the number of hours spent on activities, whereas a negative one decreases the number of hours spent on activities. The model shows that individuals who are employed full-time were spending approximately an hour less on out-of-home non-work activities than individuals who are employed part-time or self-employed. Furthermore, the time spent on out-of-home non-work activities peaked on Friday and was lower on Monday through Thursday. This makes sense as individuals can spend more time on those activities towards the end of the week. Interestingly, individuals completing or who completed a graduate or professional degree spend less time on out-of-home activities as they are likely spending more time studying or are older. The model shows that individuals with a household size greater than or equal to 3 spend less time on out-of-home non-work activities. A larger household is more likely to have kids or be multi-generational, making it difficult to spend more time on those activities. As for household location type, individuals living in suburban areas spend less time on out-of-home non-work activities compared to individuals who live elsewhere. Significantly, individuals who telework spend less time on out-of-home non-work activities than individuals who do not telework. It may be the case that teleworking individuals spend less time on these activities as teleworking allows for more bundling up of activities during the day. It may also be the case where individuals who telework engage in these types of activities during their working hours and would need to be quick to go back to work. The time of day chosen to engage in these activities will be discussed later in the study.

Modeling Average Activity Travel Distance

A Tobit regression model was fit to study the effect of telework on the average distance between home and the out-of-home non-work activity location, as shown in Table 2. A Tobit model was used to censor negative values since distances are not negative. As distance intervals were set beforehand in the activity diary, they were converted into continuous numbers such that “Less than a mile” becomes 0.5 miles, “1-2 miles” becomes 1.5 miles, “2-5 miles” becomes 3.5 miles, “5-10 miles” becomes 7.5 miles, “10-20 miles” becomes 15 miles, and “More than 20 miles” becomes 25 miles. The average distance for each individual was calculated by adding the distances of out-of-home non-work trips and dividing by the number of out-of-home non-work trips. The model shows that individuals who are 55 years old and above engage in activities closer to their home location. Significantly, individuals with a household size of 3 or more members participate in activities closer to their home location than individuals residing in smaller households. This is reasonable since household sizes of 3 or more members are likely to have children and are not able to travel as far as households with no kids. Additionally, the model shows that individuals travel to activities at farther distances from home on Friday as compared to the rest of the weekdays, coinciding with an observation found in the previous model where individuals who telework spend more time on out-of-home activities on Friday. Most importantly, the Tobit regression model shows that individuals who telework participate in out-of-home non-work activities closer to their home location than individuals who do not telework, at a 95% significance level. It seems that individuals who do not telework may be participating in those types of activities closer to their work location. In line with our findings, Saxena and Mokhtarian (1997) found that 86% of activities done by telecommuters were closer to home than they were to their work location on days when they telecommuted.

Binary Logistic Regression Model of Activity Participation

It is also important to study the time of day chosen to engage in out-of-home non-work activities. This is important from a policy decision standpoint as telework does not restrict an individual to do activities at a specific time of day. It was found that out of 747 employed individuals, 279 did not report an out-of-home non-work activity in their activity diary. This accounts for 37.35% of employed individuals. As such, it is important to study the variables affecting the decision to participate in those types of activities.

A binary logistic regression was suitable to study this effect, where the dependent variable was 1 if an individual participated in an out-of-home non-work activity or 0 if an individual did not. The results of the binary logistic regression model are shown in Table 3. The model shows that all else equal, individuals are more likely to participate in this type of activity with a 95% significance level. Individuals who are 55 years old or above are less likely to engage in this type of activity than individuals who are less than 55 years old. Furthermore, individuals with a household size greater than or equal to 3 members are less likely to engage in these activities than individuals with a household size less than or equal to 2. This is reasonable as it is easier to travel with a smaller group than with a larger one. Significantly, the model shows that individuals who have access to 1 or more vehicles are more likely to participate in these activities than individuals who do not have access to a vehicle. Furthermore, the higher the household income, the more likely individuals are to participate in out-of-home non-work activities, which is reasonable since higher-income individuals are more likely to have jobs that are flexible. At a 90% significance level, individuals are more likely to participate in those activities on Friday than on other days of the week. Finally, somewhat surprisingly, individuals who telework are less likely to participate in those activities than individuals who do not telework, at a 95% significance level. While working from home likely entails a more flexible schedule, it also has been tied to higher reliance on services such as online grocery shopping which can translate to a net effect of making fewer discretionary trips (Shamshiripour et al., 2020). Furthermore, Rafiq et al. (2022) also found that telework led to a reduction in non-work activities, which is in agreement with the findings of this model that shows individuals who telework are less likely to participate in out-of-home non-work activities.

