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Final Project Report

**An Evaluation of the Long-Term Effects of
the COVID-19 Pandemic on Public
Transportation Use**

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| 16. Abstract Public transit offers significant societal benefits, offering efficient accessibility for all and helping to reduce congestion and greenhouse gas emissions. However, the COVID-19 pandemic has altered many aspects of travel behavior and had particularly important implications for the future use of transit. Despite significant evidence of rebounds in ridership from pandemic lows, transit has not fully recovered. Various factors have contributed to this slow recovery, including continued fears of safety, service cuts, new travel habits, evolving work arrangements, and the growth of online activity participation. In this study, we examine changes in public transit use during the pandemic, as well as the potential transitory nature of these shifts. Using data from the 2022 National Household Travel Survey, we explore the permanence of pandemic-era changes to public transportation (PT) use behaviors in the United States, connecting future use intentions directly with the change in use during the pandemic. The results of this study point to significant changes of use through the pandemic and heterogeneity in the permanence of these impacts based on age, gender, race, ethnicity, income, and vehicle constraints. By identifying groups who have reduced their use of transit post-pandemic and state that this change is likely to be temporary, we identify individual groups who may be most receptive to PT service improvement interventions. More broadly, we formulate several specific policy recommendations intended to help revitalize transit services in the United States in the aftermath of the pandemic and discuss the implications of the pandemic for current and future public transportation policies. | | | |
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EXECUTIVE SUMMARY

Public transit offers significant societal benefits, offering efficient accessibility for all and helping to reduce congestion and greenhouse gas emissions. However, the COVID-19 pandemic has altered many aspects of travel behavior and had particularly important implications for the future use of transit. Despite significant evidence of rebounds in ridership from pandemic lows, transit has not fully recovered. Various factors have contributed to this slow recovery, including continued fears of safety, service cuts, new travel habits, evolving work arrangements, and the growth of online activity participation. In this study, we examine changes in public transit use during the pandemic, as well as the potential transitory nature of these shifts. Using data from the 2022 National Household Travel Survey, we explore the permanence of pandemic-era changes to public transportation (PT) use behaviors in the United States, connecting future use intentions directly with the change in use during the pandemic. The results of this study point to significant changes of use through the pandemic and heterogeneity in the permanence of these impacts based on age, gender, race, ethnicity, income, and vehicle constraints. By identifying groups who have reduced their use of transit post-pandemic and state that this change is likely to be temporary, we identify individual groups who may be most receptive to PT service improvement interventions. More broadly, we formulate several specific policy recommendations intended to help revitalize transit services in the United States in the aftermath of the pandemic and discuss the implications of the pandemic for current and future public transportation policies.

INTRODUCTION

Public transportation (PT) contributes to societal well-being in multiple ways, including (a) providing better access to out-of-home opportunities for all, and especially for those who do not have access to personal (motorized) vehicles or who have physical challenges that make travel difficult (thereby, promoting travel equity) and (b) contributing to a reduction in traffic congestion and carbon emissions (thus, improving mobility/environmental sustainability and enhancing public health). On the first issue of improved access, for example, Appleyard et. al. (2019) observed that *Coordinating* (high transit frequency and connectivity) areas, compared to *Emerging* (limited transit frequency and connectivity) areas, provided twice the access to livability opportunities (i.e. cultural arts, and entertainment institutions), and 19% more access to civic involvement opportunities (i.e. social, religious, political, and business organizations). On the second issue of traffic congestion and emissions reduction, in the U.S. at least, transit systems have been estimated to decrease congestion-related time and (un)productivity costs by billions of dollars and lower associated greenhouse gas emissions (Beaudoin et al., 2015; Harford, 2006).

While there is clear evidence of PT benefits, recent changes in travel behavior have resulted in major declines in transit ridership, to the point of even calling into question the future of this mode (Ziedan et al., 2023; Zipper, 2023). In particular, the COVID-19 pandemic raised health-related safety concerns associated with PT use (Sung et al., 2023; Transit App, 2024). Besides, the strict office and non-essential business closures in all but 11 states of the U.S. led to a decline in commuting, further adding to PT ridership declines (Bergquist et al., 2020). In turn, these ridership drops forced reductions in PT service provision that resulted in longer wait and transfer times, further reducing PT use, and then even further reducing service provision in a snowballing effect. While many individuals with personal (motorized) vehicle ownership have been able to adapt to these PT service cutbacks, it has affected the accessibility to out-of-home activities for individuals more reliant on transit services (He et al., 2022).

