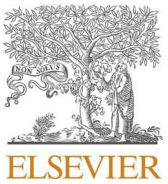
Transportation Research Part A 179 (2024) 103888



Contents lists available at ScienceDirect

Transportation Research Part A

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

An investigation of individual-level telework arrangements in the COVID-era

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ARTICLE INFO

Keywords:
ICT substitution
Telework
COVID impacts
Behavioral preferences

ABSTRACT

With work arrangements experiencing dramatic changes over the past three years due to the COVID-19 pandemic, and the possibility that altered work arrangements may persist well into the future, the implications of teleworking on activity-travel behavior are potentially profound. This paper aims to substantially add to the body of knowledge about the present and future of telework in the wake of the pandemic through a rigorous analysis of telework arrangements between two distinct time periods. The paper focuses on three key aspects of telework, including whether to telework or not, frequency of telework, and location of telework. Behavioral data for this study is derived from a workplace location choice survey conducted across Texas in February-March 2022, which included a recall component to obtain workplace location choice information in the pre-pandemic period. The evolution of telework arrangements between the pre-and after-pandemic periods is explored through a joint model system estimated using a joint multivariate methodology. Results show that, *After* COVID, the population of workers is generally inclined toward a hybrid work arrangement, with an overall tendency to engage in a higher frequency of teleworking than *Before* COVID. Finally, teleworkers have a higher propensity to work only from home as opposed to working only from a third workplace or from a combination of home and a third workplace. Overall, our results indicate that telework arrangements may remain at an elevated level into the future, with home serving as the dominant telework location. These findings suggest that transportation demand forecasting models need to be updated to reflect higher levels of teleworking, as well as the heterogeneity across individuals in teleworking adoption, frequency, and location.

1. Introduction

There is a long history of research documenting the intricate relationships between work arrangements, telework, and activity-travel demand (Mokhtarian, 2009; Moeckel, 2017; Lavieri et al., 2018; Shabanpour et al., 2018; Wang and Ozbilen, 2020). With work arrangements (also referred to as work modalities) experiencing dramatic changes over the past three years in the wake of the

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https://doi.org/10.1016/j.tra.2023.103888
Received 2 November 2022; Received in revised form 27 October 2023; Accepted 6 November 2023
Available online 30 November 2023

COVID-19 pandemic, and the possibility that altered work arrangements may continue to persist well into the future, the implications for activity-travel behavior impacts are potentially profound. In the United States, only six percent of workers primarily worked from a remote location (home or other) before the pandemic, while about three-quarters had never worked from a remote location (Coate, 2021).[1] During the height of the pandemic in 2020 and a good part of 2021, these percentages surged to 30–40 percent of all employees primarily working remote, and dropped to less than 40 percent never having worked remotely (Coate, 2021; Saad and Wigert, 2021; Flynn, 2022). As vaccination rates increased and the worst of the pandemic began to fade in late 2021, workers began to make their way back to the office, resulting in about 15–25 percent of workers primarily working from a remote location. But, rates of never working remotely remain under 40 percent (Flynn, 2022), indicating the substantial impact that COVID had on teleworking habits. In this context, research efforts on work arrangements, workplace location arrangement choices, and how these choices have changed (are changing) over the course of the pandemic can provide important insights on how roadways, office space, virtual communication technology, and other work-related infrastructure may evolve in the future. What will the workplace environment look like across the world as employees strive to retain some of the work location flexibility brought about by the pandemic? How will employers decide on their real estate needs, and how might this affect land-use patterns and commute patterns? How might employers respond to changing work pattern demands of employees, and what policies might they adopt to best harness and balance their employees' productivity, motivation and mental/emotional health? Can the paradigm change in work location perceptions brought about by the pandemic be harnessed to promote transportation equity across population groups? All these questions start from the more fundamental question of how employees' choice of work location arrangements has changed (and continues to change), based on their specific lifecycle, lifestyle, and work-related perceptions and attitudes.

Generally speaking, teleworking (that is, working remotely) is of substantial interest to the transportation planning profession due to its potentially transformative implications for mode use (particularly transit), the future of employment centers and the small businesses that depend on them, and the spatial and temporal characteristics of travel demand. In particular, travel demand forecasting models will need to be substantially updated to reflect the adoption, frequency, and location of telework, as the trajectory of human behaviors, choices, and preferences appears to have been forever altered by the pandemic (leading to a human adaptation process that has engendered the adoption of new *habits* and *routines*). Given the importance, rapidly evolving nature, and impacts of this behavioral phenomenon (i.e., telework and its various facets), and the multitude of dimensions that characterize this phenomenon, it is critical for the profession to engage in a continuous stream of telework-related research to understand its evolving nature and incorporate the latest insights into transportation demand forecasting models. This study contributes to the growing body of literature by investigating three key aspects of telework, including whether to telework or not, frequency of telework, and location of telework (home only, non-home only, or both home and non-home) across two time periods (namely, *before* COVID and *after* COVID), using a joint modeling framework that accounts for inter-temporal as well as intra-temporal unobserved correlations across the choice dimensions.

2. Previous literature

While telework was popular among some employment groups before the pandemic, it has only risen in popularity in the last couple of years. The literature on the subject can be categorized in terms of time of study performance into four distinct periods: (i) *Before* COVID, (ii) *During* COVID, (iii) after the worst of the pandemic (or *After* COVID), and (iv) fully *post*-COVID future. However, to parallel the scope of the current study, our literature review will mainly focus on the first and third time periods: *Before* COVID and *After* COVID. We do not consider the *During* COVID period because the changes in teleworking habits during this period were transient and are generally not likely to be reflective of the actual employee's choices, but rather the impositions of their employer and the government. Indeed, Jain et al. (2022) provide empirical evidence that COVID-related lockdowns were like forced 'experiments' related to workplace location (WPL) choice that are not necessarily indicators of long-term work arrangement desires or actual behavior. On the other hand, the teleworking adoption, frequency, and location choices before and after the pandemic are indications of individuals' actual preferences. We also do not consider the fully *post*-COVID future because the current timeline is not ripe enough to distinguish this *post*-COVID future from the *After* COVID period.

The next two sections (Sections 2.1 and 2.2) provide a brief overview of the existing telework literature from the *Before* COVID and *After* COVID time periods, with a greater emphasis on the latter time period. Section 2.3 discusses studies that involve a temporal aspect to employees' telework behavior and decisions.[2]

2.1. Telework in the before COVID period

There has been considerable literature exploring telework habits prior to the pandemic. As discussed in Asmussen et al. (2023), most of these studies focus only on telework adoption (that is, whether an individual has a formal employer-sanctioned with-pay

[1] The verbiage "primarily worked from a remote location" used in this sentence indicates that an employee never commuted to an in-person out-of-home designated workplace during the week prior to completion of the American Community Survey used by Coate (2021) in the analysis.

[2] Less germane to the specific technical context of the current research, but relevant to the implications from our research, is a large body of literature exploring the impacts of telework on activity-travel demand, with an interesting mix of findings. While some researchers have documented a clear inverse (substitution) relationship between teleworking and amount of travel (Lachapelle et al., 2018; Elldér, 2020), others have found a more complementary relationship between telework and travel demand – suggesting that the elimination of the commute results in discretionary time that engenders additional non-work travel (Moeckel, 2017; Zhu et al., 2018).

arrangement of working remotely one or more times over a specific time period such as a week or a month; see, for example, Hotopp, 2002, Vana et al., 2008, Ettema, 2010, Lila and Anjaneyulu, 2013, and Kazekami, 2020). A more limited number of studies have also investigated the frequency of telework (that is, the number of days of telework over a specified time period; see, for example, Popuri and Bhat, 2001, Webster-Trotman, 2010, Singh et al., 2013, and e Silva and Melo, 2018). Additionally, prior to the pandemic, almost all studies exploring telework did not consider the location of telework, or considered the individual's home as the singular telework location, except for a couple of studies by Lister and Harnish (2011) and Melo and de Abreu e Silva (2017) that considered an "other place" beyond home as a possible telework location. Overall, the overarching conclusions from this body of literature are that teleworkers (and higher frequency teleworkers) are typically young workers, holders of formal high education degrees, technologically savvy, and belong to urban households with high income.

2.2. Telework in the after COVID period

The literature on telework has witnessed an explosion since the outbreak of the pandemic, as employers and employees increasingly consider telework arrangements. Many of these studies, as in the *Before* COVID period, have examined only teleworking adoption, either in the form of actual telework adoption (using revealed preference data) or the preference for teleworking (using stated preference data). Examples of such studies, which typically are based on binary choice models of telework adoption, include Nguyen (2021), Danalet et al. (2021), Appel-Meulenbroek et al. (2022), and Bick et al. (2021). Beyond adoption, there is now also a growing body of literature that focuses on how frequently employees telework (or would like to telework), especially because of the high prevalence of work hybridization (that is, working remotely as well as from the regular work place). Examples of such studies include Zhang et al. (2020), Hensher et al. (2021), Mohammadi et al. (2022), Yamashita et al. (2022), Ton et al. (2022), and Asmussen et al. (2023). These studies adopt a variety of methodological frameworks to relate demographic and work-related variables to telework frequency, ranging from simple descriptive analysis (Yamashita et al., 2022) to multivariate econometric methods such as ordinal or count or multiple discrete–continuous models (Shabanpour et al., 2018; Zhang et al., 2020; Heiden et al., 2021; Hensher et al., 2021; Ton et al., 2022; Asmussen et al., 2023). The results from these *After* COVID studies, in general, tend to mirror the results from the *Before* COVID period, with women (especially single women with children), young individuals, self-employed workers, employees in white-collared corporate jobs, high income earners and those with a long commute time more likely to be observed to work remotely or with a higher stated preference to work remotely compared to their peers. Interestingly, though, the *After* COVID studies also do suggest a narrowing of the heterogeneity in telework adoption and frequency compared to the *Before* COVID period, with fewer sociodemographic and work-related variables having an impact (or as substantial an impact) on telework adoption/frequency in the *After* COVID period relative to the *Before* COVID period. For example, prior to the pandemic, employees in the healthcare industry consistently had lower telework adoption rates than those in other occupations (Hotopp, 2002; Sener and Bhat, 2011; Melo and Silva, 2017). But, since the beginning of the pandemic, there has been a rapid rise in telework opportunities for healthcare employees. More generally, the *After* COVID studies indicate more uniformity in telework adoption across occupation types than studies undertaken before the pandemic (see, for example, Omboni et al., 2022; Ahmed Kamal et al., 2023).

Besides the *who* and *how much* dimensions of teleworking, another important line of telework research in the *After* COVID period (that was almost completely missing in the *Before* COVID period) is related to the *where* dimension (that is, from which remote workplace location or WPL is a teleworker working). As employer and government mandates forced workers away from their in-person office locations during the pandemic, some employees began to explore different possibilities for remote WPLs (beyond the traditional work from home or WFH). Such non-home telework locations include neighborhood telecommuting centers (NTC) (Vaddadi et al., 2022) and third workplaces (Asmussen et al., 2023). In particular, Vaddadi et al. (2022) employ descriptive analysis techniques to examine the numbers of days across a three week period spent working from an NTC, relative to the regular office or home. They find that an NTC is more of a replacement for working from home, rather than replacing a commute to the in-person office. Asmussen et al. (2023) explore the "third workplace" (such as cafes) as an alternative alongside their in-person work office and home WPL options, and examine the preferred (not the actual) allocation of days across the three WPLs over the course of a work month. They elicit the preferred allocation using a stated intention question for a future period when COVID "would still be present but only in an endemic state." They observe that, while still not as preferred as the other two alternatives, younger workers and women with young children seem particularly drawn to working from a third workplace relative to their "observationally equivalent" peers.

2.3. Inter-temporal shifts in teleworking behavior

The studies in the earlier two sections examine telework at a single point in time. A couple of recent studies, however, have examined changes in teleworking brought about by COVID. For example, Bick et al. (2021) use a weekly time frame and categorize full-time employees into three work-arrangement groups – (1) commute-only, (2) work from home (WFH) some days, and (3) WFH-only. They do so for each of three separate time periods – (a) before the pandemic, (b) in May 2020, and (c) in December 2020, using a longitudinal survey. They subsequently undertake a descriptive analysis of telework adoption and frequency over the course of the week, and compare the results across time periods. They find an increase in WFH adoption and frequency from before the pandemic, especially for workers with a bachelor's degree or higher and with higher incomes. Haider and Anwar (2023) also explore telework adoption rates over the course of a month in Canada for two time periods: before the outbreak (before February 1, 2020) and during the pandemic (March and April of 2020). They adopt a *recall* technique, asking employees who teleworked during the pandemic to recall when exactly they began do so: before the COVID outbreak or due to the pandemic. Using two distinct binary logit models, Haider and Anwar examine the employee-related characteristics that differentiate those who teleworked pre-COVID from those who started to

telework only after the start of the pandemic. They find that telework adoption rates in Canada rose to 40 percent during the peak of the pandemic compared to only 12 percent prior to the pandemic, with the increase particularly the case among university-educated workers. However, both these studies do not examine telework location choice, and are rather exploratory in nature. Besides, both these studies compare teleworking between the "*Before* COVID" and "*During* COVID" periods, rather than between the "*Before* COVID" and the "*After* COVID" periods. They also do not consider the jointness in the telework adoption and frequency choices or individual-specific preferences that may permeate across time in telework choices.