Multinomial Logit Model of Time of Day

A multinomial logit model was built to study the variables behind choosing the time of day to engage in out-of-home non-work activities. To do so, only individuals who participated in those activities were considered. This was mainly done to study the effect of telework on the time of day chosen to participate in those activities, as they are no longer restricted to participate during specific hours of the day. Apollo (http://apollochoicemodelling.com/index.html), a software package for the R programming language, was used to fit the model. As there can be multiple observations per individual, Apollo takes care of this type of panel data by taking the product of probabilities across observations for the same individual. The 24-hour day was divided into 7 time segments as shown in Table 4, described as the following: early morning, late morning, early afternoon, late afternoon, evening, nighttime, and dawn, respectively. Each activity was assigned to a time group based on the start time of that activity. The results of the model are shown in **Table 4**.

TABLE 2 Tobit regression models of total duration and average distance

Dependent Variable	Total Duration (hours)		Average Distance (miles)	
	Tobit Regression		Tobit Regression	
Coefficients	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**
Intercept	1.637	2.25*	1.072	0.57
Log-Standard Deviation	1.301	37.86*	2.208	60.16*
Occupation				
Employed Full-Time	–1.179	–3.50*	–0.964	–1.14
Employed Part-Time & Other	Reference		Reference	
Age				
18-34 years old	Reference		Reference	
35-54 years old	–0.906	–2.64*	–1.000	–1.17
55 years old or above	–1.553	–3.78*	–2.694	–2.64*
Gender				
Man	Reference		Reference	
Non-man	–0.025	–0.08	–0.647	–0.86
Ethnicity				
White	0.518	1.54	1.269	1.51
Non-white	Reference		Reference	
Education				
Less than undergraduate	Reference		Reference	
Undergraduate degree	0.751	2.10*	1.399	1.57
Graduate/professional degree	0.101	0.23	0.692	0.64
Household size				
HH members ≤ 2	Reference		Reference	
HH members ≥ 3	–0.728	–2.26*	–2.788	–3.47*
Household vehicles				
HH vehicles = 0	Reference		Reference	
HH vehicles ≥ 1	1.106	1.95*	5.508	3.67*
Household location type				
Rural & Urban	Reference		Reference	
Suburban	–0.692	–2.28*	–1.051	–1.39
Household income				
Less than $74,999	Reference		Reference	
$75,000 - $149,9999	0.888	2.55*	2.913	3.39*
$150,000 and above	1.841	3.51*	4.987	3.84*
Day of week				
Monday-Thursday	Reference		Reference	
Friday	1.767	2.75*	2.746	1.71
Saturday-Sunday	0.801	1.43	–1.251	–0.86
Telework indicator				
Do not telework	Reference		Reference	

Dependent Variable	Total Duration (hours)		Average Distance (miles)	
	Tobit Regression		Tobit Regression	
Coefficients	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**
Telework	–1.282	–4.08*	–5.072	–6.51*
Number of observations		747		747
LL(β)		–1478.394		–1899.563
LL(constants)		–1514.579		–1947.273

* The coefficient is statistically significant at 95% confidence level.