Given the general benefits of PT use, as well as the lifeline it offers for activity participation to relatively mobility-challenged population groups, many studies have been undertaken to assess the use and viability of future PT services (see Etukudoh et al., 2024; Hartman et al., 2024; Pollock et al., 2024). In this study, we contribute to this stream of research by examining the impacts of the pandemic on PT use behavior, as well as investigating the potential for a return to pre-pandemic PT use behaviors. In this context, and differently from other earlier studies that have examined PT use trends at an aggregate level (see Lin et al., 2024), we undertake an individual-level analysis employing the stated PT use change of individuals between the before-COVID and after-COVID periods (for ease in presentation, we will refer to the period after the onset of the pandemic as the after-COVID period). In addition, we consider stated intentions about the permanence (or not) of these pandemic-engendered changes in PT use, revealing the extent to which the PT use changes may be transient in nature. Specifically, while many individuals have made significant lifestyle changes during the pandemic that may have permanently impacted their PT use, others may be willing to return as fears of infection decline and individual-level transportation needs continue to evolve. To our knowledge, no other study has explored this potentially transient dimension of PT use change. Our analysis is based on data from the 2022 National Household Travel Survey. In this regard, while PT use changes in other countries are referenced in our literature overview to provide a comprehensive picture, the results from our analysis should be viewed in the strict context of the U.S.

The next section titled “Literature Overview and the Current Study” provides a broad overview of the current literature that addresses PT use trends using aggregate and individual-level

data, as well as PT perceptions, attitudes and stated future use intentions. The following section titled “Methodology and Sample Description” describes the data used for the study and the mathematical framework employed. The section titled “Model Results” presents the results of the estimated model while the following section titled “Implications” discusses the implications of these results in the context of transportation planning and potential efforts to revitalize PT ridership in the United States. Finally, the section titled “Conclusions” provides a summary of the important findings and identifies future research opportunities.

LITERATURE OVERVIEW AND THE CURRENT STUDY

Extensive literature has examined the impact of the COVID-19 pandemic on PT use. These studies may be broadly grouped under three categories: (1) aggregate data studies of ridership trends, (2) individual-level data studies of *current* PT attitudes and usage changes, and (3) individual-level stated *future* PT use assessments based on intention/perceptions.

Aggregate Data Studies of Ridership Trends

Aggregate data on PT ridership has revealed substantial declines in transit use during the pandemic and a projected slow recovery, even as many other public services have returned to pre-COVID service levels (Zhang et al., 2021). National trends in the United States in 2022 showed that transit had only rebounded to about 70% of the 2019 ridership levels, revealing the continued impacts of the pandemic (Doyle, 2022). More recently, the Transit App included a comparison of ridership between February of 2020 (188.2 m) and February of 2024 (148.6 m), showing current PT ridership to be still down by a significant (though much more moderate) 21%, four years after the pandemic (Transit App, 2024). Beyond these overall trends, comparisons of the extent of changes in PT use across geographic regions have begun to reveal heterogeneity in the effects of the pandemic, based on the extent of COVID infections in the region and regional perceptions of the effectiveness of COVID vaccinations (Lin et al., 2024; Siewwuttanagul and Jittrapirom, 2023). However, both of these issues have become less important as fears of infection have, for the most part, subsided.

Other PT ridership trend studies have examined sociodemographic effects using aggregate data. These studies indicate that ridership reduction is highest in areas with high average incomes, high employment rates, and high levels of formal educational attainment, while ridership reduction is lowest in areas with a high percentage of low-income and Hispanic population groups (Jiao et al., 2023; Qi et al., 2023; Wilbur et al., 2023). Other studies have shown that areas with high concentrations of physical retail stores and fewer residential essential workers have experienced higher ridership declines (Hu and Chen, 2021).