2.4. Current paper in context

This paper aims to add to the body of knowledge about the present and future of telework in the wake of the pandemic, through an analysis of telework arrangements across two distinct time periods. The paper focuses on three key aspects of telework, including *whether* to telework or not, *frequency* of telework, and *location* of telework, and proposes a joint methodology that is capable of accounting for the unobserved correlations in the preferences across these dimensions within and between the two time-periods. Within each time period, the unobserved correlations capture idiosyncratic factors (such as attitudes, perceptions, preferences, and values) that may simultaneously increase or decrease the underlying propensities for the telework dimensions. For example, an intrinsically tech-savvy individual may be more likely to adopt telework and also telework frequently, while a socially introverted individual may not only have a high propensity to telework (and do so frequently), but also prefer to WFH. Of course, one can only speculate on the reasons for such unobserved correlations, but it is important to recognize that telework decisions are likely to be made as a joint package rather than in a piecemeal fashion. Besides, the nature of such unobserved factor effects itself may have changed from the *Before* COVID to *After* COVID periods, warranting consideration of separate correlations across the three telework dimensions within each period. Across the two time periods, the unobserved correlations capture idiosyncratic individual-level unobserved factors that permeate over time and that influence the *Before COVID* and *After COVID* telework choices of the same individual. In general, we would expect these inter-temporal correlation effects for each dimension to be positive; that is, unobserved individual-specific factors that increase the propensity of telework adoption and telework frequency at the *Before* COVID time point can be expected to increase the corresponding propensity of telework at the *After* COVID time point. Similarly, unobserved factors that increase the propensity for a specific telework location at the *Before* COVID time point can be expected to increase the propensity for that telework location at the *After* COVID time point. To our knowledge, from a methodological standpoint, this is the first paper in the literature to jointly model all the three telework dimensions of adoption, frequency, and location across both the *Before* COVID and *After* COVID periods.

From a substantive standpoint, we explicitly consider the possibility of working at a non-home location as part of the telework *location* dimension. In addition, the paper sheds deep insights on the evolution (over the pandemic period) of work arrangements for different socio-economic, demographic, and work sector groups. Through such an analysis, the paper aims to identify market segments that are more likely to continue teleworking into the future, while also uncovering those demographic groups that may be left behind by way of work arrangement options (leading to an inequitable future of work). In doing so, and unlike most studies in the teleworking literature at large, we go beyond the model estimates (that typically do not provide information about the directionality and magnitude effects of variables on the outcomes of interest) to computing the direction and size effects of exogenous variables on the actual outcomes of interest.

The data for this study is derived from a workplace location choice recall survey conducted across Texas in February-March 2022. As such, the paper examines the evolution of telework arrangements between the pre-pandemic period and the February-March 2022 period. Although it may be argued that COVID was still prevalent during February-March 2022, it can be safely assumed that the worst of the pandemic was in the rearview mirror, with high rates of vaccination, lifting of mask and social distancing mandates, reopening of all establishments and workplaces, and a substantially diminished threat of death (or even severe complications) due to the virus. In this analysis, the February-March 2022 period will be referred to as the *After* COVID period (because it is *after* the worst of the pandemic). The pre-pandemic period will be referred to as the *Before* COVID period. Through the inclusion of retrospective questions in the survey (to elicit information about *Before* COVID behaviors), the resulting dataset essentially provided information at the two time points of interest (*Before* and *After* COVID) for the same set of individuals. While there is a possibility of the presence of recall or misclassification error because of our retrospective approach to collecting the *Before* COVID data, work-related arrangements (including telework arrangements) are relatively important determinants of one's lifestyle and lifecycle rhythms, as also suggested by Ory and Mokhtarian (2006). And this was particularly so before COVID because any teleworking arrangements tended to be very structured, with clear employer-mandated regulations about the permissible extent and location of teleworking (Boland et al., 2020). Thus, it is only reasonable to expect that respondents should be able to accurately recall their work arrangements even a couple of years later. Indeed, respondents seemed to have little trouble in the survey providing details of whether or not they teleworked, and the extent and location of their teleworking, with literally no missing or inappropriate data responses.

In the empirical analysis of our paper, to appropriately tease out the effects of the pandemic on employee preferences regarding telework, we focus on only those individuals who were employed, and had the allowance (from their employer) to work remotely, both before COVID and after COVID (allowance refers here to whether the employers of the respondents formally and officially sanctioned (with pay) the performance of work from a telework location on one or more days over a period of a month). Such control is important when considering shifts in telework adoption tendencies from an employee perspective. In the *Before* COVID period, estimates of teleworking allowance were in the order of 50 to 60 percent across all industries (this includes both workers allowed to telework as a matter of their employer's universal policy, and workers allowed to telework at the discretion of their own manager; Groen et al., 2018). However, only about 20 percent of employees with such allowance appear to have adopted teleworking (Parker et al., 2022), presumably because of a desire to partake in work socialization and/or due to wanting to be visible to upper management for

professional career advancement reasons. But, in the *After* COVID period, teleworking allowance shot up to almost 80 percent of employers (Wigert, 2022), with 87 percent of these employees with the telework option availing of the opportunity for at least some portion of their week (Dua et al., 2022). Clearly, the employee adoption change due to COVID may be attributed to both increased employer allowance of telework as well as increased employee adoption of telework given allowance. The emphasis in this paper, as just indicated, however, is on the latter employee adoption shift while controlling for employer allowance. This employee adoption shift has occurred because many individuals who never worked from home before the pandemic got to experience this new (for them) work modality. For most of these individuals, the time and cost savings of telework, along with the ensuing flexibility of the work itself, led to an overall positive valuation of telework (Tursunbayeva et al., 2022). And for many who teleworked for a few days a month before the pandemic, doors opened up to work even more remotely. Further, our focus on employee adoption is also driven by the fact that, while employer allowance determined employee telework adoption in the *Before* COVID period, the tables have turned a little more toward employee telework adoption preferences influencing employer telework allowances (though, admittedly, this is also evolving). Specifically, during a period dubbed in the popular press as the era of the "great resignation", employers are increasingly aware of the need to provide work flexibility today as a means to attract new employees and retain experienced employees (Sheather and Slattery, 2021; Hopkins and Figaro, 2021). Of course, it would be of interest to investigate both the employee side adoption and employer side allowance issues together, but a rigorous study of this complex interplay is left for future investigations.[3]

The rest of this paper is organized as follows. The third section presents details of the data and sample used, while the fourth section discusses the modeling methodology. Section 5 contains the model results, followed by the determination of variable size effects in Section 6. Study discussions and conclusions are provided in Section 7.

3. Data description

3.1. Survey overview and sample characteristics

As indicated earlier, the data for this study are derived from a workplace location choice survey deployed across the state of Texas in February-March 2022. The survey was undertaken as part of a study funded by the Texas Department of Transportation. Respondent recruitment was accomplished through a multipronged strategy. Email messages were sent to several city Chambers of Commerce across the state, to businesses and professional organizations, and to media outlets (requesting visibility and publicity), as well as to a database of roughly 55,000 Texan residents' email addresses. Through this outreach effort, employees at a variety of organizations were recruited to participate in the survey.

The survey collected detailed information on household/personal socio-economic and demographic characteristics, collected at the time of the survey.[4] The survey also included questions to elicit information about travel behavior and mobility choices, mode usage, and activity engagement. Pertinent to this study, the survey included a battery of questions on work arrangements *Before* COVID and at the time of the survey (that is, the *After* COVID period). Importantly, the survey was deployed after the Omicron variant had passed its peak in Texas, and there were no mandatory pandemic-related safety measures in place in Texas. Actually, all COVID-related mandates/restrictions had been lifted in the state as early as March 2021 (Office of the Texas Governor, 2021). Also, when asked about what they believe will be their teleworking arrangement in the "not-so-distant future", respondents indicated a work modality distribution that was largely similar to the current (*After* COVID) work modality distribution, suggesting that, at least in Texas, the effects

[3] For the same reason that we consider only employees who had the option of telework both during the *Before* COVID and *After* COVID periods, we also consider only employees who had a designated out-of-home work office during both periods (even if they chose never to commute into this designated out-of-home work office). However, we did not require that the employee should have been with the same employment firm during the *Before* COVID and *After* COVID periods. In our survey, about 12 percent of employees with a designated out-of-home work office during both periods reported that they had changed jobs during the pandemic. This variable was introduced as an exogenous variable to investigate if switching jobs had any influence on the shifts in frequency and workplace location choice outcomes between the *Before* COVID and *After* COVID periods. Interestingly, the variable turned out to be insignificant even at the 68 % level of confidence (t-statistic of 1.00) for all dimensions, suggesting that job switches, by themselves, do not have much impact on work arrangement changes between the two periods after shifts due to other factors (and the generic shift) have been considered. This result is not entirely surprising, because the existing literature supports the notion that employees generally tend to stay within their industry sectors even if they do switch jobs (see, for example, Gebbels et al., 2020, Bauer et al., 2020, Dauth et al., 2017), and industry sectors play a substantial role in determining work arrangements (including any telework arrangements). In any case, this paper aims to study the adoption, frequency, and workplace location choices of teleworking of employed individuals *irrespective* of their employers, as long as the individuals had the option from their employers to engage in telework.

[4] Note that we do not have the explanatory sociodemographic variable information from the pre-COVID period. If these variables change substantially between the Before and After COVID periods, one could legitimately posit that the difference in work arrangements (between the two periods) is at least as much to the change in sociodemographics as it may be attributed to overall behavioral changes caused by the pandemic. However, given the short two-year period between the pre-COVID period to the time of the survey (January-February 2022), there is a very reasonable expectation that the independent variables would not have changed dramatically. Clearly, variables such as gender, age, and immunocompromised status would not change over short periods of time. In addition, as we discuss in the penultimate paragraph of Section 2.4, we focus on "only those individuals who were employed, and had the allowance (from their employer) to work remotely, both before COVID and after COVID (allowance refers here to whether the employers of the respondents formally and officially sanctioned (with pay) the performance of work from a telework location on one or more days over a period of a month)." Further, only 12 percent of the sample indicated that they had changed jobs. Based on all of these factors, there is a reasonable expectation that income too would not have changed much between the two periods.

Table 1
Survey Sample Characteristics (Sample Size N = 980).

Variable	Count	%	Variable	Count	%*
Individual Demographics			*Household Characteristics*		
Gender			**Household Annual Income**		
Women	600	61.2	Less than $25,000	22	2.2
Men	380	38.8	$25,000 to $49,999	56	5.7
Age			$50,000 to $74,999	136	13.9
18 to 29	67	6.8	$75,000 to $99,999	133	13.6
30 to 49	339	34.6	$100,000 to $149,999	266	27.1
50 to 64	435	44.4	$150,000 to $249,999	230	23.5
65 or older	139	14.2	$250,000 or more	137	14.0
Education Level			*Job-related Characteristics*		
Less than a Bachelor's degree	110	11.2	**Employment Status**		
Bachelor's degree	353	36.0	Full-time (≥16 days per month), self-employed	126	12.9
Graduate degree	517	52.8	Part-time (≤15 days per month), self-employed	30	3.0
Residential Characteristics			Full-time (≥16 days per month), not self-employed	782	79.8
Community Region Type			Part-time (≤15 days per month), not self-employed	42	4.3
Rural	179	18.3	**Occupation/Industry Type**		
Suburban	563	57.4	Healthcare	43	4.4
Urban	238	24.3	Education/Social Services	396	40.4
Stand-Alone House			Public Administration	56	5.4
Yes	816	83.3	Professional Services	160	16.3
Private Study			Information/Finance	97	9.9
Yes	763	77.9	Manufacturing/Construction/Farming/Warehousing	43	4.4
In-Person Workplace Characteristics			Sales/Food Services	2	0.2
Employment Density			Managerial/Technical	183	19.0
Low to medium	784	20.0	*COVID-19 Threat*		
High	196	80.0	**Immunocompromised Status**		
			Someone frequently seen is immunocompromised	387	39.5
			Individual is immunocompromised	164	16.7

of COVID on work patterns may have relatively stabilized.

Table 1 provides information on the socio-economic and demographic characteristics of the sample of 980 individuals used in our analysis. The demographic composition exhibits a greater proportion of women, with 600 of the 980 individuals (61.2 percent) being women. Only 6.8 percent of the analysis sample is aged 18–29, while 44.4 percent are aged 50–64. Given that these individuals have the option to work remotely, it is not surprising that the sample exhibits a high education level, with more than one-half having a graduate degree. In terms of residential characteristics, just under one-quarter reside in urban areas, while 57.4 percent reside in suburban areas. A vast majority (83.3 percent) reside in a stand-alone housing unit, and just about 78 percent indicate that they have a private study in their residence. About four-fifths of the sample reports working in employment locations that may be characterized as low-to-medium density. Respondents identified the zip code of their work location, which was used to link built environment variables and compute density as the ratio of number of jobs to unprotected acreage. Based on Ramsey and Bell (2014), zip codes with an employment density less than 2.2 jobs per unprotected acre of land are classified as low density, while those with 5.2 or more jobs per unprotected acre of land are classified as high density. All other zip codes are classified as medium density. In terms of household income, the sample is skewed towards higher household income levels, consistent with what one would expect for a sample of telework capable workers. Nearly 65 percent report annual household incomes of $100,000 or more.