All else equal, individuals are more likely to have an out-of-home non-work activity early afternoon, followed by late morning, then evening, then late afternoon, then all other time groups. As for occupation, full-time employees are somewhat most likely to have an out-of-home non-work activity during nighttime and least likely to have that activity during the dawn than all other time segments. Furthermore, individuals aged between 34 and 54 years old are less likely to have an out-of-home non-work activity in the evening than during the rest of the day. As for household location type, individuals living in suburban areas are less likely to have these types of activities during late afternoon and dawn when compared to the rest of the day. Individuals with a household income of $100,000 and above are less likely to have an out-of-home non-work activity from 9 AM to 3 PM than the rest of the day. Interestingly, when it comes to the days of the week including Monday through Thursday, the model shows that individuals are less likely to have these activities from 9 AM to 3 PM as well as from 6 PM to 9 PM when compared to other times of the day. Individuals are equally as likely to participate in these activities from 3 PM to 6 PM as from 6 AM to 9 AM. A similar observation is observed on Friday, where it is less likely to participate in these activities from 9AM to 3PM. Additionally, individuals are more likely to participate in out-of-home non-work trips between 9 AM and 3 PM on the weekend than on weekdays, but equally as likely to participate in those activities between 3 PM and 6 PM on all days. The final variable included in this model is the telework indicator which is equal to 1 if an individual teleworks. The results show that individuals who telework are more likely to have out-of-home non-work activities between 12 PM and 3 PM, and 6 PM and 9 PM, as compared to other times of the day. This shows that telework has allowed individuals to be more flexible during their day, as they are engaging in activities away from home, other than work, between 12 PM and 3 PM. The same comparison can be made between individuals who telework and individuals who do not, as individuals who do not are the reference. In other words, individuals who telework are more likely to engage in these activities than individuals who do not telework between 12 PM and 3 PM as well as between 6 PM and 9 PM.

TABLE 3 Binary logistic regression model of participation in out-of-home non-work activities

	Binary Logistic Regression	
Coefficients	**Estimate**	**t-Statistic**
Intercept	0.952	2.43*
Occupation		
Employed Full-Time	–0.382	–2.03*
Employed Part-Time & Other	Reference	
Age		

18-34 years old	Reference	
35-54 years old	–0.301	–1.55
55 years old or above	–0.473	–2.08*
Gender		
Man	Reference	
Non-man	–0.012	–0.07
Ethnicity		
White	0.251	1.35
Non-white	Reference	
Education		
Less than undergraduate	Reference	
Undergraduate degree	0.491	2.52*
Graduate/professional degree	0.169	0.72
Household size		
HH members ≤ 2	Reference	
HH members ≥ 3	–0.423	–2.37*
Household vehicles		
HH vehicles = 0	Reference	
HH vehicles ≥ 1	0.579	1.98*
Household location type		
Rural & Urban	Reference	
Suburban	–0.346	–2.06*
Household income		
Less than $74,999	Reference	
$75,000 - $149,9999	0.530	2.74*
$150,000 and above	1.238	3.82*
Day of week		
Monday-Thursday	Reference	
Friday	0.726	1.73
Saturday-Sunday	–0.012	–0.04
Telework indicator		
Do not telework	Reference	
Telework	–1.191	–6.28*
Number of observations		747
Null deviance		987.22
Residual deviance		904.54
AIC		936.54

* The coefficient is statistically significant at 95% confidence level.

TABLE 4 MNL model of time of day chosen to participate in out-of-home non-work activities

	Time of Day Alternative *Beta estimate (t-Statistic)*						
Variable	*6AM – 9AM*	*9AM – 12PM*	*12PM – 3PM*	*3PM – 6PM*	*6PM – 9PM*	*9PM – 12AM*	*12AM – 6AM*
Alternative specific constant	Reference	1.618	1.945	0.803	1.512	–0.749	0.262
		(2.91*)	(4.27*)	(1.98*)	(2.59*)	(–0.81)	(0.21)
Occupation	Reference	–0.675	–0.504	0.000	0.000	0.701	–0.787
Employed full-time		(-3.05*)	(–2.91*)	(NA)	(NA)	(1.47)	(–1.92)
Age	Reference	–0.263	–0.304	–0.601	–0.668	–0.773	–0.775
34-54 years old		(-0.90)	(–1.31*)	(–2.75*)	(–2.52*)	(–1.90)	(–1.69)
Age	Reference	–0.235	–0.431	–0.252	–0.865	–1.663	–1.158
55 years old and above		(–0.72)	(–1.49)	(–0.92)	(–2.52*)	(–2.53*)	(–1.89)
Ethnicity	Reference	1.051	0.182	0.000	0.000	–0.098	1.072
White		(3.47*)	(0.95)	(NA)	(NA)	(–0.27)	(2.02*)
Household size	Reference	–0.144	–0.087	–0.119	–0.136	0.000	–0.348
Continuous		(–1.64)	(–1.23)	(–1.47)	(–1.43)	(NA)	(–1.73)
Household location type	Reference	0.129	0.000	–0.391	–0.195	–0.431	–0.864
Suburban		(0.60)	(NA)	(–2.23*)	(–0.95)	(–1.21)	(–2.25*)
Household income	Reference	–0.677	–0.584	–0.157	–0.215	–0.457	0.738
$100,000 and above		(–2.34*)	(–2.59*)	(–0.72)	(–0.84)	(–0.96)	(1.63)
Day of week	Reference	–1.859	–1.009	0.160	–1.014	–0.297	–0.472
Monday-Thursday		(–4.43*)	(–2.56*)	(0.51)	(–1.98*)	(–0.35)	(–0.56)
Day of week	Reference	–1.735	–1.085	0.000	–0.757	–0.687	0.576
Friday		(–2.91*)	(–2.01*)	(NA)	(–1.25)	(–0.55)	(0.58)
Telework indicator	Reference	0.273	0.379	0.000	0.643	0.226	–0.221
Telework		(1.16)	(2.02*)	(NA)	(2.94*)	(0.57)	(–0.64)
Number of observations							468
LL(β)							–1566.18
LL(constants)							–1633.77
ρ^2							0.0414
AIC							3248.35