Individual Level Data Studies of *Current* PT Attitudes and Use Change Trends

As with aggregate data, most of the studies based on individual-level data also have focused on overall trends in PT attitudes/use through descriptive analyses, rather than examining heterogeneity across individuals per se. For example, de Haas et al. (2020) and Li et al. (2021) observed that, following the onset of the pandemic, the decline in PT ridership has coincided with an increasingly positive attitude toward private vehicle use compared with any form of shared mode. Similarly, Hamad et. al. (2024) indicate that increased fears of health safety and comfort on public transportation has led to a shift away from non-private travel modes (including PT) and a concomitant growth in private car usage. The decline in PT use has also been tied to changes in commuting behavior since the pandemic, as individuals working remotely on one or more days no longer have to commute on those days (Anable et al., 2022). In fact, about half of the reduction in PT use has been attributed to an increase in telework share (Kiko et al., 2024; Salon et al., 2021). At the same time, some studies (Anwar et al., 2023; Cusack, 2021; Gupta and Mukherjee, 2022) suggest that individuals with pro-sustainable and pro-environmental self-identities, who also were better able to adapt to remote activities and pandemic lockdown restrictions, have been further drawn toward sustainable consumption behaviors, including holding a more positive view of public transportation than before the pandemic. While these changing positive views have not yet necessarily translated to increased PT use, in part due to lingering pandemic-induced lifestyle

changes favoring personal vehicle use, they do bring some optimism for the cause of increasing PT ridership.

Only one study that we are aware of has focused on heterogeneity across individuals in the effects of the pandemic on PT use. He et. al (2022) examined the pandemic impact on relatively mobility-constrained individuals, showing that transit riders who do not have access to a vehicle and are below twice the poverty threshold (based on annual household income) were less likely to reduce their post-COVID PT use. In contrast, those whose incomes were adversely affected by the pandemic were more likely to reduce their PT use, citing the expense of transit as an important reason. Similarly, women and Hispanic non-white riders were less likely to use public transportation post-COVID, with the latter group of individuals often citing fear of isolation and vulnerability in interactions with police as reasons for their reduced transit use.

Individual-Level Stated *Future* PT Use Assessments based on Intention/Perceptions

While there has been research to uncover the immediate consequences of the pandemic, as just discussed, there are still lingering questions regarding the pandemic's enduring effects on PT use. Some studies elicit information about future PT use through stated intentions/perceptions. For example, Zhao and Gao (2022) examined post-pandemic PT use intentions using the Theory of Planned Behavior, revealing that future public transportation use intentions are impacted by an individual's perceived knowledge and psychological risk of the pandemic, as well as their pre-pandemic public transit travel habits. In addition to COVID risk perceptions and pre-pandemic PT use, Downey et. al. (2022) examined the effects of other demographic/employment factors and the media platform through which individuals obtained data about the pandemic. They observed that, while unemployed individuals, in general, expressed less of an intent for future PT use relative to employed individuals, those unemployed because of long-term illness or disabilities expressed the highest future public transportation use intention. Downey et al. (2022) attributed this to the possibility that health-affected individuals may perceive fewer viable post-pandemic private mobility options. Further, they observed that those who used digital news platforms (such as websites or social media) rather than conventional news platforms (such as papers, TV, and radio) had lower future public transportation use intentions, ascribing this to the more rapid spread of pandemic-related information through these digital sources and highlighting the potential of targeted publicity campaigns. Unlike Zhao and Gao (2022) and Downey et al. (2022) who used intention data, Bandyopadhyaya and Bandyopadhyaya (2022) examined PT perceptions in a post-COVID world, showing that perceptions of transit travel comfort, convenience, and safety (especially in relation to social distancing) are important considerations. Finally, Tsavdari et al. (2022) is the only study we are aware of that examines future public transit use intentions based on PT use changes during the pandemic. They found that, compared to those who continued using PT (even if only occasionally), individuals who completely shifted away from PT after the onset of the pandemic were much less likely to express any intention of a future return to PT.

Study Contribution

This study contributes to the public transportation literature above in several ways. First, we go beyond a point-in-time view of public transportation use or a single future use intention. Specifically, we use a U.S. national sample of individual-level data to investigate both reported PT use change through the pandemic and the expected permanence (or not) of this change (the use change and the expected permanence constitute the two outcomes in our study). While many previous studies have used aggregate use change trends or stated perceptions/intentions of future

PT use, we identify those individuals who are most likely to return to their previous levels of public transportation ridership and identify strategies to encourage such a return. Second, we model the two outcomes of interest as a function of a comprehensive set of individual- and household-level characteristics to capture the heterogeneity in PT use intentions, which is important for developing effective future investment strategies to promote ridership and service equity. For instance, we investigate the differential impacts of the pandemic by race, gender, and income groupings. Such differential impacts of the pandemic have been shown in some earlier studies (see, for example, Giuliano, 2005; Paulley et al., 2006; Zhao and Gao, 2022), but we probe further into the permanency or transitory nature of such impacts. Finally, we use a joint model to account for unobserved correlation effects between the two outcomes, accounting for potential unobserved factors that could influence PT use changes during the pandemic and the stated permanence of the changes. For instance, an individual with an elevated health safety sensitivity (an unobserved variable) might be more inclined to both reduce their PT use after the pandemic and perceive those changes as permanent. Such common unobserved effects influencing both outcomes result in a sample selection problem. That is, if we model the two outcomes independently, the effects estimated for the permanency of a PT use change cannot be extrapolated to a random individual in the population (who may not be health safety sensitive) but changes PT use for other reasons. However, by estimating the two dimensions jointly, the resulting estimates for the permanency/non-permanency effect applies to any individual in the population. This allows for policies that can be designed to “move the needle” toward a temporary change for any individual in the population who might change PT use, as discussed in the implications section.