Just about 80 percent of the workers indicate that they are full-time (working 16 days or more per month), not-self-employed. About 13 percent report that they are full-time self-employed workers. A total of 7.3 percent of respondents are part-time workers (working 15 days or less per month. The respondents are largely employed in occupations that are remote-work friendly (e.g., education/social services, professional services, information/finance). Very small percentages are employed in occupations that may be viewed as more of in-person in nature (e.g., manufacturing/construction/farming/warehousing, sales/food service, healthcare). Nearly 40 percent indicate that they see an immunocompromised individual frequently, while 16.7 percent indicate that they themselves are immunocompromised (these two groups are not necessarily mutually exclusive).

3.2. Telework dimensions

This study is concerned with modeling three aspects of telework arrangements at each of the *Before* COVID and *After* COVID periods.

- Adoption: whether to work at a remote location or not (a binary outcome),
- Frequency: number of times that the individual engages in telework (characterized as an ordinal outcome with the alternatives of "Few times/month", "Once/week", "2–4 days/week", and "5 days per week"),
- Location: location of telework, if the individual participated in telework (characterized as a nominal outcome with the alternatives of "Home only", "Third location Only", and "Both home and third location"; note that we will use the label "third location" instead

Table 2
Descriptive Characteristics of Endogenous Work Arrangement Variables (Sample Size N = 980).

Has individual worked remotely in the past month?	Telework Adoption *Before* COVID		*After* COVID	
	Count	Percent	Count	Percent
No	582	59.4 %	334	34.1 %
Yes	398	40.6 %	646	65.9 %
Telework Frequency				
How often does individual telework?				
Few times/month	161	40.5 %	133	20.6 %
Once/week	58	14.6 %	71	11.0 %
2–4 days/week	68	17.0 %	195	30.2 %
5 days/week	111	27.9 %	247	38.2 %
Telework Location				
Where has individual teleworked?				
Home only	340	85.4 %	580	89.8 %
Third Location only	17	4.3 %	25	3.9 %
Both Home and Third Location	41	10.3 %	41	6.3 %

Telework Adoption/Frequency Transition Between *Before* COVID and *After* COVID

Telework Adoption/Frequency *Before* COVID	Telework Adoption/Frequency *After* COVID										
	Not adopting		A few times/ month		Once/week		2–4 days/week		5 days/week		Total
	Count	Percent	Count	Percent	Count	Percent	Count	Percent	Count	Percent	
Not adopting	307	52.7 %	74	12.7 %	38	6.5 %	96	16.6 %	67	11.5 %	100.0 %
A few times/month	12	7.5 %	52	32.3 %	17	10.6 %	39	24.2 %	41	25.5 %	100.0 %
Once/week	4	6.9 %	1	1.7 %	10	17.2 %	22	37.9 %	21	36.3 %	100.0 %
2–4 days/week	5	7.4 %	4	5.9 %	2	2.9 %	31	45.6 %	26	38.2 %	100.0 %
5 days/week	6	5.4 %	2	1.8 %	4	3.6 %	7	6.3 %	92	82.9 %	100.0 %

of "non-home", just to emphasize that non-home here is in the context of teleworking, and should not be confused with the designated out-of-home employer work office).

Table 2 presents a detailed description of the endogenous variables of interest. Note that, because the sample is limited to those employed individuals with the option to work remotely at both the *Before* COVID and *After* COVID points in time, the statistics naturally depict a high level of telework engagement (when compared with typical employment level census statistics). Before COVID, about 59.4 percent indicated that they never teleworked, while this percentage decreased to 34.1 percent in the *After* COVID period. Among teleworkers (see the teleworking frequency distribution in Table 1), there is a tangible decrease in the lower frequency ordinal categories and a clear increase in the higher frequency ordinal categories between the *Before* COVID and *After* COVID periods, indicating that not only are more individuals adopting telework in the *After* COVID period, but also the teleworking frequency of teleworkers has increased. Overall, in the *After* COVID period (which reflects a period when vaccinations were widespread and the worst of the pandemic was in the past), a hybrid work arrangement of working both from the regular workplace as well as from a telework location emerged as the dominant modality, with 34.1 percent of employees working only from the work office (never adopted teleworking), 40.7 percent [=(20.6 + 11.0 + 30.2) × 65.9/100] working in hybrid mode fashion, and 25.2 percent [=38.2 × 65.9/100] working only remotely.

The next telework location part of the table shows that, in both the *Before* COVID and *After* COVID periods, more than 85 percent of teleworkers reported doing so only from home.[5] In fact, as one would expect, the "home only" teleworkers increased from the *Before* COVID to *After* COVID periods, given individuals may have gotten somewhat comfortable working from home after being strictly restricted to do so by government mandates during the height of the pandemic. However, also important to note is that the number of

[5] Respondents were reminded multiple times throughout the survey that a third (workplace) location refers to locations such as a coffee shop, a designated co-working space, a hotel, or a restaurant, but does not include working from a client's site, which would instead be categorized as an in-person workplace, and therefore not telework. The survey also continually reminded respondents that telework did not include their company's office or worksite, their school's building or campus, or a client's site, to further clarify what an in-person workplace is and what a third workplace location is.

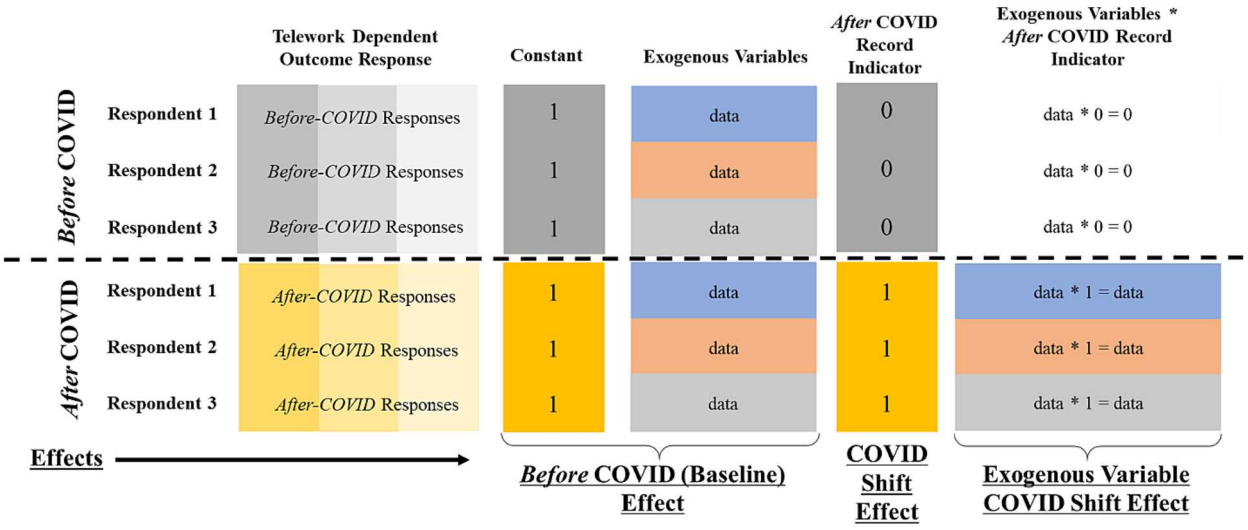

Fig. 1. Data Configuration and Format.

teleworkers working from a third location increased by 47 percent (from 17 to 25 teleworkers) between the *Before* COVID and *After* COVID periods.[6]

The final part of the table depicts the transition in telework adoption/frequency between the *Before* COVID period and the *After* COVID period. Among those who did not adopt telework prior to COVID, 47.3 percent transitioned to some level of telework with 11.5 percent doing so every day. Among those who teleworked a few times per month before COVID, about one-third continued to do so at that level in the *After* COVID period, but one-quarter teleworked 2–4 days per week and another one-quarter transitioned to full-time telework. Similar patterns are seen among other occasional teleworker groups; in general, they transitioned to higher levels of teleworking in the *After* COVID period compared with *Before* COVID. Not surprisingly, only 47 individuals (see the lower diagonal cells of the table), constituting roughly 4.8 percent of all individuals in the sample, experienced a decrease in the level of telework in the *After* COVID period. Overall, the trends again depict a pattern of greater adoption of hybrid work arrangements after COVID.

4. Modeling framework

The modeling framework considers the transition in telework arrangements between the *Before* COVID and *After* COVID period.

4.1. Data Format and model structure

The aim of the modeling effort in this study is to determine the *COVID-effect*, i.e., the impact of COVID on telework *adoption*, telework *frequency*, and telework *location*. To do so, we stack the dataset in a configuration as depicted in Fig. 1. For each respondent, there is a pair of records – one corresponding to the *Before* COVID period with a set of dependent outcome responses for the three endogenous variables of interest (telework adoption, frequency, and location), and a second corresponding to the *After* COVID period with again a set of dependent response outcomes to the three endogenous variables of interest. The *Before* COVID telework dependent outcome for all individuals are first stacked up in the top row panel labeled "*Before* COVID", followed by the *After* COVID responses for all individuals in the bottom row panel labeled "*After* COVID". Next, there is a constant followed by a set of exogenous variables, all of which are considered static and invariant between the two time periods (in the survey, the static values of the exogenous variables correspond to those in the current or *After* COVID period).[7] Thus, as shown in Fig. 1, the same "data" will appear under the "exogenous variables" column for each individual for the *Before* COVID and *After* COVID periods. This is followed by an "*After* COVID record" indicator that takes a value of 1 if a record corresponds to the *After* COVID period and 0 otherwise. Finally, the dataset has an interaction element, corresponding to interaction terms between the exogenous variables and the "*After* COVID record" indicator. Essentially, this configuration allows the estimation of a model system that is capable of revealing three types of effects, as identified at

[6] At an aggregate-level, simple paired tests on the statistics shown in Table 2 indicated statistically significant differences in telework adoption, telework frequency, and telework location between the *Before* COVID and *After* COVID periods.

[7] While some demographics, such as the categorizations of income, education level, and age as used in our final empirical specification, may have changed between the two time periods, these changes are likely to be rather minimal within a span of two years. Thus, we do not expect that our results will be substantially different because of ignoring the time-varying nature of the exogenous variables. In any case, as we acknowledge in the conclusions section, this is a limitation of our recall-based survey where we elicited only current (that is, "*After* COVID") exogenous variable values so as to keep the survey response time reasonable.

the bottom of the figure – (1) a *Before* COVID (or baseline) effect corresponding to the column labeled at the top as "constant" and "exogenous variables", (2) a generic COVID shift effect (from the baseline effect) corresponding to the column labeled at the top as "*After* COVID record indicator", and (3) an exogenous variable COVID shift effect from the baseline, corresponding to the column labeled at the top as "exogenous variables*After* COVID record indicator. It should be noted that the baseline and shift effects for the constant or any exogenous variable may manifest themselves in different forms. Both baseline and shift effects may be positive, or both effects may be negative, or they may be of opposite sign; by algebraically adding the two effects, it will be possible to determine the *After* COVID effect of the exogenous variable on telework arrangements. Also, if an exogenous variable only has a baseline effect and no shift effect, that implies that the effect of the exogenous variable is the same across both time periods. On the other hand, if an exogenous variable only has a shift effect and no baseline effect, it implies that the variable did not have an impact in the *Before* COVID period, but had an impact in the *After* COVID period. Additional explanations and interpretations of these effects will be provided in the section describing the model estimation results.

4.2. The model

4.2.1. Formulation

The model formulation is based on the joint analysis of a binary outcome, an ordered outcome, and a nominal outcome. Such joint estimations have been undertaken in the past (see, for example, Paleti et al., 2013). But, we are not aware of an earlier application of a multi-period version for the joint analysis of multiple outcomes of different types, as we undertake in this paper. The model was estimated using libraries and routines written by the research team in the GAUSS matrix programming language (Aptech, 2022).

Let q be an index for individuals ($q = 1, 2, \ldots, Q$), and let t be an index for the t^{th} observation on individual q ($t = 1, 2, \ldots, T$, where T denotes the total number of observations on individual q; $T = 2$ in the current analysis context, with $t = 1$ representing the *Before* COVID period and $t = 2$ representing the *After* COVID period). For ease of presentation, we assume that the number of observations is the same across individuals, as is the case in the empirical analysis of this paper.

The first dimension of our analysis, the telework adoption dependent variable, is a binary choice outcome. Define a latent propensity y_t^* underlying the binary telework adoption outcome y_t at choice occasion t (for convenience, we suppress the index q for the individual). Now consider the following structure:

$$y_t^* = \boldsymbol{\beta}' \boldsymbol{z}_t + \varepsilon_t, \quad y_t = 1, \quad \text{if} \quad y_t^* > 0, \quad y_t = 0 \text{ otherwise}, \tag{1}$$

where z_t is an $(L \times 1)$ vector of exogenous variables (including a constant), $\boldsymbol{\beta}$ is a corresponding $(L \times 1)$ vector of binary outcome-specific coefficients to be estimated, and ε_t is a random error term assumed to be standard normally distributed (the scale of ε_t is not identified and so is arbitrarily set to one).