* The coefficient is statistically significant at 95% confidence level.

Discussion, Policy Implications, and Conclusion

This study focuses on understanding the effect of telework in the post-pandemic world on the total duration, average distance, and time-of-day chosen to perform out-of-home non-work activities. To answer the research questions presented, a survey was deployed in the U.S. between March and April of 2022 with a representative sample in terms of gender, age, and ethnicity. Respondents were asked to fill in their previous day's activity diary. The diary covered 12 different types of activities done out of home, excluding work. Out of a total sample number of 1116 respondents, 747 were working adults. Results show that the telework group represents 67.3% of the employed adults.

A Tobit regression model, a binary logistic regression model, and a multinomial logit model were used to study the effect of telework on total duration, average distance, participation in an activity, and time of day chosen to participate in an activity. The models included socio-demographic as well as other variables which were used as a control to focus on the effect of telework on the abovementioned dependent variables. The main findings from the study are as follows:

- Individuals are significantly more likely to telework than not to do so if they are of any gender, older than 35 years old, have a higher household income, have a smaller household size or a much larger one, live in an urban area, completed or are completing an undergraduate or graduate degree, have access to a low number of vehicles, live alone, or have a suitable job that allows doing everything from home.
- Individuals who telework sleep less on Sunday through Thursday and more on Friday and Saturday compared to individuals who do not telework. They also spend more time working at their main job as well as another job. Interestingly, and in agreement with other studies, individuals who telework spend less time driving and traveling (Mokhtarian et al., 1995).
- Individuals who telework spend approximately an hour less than individuals who do not telework on out-of-home activities throughout the week.
- Individuals who telework engage in out-of-home non-work activities closer to their home location than individuals who do not telework.
- Individuals who are 55 years old or above or have a household size of 3 members or more were spending less time and engaging in closer distances to home on out-of-home non-work activities.
- Individuals who have access to one vehicle or more or who have a household income of $75,000 were spending more time and engaging in farther distances from home on out of-home non-work activities.
- Individuals who telework are more likely to perform out-of-home non-work activities from 9 AM to 3 PM as well as 6 PM to 9 PM, compared to other times of the day.

In terms of policy recommendations, firstly, employers need to recognize that individuals who telework are in fact spending more time working than individuals who do not. This is an insight that employers who are evaluating a hybrid work model can take away from our work, while also taking into consideration the productivity of employees, as found in previous studies (Yen and Mahmassani, 1997; Yen et al., 1994). While doing so, it is also important for them to consider individuals who are not able to work from home and cater to them. Our findings also offer insights for transportation and urban planners to prepare for the impact of telework in the post-pandemic world. Now that individuals have the freedom to work from home, they may resort to relocating their home location. Considering there is a sizeable share of individuals who telework living in urban areas as compared to individuals who do not telework, it becomes crucial to assess the performance of the multimodal transportation system. There will be implications for a robust public transit system and, most likely, an entity will have to step in and make changes in accordance with the future of hybrid work.

