A U-Shaped Paradigm: Understanding the Impact of Telecommuting on Public Transit Ridership Before and After the Pandemic

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ABSTRACT
This paper aims to quantify the impacts of telecommuting on transit use. Data for this analysis is derived from the 2019 and 2023 editions of the Puget Sound Regional Council (PSRC) household travel survey and a joint model of telecommuting and transit use frequency is estimated to understand the nature of the relationship in the pre- and post-pandemic periods. The findings reveal a U-shaped relationship between telecommuting and transit use. Lower transit frequency was observed at both the highest and lowest levels of telecommuting, while higher transit frequency was associated with medium or hybrid levels of telecommuting. This pattern became even more pronounced in 2023. Computations of average treatment effects show that transitioning from medium-level (hybrid) telecommuting to non-telecommuting resulted in a 21 percent decrease in transit use in 2019, and a steeper 35 percent decrease in 2023. Similarly, moving from hybrid to frequent telecommuting led to a six percent reduction in transit use in 2019, and a larger nine percent reduction in 2023. These findings suggest that the loss in transit ridership in the post-pandemic era is likely to persist and that compelling workers to return to the workplace full-time is unlikely to yield significant gains unless transit agencies find innovative ways to attract non-telecommuters (full commuters) back to transit. Instead, embracing a hybrid work modality while providing incentives to promote transit use may yield greater benefits.

Keywords: joint modeling, longitudinal analysis, telecommuting, mode choice, public transit

1. INTRODUCTION

Transit ridership has been on the steady decline in the United States for nearly a decade, after reaching a peak in about 2014 (*1*). During the pandemic, transit ridership plummeted, largely because of reduced travel and out-of-home activity engagement, increased virtual activity participation, and concerns about contagion in shared modes of transportation. Ever since the pandemic began to fade in 2022, ridership has generally rebounded to about 80 percent of pre-pandemic levels, with considerable variations among geographical contexts (*2, 3*). There is widespread concern about the financial and operational sustainability of transit systems due to substantially lower farebox revenues in the post-pandemic era.

One key behavioral change that has persisted into the post-pandemic era is the widespread adoption of work from home, hereafter referred to as *telecommuting*. An analysis of the American Time Use Survey (ATUS) data shows that the percent of full-time workers telecommuting on weekdays has been steadily rising even before the pandemic (*4*). While just four percent of full-time workers reported working exclusively from home on a weekday in 2003, that percentage more than doubled to 8.5 percent by 2019. While technological improvements and changes in occupational profiles likely contributed to this gradual increase, the increases in telecommuting percentages were incremental and modest in this period. The pandemic, however, has been a gamechanger, with telecommuting surging during the pandemic. At the height of the pandemic in 2020, nearly 28 percent of full-time workers reported working exclusively from home on a weekday; this percentage has since decreased, but remains stubbornly high at 21.8 percent, according to the most recent 2023 ATUS data.

The widespread adoption of telecommuting has significant implications for transit ridership, which has historically been dominated by commuters. Transit systems are often designed to meet the travel needs of peak-period commuters, and with fewer people commuting in the wake of the pandemic, transit is struggling to regain lost ridership. Before the pandemic, commuting to work was the primary reason for riding public transportation, accounting for 59.2 percent of all transit trips, while trips to school made up 10.6 percent (*5*). The heavy reliance on commute travel contributes to transit systems seeing continued loss of ridership compared to pre-pandemic times. With telecommuting now nearly three times more prevalent than in pre-pandemic years, the decrease in commuters is undoubtedly impacting transit ridership significantly.

Despite the strong connection between transit ridership and commuting, there is limited research examining and quantifying the impacts of telecommuting on transit ridership. This study is therefore intended to determine the extent to which transit use drops as telecommuting increases. Understanding this relationship can help in designing transit services that meet the needs of travelers in an era of higher telecommuting frequency, specifying mode choice and other travel model components that accurately reflect the effects of telecommuting on mobility patterns, and crafting policies that may help maintain levels of service for transit-dependent riders.

The data for this analysis is derived from the 2019 and 2023 editions of the Puget Sound Regional Council (PSRC) household travel survey, administered in the Greater Seattle region of the State of Washington. The datasets include variables on telecommuting and transit use frequencies, thus enabling the estimation of a joint econometric model system that treats both variables as endogenous. The model system accounts for the direct relationship between these endogenous variables while also accounting for any error correlations arising from unobserved attributes that simultaneously affect both variables. The model takes the form of a multivariate ordered probit (MORP) to reflect the ordered nature of the endogenous variables, account for simultaneity in their relationship, and recognize that the data are derived from two different years in vastly different eras (pre- and post-pandemic).

The remainder of this paper is organized as follows. The next section offers a brief description of the datasets used in this study. The third section presents the modeling approach and methodology. The fourth section presents model estimation results, together with treatment effects to quantify the impacts of telecommuting on transit use. The final section offers conclusions and a discussion of policy implications.

2. DATA DESCRIPTION

This section provides a brief description of the datasets, which are derived from the 2019 and 2023 editions of the Puget Sound Regional Travel Study program. This survey has been conducted every odd year since 2015 (*6*). The multiyear survey program collects detailed information on household- and person-level activity-travel patterns, together with information about person and household socio-economic and demographic characteristics. Movements of individuals are recorded through a mobile app (*6*). The survey covers four counties in the region – King, Kitsap, Pierce, and Snohomish – encompassing a population of more than four million people. The sampling frame included all households in five sampling geographies, comprising the four counties and the City of Seattle in 2019, and expanded to six geographies in 2023 with the addition of the City of Bellevue. Address-based sampling was used to randomly draw residential addresses from each sampling geography.

The 2019 edition of the survey collected information from 3,044 households, resulting in 5,711 person records. The 2023 version gathered data from 3,661 households, yielding 6,942 person records. This study uses person-level data from both years, including socio-economic and demographic variables as exogenous variables, and transit and telecommuting frequencies as endogenous variables. The sample was filtered to include only respondents who are full-time employees aged 18 years or older. It was further refined to include only those who responded to questions about the frequency of telecommuting and transit use. The final samples consisted of 1,750 observations for 2019 and 2,257 observations for 2023.

The 2019 and 2023 versions of the survey include a set of questions that can be used to construct telecommuting and transit use frequency as ordered response variables. Since the raw responses provided very disaggregate frequency information, some response categories were combined to ensure adequate sample sizes in each category for modeling purposes. After extensive exploratory data analysis and preliminary model building efforts, the response variables were categorized into three user groups for transit use frequency and four user groups for telecommuting frequency. The transit user groups are as follows:

- Non-transit users: never use transit or use transit less than once per month
- Occasional transit users: use transit 1-3 times per month to 1 day per week
- Regular transit users: use transit 2 or more days per week

The categories for telecommuting frequency are defined as:

- Non-telecommuter: never telecommutes or telecommutes less than once per month
- Occasional telecommuter: telecommutes 1-4 times per month
- Regular telecommuter: telecommutes 2-3 days per week
- Frequent telecommuter: telecommutes 4 or more days per week

TABLE 1 Socioeconomic and Demographic Characteristics of the 2019 and 2023 Samples
(N_{2019}=1,750; N_{2023}=2,257; Full-time Workers 18+ years)