The second dimension of our analysis is the telework frequency outcome, which takes the form of an ordinal variable and which is observed only if the teleworking adoption choice is positive (that is, only if $y_t = 1$). Define a latent propensity $\widetilde{y}_t^*$ underlying the telework frequency variable $\widetilde{y}_t$ at choice occasion t. Now consider the following structure:

$$\widetilde{y}_t^* = \boldsymbol{\alpha}' \boldsymbol{w}_t + \widetilde{\varepsilon}_t, \quad \widetilde{y}_t = k, \text{ if } \quad \psi_{k-1} < \widetilde{y}_t^* < \psi_k, \tag{2}$$

where $\boldsymbol{w}_t$ is an $(H \times 1)$ vector of exogenous variables (including a constant), $\boldsymbol{\alpha}$ is a corresponding $(H \times 1)$ vector of ordered outcome-specific coefficients to be estimated, and $\widetilde{\varepsilon}_t$ is a random error term assumed to be standard normally distributed (the scale of $\widetilde{\varepsilon}_t$ is not identified and so is arbitrarily set to one). The latent propensity $\widetilde{y}_t^*$ is mapped to the observed frequency variable $\widetilde{y}_t$ by the thresholds ψ_k, which should satisfy the ordering conditions $(k = 1, 2, \ldots, K; \psi_0 = -\infty;\ \psi_1 = 0; -\infty < 0 < \psi_2 < \ldots \psi_{K-1} < \infty)$ in the usual ordered-response fashion. For later use, define the $(K-1) \times 1$ vector $\boldsymbol{\Psi} = (\psi_1 = 0, \psi_2, \ldots, \psi_{K-1})'$. The first threshold ψ_1 is set to zero due to identification considerations, because $\widetilde{y}_t^*$ has no cardinal scale and so some restriction needs to be placed on its location after including a constant in $\boldsymbol{w}_t$.

Next, consider a single nominal variable (this corresponds to the location of telework dimension in our analysis, given that an individual teleworks) with the following utility specification for alternative i and choice occasion t:

$$U_{it} = \boldsymbol{\gamma}' \boldsymbol{x}_{it} + \xi_{it}, \ t = 1, 2, \ldots, T, \ \ i = 1, 2, \ldots, I. \tag{3}$$

In our case, $I = 3$. $\boldsymbol{x}_{it}$ is an $(A \times 1)$-column vector of exogenous attributes whose first $(I–1)$ elements correspond to alternative specific constants for $(I–1)$ alternatives (with one of the alternatives being the base alternative) and the remaining variables being the non-constant variables and $\boldsymbol{\gamma}$ is an individual-specific $(A \times 1)$-column vector of corresponding coefficients (for identification purposes, given that all the exogenous variables in our model are individual-specific and do not vary across alternatives, all elements of $\boldsymbol{x}_{it}$ will be uniformly zero for a base alternative; in our empirical analysis later, this base alternative is considered as the "home only" alternative). We also assume that ξ_{it} is independent and identically normally distributed across *individuals*, but allow a general covariance structure across alternatives for each choice instance of each individual. Specifically, let $\boldsymbol{\xi}_t = (\xi_{1t}, \xi_{2t}, \ldots \xi_{It})'$ $(I \times 1$ vector). Then, we assume $\boldsymbol{\xi}_t \sim MVN_I(0, \boldsymbol{\Lambda}_t)$. Note that the covariance matrix $\boldsymbol{\Lambda}_t$ is specific to the choice occasion t, i.e., we allow the covariance matrix to be different across choice occasions (that is, between the *Before* COVID and *After* COVID periods in our empirical analysis). As usual, appropriate scale and level normalization must be imposed on $\boldsymbol{\Lambda}_t$ for identifiability. Specifically, only utility differentials matter at each choice occasion. Taking the utility differentials with respect to the first alternative, only the elements of the covariance matrix $\boldsymbol{\Lambda}_{t1}$ $[(I-1) \times$

$(I-1)]$ of $\widetilde{\xi}_{it1} = \xi_{it} - \xi_{1t}$ $(i \neq 1)$ are estimable. For identifiability, one of the diagonal elements of $\mathbf{\Lambda}_{t1}$ is set to 1. Also, in multinomial probit models, there is an interpretation issue because, technically speaking, only $\mathbf{\Lambda}_{t1}$ matters and there can be multiple covariance matrices of the original error terms $\mathbf{\Lambda}_t$ that can map to the same differenced covariance matrix $\mathbf{\Lambda}_{t1}$. Further, some seemingly estimable covariance matrices for $\mathbf{\Lambda}_t$ may not be consistent with an actually estimated $\mathbf{\Lambda}_{t1}$ (see Bunch, 1991). Besides, especially in a trinomial multinomial probit model, as in the empirical application in the current paper at each of the *Before* COVID and *After* COVID periods, estimation can be unstable. In our estimations, we noticed substantial stability (without much effect on data fit considerations) when we further restricted all diagonal matrix elements of $\mathbf{\Lambda}_{t1}$ at each period to be one (see Dansie, 1985 for a discussion of such a normalization; this essentially makes $\mathbf{\Lambda}_{t1}$ a correlation matrix).

Now, define the following vectors and matrices: $\boldsymbol{U}_t = (U_{1t}, U_{2t}, ..., U_{It})^{'}$ $(I \times 1$ vector), and $\boldsymbol{x}_t = (\boldsymbol{x}_{1t}, \boldsymbol{x}_{2t}, \boldsymbol{x}_{3t}, ..., \boldsymbol{x}_{It})^{'}$ $(I \times A$ matrix). Next, if the individual teleworks at the tth choice occasion, define the following:

$$\boldsymbol{B}_t = \begin{bmatrix} \boldsymbol{\beta}^{'} z_t \\ \boldsymbol{\alpha}^{'} \boldsymbol{w}_t \\ \boldsymbol{\gamma}^{'} \boldsymbol{x}_t \end{bmatrix}, \text{ an } (I+2) \times 1 \text{ vector, and } \mathbf{\Sigma}_t = \begin{bmatrix} 1 & \rho_t & \mathbf{\Theta}_t \\ \rho_t & 1 & \Upsilon_t \\ \mathbf{\Theta}^{'}_t & \Upsilon^{'}_t & \mathbf{\Lambda}_{t1} \end{bmatrix}, \text{ an } (I+1) \times (I+1) \text{ matrix,}$$

where, ρ_t is the correlation between telework adoption and telework frequency at choice occasion t, $\mathbf{\Theta}^{'}_t$ is an $[(I-1) \times 1)]$ matrix capturing the correlations between telework adoption and the nominal outcome (in the utility differenced form, with the difference taken with respect to the first alternative) at choice occasion t, and $\Upsilon^{'}_t$ is another $[(I-1) \times 1)]$ matrix capturing the correlations between telework frequency and the nominal outcome (again in the utility differenced form, with the difference taken with respect to the first alternative) at choice occasion t. If the individual does not telework at the tth choice occasion, define $\boldsymbol{B}_t = [\boldsymbol{\beta}^{'} z_t]$ and $\mathbf{\Sigma}_t = [1]$.

Next also, define $\mathbf{B} = (\boldsymbol{B}^{'}_1, \boldsymbol{B}^{'}_2)$, and $\mathbf{\Sigma} = \begin{bmatrix} \mathbf{\Sigma}_1 & \mathbf{\Omega}_{12} \\ \mathbf{\Omega}^{'}_{12} & \mathbf{\Sigma}_2 \end{bmatrix}$. The off-diagonal $\mathbf{\Omega}_{12}$ matrix captures the panel correlations or the correlations among the unobserved components of the dependent outcomes across choice occasions. To impart a parsimonious and interpretable specification, while also imposing a logical identifiable structure on the correlation matrix, we restrict the panel correlations to those between the same outcome variables across the choice occasions. Thus, for example, we allow the telework adoption outcome at the first choice occasion to be correlated with the telework adoption outcome at the second choice occasion (and similarly for the other two dimensions). But we do not allow, for example, the correlation between the telework adoption outcome at the first choice occasion with the telework frequency outcome at the second choice occasion (although they are allowed to be correlated within the same choice occasion). Importantly, note that all the elements in the $\mathbf{\Sigma}_t$ matrices ($\mathbf{\Sigma}_1$ and $\mathbf{\Sigma}_2$) are identifiable (because the correlation matrix of the nominal outcome at any choice occasion, $\mathbf{\Lambda}_{t1}$, is in the differenced form), and therefore the correlation matrix $\mathbf{\Sigma}$ is estimable.[8]

4.2.2. Estimation

For ease in presentation, we will consider the most comprehensive estimation case here when an individual is observed to be teleworking in both the *Before* COVID and *After* COVID periods. In this situation, both the teleworking frequency and the teleworking location dimensions come into play at both choice occasions. If an individual is not teleworking at one or both occasions, the procedure discussed below needs to be only slightly modified to obtain the corresponding matrices marginalized to include only the telework adoption equation elements.

Let the individual under consideration be observed to choose ordinal category $g_t (g_t \in \{1, 2, ..., K\})$ for the telework frequency and the nominal category m_t for telework location at choice occasion t. Construct a $1 \times (K+1)$ vector $\boldsymbol{G}_{t,low}$ and another $1 \times (K+1)$ vector $\boldsymbol{G}_{t,high}$. Populate both these row vectors with zeros, and then position the value of '1' in the g_t th column of $\boldsymbol{G}_{t,low}$ and position the value of '1' in the (g_t+1) th column of $\boldsymbol{G}_{t,high}$. Also, construct the $(K+1) \times 1$ vector $\widetilde{\mathbf{\Psi}} = (-\infty, \mathbf{\Psi}^{'}, +\infty)^{'}$. In terms of the nominal variable, in our estimation, we will need the correlation matrix corresponding to the error term differences taken with respect to the chosen nominal alternative; that is, the correlation matrix corresponding to the error term difference $\widetilde{\xi}_{itm_t} = \xi_{it} - \xi_{m_t t}$ $(i \neq m_t)$. To obtain this correlation matrix, first define a matrix $\mathbf{D}$ of size $[(T^*(I+2)) \times (T^*(I+1))]$. Since $T = 2$ and $I = 3$ in our empirical context, matrix $\mathbf{D}$ is of size (10×8). This matrix $\mathbf{D}$ is constructed by first taking an identity matrix of size eight (in our case) and then supplementing two additional zero row vectors of length (1×8) at the third and seventh row indices. Next, define a matrix $\mathbf{M}_1$ of size $[(I+1)] \times [(I+2)]$ for choice occasion one ($\mathbf{M}_1$ is a (4×5) matrix in our case). Fill this matrix with values of zero. Then, in the first two rows and two columns, insert an identity matrix of size two. Next, consider the 3rd row through the $(I+1)^{\text{th}}$ row (fourth row in our empirical case), and the 3rd column through the $(I+2)^{\text{th}}$ column (fifth column in our empirical case); insert an identity matrix of size $(I-1)$ after supplementing with a column of '-1' values in column m_t. Using the same procedure, create another matrix, $\mathbf{M}_2$, corresponding to the second choice occasion. Now define a matrix $\mathbf{M}$ of size $[T \times (I+1)] \times [T \times (I+2)]$ $(8 \times 10$ in our empirical analysis). Fill all elements of this matrix with zeros. Then, place the matrix $\mathbf{M}_1$ as the first block diagonal matrix and the matrix $\mathbf{M}_2$ as the second block diagonal matrix within matrix $\mathbf{M}$.

[8] In our presentation of the estimated correlation matrix in Table 4 (and discussed in Section 5.4), we provide the correlation structure corresponding to the estimable Σ matrix. In other words, in our estimation presentation of the correlation matrix, we provide the correlation matrix Σ with the embedded Λ_{t1} matrix representing the difference being taken with respect to the first "Home only" location alternative (which is also the base alternative).

Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = (\boldsymbol{\beta}', \boldsymbol{\alpha}', \boldsymbol{\Psi}, \boldsymbol{\gamma}, [\text{Vechup}(\Sigma)]')'$, where the operator Vechup(.) row-vectorizes the non-zero upper diagonal elements of a matrix.