This study possesses some limitations. First, several variables included in the different models presented are insignificant, also affecting the fit of the multinomial logit model. With a larger sample size, these issues can be addressed. Second, the models presented in the study do not take into account the lifestyle of respondents, such as being a morning person or a night owl, which could affect their choices made in their activity diary. More accurate results can be generated when considering the lifestyle as well as the preference of individuals. Third, the results shown in this study are based on a point in time. Further investigation is needed to capture the change in travel behavior in the future.

Chapter 4
Summary, Key Findings, Policy Implications and Future Work

In this report, we present a collection of three studies focused at gaining deeper understanding of individual experiences with telework during the pandemic, the evolution of telework through the pandemic and the expected post-pandemic telework trends, and the interaction of telework with out-of-home activity participation.

In the first study, using data from a U.S. representative sample (based on gender, age and ethnicity variables) of 318 working adults, we study individual satisfaction with telework using a multiple indicator multiple cause model (MIMIC). The study also presents an ordered probit model without the latent variables, which reveals systematic heterogeneity in telework satisfaction. The MIMIC model consists of an ordered probit component relating socio-demographic information and perceived/experienced telework benefits and barriers to telework satisfaction. Additionally, we anchor the modeling on personal, work, and household environment factors that help disentangle structural differences in how people experienced remote work.

The results from the ordered probit model without latent variables suggests that telework satisfaction was higher for middle aged individuals compared to younger and older individuals, Hispanic or Latino respondents, respondents with less than an undergraduate degree, and respondents with higher levels of concern about contracting the COVID-19 virus. On the other hand, satisfaction was found to be lower for individuals with children attending school virtually from home. The results from the MIMIC model confirms the ordered probit reference findings, namely that Hispanic or Latino ethnicity, education level, presence of an online-schooling child and worry related to contracting the COVID-19 virus are the main factors to drive satisfaction. Age, however, is now included in the structural component of the MIMIC model, revealing instead an indirect impact on satisfaction. The model also suggests a positive impact of telework related benefits and negative impact of barriers to telework. Epidemic-induced telework *benefits* can be associated with several demographic and household factors, namely: it is lower for individuals with Black ethnicity, those living alone or with presence of at least one child attending online school from home. The benefits were found to be higher for individuals without a vehicle and those who are suburban dwellers. Lastly, the barriers to telework were found to be most pronounced for essential workers and those with a remote-schooled child in the household. On the other hand, barriers were found to be lower for individuals employed in remote work suitable jobs and those with higher household income. A non-linear impact of age was also found to be a significant factor for both benefits and barriers latent variables.

Overall, three important take-aways emerged from the presented analysis. First, benefits and barriers to telework are disproportionately distributed across age groups. For younger individuals, this may be related to loss of networking opportunities that they need to advance in their careers or maybe related to the younger individuals mostly being employed in jobs that are not suitable for telework. For older individuals, the issue might be related to workplace anchoring, difficulty of managing their teams in more senior positions, and possible technology limitations in performing usual work activities. A second important finding is the evidence for inequity along the lines of racial/ethnic identity. Our findings are in line with other reports that Black and Hispanic or Latino individuals are disproportionately impacted in term of not being able to telework (Cerullo, 2020). Third, the presence of children attending online school is a consistently important factor impacting telework satisfaction. This is not surprising since several recent studies have pointed to negative impact of the pandemic on working parents with younger children (Feinberg et al., 2021; Patrick et al., 2020).

From a policy standpoint, our results suggest several implications for employers and policy makers in planning for the pandemic and post-pandemic periods. For employers who plan to adopt a hybrid or remote workplace in the long run, our study highlights several core factors that shape barriers and benefits of telework that can be used for communication and promotion of future efforts (e.g., the benefits of commute time savings). Furthermore, the causal structure of the model reveals the diverse experiences of different employer segments with regard to barriers and benefits. These insights can be used to design worker support strategies (e.g., on-site school/day-care pods assisting with challenges of inconsistent schooling access). If remote work were to become a norm at least for positions or tasks where physical presence is not necessary, employers must ensure support that is mindful of the diverse experiences and circumstances of workers, including the more complex non-linear effects such as those related to worker age. For younger employees, a hypothesis is that higher barriers or lower benefits are perceived due to lack of networking opportunities that they need to excel and advance in their careers. Employers could alleviate these by creating an environment to facilitate networking opportunities like organizing mandatory on-site days at regular intervals or hosting online networking hours. For older individuals who might perceive high barriers and lower benefits to teleworking potentially due to difficulty with technology, employers must invest in providing technology support. Concerns about social isolation, especially for workers for whom work provides an important environment for social interaction may also need to be addressed.