Individual Demographics			*Household and Other Characteristics*		
Variable	**2019** (%)	**2023** (%)	**Variable**	**2019** (%)	**2023** (%)
Gender			**Household income**		
Female	46.3	47.4	Less than $25,000	1.3	1.0
Male	53.7	52.6	$25,000 to $49,999	9.5	6.4
Age category			$50,000 to $99,999	29.2	23.4
18-24 years	4.3	4.4	$100,000 or more	60.0	69.2
25-34 years	41.9	34.9	**Household size**		
35-44 years	26.1	28.3	One	27.4	26.5
45-54 years	15.0	17.5	Two	47.1	41.8
55-64 years	10.6	12.2	Three or more	25.5	31.7
65 years or older	2.1	2.6	**Household child status**		
Education attainment			Yes	20.6	25.6
Less than high school	0.2	0.6	No	79.4	74.4
High school graduate	4.2	4.9	**Vehicle ownership**		
Some college	14.1	16.4	0 vehicle	14.1	5.4
Bachelor's degree(s)	46.0	41.1	1 vehicle	46.8	45.1
Graduate degree(s)	35.5	37.0	2 vehicles	29.3	36.4
Race			3 or more vehicles	9.8	13.1
Asian/Pacific Islander	15.9	22.6	**Vehicle deficiency (less than one vehicle per adult)**		
Black	3.0	3.0	Yes	57.3	50.3
Native American	0.9	1.3	No	42.7	49.7
White	78.3	70.7	**County**		
Other	1.9	2.4	King County	77.4	73.8
Ethnicity			Kitsap County	3.4	4.6
Hispanic	3.2	6.4	Pierce County	10.5	9.9
Student status			Snohomish County	8.7	11.7
Full time	1.7	1.1	**Employee transit benefit**		
Part time	2.7	3.3	Yes	46.4	37.9
Not student	95.6	95.7	No	53.6	62.1
Main Outcome Variables					
Telecommute Frequency			**Public Transit Frequency**		
Never	35.9	33.1	Never	39.7	58.7
Occasional	42.0	13.0	Occasional	19.6	19.8
Regular	14.9	24.3	Regular	40.7	21.5
Frequent	7.2	29.5	---	---	---

The gender distributions are fairly consistent between the two samples, but the 2023 sample is slightly older, with a substantially lower percent of respondents in the 25-34 years category. The 2023 sample has a larger percent of Asian/Pacific Islanders and a lower percent of Whites, along with a greater percent of Hispanics. Additionally, the 2023 sample depicts a higher income profile, with nearly 70 percent of households earning over $100,000 annually. The 2023 sample also shows a greater presence of larger household sizes and a higher share of households with children. There is a higher level of vehicle ownership in 2023, with only 5.4 percent of respondents reporting zero vehicles in their households, compared to 14.1 percent in 2019. Correspondingly, the 2023 sample is less transit-oriented. A smaller percent of respondents takes advantage of employee transit benefits, and a substantially larger percent never uses transit (58.7 percent in 2023 versus 39.7 percent in 2019). The percent of *regular* transit users also declined noticeably, from 40.7 percent in 2019 to 21.5 percent in 2023. In terms of telecommuting frequency, the percent reporting *never* telecommuting is rather similar between two years. However, the percent reporting occasional telecommuting dropped from 42 percent in 2019 to 13 percent in 2023. The percent of regular telecommuters increased from 14.9 percent to 24.3 percent, and the percent of frequent telecommuters increased from 7.2 percent to 29.5 percent. This indicates a substantial increase in telecommuting frequency in 2023, consistent with post-pandemic trends.

It can be seen that transit use experienced a substantial decline, while telecommuting experienced a surge in frequency. To better understand the relationship between these two phenomena, bivariate plots were generated. Figure 1 shows the bivariate relationship between transit use and telecommuting frequencies for 2019 and 2023 in the PSRC travel survey datasets. The plot depicts the distribution of transit use frequency within each telecommuter group. What is quite discernible is a sideways U-shaped pattern where the percent of regular transit users is greatest among those with hybrid work arrangements (occasional and regular telecommuters). The transit use frequency is lowest for non-telecommuters and frequent telecommuters. This pattern is seen in both years, with the percent of regular transit users among frequent telecommuters found to be quite small at 10.4 percent in 2023. Overall, from 2019 to 2023, the percent of regular transit users dropped dramatically, but the sideways U-shaped relationship largely held fast.

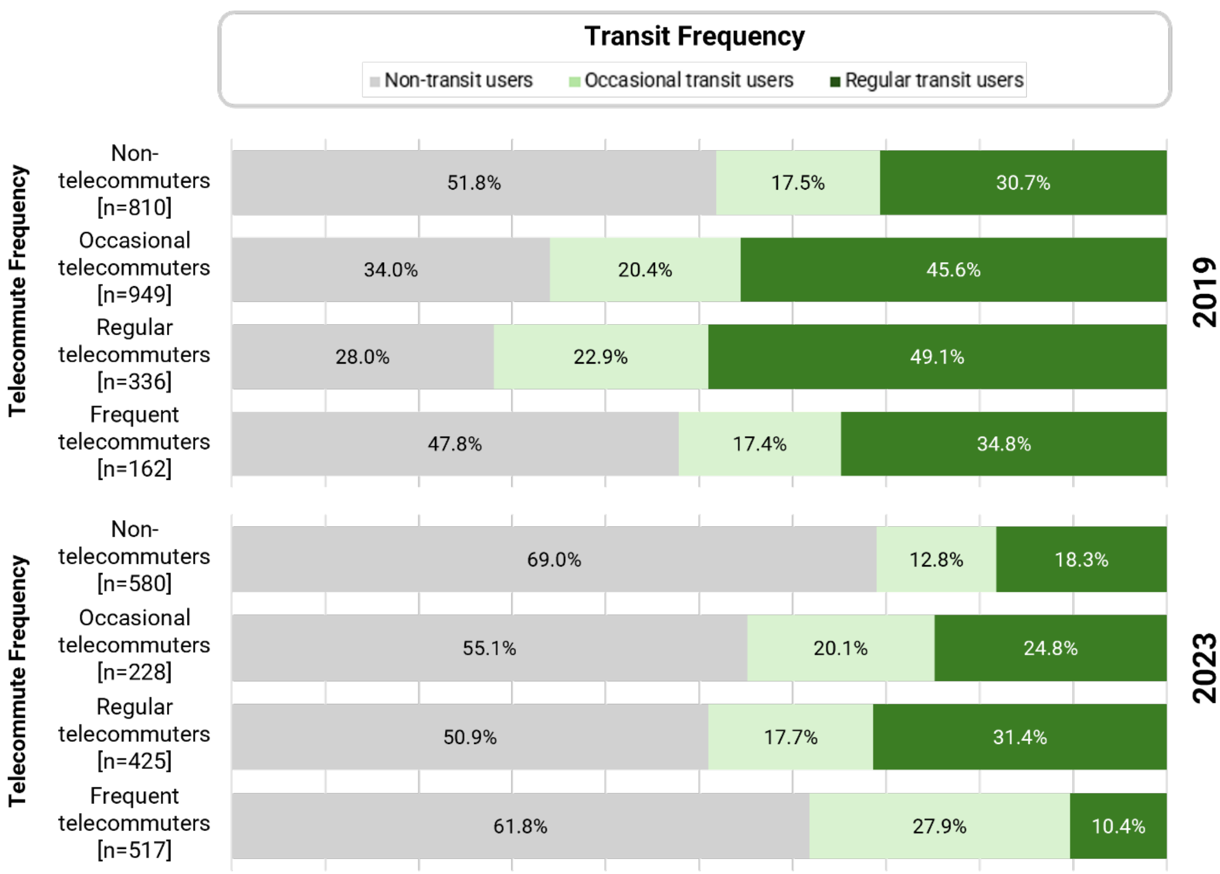

FIGURE 1 Bivariate Relationship Between Transit and Telecommuting Frequency in the 2019 and 2023 Puget Sound Region Travel Survey Data

In order to check the validity of this sideways U-shaped relationship, a similar plot was developed using data from the recent 2022 National Household Travel Survey (NHTS) in the United States (*7*). Figure 2 shows the distribution of transit users by telecommuting frequency and the distribution of transit users by monthly level of usage for each telecommuting frequency level. In other words, the bottom half of the plot is limited to those who indicated that they are a transit user in the top half of the plot. The top graph in the figure shows a sideways U-shaped pattern, similar to that seen in the PSRC travel survey data sets. In the transit monthly frequency part of the plot, there is a discernible sideways U-shaped pattern in the relationship if one were to combine the categories of 16-30 days a month and 6-15 days a month.