Next, define the following $[T \times (I+1)] \times 1$ $(= 8 \times 1)$ threshold vectors:

$\overleftrightarrow{\boldsymbol{\Psi}}_{low} = \left[0, (G_{1,low} \times \widetilde{\boldsymbol{\Psi}}), -\infty_{I-1}, 0, (G_{2,low} \times \widetilde{\boldsymbol{\Psi}}), -\infty_{I-1}\right]'$ and

$\overleftrightarrow{\boldsymbol{\Psi}}_{high} = \left[\infty, \left(G_{1,high} \times \widetilde{\boldsymbol{\Psi}}\right), \mathbf{0}_{I-1}, \infty, \left(G_{2,high} \times \widetilde{\boldsymbol{\Psi}}\right), \mathbf{0}_{I-1}\right]'$

Then the likelihood function may be written as:

$$L(\boldsymbol{\delta}) = \int_{D_r} f(\boldsymbol{r} | \mathbf{MB}, \mathbf{MD\Sigma D}'\mathbf{M}') dr \tag{4}$$

where the integration domain $D_r = \{\boldsymbol{r} : \overleftrightarrow{\boldsymbol{\Psi}}_{low} \leqslant \boldsymbol{r} \leqslant \overleftrightarrow{\boldsymbol{\Psi}}_{high}\}$ is simply the multivariate region of integration determined by the observed binary/ordinal outcomes and the the utility differences taken with respect to the utility of the chosen alternative for the multinomial outcome. This would be an eight-dimensional integral.

The likelihood function above is for an individual who teleworks both in the *Before* COVID and *After* COVID periods. If an individual is observed to telework in only one period but not both, minor modifications need to be made and the likelihood function collapses to a five-dimensional integral. If an individual does not telework in both periods, with minor modifications, the likelihood dimension collapses to a two-dimensional integral.

The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions. Since a closed form expression does not exist for the integral and evaluation using simulation techniques can be time consuming, we used the One-variate Univariate Screening technique proposed by Bhat (2018) for evaluating the integral. Further, to ensure positive definiteness of the correlation matrix $\boldsymbol{\Sigma}$, we adopted a spherical parameterization approach for the Cholesky of $\boldsymbol{\Sigma}$ (see Forrester and Zhang, 2020; Bhat and Mondal, 2021). In addition, to maintain the zero correlation restrictions on specific elements of $\boldsymbol{\Omega}_{12}$, while maintaining positive definiteness of $\boldsymbol{\Sigma}$, we adopted the procedure recently proposed by Saxena et al. (2023).

5. Model estimation results

In the model specifications, we explored a range of alternative functional forms for the explanatory variables. These included a linear form, a dummy variable categorization, as well as piecewise spline forms for the non-dummy variables (respondent age, commute time, and days worked per month). But, except for the commute time variable, the dummy variable specification turned up to consistently provide the best data fit for all other variables. In this dummy variable form, we tested different sets of finer categories, and progressively combined categories based on statistical tests and intuitive reasoning to yield parsimonious specifications.

The final model specification was obtained after a systematic process of testing alternative combinations (and interactions) of explanatory variables based on statistical fit and parsimony considerations. In the final model specification, we used a t-statistic threshold of 1.00 to retain variables (corresponding to a 0.32 level of significance or 68 % confidence level), because of the moderate-sized sample used in the analysis, the small share of individuals who use the third location only and "both home and third location" alternatives in the location model, and the potential for such included variables to guide future telework-related investigations with larger sample sizes. After all, choosing a level of significance is closely related to Type II error. Especially, one needs to worry not only about including variables incorrectly (Type I error), but also rejecting variables incorrectly (Type II error). In selecting a level of significance, we face a trade-off between making the two different types of errors. In multidimensional models, we would rather make a slightly larger Type I error if it means identifying variables that are suggestive and that may aid researchers working with more data in the future.[9]

Table 3 presents the estimation results for all choice dimensions of interest in this study. The results for each choice dimension are presented in turn. Important to note is that the coefficients in Table 3 characterize the effects of exogenous variables on (1) the underlying propensity for telework adoption (for the telework adoption binary choice model), (2) the underlying propensity for telework frequency (for the telework frequency ordinal choice model), and (3) the utility for the "third location only" and "both home and third location" alternatives, with the "home only" alternative serving as the base alternative for identification purposes. Also, for dummy variables, the base variable in identified in parenthesis.

5.1. Telework adoption (binary choice)

The first set of results in Table 3 presents the influence of exogenous variables and COVID on the adoption of teleworking (choosing of whether to telework or not). The findings are largely intuitive and consistent with the literature. Women are less inclined to adopt teleworking compared to men and there is no change in this gender-based differential between the two time periods. That women are

[9] It is not uncommon in scholarly research to retain variables with a t-statistic of 1.00 (see, for example, Hamed and Mannering, 1993; Wen and Koppelman, 1999; Bhat and Sardesai, 2006; Rossetti et al., 2018; and Blazanin et al., 2022). Researchers have to make judgments specific to each situation, and not follow a blanket statistical confidence level for all studies, especially because there is nothing universally absolute about the 0.05 level of significance.

Table 3
Model Estimation Results.

Exogenous Variables (base category – *WITHOUT THE COVID SHIFT EFFECT*)	Adoption (Binary) Propensity		Frequency (Ordered) Propensity		Location (Multinomial) Propensity (base category – Home Only Utility)			
					Third Location Only Utility		Both Home and Third Location Utility	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Individual-level Characteristics								
Gender (base: men)								
Women	−0.164	−2.06	–		–		–	
Age (base: 18–29 years *before* COVID)								
18 to 29 *COVID SHIFT EFFECT*	0.570	2.62	–		–		–	
30 to 64 years	–		–		–		−0.239	−1.05
30 to 64 years *COVID SHIFT EFFECT*	0.279	2.17	0.192	1.49	–		–	
65 years or older	0.294	2.34	0.149	1.18	–		−0.582	−1.72
Education Level (base: undergraduate degree or less)								
Graduate degree *COVID SHIFT EFFECT*	0.124	1.53	–		–		–	
Household Characteristics								
Income (base: <$100,000)								
$100,000 to $249,999	0.190	2.41	–		–		–	
≥$250,000	0.190	2.41	–		–		−0.601	−1.90
Job Characteristics								
Employment Status (base: not self-employed)								
Self-employed	0.269	2.16	0.486	3.53	–		–	
Self-employed *COVID SHIFT EFFECT*	−0.381	−2.82	−0.398	−2.71				
# Days Worked per Month (base: 16 days or more is full time)								
1 to 15 days (part time)	0.446	2.50	−0.262	−1.63	–		–	
1 to 15 days (part time) *COVID SHIFT EFFECT*					–		0.326	1.25
Occupation (base: managerial/technical job)								
Healthcare	−0.735	−3.40	–		–		–	
Healthcare *COVID SHIFT EFFECT*	0.512	1.99	–		–		–	
Education/Social service	−0.768	−9.03	–		–		–	
Educ./Social service *COVID SHIFT EFFECT*	–		–		0.449	1.27	–	
Public services	–		−0.381	−1.40	–		–	
Public services *COVID SHIFT EFFECT*	–		0.466	1.91	–		–	
Professional Services	–		–		−0.407	−1.25	–	
Professional Services *COVID SHIFT EFFECT*	–		0.212	1.92	–		–	
Information/Finance	0.295	2.10	0.300	2.03	–		–	

(*continued on next page*)

Table 3 (*continued*)

Exogenous Variables (base category – *WITHOUT THE COVID SHIFT EFFECT*)	Adoption (Binary) Propensity		Frequency (Ordered) Propensity		Location (Multinomial) Propensity (base category – Home Only Utility)			
					Third Location Only Utility		Both Home and Third Location Utility	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Information/Finance *COVID SHIFT EFFECT*	–		0.268	1.68	–		–	
Commute Time (/100)	0.786	2.87	–		–		–	
Daily Work Hours (base: 6 h or more each day)								
Less than 6 h per day *COVID SHIFT EFFECT*	0.605	2.16	–		–		–	
In-Person Workplace Characteristics								
Employment Density of the in-person workplace (base: medium-to-low)								
High	0.191	1.94	−0.355	−2.66	–		–	
High *COVID SHIFT EFFECT*	–		0.357	2.56	–		–	
Residential Characteristics								
Land Use Type (base: rural)								
Suburban	0.160	1.63	–		–		–	
Urban	0.356	3.07	–		–		0.383	2.18
House Characteristics								
Private Study	0.161	1.75	−0.289	−1.98	−0.289‘	−1.98	−0.289	−1.98
Household Type (base: not a stand-alone home)								
Stand-alone home	–		−0.337	−2.15	−0.337	−2.15	−0.337	−2.15
COVID Threat								
Immunocompromised *COVID SHIFT EFFECT*	0.232	2.78	–		–		–	
Constant	−0.638	−4.14	0.209	1.43	−1.255	−4.08	−0.511	−0.98
Constant Shift Effect of the Pandemic Thresholds[1]	0.304	2.21	0.325	1.57	−0.080	−0.39	−0.448	−0.95
Few times per month – Once per week	NA		0.000	–	NA		NA	
Once per week – 2–4 days per week	NA		0.357	1.74	NA		NA	
2–4 days per week – 5 days per week	NA		1.134	2.67	NA		NA	

[1] The first threshold (that between few times per month and once per week) below is normalized to 0.00 for identification, given that we have now included a constant in the ordinal propensity (see the methodological write-up in Section 4.2.1). That is, the first ordinal alternative of “few times per month” is mapped to the real line between the value of -infinity and 0.000. The second threshold (that between once per week and 2–4 days per week) is 0.357, which is statistically significantly different from the first threshold of 0.00 at the 92 % confidence level (corresponding to the reported t-statistic in the table of 1.74). The third threshold (that between 2 and 4 days per week and 5 days per week) is 1.134, which is statistically significantly different from the second threshold of 0.357 at beyond the 99 % confidence level (corresponding to the reported t-statistic in the table of 2.67).

Table 4
Error Correlation Matrix of Dimensions.

Time Period		*Before* COVID				*After* COVID			
Outcome Variable		Telework Adoption Propensity	Telework Frequency Propensity	Location: Third Location Only Utility**	Location: Both Home and Third Location Utility**	Telework Adoption Propensity	Telework Frequency Propensity	Location: Third Location Only Utility**	Location: Both Home and Third Location Utility**
Before COVID	Telework Adoption	1.000	−0.340*	0.191*	−0.012	*0.892**	0.000***	0.000***	0.000***
	Telework Frequency	–	1.000	−0.261	0.108	0.000***	*0.656**	0.000***	0.000***
	Location: Third Location Only**	–	–	1.000	0.055	0.000***	0.000	*0.708**	0.000***
	Location: Both Home and Third Location**	–	–	–	1.000	0.000***	0.000***	0.000***	*0.621**
After COVID	Telework Adoption	–	–	–	–	1.000	0.261*	−0.028	−0.079
	Telework Frequency	–	–	–	–	–	1.000	−0.118	0.051
	Location: Third Location Only**	–	–	–	–	–	–	1.000	−0.513*
	Location: Both Home and Third Location**	–	–	–	–	–	–	–	1.000

*Significant at 85 % confidence level; other non-zero correlation terms without an asterisk are statistically significant at the 68 % confidence level.
**With respect to the base category “Location: Home”.
***Fixed/Not Estimated.

less inclined to telework has been reported in the literature, and has been attributed, among other reasons, to blurred responsibility boundaries between home/family life and work life when working remote, leading women to use their in-person office as a means to compartmentalize their varied responsibilities (Elldér, 2020; Danalet et al., 2021; Nguyen, 2021). On the other hand, a COVID shift effect is observed for individuals 18–29 years old; this group is more inclined to telework after COVID than before COVID. A similar COVID shift effect is found for those in the 30–64 year old age group, while older workers (65 years of age or over) have a constant effect across both the *Before* and *After* COVID periods. The net result is that older workers tended to adopt teleworking more than their younger peers before the pandemic, but younger individuals have started to adopt teleworking much more than their middle-aged and older counterparts in the *After* COVID period. This intertemporal shift in age effects may be because older individuals had more stability in their careers before the pandemic, and so availed of the option to telework at higher rates than their younger peers, as suggested by Cheng et al. (2022). On the other hand, younger individuals may have felt some pressure to show up and be visible to upper management before the pandemic. However, after the pandemic, while older individuals continued to turn up at the regular workplace at similar rates as before the pandemic (because of their limited socialization networks outside their work place; see Tahlyan et al., 2022), younger individuals, who are known to have an extended social network outside their workplace, appear to have embraced teleworking at higher rates given less pressure to show up at the workplace (due to the general acceptance of telework arrangements among many employers). Also consistent with expectations, those with a graduate degree are more likely to telework after COVID relative to before COVID (see Zhang et al., 2020; Asfaw, 2022 for a similar result). However, in the *Before* COVID period, it appears that education level had no significant effect on telework adoption, which is somewhat counter to earlier findings that show those with a higher education level are more likely to telework (Nguyen, 2021).

As expected (see, for example, Tahlyan et al., 2022), workers in the higher income groups ($100 K or higher) are more likely to telework than their lower income (<$100 K) peers; however, there is no COVID shift effect for this variable, suggesting that the relative propensities across income groups for telework adoption have not changed from earlier. Self-employed individuals, who presumably have greater flexibility in their work arrangements, in general teleworked more than others before the pandemic; however, in the *After* COVID period, the reverse seems to have taken hold, presumably because of a higher perceived need among those self-employed to resume face-to-face interactions with clients (Ono and Mori, 2021). Part-time workers (in terms of the number of days of work per month) are more likely to adopt telework due to the part-time flexible nature of their work. The occupation effects are all consistent with expectations, with frontline occupations such as healthcare and education exhibiting a lower likelihood of teleworking, while those in the information/finance occupation category more likely to telework (Astroza et al., 2020). What is interesting to note is that a positive COVID shift effect is observed for the healthcare occupation; the higher telework propensity in the *After* COVID period is enabled by the uptake of telemedicine during COVID (Wosik et al., 2020). However, the net effect (-0.735 + 0.512) remains negative, suggesting that – even after COVID – healthcare workers are less likely to telework than other occupations, except those in education/social service (who are the least likely to telework in the "*After* COVID" period.