On the other end, if employers opt to have an in-person/office-centric plan for the future, creating a safe working environment will be important to phase in the return to the office since our results indicates a positive relationship between telework satisfaction and COVID-19 related worry. This could potentially be achieved by clear policies on social distancing, masking, and vaccination. As employers seek to determine the appropriate mix of telework and in-person presence, the factors identified in this study could assist in bringing out the positive features of each mode while mitigating some of the negative aspects. As a broader implication for public agencies planning for transportation and other infrastructure, it is important to thoroughly gauge the extent to teleworking in the post pandemic era, since basing future policies solely on trends during the pandemic could be erroneous (Hensher et al., 2021).

Some limitations of this study are worth mentioning here. First, for at least for some of the respondents, the satisfaction data was related to a hypothetical scenario of teleworking, and results could potentially be impact by the hypothetical bias (Hensher, 2010). Second, our study uses a relatively small sample size and additional insights could potentially be derived from a larger sample. Third, our study provides only a snapshot in time in an otherwise dynamic process; it would be important to examine the longer-term impacts of telework on both employees and employers, particularly with regard to factors such as productivity, creativity and worker retention, as well as personal satisfaction, work-life balance and happiness. The results presented in this study highlight important factors impacting telework satisfaction and provide insights for employers and policy makers to help design future telework policies.

In the second study, using data from a U.S representative sample of 905 respondents, we present a trajectory-based clustering analysis of work location trajectories through the pandemic. We identified 4 distinct clusters of telework trajectories with distinct levels of telework adoption patterns. Following the clustering analysis, the study presented results from a cluster membership model focused at understanding the factors associated with various telework trajectories including sector of occupation and socio-economic factors. This was followed by a two-part model focused at understanding the April 2024 expected work location, four years since the beginning of the pandemic.

A few key insights emerged from the cluster membership model. First, trajectories of telework through the pandemic are highly associated with nature of the job in which one is employed. For example, the model suggested that those in transportation/warehousing sector were more likely to higher in-person work compared to much higher at-home work for those in the information sector. The model also suggested lower telework adoption amongst those who are younger and those who are students and higher remote work for those without a vehicle. Further, those in urban households were more likely to present in clusters 2 or 3 where some form of hybrid work arrangement is expected going forward.

From the April 2024 work location models, key insights include presence of higher uncertainty amongst female respondents, students and those who were in cluster 4 (high telework through the pandemic) and lower uncertainty amongst those with a graduate degree. Finally, the ordered probit model for April 2024 work location for those who are certain suggests higher in-person work for transportation, healthcare and education sectors and lower in-person work for information, finance/insurance and professional services sectors. Further, the model also suggests higher in-person work for students and younger individuals, and those with higher education degrees but lower for those without a vehicle, those in lower income groups or those with age greater than 65 years.

There are several important policy takeaways from these results. There is strong evidence for telework to stay beyond the pandemic and this might have several implications for urban cities. The results from the clustering analysis suggest that some form of telework is expected to persist in the future for about 75% of the individuals (cluster 2, 3, and 4) and it is likely to be more amongst those without a vehicle and those living in urban areas and those working in information or related sectors. Given that most transit users are in urban areas and less likely to have access to a vehicle, telework trends in the future may significantly impact transit revenue which may further deteriorate service quality in the longer term, especially for those who really need it. Reduced demand due to telework might also hurt local businesses like coffee shops in downtown areas and business districts and policy makers need to plan how to alleviate the adverse impact of these changing trends on cities. Lastly, given that the information sector is likely to be more remote going forward, these trends will likely have high impact on cities with higher share of information sector jobs like San Francisco.