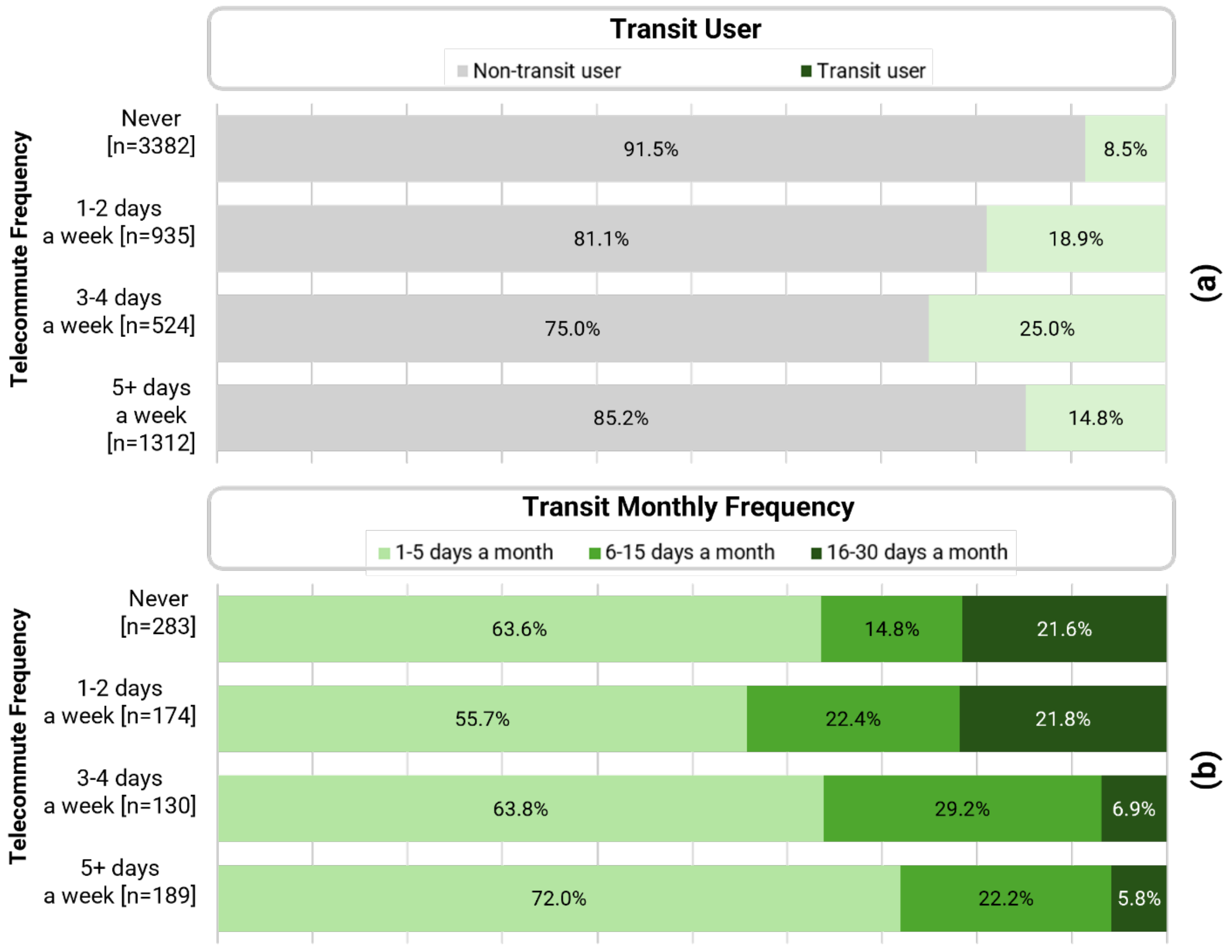

Figure (a): distribution of transit users (Yes/No) across telecommute categories.
Figure (b): frequency of transit usage among transit users across telecommute categories

FIGURE 2 Bivariate Relationship Between Transit and Telecommuting Frequency in the 2022 National Household Travel Survey (NHTS)

The prevalence of the sideways U-shaped pattern in the relationship between transit use and telecommuting frequencies suggests that the nature of the relationship is complex and confounded by other factors. The bivariate graphs show that lower levels of transit use are seen among those who telecommute frequently and among those who do not telecommute at all. It generally makes sense that frequent telecommuters would use transit less; they do not commute and are likely more homebound on workdays. However, it is surprising to see non-telecommuters also depicting lower levels of transit use compared to hybrid telecommuters. To further unravel and understand the nature of the relationship, this study involves the estimation of a simultaneous equations model system that explicitly accounts for the impact of telecommuting frequency on transit use frequency.

3. MODELING METHODOLOGY

This section presents the modeling framework and methodology adopted in this study. The overall model framework is presented first, and the model formulation is presented second.

3.1. Model Framework

The model structure is shown in Figure 3. This model aims to depict the relationship between telecommuting and transit use frequencies in both 2019 and 2023, with a view to capture the nature of the relationship in pre-pandemic and post-pandemic eras. The left-hand side of Figure 3 includes a series of exogenous variables, reflecting socio-economic, demographic, and built environment attributes influencing outcome variables. The right-hand side of the figure displays the four ordinal outcome variables of interest: (1) telecommuting frequency in 2019; (2) telecommuting frequency in 2023; (3) transit use frequency in 2019; and (4) transit use frequency in 2023.

The influence of exogenous variables on observed ordinal telecommuting and transit frequencies in each year is captured using fixed effects and shifter effects. The fixed component captures the influence of exogenous variables on the latent propensity of telecommuting and transit use frequencies, irrespective of the year. These time-invariant fixed effects may be viewed as representing baseline effects of exogenous variables on the two endogenous variables. To account for potential changes in these relationships over time, the model framework introduces shifter effects that capture the unique impact of exogenous variables on outcomes in 2023. In essence, the fixed effects represent the baseline impact of exogenous variables, while the shifter effects quantify the additional influence they exert in 2023.