Those with longer commute times are more likely to telework, a finding reported extensively in the literature (see, for example, Danalet et al., 2021; Nguyen, 2021), and there is no shift in this effect between the two time periods. Those who work less than six hours per day are more likely to telework after COVID. This suggests that part-time workers, both in terms of having 15 days or less of days of work in the month and/or in terms of having less than six hours of work per day, have a higher telework adoption tendency than their peers. As reported previously in the literature, workers in higher density urban areas are more likely to telework as are those in the suburban locations (when compared to workers in rural low density areas). Generally, urban and suburban locations have the necessary infrastructure to facilitate teleworking, and office workers in high density urban locales have greater work flexibility (López-Igual and Rodríguez-Modroño, 2020). However, there is no COVID shift effect in teleworking adoption for density or land use type. As expected, the availability of a private study in the home facilitates a greater level of teleworking. Individuals who are immunocompromised do not necessarily telework at a higher rate relative to other individuals before COVID, but they do so after COVID (consistent with expectations), a finding also reported by Irawan et al. (2022).

A review of the two constants shows that the pandemic has a positive effect overall on the propensity to telework.

5.2. Telework frequency (ordered choice)

Telework frequency is modeled as an ordered choice, with choice categories of few times per month, once per week, 2–4 days per week, and 5 days per week (equivalent to everyday). The coefficients may be interpreted similar to what has been presented earlier for the telework adoption model. As such, in the interest of brevity, only a few key findings are highlighted in this subsection.

The results show that individuals in the 30–64 year old age group not only are more likely to adopt teleworking in the *After* COVID period (relative to the Before COVID period), but also show a greater propensity to telework frequently in the *After* COVID period (relative to the *Before* COVID period); this is presumably because they have household obligations (greater presence of children) and the flexibility and seniority in the workplace to do so (Ahmadi et al., 2022). Interestingly, individuals in this age group have the highest propensity associated with the frequency of teleworking (conditional on teleworking at all) in the *After* COVID period, even more so than the youngest age group (though the youngest age group are the most likely to adopt teleworking in the first place in the *After* COVID period). Also, as in the case of telework adoption, the results reveal that older teleworkers (65 years of older) do so more frequently than their younger teleworker peers. Self-employed workers depict a COVID shift effect in the propensity related with frequency. The combination of the negative shift effect on this variable in the binary adoption model as well as the ordinal frequency model indicates that there is a substantial tempering of the difference in teleworking tendency between self-employed and not-self-employed workers in the *After* COVID period. However, there is no such shift effect in the propensity to telework frequently for part-time workers (in terms of number of days of work per month); part-time workers, while adopting telework at a higher rate than

Table 5
Disaggregate Fit Measures.

Metric	Proposed Joint model	Independent model
Log Likelihood at convergence	−2618.73	−2823.36
Number of non-constant parameters	67	51
Log Likelihood at constants-only	−3392.41	−3392.41
Adjusted rho-squared value	0.2083	0.1527
Average Probability of correct prediction	0.389	0.361
Likelihood ratio test: Proposed Joint vs Independent model	$LR = 409.26 > \chi^2_{(16,0.01)} = 32.00$	

Table 6
Aggregate Fit Measures.

Combination			Observed	Prediction	
Adoption	Frequency	Telework Location		Joint model	Independent model
No	–	–	916	911	903
Yes	Few times/month	Home only	265	261	272
Yes	Few times/month	Third location only	14	16	13
Yes	Few times/month	Both Home & Third location	15	17	21
Yes	Once/week	Home only	112	116	121
Yes	Once/week	Third location only	6	7	5
Yes	Once/week	Both Home & Third location	11	9	9
Yes	2–4 days/week	Home only	231	236	239
Yes	2–4 days/week	Third location only	8	10	11
Yes	2–4 days/week	Both Home & Third location	24	19	16
Yes	5 days/week	Home only	325	324	314
Yes	5 days/week	Third location only	13	11	15
Yes	5 days/week	Both Home & Third location	20	23	21
Weighted Absolute Percentage Error			**–**	**1.94 %**	**3.67 %**

full time workers, actually have a lower frequency propensity compared to full time workers who adopt teleworking. That is, full-time workers, if they telework, tend to do so with more intensity compared to a teleworking part-time worker. And this situation is the same between the *Before* COVID and *After* COVID periods. This suggests some pressure (either employer-imposed or employee-imposed), or even a general desire, among part-time employees to show up more frequently at the workplace, even if they are more likely than full-time workers to telework at all. These findings are aligned with those reported by Ono and Mori (2021). With respect to occupation category, white collar office worker occupations are more likely to increase the intensity of teleworking after COVID (public services, professional services, and information/finance), suggesting the presence of significant COVID shift effects for these workers as also reported elsewhere in the literature (Galasso and Foucault, 2020). Significant shift effects are also observed for the propensity to engage in higher levels of teleworking for workers in high density urban areas and suburban areas. Individuals working in such areas have the infrastructure, occupational flexibility, and home setup that is conducive to higher levels of teleworking frequency (López-Igual and Rodríguez-Modroño, 2020). The pandemic shift effect constant shows that the overall propensity tendency to engage in teleworking in the *After* COVID period, which is entirely consistent with real world evidence (Gallup, 2020; Parker et al., 2022).

The thresholds at the bottom of the "Frequency Propensity" column of Table 3 do not have any substantive interpretation, but serve the role of mapping the underlying frequency propensity to the observed ordinal frequency category.

5.3. Telework location (multinomial choice)

Table 3 indicates that, in general, the older age groups of 30–64 years and 65-plus years are less likely to telework in a hybrid "both home and third location" relative to those in the youngest age group of 18–29 years, and this relative age preference variation for work location holds stable over time; individuals in the older age groups are likely to have the flexibility "muscle" to telework at a single location consistently (Ahmadi et al., 2022; Cheng et al., 2022). Similarly, very high income individuals are less likely to adopt a remote-hybrid workplace. Those who work part-time (in terms of number of days per month of work) show a greater propensity to adopt a remote-hybrid workplace model in the *After* COVID period, presumably because of the need to engage in more face-to-face interactions in the *After* COVID period after a prolonged period of isolation during the height of COVID. On the other hand, those in the education/social service occupation are more likely to choose the "third location only" option for teleworking in the *After* COVID period relative the *Before* COVID period, presumably because a third location offers the space and safety necessary to meet with students/clients needing support after a period of no face-to-face time. Those residing in urban environments are more likely (relative to those living in other environments) to adopt a hybrid telework location arrangement during both the before and after periods, possibly because urban environments offer such locational opportunities within close proximity of home. Finally, and not surprisingly, individuals who have a private study in their homes and have a stand-alone home are much more likely than their peers to choose "home only" as their teleworking location.

The constants (both the overall constant and the pandemic-specific shift constant) are negative for the third location only option, as

Table 7
Estimates of Exogenous Variable and COVID Period Effects on Teleworking Arrangements.

Exogenous Variables	*Before* COVID					*After* COVID					% change (*Before* to *After* COVID)				
			Location					Location					Location		
	Adoption	Freq. (Days)	Home only	Third location only	Both home and a third location	Adoption	Freq. (Days)	Home only	Third location only	Both home and a third location	Adoption	Freq. (Days)	Home only	Third location only	Both home and a third location
Individual-level Characteristics															
Gender															
Men	43.4 %	10.27	87.4 %	4.7 %	7.9 %	68.5 %	13.79	90.7 %	4.1 %	5.2 %	57.8 %	34.3 %	3.8 %	−11.8 %	−34.5 %
Women	38.0 %	10.33	87.6 %	4.8 %	7.6 %	63.4 %	13.58	90.8 %	4.0 %	5.2 %	66.9 %	31.4 %	3.6 %	−16.0 %	−31.9 %
Age															
18 to 29 years old	38.8 %	10.12	83.6 %	4.7 %	11.7 %	73.6 %	12.73	88.0 %	4.0 %	8.0 %	89.6 %	25.8 %	5.3 %	−14.6 %	–32.1 %
30 to 64 years old	38.8 %	10.12	87.4 %	4.8 %	7.9 %	64.8 %	13.80	90.9 %	4.0 %	5.1 %	67.1 %	36.4 %	4.1 %	−15.4 %	−35.7 %
65 years and older	48.7 %	11.07	90.9 %	4.6 %	4.5 %	65.3 %	13.50	93.3 %	4.2 %	2.5 %	34.1 %	21.9 %	2.6 %	−8.8 %	−44.1 %
Education Level															
No graduate degree	40.2 %	10.29	87.6 %	4.7 %	7.7 %	63.2 %	13.59	90.9 %	4.0 %	5.2 %	57.3 %	32.0 %	3.8 %	−15.3 %	–33.2 %
Graduate degree	40.2 %	10.29	87.6 %	4.7 %	7.7 %	67.1 %	13.75	90.8 %	4.1 %	5.2 %	67.0 %	33.6 %	3.7 %	−13.8 %	–33.0 %
Household-level Characteristics															
Income Level															
Less than $100 K	36.1 %	10.34	86.5 %	4.9 %	8.6 %	61.5 %	13.48	90.3 %	4.0 %	5.8 %	70.4 %	30.3 %	4.3 %	−18.0 %	−33.0 %
$100 K to $249 K	42.4 %	10.27	86.3 %	4.7 %	9.0 %	67.6 %	13.74	90.1 %	4.1 %	5.8 %	59.5 %	33.7 %	4.4 %	−13.1 %	−35.8 %
Over $250 K	42.4 %	10.27	92.3 %	4.8 %	2.9 %	67.6 %	13.74	94.0 %	4.4 %	1.7 %	59.5 %	33.7 %	1.8 %	−9.0 %	−41.4 %

(*continued on next page*)

Table 7 (*continued*)

Exogenous Variables	*Before* COVID					*After* COVID					% change (*Before* to *After* COVID)				
	Adoption	Freq. (Days)	Location			Adoption	Freq. (Days)	Location			Adoption	Freq. (Days)	Location		
			Home only	Third location only	Home and a third location			Home only	Third location only	Home and a third location			Home only	Third location only	Home and a third location
Exogenous Variables	***Before* COVID**					***After* COVID**					**% change (*Before* to *After* COVID)**				
	Adoption	**Freq. (Days)**	**Location**			**Adoption**	**Freq. (Days)**	**Location**			**Adoption**	**Freq. (Days)**	**Location**		
			Home only	**Third location only**	**Home and a third location**			**Home only**	**Third location only**	**Home and a third location**			**Home only**	**Third location only**	**Home and a third location**
Job Characteristics															
Employment Status															
Not self-empl.	38.8 %	9.52	87.6 %	4.8 %	7.7 %	65.8 %	13.60	90.8 %	4.0 %	5.2 %	69.7 %	42.8 %	3.7 %	−15.5 %	–32.5 %
Self-empl.	47.9 %	12.96	87.2 %	4.6 %	8.2 %	62.2 %	14.10	90.9 %	4.0 %	5.1 %	29.9 %	8.7 %	4.2 %	−13.3 %	−37.3 %
Occupation Type															
Manager/ Technical	50.8 %	10.03	86.8 %	5.2 %	8.0 %	75.9 %	13.19	91.7 %	3.1 %	5.2 %	49.4 %	31.5 %	5.6 %	−40.5 %	−34.2 %
Healthcare	24.9 %	10.27	87.6 %	6.1 %	6.2 %	68.9 %	12.82	91.7 %	3.1 %	5.2 %	176.9 %	24.9 %	4.7 %	−49.7 %	−17.1 %
Education	23.9 %	10.28	87.6 %	6.2 %	6.2 %	49.3 %	11.71	87.7 %	7.6 %	4.7 %	106.1 %	13.9 %	0.0 %	23.3 %	–23.9 %
Public Service	50.8 %	7.52	86.8 %	5.2 %	8.0 %	75.9 %	13.84	91.7 %	3.1 %	5.2 %	49.4 %	84.1 %	5.6 %	−40.5 %	−34.2 %
Professional	50.8 %	10.03	89.8 %	2.2 %	8.0 %	75.9 %	14.77	93.4 %	1.2 %	5.4 %	49.4 %	47.3 %	4.0 %	−46.1 %	–32.7 %
Information/ Finance	61.8 %	12.10	86.4 %	5.0 %	8.6 %	83.7 %	17.43	91.6 %	3.1 %	5.3 %	35.3 %	44.0 %	6.0 %	−36.7 %	−38.5 %
Commute Time															
10 min	36.4 %	10.34	87.6 %	4.8 %	7.6 %	61.7 %	13.51	90.8 %	4.0 %	5.2 %	69.4 %	30.7 %	3.7 %	−17.3 %	−31.6 %
30 min	41.6 %	10.28	87.4 %	4.7 %	7.9 %	66.8 %	13.72	90.7 %	4.1 %	5.2 %	60.5 %	33.4 %	3.8 %	−13.3 %	−34.1 %
60 min	49.6 %	10.20	87.1 %	4.5 %	8.3 %	73.8 %	14.00	90.6 %	4.2 %	5.2 %	48.7 %	37.3 %	4.0 %	−7.3 %	−37.4 %
COVID Threat															
Employee is Immunocompromised?															
No	40.2 %	10.29	87.6 %	4.7 %	7.7 %	61.0 %	13.49	90.9 %	3.9 %	5.1 %	51.7 %	31.1 %	3.9 %	−16.2 %	−33.8 %
Yes	40.2 %	10.29	87.6 %	4.7 %	7.7 %	68.4 %	13.79	90.8 %	4.1 %	5.2 %	70.1 %	34.0 %	3.6 %	−13.3 %	−33.2 %

well as for the "both home and third location" alternative, suggesting that teleworkers are more prone to working from home only as opposed to choosing a third location or a remote-hybrid workplace location option. These findings are entirely consistent with real world evidence (Stiles and Smart, 2021).