METHODOLOGY AND SAMPLE DESCRIPTION

Data Description

The primary data source for this study is the 2022-2023 NextGen U.S. National Household Travel Survey (NHTS), administered by the US Department of Transportation. The NHTS was conducted during the period from January 2022 to January 2023, based on an address-based sampling framework provided by Marketing Systems Group. Notably, this survey included questions focused on assessing the short and long-term impacts of the COVID-19 pandemic on individual PT use (Federal Highway Administration, 2023). The NHTS collected data from a total of 16,997 respondents across 7,893 households. Of the 16,997 respondents, 7,076 adults (all participants under the age of 18 were excluded) were included in the sample. These individuals had (a) some experience with using PT before COVID, (b) provided their change (or not) in PT use and their view of the permanence of any change, and (c) responded to all the demographic details sought in the survey.

Endogenous Outcomes

As already indicated, there are two endogenous outcomes in this study. First, respondents were asked about their change in PT use since the onset of the pandemic. Respondents could indicate that they increased PT use (“Do more often than before”), maintained pre-pandemic use levels (“Do the same as before”), or decreased PT use (“Do less often than before”). Second, the survey asked respondents who used PT either more or less than they had before the pandemic whether they thought this change was permanent or temporary.

Descriptive statistics for these outcome variables are shown in Table 1, providing aggregate information about short-term adjustments in public transit use and potential long-term implications for PT use. In this data sample, only a small portion (4.63%) of responders indicated an increase in usage compared to before the pandemic, an unsurprising result given the challenges in PT use in the immediate aftermath of the onset of the pandemic. In addition, more than half of all respondents reported using public transit the same as before the pandemic. These respondents may represent individuals who had fewer safety concerns during the pandemic or may be “captive” riders who are unable to afford private vehicles or have other significant mobility constraints preventing private vehicle use. Finally, 42.20% of the total sample indicated they had reduced PT use. Regarding the permanence of change, a majority of riders indicated that the change was permanent rather than temporary (73.48% for those who said they ride more often, and 62.46% of those who ride less often). At an aggregate level, these statistics suggest that there have been significant declines in PT usage, which may also be permanent for many individuals. However, there is a significant percentage of individuals who appear to leave the possibility open to returning to a higher level of PT use. These expectations are not only influenced by individuals’ anticipated lifestyle changes, but also to their predictions on how PT transit service provisions will evolve in the post-pandemic era. Thus, some individuals who suspended their use of PT during the pandemic due to service cuts may indicate this shift as permanent if they believe services will not be fully restored. Others may expect the services to return but do not anticipate resuming their own use of these services, based on altered routines or preferences.

Table 1: Descriptive Statistics of Outcome Variables

| | Total (%) | Temporary | Permanent |
|--|------------------|------------------|------------------|
| Use public transit more often than before COVID | 328 4.63% | 87 26.52% | 241 73.48% |
| Use public transit the same as before COVID | 3,762 53.17% | -- | -- |
| Use public transit less often than before COVID | 2,986 42.20% | 1121 37.54% | 1865 62.46% |

Exogenous Variables

The descriptive statistics of the exogenous variables are included in Table 2. This table includes the household/individual-level demographics of the sample, as well as corresponding statistics from the 2020 National Census Data (“U.S. Census Bureau,” 2022). Our sample statistics are not comparable to those from the 2020 Census data, because our sample is restricted to individuals who used PT before the pandemic. Nonetheless, we report the 2020 Census data statistics to provide a sense of the composition of our sample relative to the entire U.S. population. Table 2 shows that our sample is relatively evenly distributed between responders identifying as female and male, as is also the case with the Census Data. However, our sample is more loaded toward older, more educated, less ethnically and racially diverse, and unemployed individuals from two-member and two-adult, high income households with more vehicles than drivers. This reflects representation in the overall NHTS sample in addition to the removal of respondents with no PT use before the pandemic. While our sample characteristics may not seem consistent with the population subgroup of the U.S. who may have had some PT experience before the pandemic, the presence of a high share of unemployed individuals in our sample (relative to the census data) appears to more than make up for the high share of more educated, white, and high income households in the sample. In any case, the sample includes sufficient variability within each demographic category to provide accurate and precise estimation results regarding changes in PT usage dynamics in the population segment of existing PT users.