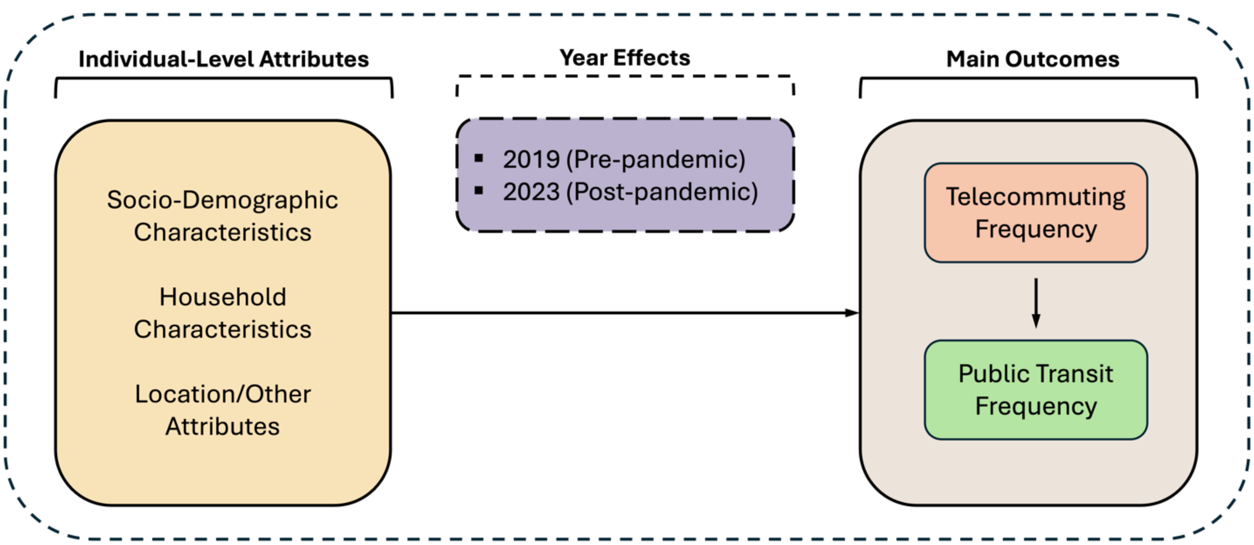

FIGURE 3 Model Structure and Framework

The model formulation encompasses four separate equations – two for each year – with the 2023 equations including additional shifter effects. This approach allows the estimation of separate correlations for 2019 and 2023, and each year's equations are estimated only for respondents from that specific year. This approach allows for the estimation of separate correlations between transit use and telecommuting frequency for 2019 and 2023, capturing potential changes in their relationship over time. This is particularly important given the significant societal changes that occurred between these years. More importantly, this approach accurately represents the underlying data structure, where 2019 and 2023 responses come from different sets of individuals. The separate modeling of years allows for better model fit, especially if there are significant differences in the correlation structure or other year-specific effects.

A multivariate ordered response probit (MORP) model system is employed to jointly model telecommuting and transit use behavior. This approach controls for unobserved factors that lead to associations among the outcomes before estimating any endogenous effects of one outcome on the other. A methodology that ignores the resulting correlation due to these individual unobserved factors, and simply introduces one outcome variable (e.g., telecommute frequency) as an explanatory variable for another outcome variable (e.g., transit use frequency), would inaccurately estimate the causal effect between these outcomes due to the presence of confounding factors. In contrast, the methodology controlling for such error correlations can isolate the "true" causal impact of one endogenous variable on the other.

For any given individual who participated in the 2019 survey, the joint probability of interest corresponds to the frequency of telecommuting and the frequency of transit use in 2019. Conversely, if the individual participated in the 2023 survey, the joint probability of interest is the frequency of telecommuting and transit use in 2023. Due to the repeated cross-sectional nature of the data, with no individual observed in both years, correlations between outcomes are limited to within-year relationships. All of the outcomes are estimated jointly, resulting in a four-dimensional MORP model.

To implement the proposed modeling framework, the two cross-sectional datasets from 2019 and 2023 are stacked into a single dataset. Two binary variables are created to indicate the year to which each observational record belongs. This stacking process enables the simultaneous modeling of data from both years. The model incorporates year-specific shifter effects by interacting year variables with exogenous variables. The inclusion of these interaction terms allows for a nuanced analysis of how different factors influenced transit and telecommuting behaviors differentially across the two distinct time periods.

3.2. Model Estimation Methodology

In the following presentation, the likelihood contribution is derived for each individual while suppressing the notation q for individuals. Let k_i represent the ordered-response level for each outcome i (i=1,2,…, I=4). Specifically, let $k_i \in \{1, 2, \ldots, K_i\}$, where K_i is the highest level corresponding to variable i. Also, define the latent propensities y_1^* and y_2^* (for telecommuting frequency in 2019 and 2023, respectively) and y_3^* and y_4^* (for transit frequency in 2019 and 2023, respectively) as follows:

$$y_1^* = \boldsymbol{\beta}'\mathbf{x} \ + \varepsilon_1, y_1 = k_1 \text{ if } \theta_{k_1-1}^1 < y_1^* < \theta_{k_1}^1,$$
$$y_2^* = (\boldsymbol{\beta}' + \boldsymbol{\alpha}')\mathbf{x} + \varepsilon_2, y_2 = k_2 \text{ if } \theta_{k_2}^2 < y_2^* < \theta_{k_2}^2$$
$$y_3^* = \boldsymbol{\lambda}'\mathbf{x} + \varepsilon_3, y_3 = k_3 \text{ if } \theta_{k_3-1}^3 < y_3^* < \theta_{k_3}^3$$
$$y_4^* = (\boldsymbol{\lambda}' + \boldsymbol{\gamma}')\mathbf{x} + \varepsilon_4, y_4 = k_4 \text{ if } \theta_{k_4-1}^4 < y_4^* < \theta_{k_4}^4 \quad (1)$$

where $\mathbf{x}$ is an $H\times1$ vector of exogenous variables (without a constant). The parameters $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are $H\times1$ vectors representing the fixed exogenous variable effects on telecommute frequency and transit frequency, respectively. Similarly, $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ are $H\times1$ vectors capturing the shifter effects of variables on telecommute frequency and transit frequency in 2023, respectively. Each of the latent propensities y_1^*, y_2^*, y_3^*, and y_4^* are mapped to the observed ordinal levels y_1, y_2, y_3, and y_4 through elements of threshold vectors $\boldsymbol{\theta}^i=(\theta_0^i,\theta_1^i,...,\theta_{K_i-1}^i)'$. The elements of each threshold vector are in strictly ascending order for each individual q, with the convention that $\theta_0^i=-\infty$ and $\theta_0^i<\theta_1^i<...<\theta_{K_i-1}^i<\theta_{K_i}^i=+\infty$. The stochastic components of Equation 1 are assumed to follow a multivariate normal distribution with an $(I\times1)$ mean vector of zeros $\mathbf{0}_I$ and an $(I\times I)$ covariance matrix $\boldsymbol{\Sigma}$, as follows (for this specific empirical application):

$$\boldsymbol{\varepsilon}=(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_I)'\sim MVN_I\left[\mathbf{0}_I,\boldsymbol{\Sigma}\right],\ \text{or}\ \boldsymbol{\varepsilon}\sim MVN_I\left(\begin{pmatrix}0\\0\\0\\0\end{pmatrix},\begin{pmatrix}1&0&\rho_{13}&0\\0&1&0&\rho_{24}\\\rho_{13}&0&1&0\\0&\rho_{24}&0&1\end{pmatrix}\right) \tag{2}$$

ρ_{13} corresponds to the correlation in the error terms underlying the latent continuous variables corresponding to the frequency of telecommuting and transit outcomes in 2019, and ρ_{24} is the corresponding correlation between the frequency of telecommuting and transit in 2023. Note that the zero elements in $\boldsymbol{\Sigma}$ correspond to the inestimable correlations between variables across years.