5.4. Correlations among the dependent outcomes

An examination of the error correlation matrix presented in Table 4 provides credence to the use of a joint modeling framework to jointly model the adoption, frequency, and location of teleworking. Theoretically speaking, it is not possible to meaningfully interpret the correlation elements involving the nominal alternatives without imposing certain assumptions on the original structural matrix of the error terms. Therefore, to facilitate interpretability (especially because our results indicate a negative correlation, in differenced form from the first "home alternative", between the "third work place only" and "third home and third work place" alternatives for the After-COVID period), we assume away the error term for the home alternative (see Bunch, 1991). Then, the estimated correlations may be interpreted in a straightforward manner as those corresponding to the "third work place only" and "third home and third work place" structural error terms (between themselves and with the adoption/frequency error terms in each period; see also discussion toward the end of Section 4.2.1). This seems quite reasonable, as we would expect much of the unobserved individual-specific factors to be associated with the non-home location utilities. Also, because there would be little reason to expect cross-correlations between the many dimensions across the two time periods, and also for estimation parsimony and stability, we only consider the correlations between the same outcomes across the two time periods. That is, the off-diagonal entries in the off-diagonal block of Table 4 are all restricted to zero, and only the diagonal entries of the off-diagonal block are estimated.

The matrix in Table 4 reveals several statistically significant correlations. This includes a negative correlation between telework adoption and telework frequency in the *Before* COVID period, but a positive correlation in the *After* COVID period. The negative correlation (of −0.340) before COVID may be an indication of employers' general reluctance to see employees telework (even if officially sanctioned), which then translates to employees with an elevated telework tendency also feeling pressure to report to the office. But, in the *After* COVID period, with less such pressure from employers, unobserved factors (such as say being technology-savvy or being introverted) that contribute to telework adoption also contribute positively to a higher frequency of teleworking (see the correlation value of 0.261 in the first row of the lower diagonal block). The table also indicates relatively small and statistically insignificant correlations of the telework frequency error term with the work location outcomes, both in the *Before* COVID and *After* COVID periods.

Table 4 also presents a positive and significant correlation of 0.191 between telework adoption before COVID and working from only a third location before COVID, suggesting that, after controlling for other observed exogenous factors, teleworkers before COVID had a preference to work from outside home. However, after COVID, based on the negative correlations of the telework adoption error terms with the third location only and third location/home combination (see the values of −0.028 and −0.079 in the first row of the lower diagonal block of the matrix), the indication is that teleworkers shifted to work primarily from home. These interpretations are also consistent with the positive, albeit statistically insignificant correlation of 0.055 between the "third location" and "both home and third location" alternatives in the *Before* COVID period, but a reversed negative and statistically significant correlation of −0.513 between these two location alternatives in the *After* COVID period.

The diagonal entries on the off-diagonal block of the correlation matrix are all positive and statistically significant, which is intuitive. Unobserved factors that increase the propensity of any outcome in the *Before* COVID period also increase the propensity of that same outcome in the *After* COVID period.

5.5. Model goodness of fit

The joint model used in modeling the adoption, frequency and workplace location of teleworking provides important insights on the different factors influencing individuals' telework preferences. But it is also important to consider the data fit provided by such a model relative to a naïve independent model that ignores jointness (or, the correlations) among the three dimensions, i.e., the Σ correlation matrix is assumed to be an identity matrix.[10] The two models can be compared using a simple nested likelihood ratio test because the independent model is a nested (and restricted) version of our proposed joint model. We also evaluate the data fit of the joint and the independent models intuitively and informally at both the disaggregate and aggregate levels. At the disaggregate level, for the joint model, we compute an average (across individuals) probability of correct prediction of the observed adoption, frequency and workplace location choice combination. A similar disaggregate measure is computed for the independent model. At the aggregate level, we first compute, at the individual level, the multivariate probability prediction at each time period for each of the 13 multivariate combination outcomes of the three dimensions of adoption, frequency, and telework location choice (see Table 6 for the combination list); then, we can aggregate these probability predictions across individuals for each of the 13 combinations and compare our model-predicted aggregate values with the actual number of individuals in each of these combinations. We then compare the observed and model-predicted numbers of individuals in each of the resulting 13 combination bins, to compute a weighted absolute percentage error (WAPE) value (the weighting here is based on the actual observed share of individuals in each of the 13 combination bins).

[10] The independent model estimation results are available in the Appendix to this paper.

The results of the disaggregate data fit evaluations are provided in Table 5, while the result of the aggregate data fit evaluations (across both the *Before* and *After* COVID periods) are provided in Table 6. The average probability of correct prediction from the joint model indicate a better fit relative to the independent model (0.389 in the joint model relative to 0.361 for the independent model; see the penultimate row of Table 5). The joint model also clearly rejects the independent model at any reasonable level of statistical significance, as can be observed from the likelihood ratio test result presented in the final row of Table 5. In terms of aggregate data fit too (see Table 6), the numbers predicted by the joint model are better than those predicted by the independent model. Overall, across the 13 combinations, the weighted average (weighted on the observed shares) of the absolute percentage error is 1.94 percent for the joint model and 3.67 percent for the independent model, once again highlighting the superior fit of the joint model.

6. Estimation of exogenous variable and covid shift effects

The model results presented in Table 3 provide, for each of the *Before* and *After* COVID periods, the exogenous variable effects on the underlying latent propensities for the telework adoption and telework frequency dimensions, and on utilities for the work location choice dimension. However, these results do not immediately provide a sense of the direction and magnitude of exogenous variable effects on the actual telework adoption/frequency/location choices themselves. We determine such directionality and magnitude effects using the concept of average treatment effects or ATEs. The ATE computes the impact on a downstream posterior variable of interest due to a treatment that alters the state of an antecedent variable from *A* to *B*. In our case, the intent is to estimate the "treatment" effect of the COVID period on the teleworking behavior for each level of the exogenous variables; therefore, *A* can be the state where an individual is in the *Before* COVID period and *B* can be the state where the individual is in the *After* COVID period. To quantify the magnitude impact of the COVID time period across the exogenous variables, all individuals in the dataset are set to a particular category of an exogenous variable and also set to the "base" *Before* COVID state. Then, using our estimates, we can compute the joint probability of all possible multivariate combinations of our outcome variables at the individual level; next, we take the average across individuals to obtain the average probability of each of the multivariate combinations; finally, we take the marginal for each of our outcome variable (i.e., telework adoption percent, frequency and telework location shares) and present them as the magnitude effect corresponding to the specific state of the exogenous variable. We then do this for the "treatment" *After* COVID state. And finally, we compute the shifts in our dependent outcomes between the "base" and the "treatment" states i.e., the COVID period effects. Also, to facilitate an understanding of the order-of-magnitude effects of variables, cardinal values on a monthly basis are assigned to each of the ordinal levels of the telework frequency dimension. The cardinal value assignments for the ordinal frequency levels in the model are as follows: (1) Few times/month = 2 instances per month, (2) Once/week = 5 instances per month, (3) 2–4 days/week = 15 instances per month, (4) 5 days per week = 22 instances per week. With these cardinal value assignments, the expected value of monthly frequency among telework adopters is computed using the ATE approach just discussed.

The ATE results are presented in Table 7 (in the interest of brevity, effects are not shown for all variables). The table shows estimated percentages for adopting telework in the *Before* COVID and *After* COVID periods, the estimated number of days of teleworking per month (among those who choose to telework), and the predicted telework location (for those who choose to telework). As explained earlier in the paper, it should be kept in mind that this particular sample of workers is a high-telework sample (recall that they had to have the option to telework before and after COVID). Hence, the levels of telework adoption are higher than in the general worker population.

The results are quite intuitive and consistent with expectations, and provide a clear picture of exogenous variable effects and differences in these effects across the *Before* and *After* COVID periods. For example, according to the table, a higher percentage of men (43.4 percent) adopt teleworking in the *Before* COVID period compared to women (38.0 percent). The same gender trend holds in the *After* COVID period, though both men and women adopt telework at much higher rates than in the *Before* COVID period (68.5 percent of men relative to 63.4 percent of women. Interestingly, the percent uptake in the *After* COVID period (from the *Before* COVID period) in telework adoption is actually higher for women at a 66.9 percent adoption increase relative to men who had a lower 57.8 percent adoption increase (see the entries under the "Adoption" column within the "% change (*Before* to *After* COVID)" column panel on the right side of Table 7). The net result is that the difference in teleworking adoption between men and women diminishes considerably in the *After* COVID period. From a frequency standpoint among teleworkers, there is little difference between men and women in both the time periods, though, again, telework frequency increases from about 10 days per month in the *Before* COVID period to closer to 14 days per month in the *After* COVID period (also revealed by the 34.3 percent and 31.4 percent entries in the "frequency" column within the "% change (*Before* to *After* COVID)" column panel). Other results may be interpreted in a similar fashion based on the results in Table 7. For literally all subgroups across the table, the probability of choosing "home-only" as the telework location increases (from the *Before* COVID to *After* COVID period), suggesting a greater level of comfort with working from home on a more exclusive basis. Young individuals in the 18–29 year old segment show the greatest uptake in telework adoption (from 38.8 percent to 73.6 percent) and maintain a higher proportion of teleworkers adopting a hybrid workplace model. While 40.2 percent of those with a graduate degree teleworked prior to COVID, that percentage increased to 67.1 percent in the *After* COVID period. The highest income group shows the largest percentage teleworking from home only, suggesting that individuals in this income group reside in homes with the infrastructure and space necessary to telework effectively.

Those who are self-employed telework at a greater rate prior to COVID, but a lower rate after COVID, consistent with the interpretation of the estimation results in Section 5. As expected, their telework frequency (days per month) remains higher than for non-self-employed individuals, though the margin of difference shrinks quite substantially in the *After* COVID period. Occupation type depicts a pattern consistent with the interpretations from the estimation results. Telework adoption and frequency show an increase in the *After* COVID period relative to the *Before* COVID period for all occupation categories, with differences across the occupation

categories much more tempered in the *After* COVID period relative to the *Before* COVID period. Those with longer commutes consistently exhibit higher levels of telework adoption in the *Before* and *After* COVID periods, as well as a higher telework frequency in the *After* COVID period (when compared with those having shorter commutes).

As expected, individuals who are immunocompromised exhibit a greater uptake in telework adoption than those who do not experience such a health condition (70.1 percent increase between the two time periods for immunocompromised individuals relative to 51.7 percent for those who are not). Not shown in the table (in the interest of brevity) is the influence due to residential unit characteristics (stand-alone home and presence of private study). But, as would be expected, the presence of a private study is associated with greater levels of teleworking and a higher propensity of teleworking exclusively from home.

These results are all behaviorally intuitive, and reflect the COVID shift effects in the telework arena. It does appear that telework arrangements will remain at an elevated level into the future, with home serving as the dominant telework location.

7. Conclusions

This paper presents an exploration of telework arrangements in the wake of the COVID-19 pandemic with a focus on three key dimensions, namely, the *adoption*, *frequency*, and *location* of telework. Using a dataset collected from a sample of workers in the state of Texas in the United States, a joint econometric model is estimated to understand how exogenous personal, household, and work characteristics affect these three dimensions of teleworking *Before* and *After* COVID. In the following two sections, we summarize the results with implications for demand modeling and equity, followed by a third section on limitations and directions for future research.

7.1. Land-use transformation and demand model considerations

As we remain in a period of instability for the next few post-pandemic years, it is essential to track and observe workplace location choices and the associated travel behavior trends, specifically in the context of telework options. The bottom line is that telework acceptance, or at least hybrid options for workplace location arrangements, are here to stay, at least in the not-so-distant future. In general, all individuals in all demographic groups exhibit a propensity toward greater levels of telework adoption after COVID. However, the increases are not uniform across all market segments. In the category of demographics, young individuals are the most likely to embrace telework. This is not surprising. Studies show that the younger generation tends to be more productive when in their own "dens" at home (Martin et al., 2022). Younger individuals also have expansive social networks outside of their co-worker group, while older adults are more likely to view the in-person workplace as an important socialization outlet (Tahlyan et al., 2022). This higher tendency to adopt teleworking in the younger generation, who also are generally more concerned about career performance and how they will be evaluated, suggests that employers need to revisit their productivity assessment approaches in the new work landscape. Also, from the more specific perspective of travel demand, younger adults are known to generate more non-work social and leisure trips relative to older adults (LaMondia and Bhat, 2012). Thus, with the increased flexibility of the workplace, it is important that future studies examine the overall activity-travel patterns of this younger adult age group in particular.