Lastly, we focus on understanding the effect of telework in the post-pandemic world on the total duration, average distance, and time-of-day chosen to perform out-of-home non-work activities. To answer the research questions presented, a survey was deployed in the U.S. between March and April of 2022 with a representative sample in terms of gender, age, and ethnicity. Respondents were asked to fill in their previous day's activity diary. The diary covered 12 different types of activities done out of home, excluding work. Out of a total sample number of 1116 respondents, 747 were working adults. Results show that the telework group represents 67.3% of the employed adults.

A Tobit regression model, a binary logistic regression model, and a multinomial logit model were used to study the effect of telework on total duration, average distance, participation in an activity, and time of day chosen to participate in an activity. The models included socio-demographic as well as other variables which were used as a control to focus on the effect of telework on the abovementioned dependent variables. The main findings from the study are as follows:

- Individuals are significantly more likely to telework than not to do so if they are of any gender, older than 35 years old, have a higher household income, have a smaller household size or a much larger one, live in an urban area, completed or are completing an undergraduate or graduate degree, have access to a low number of vehicles, live alone, or have a suitable job that allows doing everything from home.
- Individuals who telework sleep less on Sunday through Thursday and more on Friday and Saturday compared to individuals who do not telework. They also spend more time working at their main job as well as another job. Interestingly, and in agreement with other studies, individuals who telework spend less time driving and traveling (Mokhtarian et al., 1995).
- Individuals who telework spend approximately an hour less than individuals who do not telework on out-of-home activities throughout the week.
- Individuals who telework engage in out-of-home non-work activities closer to their home location than individuals who do not telework.
- Individuals who are 55 years old or above or have a household size of 3 members or more were spending less time and engaging in closer distances to home on out-of-home non-work activities.
- Individuals who have access to one vehicle or more or who have a household income of $75,000 were spending more time and engaging in farther distances from home on out of-home non-work activities.

- Individuals who telework are more likely to perform out-of-home non-work activities from 9 AM to 3 PM as well as 6 PM to 9 PM, compared to other times of the day.

In terms of policy recommendations, firstly, employers need to recognize that individuals who telework are in fact spending more time working than individuals who do not. This is an insight that employers who are evaluating a hybrid work model can take away from our work, while also taking into consideration the productivity of employees, as found in previous studies (Yen and Mahmassani, 1997; Yen et al., 1994). While doing so, it is also important for them to consider individuals who are not able to work from home and cater to them. Our findings also offer insights for transportation and urban planners to prepare for the impact of telework in the post-pandemic world. Now that individuals have the freedom to work from home, they may resort to relocating their home location. Considering there is a sizeable share of individuals who telework living in urban areas as compared to individuals who do not telework, it becomes crucial to assess the performance of the multimodal transportation system. There will be implications for a robust public transit system and, most likely, an entity will have to step in and make changes in accordance with the future of hybrid work.

This study possesses some limitations. First, several variables included in the different models presented are insignificant, also affecting the fit of the multinomial logit model. With a larger sample size, these issues could be addressed. Second, the models presented in the study do not take into account the lifestyle of respondents, such as being a morning person or a night owl, which could affect their choices made in their activity diary. More accurate results could be generated when considering the lifestyle as well as the preference of individuals. Third, the results shown in this study are based on a point in time. Further investigation is needed to capture the change in travel behavior in the future.

Future Work

There are several avenues for future research that are of interest. First, there is a need to track the evolving telework trends well beyond what is currently done in this study to understand the extent of impact these changing trends may have on urban and transportation planning decisions. Given that the employers are still evaluating the benefits and drawbacks of telework on business decisions, it becomes important to gain a deeper understanding of expected long-term telework patterns. Second, given that the ultimate telework policy decisions are going to be governed by employers (not only the employees), there is a need to understand the employer perspective on telework policies as well. The studies in this report focus on the employee side perspective, where the choice of teleworking is conditional on availability of remote work option. In this regard, a survey of employers across the U.S. could shed light on the employers' opinion and future remote work policies. Lastly, gaining a deeper understanding of remote work patterns across different major cities in the U.S. is also of interest. Our current studies show that the pattern of remote work is a function sector of operations of a company and since many cities have their economy governed by a particular sector (like information sector making up a large portion of economy in the Silicon Valley), the impact of remote work trends on local mobility and economy might be different across different cities.

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