To simplify the notation, this formulation may be expressed in matrix form. Let $\boldsymbol{\Lambda}=(\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\lambda},\boldsymbol{\gamma})'$ [$(I\times H)$ matrix] be a matrix of parameters. Also, vertically stack the threshold vectors for all outcomes $\boldsymbol{\theta}^i$ into a single vector $\boldsymbol{\theta}$. For an individual who selects level k_i for each outcome (i = 1,2,.., I), two $(I\times1)$ vectors $\boldsymbol{\theta}_{low}$ and $\boldsymbol{\theta}_{high}$ are created. $\boldsymbol{\theta}_{low}$ contains the lower thresholds $\theta_{k_i-1}^i$ for each observed outcome, while $\boldsymbol{\theta}_{high}$ contains the upper thresholds $\theta_{k_i}^i$ for each observed outcome. Also, stack the y_i^* latent variables into an $(I\times1)$ vector $\mathbf{y}^*$. Using this matrix notation, the latent propensities underlying the observed multivariate outcome for the individual may be expressed as follows:

$$\mathbf{y}^*=\boldsymbol{\Lambda}'\mathbf{x}+\boldsymbol{\varepsilon},\ \boldsymbol{\theta}_{low}<\mathbf{y}^*<\boldsymbol{\theta}_{high},\ \text{where}\ \mathbf{y}^*\sim MVN_I(\boldsymbol{\Lambda}'\mathbf{x},\boldsymbol{\Sigma}). \tag{3}$$

Lastly, define a vector $\boldsymbol{\delta}$ that encompasses all parameters to be estimated $\boldsymbol{\delta}=\left(\left[\text{Vech}(\boldsymbol{\Lambda})\right]',\boldsymbol{\theta}',\left[\text{Vechup}(\boldsymbol{\Sigma})\right]'\right)'$, where the operator "Vech(.)" row-vectorizes all the non-zero elements of its matrix/vector argument, and the operator Vechup(.) row-vectorizes the upper diagonal elements of a matrix. Then, the likelihood function of a single individual may be written as:

$$\begin{aligned}L(\boldsymbol{\delta})&=\Pr\left[\boldsymbol{\theta}_{low}<\mathbf{y}^*<\boldsymbol{\theta}_{high}\right],\\&=\int_{D_r}f_I(\boldsymbol{r}\,|\,\boldsymbol{\Lambda}'\mathbf{x},\boldsymbol{\Sigma})d\boldsymbol{r}.\end{aligned} \tag{4}$$

This likelihood function integrates the multivariate normal (MVN) density function over a region $D_r = \{\boldsymbol{r} : \boldsymbol{\theta}_{low} < \boldsymbol{r} < \boldsymbol{\theta}_{high}\}$, defined by the upper and lower thresholds for each outcome. The error terms follow an I-dimensional MVN distribution with zero mean and covariance matrix $\boldsymbol{\Sigma}$. The model is estimated using maximum likelihood inference. The log-likelihood for the entire sample of Q individuals is the sum of their individual log-likelihoods. The matrix-based approximation method proposed by Bhat (*8*) was employed to overcome the computational difficulties associated with evaluating the multivariate normal cumulative distribution function (MVNCDF).

4. MODEL RESULTS AND COMPUTATION OF TREATMENT EFFECTS

This section presents estimation results together with a computation of average treatment effects to quantify the impact of telecommuting on transit use frequency.

4.1. Joint Model Estimation Results

Table 2 presents model estimation results. The critical relationship of interest pertains to the impact of telecommute frequency on transit use frequency. The results show that frequent telecommuters are more likely to use transit at a lower frequency, as evidenced by the negative coefficient (-0.45). This relationship holds true in both 2019 and 2023 and may be considered a baseline trend that occurs regardless of time point. This finding aligns with expectations, as frequent telecommuters generally do not need to use transit as much as those who commute to the workplace (*9*). A notable finding is the significant year-specific effect associated with non-telecommuters. The "Never × 2023" variable captures the differential influence of never telecommuting on transit frequency in 2023 when compared to 2019. This variable has a marginal level of significance (t-stat = -1.56) and a negative coefficient (-0.2), indicating that non-telecommuters were less likely to use transit in 2023 than in 2019. This suggests a behavioral shift occurred among regular commuters (non-telecommuters) with this group depicting a lower level of transit use in 2023 compared to 2019. This particular result is quite intriguing and will be explored in more detail later in this paper.

The table also depicts the influence of exogenous variables. In the interest of brevity, only a few illustrative results are explained here, with a focus on the year-specific shift effects. In general, all of the indications are quite intuitive and consistent with findings reported in the literature. Younger individuals (25-34 years) are more likely to use transit more frequently. Older individuals (55-64 years) are less likely to telecommute at higher frequencies, but there is a significant year-specific shift effect, suggesting that they depicted a higher propensity to telecommute more frequently in 2023 (*10*). This reflects the widespread adoption of telecommuting in the pandemic era with older workers who began telecommuting during the pandemic continuing to do so at high(er) levels even after the pandemic faded. Higher educational attainment is associated with a greater likelihood of adopting higher levels of both telecommuting and transit use, consistent with the region's technology-oriented workforce and high level of transit choice ridership. The education variable also has a shift effect, with college graduates showing a greater shift towards higher levels of telecommuting in 2023 compared to their non-college-educated counterparts.

TABLE 2 Estimation Results for Transit and Telecommuting Model System (N= 4,007)

Explanatory Variables		Main Outcome Variables			
Variables (base)	**Attributes**	**Telecommute** *(4-level: never to Frequent)*		**Transit** *(3-level: never to Regular)*	
		Coef.	t-Stat	Coef.	t-Stat
Endogenous variables					
Telecommute frequency	Never × 2023	---	---	-0.2	-1.56
	Frequent	---	---	-0.45	-4.81
Individual characteristics					
Age (*)	25-34 years	---	---	0.08	1.84
	55-64 years	-0.2	-2.69	---	---
	55-64 years × 2023	0.24	2.25	---	---
Education (*)	Bachelor's and higher	0.33	5.76	0.38	6.64
	Bachelor's and higher × 2023	0.38	4.47	---	---
Race (*)	Asian	0.19	3.97	---	---
	Black	---	---	-0.25	-2.22
Student status (*)	Full-time	---	---	0.32	1.92
Household characteristics					
Household income (*)	Less than $25,000	---	---	0.73	3.43
	Less than $50,000 × 2023	-0.49	-4.31	---	---
	$100,000 or more	0.31	6.22	---	---
	$100,000 or more × 2023	0.17	2.12	-0.15	-1.73
Household size (*)	One	0.24	5	0.19	3.32
	Three or more × 2023	---	---	-0.21	-2.69
Vehicle ownership (*)	0 vehicle	---	---	0.59	7.4
Household child status (No)	Yes	---	---	-0.41	-6.46
Vehicle deficiency (No)	Yes	0.09	2.34	0.48	8.9
Other characteristics					
County (*)	King County	0.23	5.39	0.16	2.32
	Pierce County	---	---	-0.28	-3.22
City of Seattle (No)	Yes	---	---	0.41	8
Employee transit benefit (No)	Yes	---	---	0.17	4.26
Thresholds					
Year 2019	0|1	0.39	5.84	0.78	9.81
	1|2	1.57	23.77	1.37	17.07
	2|3	2.26	34.96	---	---
Year 2023	0|1	0.68	8.15	0.82	6.8
	1|2	1.07	12.62	1.49	12.86
	2|3	1.76	20.46	---	---
Correlation Matrix		**2019**	**2023**	**2019**	**2023**
Telecommute	**2019**	1	---	0.15	---
	2023		1	---	0.21
Transit	**2019**			1	---
	2023				1
Data Fit Measures		**Joint Model**		**Independent Model**	
Log-likelihood at convergence		-8375.27		-8536.39	
Number of parameters		44		42	
Bayesian Information Criterion		8557.78		8710.60	
Average probability of correct prediction		0.17		0.15	

Note: **(*)** Base category is all other complementary categories for the corresponding variable; **(×)** refers to interaction terms that indicate the year-specific effects of variables.