The results associated with job characteristics in Table 4 show that those employed in the healthcare industry will experience the highest percentage change in telework adoption, by a whopping 177 percent between the pre-COVID period to now. This is consistent with other studies (see, for example, Wosik et al., 2020) showing that the health-care industry has been an employment sector particularly transformed in terms of work location because of the pandemic. From a land-use transportation standpoint, this move to telework in the healthcare industry may reduce the need for the sprawling on-site medical centers in many urban areas; how this may change urban land-use patterns is an open area for further enquiry.

Another segment of the population with a high percentage change in telework adoption corresponds to part-time workers (with 15 days or less of work per month and/or with less than six hours of work on their work days). In a pre-pandemic study, Singh et al. (2013) noted that part-time employed individuals were less likely to have the teleworking option compared to those working full-time (because employers appeared to feel a need to have face-to-face contact with individuals who already worked only for limited hours). But, given the option to telework, part-time employees are more likely to adopt teleworking. In a changed landscape, employers may continue to provide options for telework to employees, if not for any other reason than to retain their workforce, driving the substantial change in telework adoption before and after COVID among part-time employees. At the same time, it is well established in the literature that those who work part-time in terms of number of days of work and/or number of work hours per day have typically more space–time flexibility, which leads to more trip-making and vehicle miles of travel (López-Igual and Rodríguez-Modroño, 2020; López Soler et al., 2021). Thus, the increased work-from-home among part-time employees needs specific attention in future travel behavior and demand modeling analyses.

Overall, the findings above suggest that transportation demand forecasting models need to be updated to reflect higher levels of teleworking than prior to the pandemic, with differential adoption, rates, and locations of telework for different market segments. As of today, it is clear that telework and location choices have become substantially hybridized relative to before the pandemic. Furthermore, hybridization choices differ by sociodemographics and job-related characteristics. The majority of current transportation and travel models consider telework as a full-time, binary decision – an employee either teleworks every single day or does not. This is because of the single weekday focus of the models. However, our model clearly shows that this is not the case anymore and that employees are increasingly adopting hybrid work arrangements over longer periods of time (such as the work month). How this work hybridization over longer periods is considered within travel demand models requires additional thought and research, either by moving toward multi-day models or incorporating elements of longer (multi-day) period work arrangements within traditional single-day models. In any case, it is imperative that differential workplace hybridization propensities (over longer than a single day period)

Table A1
Independent Model Estimation Results.

Exogenous Variables (base category – *WITHOUT THE COVID SHIFT EFFECT*)	Adoption (Binary) Propensity		Frequency (Ordered) Propensity		Location (Multinomial) Propensity (base category – Home Only Utility)			
					Third Location Only Utility		Both Home and Third Location Utility	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Individual-level Characteristics								
Gender (base: men)								
Women	−0.172	−2.58	–		–		–	
Age (base: 18–29 years *before* COVID)								
18 to 29 *COVID SHIFT EFFECT*	0.473	1.86	–		–		–	
30 to 64 years	–		–		–		−0.285	−1.49
30 to 64 years *COVID SHIFT EFFECT*	0.208	1.22	0.241	1.67	–		–	
65 years or older	0.253	2.15	0.226	1.87	–		−0.584	−2.12
Education Level (base: undergraduate degree or less)								
Graduate degree *COVID SHIFT EFFECT*	0.221	2.38	–		–		–	
Household Characteristics								
Income (base: <$100,000)								
$100,000 to $249,999	0.203	3.00	–		–		–	
≥$250,000	0.203	3.00	–		–		−0.575	−2.34
Job Characteristics								
Employment Status (base: not self-employed)								
Self-employed	0.278	2.32	0.450	3.35	–		–	
Self-employed *COVID SHIFT EFFECT*	−0.404	−2.31	−0.337	−1.87	–		–	
# Days Worked per Month (base: 16 days or more is full time)								
1 to 15 days (part time)	0.425	2.67	−0.279	−1.80	–		–	
1 to 15 days (part time) *COVID SHIFT EFFECT*	–		–		–		0.538	2.20

Table A2
Independent Model Estimation Results.

Exogenous Variables (base category – *WITHOUT THE COVID SHIFT EFFECT*)	Adoption (Binary) Propensity		Frequency (Ordered) Propensity		Location (Multinomial) Propensity (base category – Home Only Utility)			
					Third Location Only Utility		Both Home and Third Location Utility	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Occupation (base: managerial/technical job)								
Healthcare	−0.632	−3.01	–		–		–	
Healthcare *COVID SHIFT EFFECT*	0.313	1.05	–		–		–	
Education/Social service	−0.765	−10.61	–		–		–	
Educ./Social service *COVID SHIFT EFFECT*	–		–		0.496	2.65	–	
Public services	–		−0.359	−1.08	–		–	
Public services *COVID SHIFT EFFECT*	–		0.466	1.20	–		–	
Professional Services	–		–		−0.424	−1.69	–	
Professional Services *COVID SHIFT EFFECT*	–		0.308	2.57	–		–	
Information/Finance	0.313	2.78	0.301	2.09	–		–	
Information/Finance *COVID SHIFT EFFECT*	–		0.464	2.19	–		–	
Commute Time (/100)	0.782	3.41	–		–		–	
Daily Work Hours (base: 6 h or more each day)								
Less than 6 h per day *COVID SHIFT EFFECT*	0.641	1.99	–		–		–	
In-Person Workplace Characteristics								
Employment Density of the in-person workplace (base: medium-to-low)								
High	0.165	2.03	−0.355	−2.62	–		–	
High *COVID SHIFT EFFECT*	–		0.455	2.54	–		–	

across population groups be accounted for in travel demand modeling to circumvent the ecological fallacy that may arise when ignoring the effects of such heterogeneity on broader activity-travel behavior patterns. Beyond travel demand models, hybrid work arrangements could also affect land-use patterns, including employers opting to downsize their offices or having multiple smaller office sites spread over a metropolitan area. The implications of these types of land-use changes on travel demand will need careful attention.

Table A3
Independent Model Estimation Results.

Exogenous Variables (base category – *WITHOUT THE COVID SHIFT EFFECT*)	Adoption (Binary) Propensity		Frequency (Ordered) Propensity		Location (Multinomial) Propensity (base category – Home Only Utility)			
					Third Location Only Utility		Both Home and Third Location Utility	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Residential Characteristics								
Land Use Type (base: rural)								
Suburban	0.169	2.01	–		–		–	
Urban	0.356	3.55	–		–		0.309	2.17
House Characteristics								
Private Study	0.127	1.64	−0.273	−2.14	−0.338	−2.64	−0.338	−2.64
Household Type (base: not a stand-alone home)								
Stand-alone home	–		−0.238	−1.56	−0.387	−2.74	−0.387	−2.74
COVID Threat								
Immunocompromised *COVID SHIFT EFFECT*	0.253	2.69	–		–		–	
Constant	0.323	1.83	−0.103	−0.59	−0.277	−1.63	−0.323	−2.30
Constant Shift Effect of the Pandemic	0.604	4.47	0.269	3.37	−0.973	−5.52	−0.548	−2.62
Thresholds								
Few times per month – Once per week	NA		0.000	–	NA		NA	
Once per week – 2–4 days per week	NA		0.098	1.23	NA		NA	
2–4 days per week – 5 days per week	NA		0.790	9.82	NA		NA	

7.2. Equity considerations

A general result from our study is that differences across population groups and occupation sectors in the adoption and frequency of teleworking are much more tempered than before the pandemic, suggesting a more open mind among employers (and employees) about telework arrangements. This is a good result from an equity standpoint. Of course, there is some pulling back of telework allowance by some employers more recently, which may bring back the differences across population groups to the more inequitable patterns that existed before the pandemic. Regardless of how the future may unfold on this front, it is important to recognize that there are still variations across population groups in the *After* COVID period of our study. Importantly, from an equity standpoint, it is clear that workers who are (1) women, (2) residing in rural settings, (3) lower income, and (4) in smaller homes with no private study do not adopt teleworking at the same levels as their counterparts. Enacting certain policies and provisions would help level the playing field and allow all demographic groups to take advantage of telework arrangements. For the first of these, women, in general, still tend to bear much of the domestic responsibilities of household chores and childcare even when with a partner (Zamarro and Prados, 2021). Working remote from home may be unappealing to mothers, as their domestic responsibilities may act as a distraction for their non-domestic paid work. On the other hand, remote third workplace locations may not be entirely desirable for women employees as well (regardless of whether they are a mother or not). Third workplace locations can be more unsafe for women, relative to men, and relative to their in-person office. In particular, in such spaces, women have been known to feel socially isolated from both men and women peers, and fear sexual harassment or other instances of workplace sexism, as there is less structure and imposed workplace regulations in these third workplace locations (Rodríguez-Modroño, 2021). Therefore, policies and provisions to provide affordable and accessible childcare may incentivize working mothers to work from home more often, and investing in the safety, diversity and inclusively of third workplace locations may encourage women more generally to work outside of both their homes and in-person offices more frequently.

Similarly, rural areas have less access to high speed broadband internet or have weaker connectivity within homes (Zhang et al., 2019; Phillipson et al., 2020). In 2019, the FCC reported that more than 30 % of rural residents lack broadband services altogether (Bauerly et al., 2019). Therefore, investing in and boosting high-speed bandwidth in remote rural locations may facilitate teleworking among rural dwellers who seek to do so. With regard to the lower teleworking adoption among lower income households living in smaller houses, one possible intervention may be to create less expensive third workplace locations close to areas with a high density of low income households. In general, new policies and provisions must be considered to encourage the provision of options for work locations across all segments of our society.

7.3. Study limitations and final conclusions

As with most research efforts, our study is not without its own share of limitations. First, the sample only includes employed individuals who had the opportunity to telework both before and after the pandemic. Our focus in the current study is explicitly to investigate the *change* in teleworking habits from an employee standpoint before and after the pandemic and the factors that impact these choices. This, inevitably, led us to exclude a significant proportion of employed individuals who did not have the option to telework before the pandemic. Future studies and policies aimed at the population at large must also consider this set of excluded (from our study) employees to more accurately reflect and forecast teleworking adoption, frequency and location behavior in the context of

travel demand modeling. Second, for convenience, we used a recall survey to obtain telework responses at two points in time. This may lead to recall errors and biases. Future studies can consider a true longitudinal panel survey, and observe the actual telework arrangements as well as corresponding demographic/other exogenous variables at each of multiple points in time. Third, the sample used in our study was moderate in size. The relatively small sample size mostly hindered us from testing and including interaction effects, since we did not have enough data points in finer subgroups formed from combinations of exogenous variables (such as young women or self-employed high income workers). Nevertheless, in our research, the sample size limitation did not have a substantial impact on the robustness of the results. An effective way to check for this is to estimate several models by changing a few of the exogenous variable specifications randomly, and checking if the resulting estimates vary substantially across each estimation; and then to undertake a prediction exercise for the dependent outcomes for each of such estimations (see for example, Lu and White, 2014, Srivastava et al., 2018, and Brennan et al., 2021). In our analysis, the estimates for each of the variables were consistently around the estimates reported in Table 3 (in terms of magnitude and signs) across all such estimations. Moreover, the predictions were also consistent (and remarkably good) around those reported in Table 6. Thus, the conclusions we draw from our study are quite robust, although we do believe that a larger sample would definitely help draw additional insights. Fourth, investigating telework arrangements and COVID effects in different geographic areas of the country would be a fruitful avenue for further research. While telework rates are nearly identical between Texas and the rest of the country (see Cobler, 2022), this does not necessarily imply transferability of model estimates. The effects of exogenous variables can be quite different based on such context-specific variables as the local government's policies, the economic conditions in the region, and people's attitudes. Thus, additional investigations in different geographic contexts as well as over time can provide important insights about spatial–temporal variations in telework uptake, frequency, and location preferences.

Declaration of Competing Interest

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

Acknowledgement

This research was partially supported by the Center for Teaching Old Models New Tricks (TOMNET), a Tier 1 University Transportation Center sponsored by the US Department of Transportation under grant 69A3551747116, as well as by the Center for Understanding Future Travel Behavior and Demand (TBD), a National University Transportation Center also sponsored by the US Department of Transportation under grant 69A3552344815 and 69A3552348320. The data used in this paper was collected as part of a survey funded by the Texas Department of Transportation. The authors are grateful to Lisa Macias for her help in formatting this document, and to three anonymous reviewers who provided useful comments and suggestions on an earlier version of this paper. Special thanks also to Elisabetta Cherchi for her wise counsel and guidance in improving the paper.

Appendix A

A.1. Model results from three independent models

Tables A provides the results for three independent models for the telework dimensions of adoption, frequency, and location.

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