The income variable offers reasonable baseline indications, with lower income associated with greater levels of transit use and higher income associated with greater levels of telecommuting. Notably, there are significant shift effects signaling the emergence of equity challenges in the post-pandemic era. The 2023 shift effect corresponding to telecommuting frequency is negative for the lower income group (<$50,000) and positive for the higher income group (≥$100,000), while the shift effect on transit use is negative for the higher income group. This indicates an amplification of the differences between income groups with respect to telecommuting and transit frequency in the post-pandemic era (*11*). Another variable with a shift effect is that of larger households with three or more members. Individuals in these households were less likely to adopt higher levels of transit use in 2023. It is likely that these individuals stopped using transit during the pandemic to avoid spreading contagion to household members and continued with lower transit use in the post-pandemic era.

In summary, telecommuting frequency affects transit use frequency significantly, with a more pronounced relationship prevailing in 2023. This finding is consistent with the sideways U-shaped pattern of the relationship between these endogenous variables, as seen in Figures 1 and 2. A number of other socio-economic and demographic variables depict similar shift effects for 2023, suggesting that the nature of the relationship between the variable in question and the corresponding endogenous variable experienced a significant change from pre-pandemic to post-pandemic times. The table also presents goodness-of-fit statistics that show that the joint model that accounts for error correlations provides a statistically superior fit than the independent model that ignores error correlations. Also, the correlation matrix shows that telecommuting frequency and transit frequency are positively correlated, implying the presence of common unobserved variables (e.g., environmentally conscious attitudes) affecting both endogenous variables.

As mentioned earlier, model estimation results show a year-specific shift effect in the influence of telecommuting frequency on transit use frequency, with those who commuted regularly (non-telecommuters) exhibiting a lower propensity to adopt a higher transit use frequency level in 2023. In other words, this group exhibited lower levels of transit use frequency in 2023 when compared with 2019, suggesting that regular commuters who used transit in 2019 abandoned transit at the height of the pandemic in 2020 and then never returned in full measure to the transit mode for their commute (*2*). To see if that is indeed the case, data from the nationwide COVID Future Panel Survey (*12*) was analyzed in-depth to examine transitions in commute mode choice between the pre-pandemic period and the post-pandemic period. The stayer sample of the survey responded to the survey during three distinct waves conducted between April 2020 and November 2021, with a specific question included in each wave inquiring about the commute mode used most often. There were 1,156 employed individuals in the stayer sample, and the Sankey diagram shown in Figure 4 is generated for this stayer subsample.

The Sankey diagram shows the transition between commute modes across the two time points. In the pre-pandemic period, 88.4 percent of the employed stayer sample utilized modes other than transit for commuting to work. The remaining 11.6 percent used transit most frequently for their commute. The diagram illustrates the extent to which the sample transitioned between modes into the third wave of the survey which took place in October-November 2021. Although this does not necessarily reflect a post-pandemic period, it does provide an initial indication of the modal transitions that occurred by the time vaccines were widely available and many establishments were beginning to resume more normal operations. Among transit users in the pre-pandemic period, it is found that 33.1 percent of them transitioned to the private vehicle in the third wave with another 26.1 percent transitioning to telecommuting. Only 34.6 percent of the transit users in the pre-pandemic period continued to use transit as their commute mode in the third wave. In other words, a large share of transit users in the pre-pandemic era shifted to other modes of commuting (private vehicle and telecommuting) by late 2021; it is likely that many of them quit using transit during the height of the pandemic and then never returned to the transit mode even after the threat of COVID subsided simply because the new modes that they adopted during the pandemic (automobile and telecommuting) provided greater levels of satisfaction than the transit mode. This implies a shift effect, with regular commuters depicting lower levels of transit use in late 2021 than in the pre-pandemic period as they abandoned transit during the pandemic and never returned. The model results in Table 2 suggest that the pattern of reduced transit use for commuting continued into 2023. The shift effect captures these types of transitions which are often characterized by hysteresis (where a system does not return to the original state even after the disruption is lifted).

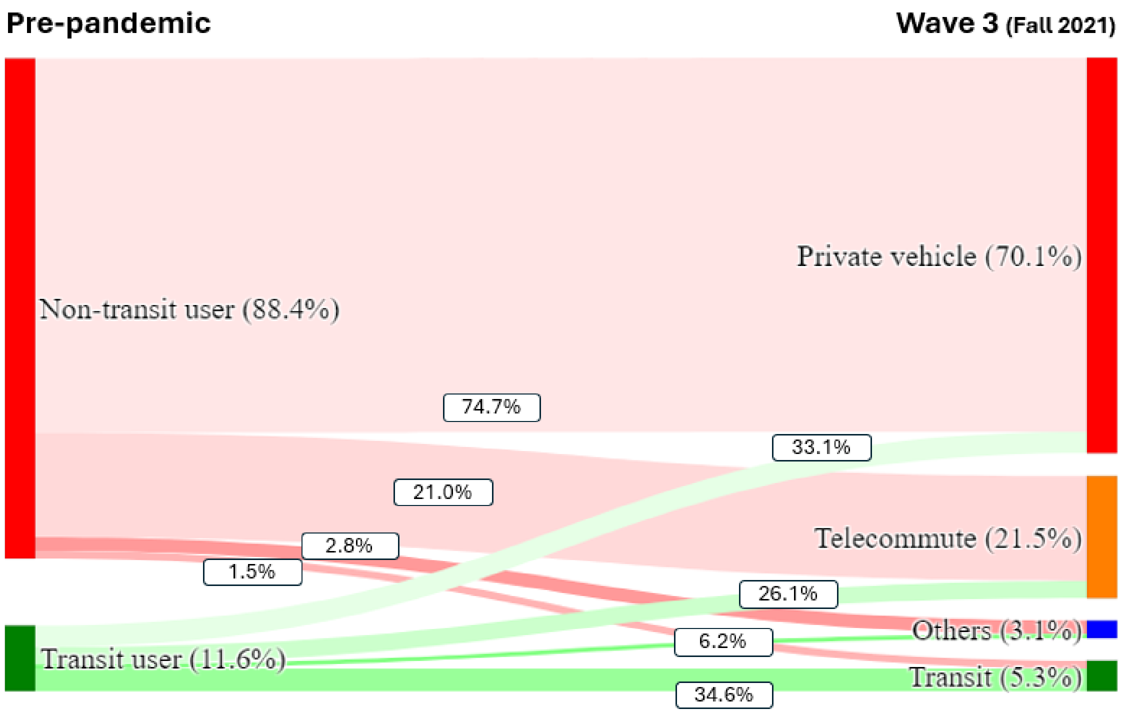

FIGURE 4 Transition in Commute Mode Between 2019 and 2021 for the Employed Stayer Sample of the COVID Future Panel Survey (N=1,156)

4.2. Computation of Average Treatment Effects

The coefficients in Table 2 indicate the impact of explanatory variables on the underlying propensities for telecommuting and transit frequency. However, the effects of the variables on the shares of different ordinal categories are not immediately apparent from the estimates alone. Endogenous outcome effects further amplify the model's complexity, where the total impact of an exogenous variable comprises both direct and indirect effects through other outcomes. Consequently, the interplay of these indirect influences, outcome correlations, and the ordered-response model structure introduces non-linearities, rendering it difficult to interpret the overall magnitude and direction of effects solely from the coefficient estimates in Table 2. To address these challenges, this section presents an Average Treatment Effect (ATE) analysis, which allows the quantification of the overall effects of variables on outcomes. Also, this analysis enables the estimation of behavioral outcomes for counterfactual scenarios, such as predicting the likelihood of different transit or telecommuting behaviors in the year 2023 for individuals who only participated in the 2019 survey, and vice versa. The ATE analysis begins by computing, for each individual, the multivariate probability predictions for all 144 possible outcome combinations across the four outcome dimensions ($4 \times 4 \times 3 \times 3 = 144$), including counterfactual scenarios. However, since the ordinal levels cannot be directly converted to frequency counts, specific ordinal categories are considered. In particular, the share of regular and frequent categories for telecommuting frequency and the share of occasional and regular categories for transit frequency are considered. Then, ATEs are computed as the change in the share of these categories due to a shift in an antecedent variable from a base level (BL) to a treatment level (TL). This process involves assigning all individuals to the baseline condition, calculating multivariate probabilities, and deriving population-level outcome proportions. The same procedure is then repeated for the treatment condition. The percentage difference in outcomes between these two scenarios represents the ATE, providing the magnitude and direction of the exogenous variable's impact on the outcome variables (*13*).

The results of the ATE analysis are presented in Table 3. For ease of presentation and interpretation, the two main outcome variables, telecommuting frequency and transit frequency, are transformed into binary variables for ATE estimation. For telecommuting frequency, the categories of regular and frequent telecommuting are combined to represent a consolidated telecommuter category and the categories of occasional telecommuter and non-telecommuter are combined to form an aggregate non-telecommuter category. For transit frequency, the binary categories represent non-transit users and transit users (who use transit on an occasional or regular basis). The table presents percent average treatment effects (PATEs) to provide a more standardized approach to interpreting ATEs. The numbers may be interpreted as follows. In 2019, the effect of individuals moving from occasionally and regularly telecommuting (base) to never telecommuting (treatment) is estimated to be a 21 percent decrease in transit use. This means that, if 100 individuals who occasionally or regularly telecommuted switched to never telecommuting, the sample would see 21 fewer instances of transit use, suggesting that switching from a hybrid mode of work to a full workplace presence (non-telecommuter status) contributes to a reduced level of transit use. The effect of transitioning from a base level of occasional or regular telecommuting frequency to frequent telecommuting has the effect of reducing incidences of transit use by six percent. In other words, the effect of transitioning to a more intense state of telecommuting has a smaller detrimental impact on transit use than the effect of transitioning to a non-telecommuter state. This result is consistent with the sideways U-shaped pattern of the relationship between telecommuting frequency and transit use frequency depicted in Figures 1 and 2. In the post-pandemic year of 2023, the treatment effects are even more pronounced. The transition to a non-telecommuting status is associated with a 35 percent drop in transit use, and the transition to frequent telecommuting status is associated with a nine percent drop in transit use. In other words, the sideways U-shaped relationship became more pronounced in 2023 when compared with 2019. The rest of the ATEs may be interpreted similarly and are found to be behaviorally intuitive; in the interest of brevity, they are not described in detail.

TABLE 3 Average Treatment Effects for Transit and Telecommuting Frequency Outcomes

Variable	Base Level	Treatment	PATE (%)			
			2019		2023	
			Transit (user)	Telecommute (regular or frequent)	Transit (user)	Telecommute (regular or frequent)
Endogenous Effect						
Telecommute frequency	Occasional and regular	Never	-21.0	---	-35.0	---
		Frequent	-6.0	---	-9.0	---
Exogenous Effect						
Age	Not 25-34 and 55-64 years	25-34 years	4.6	0.0	5.6	0.0
		55-64 years	0.7	-23.7	-0.1	4.4
Education	No college degree	Bachelor's and higher	27.3	57.7	31.6	79.9
Race	Neither Asian nor Black	Black	-15.0	0.0	-18.0	0.0
		Asian	-0.7	26.5	0.0	12.4
Household income	Less than $50k	$100k or more	-28.7	52.1	-41.2	130.5
Household size	Two	One	10.3	35.4	12.5	16.3
		Three or more	0.0	0.0	-15.7	0.0
Household child status	No	Yes	-23.3	0.0	-28.2	0.0
Vehicle deficiency	No	Yes	33.4	13.0	42.5	6.4
Vehicle ownership	With any vehicles	0 vehicle	34.4	0.0	46.7	0.0
Student status	Part-time and not student	Full-time	18.8	0.0	24.3	0.0
Employee transit benefit	No	Yes	10.5	0.0	13.2	0.0
City of Seattle	No	Yes	33.0	0.0	42.5	0.0
County	Neither King nor Pierce	King County	12.0	36.4	14.4	17.3
		Pierce County	-22.1	0.0	-25.8	0.0

Note: (---) not applicable

5. DISCUSSION AND CONCLUSIONS

This paper addresses the relationship between the frequency of telecommuting and the frequency of transit use. In a post-pandemic era, where telecommuting rates are substantially higher than in the pre-pandemic era and transit ridership numbers are substantially lower than in the pre-pandemic era, there is considerable attention being paid to the relationship between these two behavioral phenomena (*14, 15*). If workers stay at home and do not commute to the workplace, then it naturally follows that they do not ride transit – thus contributing to lower transit ridership. As a result, there has been a push to get workers to return to the workplace to help recover transit ridership. Despite the attention being paid to these two phenomena, there is scant research dedicated to understanding and quantifying the nature of their relationship. Using data from the 2019 and 2023 instances of the Puget Sound region travel survey program, this study aims to unravel the relationship between these two behavioral choices while explicitly accounting for the possibility that the nature of the relationship may have changed in the post-pandemic era. A joint model of telecommuting and transit use frequency that explicitly accounts for the possible presence of year-specific shift effects is estimated, thus capturing the differential nature of the influence of a variable on an outcome of interest in one year versus the other.

The first key finding in this study is that the percent of regular transit users is lower in 2023 for *all* telecommuting groups. This decrease in the numbers of regular transit users has clearly contributed to the decrease in transit ridership seen around the country. The second key finding is that there is a non-linear relationship between telecommuting frequency and transit use frequency. Transit use frequency does not simply increase with a decrease in telecommuting frequency. Rather, transit use frequency is found to be higher for those who adopt a hybrid work modality (occasional or regular telecommuting) than for those who telecommute frequently or do not telecommute. There is essentially a sideways U-shaped relationship between telecommuting frequency and transit frequency with lower transit frequency associated with high and low telecommuting levels, and higher transit frequency associated with medium levels of telecommuting. In addition, this U-shaped relationship became more pronounced in 2023 with a clear shift effect seen for those who are non-telecommuters. That is, non-telecommuters depicted an even lower propensity to use transit regularly in 2023 than they did in 2019.

What is happening in 2023 may essentially be described as follows. First, there are far more frequent telecommuters than in 2019, which has clearly contributed to a downturn in transit ridership. There are also more hybrid telecommuters in 2023 when compared to 2019; these individuals depict higher levels of transit use than other groups, but even their usage of transit dropped relative to levels seen in 2019. Also, hybrid telecommuters outnumbered frequent telecommuters in 2019, but this has now reversed with the number of frequent telecommuters greater than the number of hybrid telecommuters in 2023 (although this pattern may be specific to the Greater Seattle context). This further contributes to a decrease in transit ridership. Finally, in both 2019 and 2023, non-telecommuters depict lower levels of transit use compared to hybrid telecommuters (thus contributing to the U-shaped relationship). However, the shift effect in 2023 for this group means that they are more likely to shun transit in 2023 than they did in 2019. A further dive into this finding shows that, during the pandemic, regular transit commuters of the pre-pandemic era shifted in large numbers to automobiles for commuting (along with the adoption of telecommuting), possibly due to fear of contagion and reductions in transit service. Even as the pandemic lifted, they have not returned to transit, continuing to use the automobile mode (or telecommute) for work. Regular commuters, likely tied to a fixed work schedule, may have found the shift to the automobile more convenient and are therefore not returning to transit (*16*). This suggests that compelling workers to return to the workplace on a full-time basis may not necessarily help the cause of transit as much as might be expected, while exacerbating all of the congestion-related ill-effects of automobile travel. On the other hand, hybrid work modalities (1-3 days of telecommuting per week) may actually help enhance transit use as these workers probably enjoy some flexibility in their work schedules and are more willing to use transit for their commute as they go into the workplace only a few days per week.

In summary, study findings suggest that the loss of ridership due to telecommuting is likely to persist, and that compelling workers to return to the workplace on a full-time basis is unlikely to yield dividends. Embracing a hybrid work modality with employer-provided incentives to promote transit use may yield greater benefits than an attempt to push a complete return to the workplace (*17*). In fact, non-telecommuters represent the largest percent of non-transit users, further reinforcing that a full return to work does not necessarily work in transit's favor. In examining transit use trends, it appears that the current normal for transit is one of depressed ridership compared to pre-pandemic times, especially if transit agencies continue to rely on commuters for ridership. Given this reality, it would behoove transit agencies to begin reimagining their service to cater to non-work travel. In addition, transit agencies can offer specialized services for special/major events and large trip attractors, university campuses, and entertainment districts to foster a sense of community and increase ridership further (*18*). Designing and configuring transit services virtually entirely around commuting patterns (as has often been done in the past) would appear to be an exercise in futility in the new post-pandemic era.

ACKNOWLEDGMENTS

This research was partially supported by the Center for Understanding Future Travel Behavior and Demand (TBD), a National University Transportation Center sponsored by the U.S. Department of Transportation under grants 69A3552344815 and 69A3552348320, as well as 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.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: F. Yu, I. Batur, R.M. Pendyala, C.R. Bhat; data collection: F. Yu, I. Batur, R.M. Pendyala, C.R. Bhat; analysis and interpretation of results: F. Yu, I. Batur, A. Haddad, R.M. Pendyala, C.R. Bhat; draft manuscript preparation: F. Yu, I. Batur, A. Haddad, E.M Hennessy, M.G. Rodriguez Ocana, C. Chen, X. Zhou, R.M. Pendyala, C.R. Bhat; All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Boisjoly, G., E. Grisé, M. Maguire, M.P. Veillette, R. Deboosere, E. Berrebi, and A. El-Geneidy. Invest in the Ride: A 14 Year Longitudinal Analysis of the Determinants of Public Transport Ridership in 25 North American Cities. *Transportation Research Part A*, 2018. 116:434-445.
2. Carvalho, T., and A. El-Geneidy. Everything Has Changed: The Impacts of the COVID-19 Pandemic on the Transit Market in Montréal, Canada. *Transportation*, 2024.
3. Shamshiripour, A., E. Rahimi, R. Shabanpour, and A.K. Mohammadian. How Is COVID-19 Reshaping Activity-Travel Behavior? Evidence from a Comprehensive Survey in Chicago. *Transportation Research Interdisciplinary Perspectives*, 2020. 7:100216.

4. Batur, I., A.L. Bhat, R. Varghese, C.R. Bhat, P.L. Mokhtarian, S.E. Polzin, C. Chen, and R.M. Pendyala. *The Time Use, Travel, and Telework Dashboard (T3D)*. Accessed August 1, 2024, https://tomnetutc. github.io/t3d/
5. APTA (American Public Transportation Association). *A Profile of Public Transportation Passenger Demographics and Travel Characteristics Reported in On-Board Surveys*. Washington, DC, 2007.
6. PSRC (Puget Sound Regional Council). *2023 Puget Sound Regional Travel Study: Final Report*, 2024.
7. Bricka, S., T. Reuscher, P. Schroeder, M. Fisher, J. Beard, and L. Sun. *Summary of Travel Trends: 2022 National Household Travel Survey*. Publication FHWA-HPL-24-009. FHWA, U.S. Department of Transportation, 2024.
8. Bhat, C.R. New Matrix-Based Methods for the Analytic Evaluation of the Multivariate Cumulative Normal Distribution Function. *Transportation Research Part B*, 2018. 109:238-256.
9. Victoriano-Habit, R., and A. El-Geneidy. Why Are People Leaving Public Transport? A Panel Study of Changes in Transit-Use Patterns Between 2019, 2021, and 2022 in Montréal, Canada. *Journal of Public Transportation*, 2024. 26:100087.
10. Tahlyan, D., M. Said, H. Mahmassani, A. Stathopoulos, J. Walker, and S. Shaheen. For Whom Did Telework Not Work During the Pandemic? Understanding the Factors Impacting Telework Satisfaction in the US Using a Multiple Indicator Multiple Cause (MIMIC) Model. *Transportation Research Part A*, 2022. 155:387-402.
11. Berrebi, S. J., and K.E. Watkins. Who's Ditching the Bus? *Transportation Research Part A*, 2020. 136:21-34.
12. Chauhan, R.S., M.W. Bhagat-Conway, D. Capasso da Silva, D. Salon, A. Shamshiripour, E. Rahimi, S. Khoeini, A.K. Mohammadian, S. Derrible, and R.M. Pendyala. A Database of Travel-Related Behaviors and Attitudes Before, During, and After COVID-19 in The United States. *Scientific Data*, 2021. 8:1-7.
13. Haddad, A.J., A. Mondal, and C.R. Bhat. Eat-In or Eat-Out? A Joint Model to Analyze the New Landscape of Dinner Meal Preferences. *Transportation Research Part C*, 2023. 147:104016.
14. Smith, B.V., D. Robbennolt, and C.R. Bhat. *An Evaluation of the Long-Term Effects of the COVID-19 Pandemic on Public Transit Use*. Technical Paper, The University of Texas at Austin, 2024.
15. Mashrur, S.M., K. Wang, and K.N. Habib. Will COVID-19 Be the End for the Public Transit? Investigating the Impacts of Public Health Crisis on Transit Mode Choice. *Transportation Research Part A,* 2022. 164:352-378.
16. Magassy, T.B., I. Batur, A. Mondal, K.E. Asmussen, S. Khoeini, R.M. Pendyala, and C.R. Bhat. Influence of Mode Use on Level of Satisfaction with Daily Travel Routine: A Focus on Automobile Driving in the United States. *Transportation Research Record*, 2022. 2676(10):1-15.
17. Zhang, S., R. Moeckel, A.T. Moreno, B. Shuai, and J. Gao. A Work-Life Conflict Perspective on Telework. *Transportation Research Part A*, 2020. 141: 51-68.
18. Malokin, A., G. Circella, and P.L. Mokhtarian. How Do Activities Conducted While Commuting Influence Mode Choice? Using Revealed Preference Models to Inform Public Transportation Advantage and Autonomous Vehicle Scenarios. *Transportation Research Part A*, 2019. 124: 82-114.