Table 2: Sample Distribution of Exogenous Variables

| Variable | NHTS Dataset | | Census Data | Variable | NHTS Dataset | | Census Data |
|---|--------------|-------|-------------|---|--------------|-------|-------------|
| | Count | % | % | | Count | % | % |
| <u>Individual-Level Demographics</u> | | | | <u>Household-Level Demographics</u> | | | |
| Gender | | | | Household Size | | | |
| Female | 3,642 | 51.47 | 50.92 | 1 | 1,226 | 17.33 | 20.17 |
| Male | 3,434 | 48.53 | 49.08 | 2 | 3,278 | 46.33 | 24.02 |
| Age | | | | 3+ | 2,572 | 36.35 | 55.81 |
| 18-24 | 447 | 6.32 | 12.00 | Number of Adults | | | |
| 25-34 | 1,067 | 15.08 | 17.37 | 1 | 1,337 | 18.89 | 28.88 |
| 35-44 | 1,059 | 14.97 | 16.35 | 2 | 4,378 | 61.87 | 34.72 |
| 45-54 | 991 | 14.01 | 15.84 | 3+ | 1,361 | 19.23 | 36.40 |
| 55-64 | 1,271 | 17.96 | 16.82 | Presence of Children (no children) | | | |
| 65+ | 2,241 | 31.67 | 21.62 | Children | 1,586 | 22.41 | 30.39 |
| Education Level | | | | No children | 5,490 | 77.59 | 69.61 |
| High School diploma or less | 1,148 | 16.22 | 48.23 | Number of Workers | | | |
| Some college or associates | 1,830 | 25.86 | 27.37 | 0 | 2,408 | 34.03 | 26.63 |
| Bachelor's degree | 2,238 | 31.63 | 15.54 | 1 | 2,138 | 30.21 | 37.30 |
| Graduate degree | 1,860 | 26.29 | 8.86 | 2+ | 2,530 | 35.75 | 36.07 |
| Ethnicity | | | | Resident Location | | | |
| Hispanic | 582 | 8.22 | 18.73 | Urban | 6,810 | 83.13 | 79.60 |
| Non-Hispanic | 6,494 | 91.78 | 81.27 | Rural | 1,382 | 16.87 | 20.40 |
| Race | | | | Household Number of Vehicles and Drivers | | | |
| White | 6,065 | 85.71 | 61.63 | Vehicles ≥ Drivers | 5,893 | 83.28 | 56.61 |
| Black or African American | 465 | 6.57 | 12.40 | Vehicles < Drivers | 1,183 | 16.72 | 43.39 |
| Asian | 466 | 6.59 | 6.00 | Household Income (thousands) | | | |
| Other | 80 | 1.13 | 19.97 | <\$50,000 | 1,785 | 25.23 | 48.00 |
| Worker | | | | \$50,000-\$74,999 | 1,039 | 14.68 | 14.67 |
| Yes | 3,504 | 49.52 | 73.37 | \$75,000-\$99,999 | 1,004 | 14.19 | 10.89 |
| No | 3,572 | 50.48 | 26.63 | \$100,000-\$149,999 | 1,478 | 20.89 | 13.34 |
| Driver | | | | ≥\$150,000 | 1,770 | 25.01 | 13.11 |
| Yes | 6,406 | 90.53 | | | | | |
| No | 670 | 9.47 | | | | | |

The Model

The model entails the joint analysis of a nominal outcome (for PT use change) and a binary outcome (for the permanency of the change). Let q be the index for each individual. Let J be the number of nominal alternatives available (in this case $J = 3$) and let j be the corresponding index ($j = 1, 2, \dots, J$). Then, the following expression gives the utility for alternative j (for convenience, we suppress the index q for the individual):

$$U_j = \boldsymbol{\gamma}' \mathbf{x}_j + \xi_j \quad (1)$$

where \mathbf{x}_j is an $(A \times 1)$ column vector of individual-specific exogenous attributes, including $(J - 1)$ alternative specific constants for each outcome. Since no exogenous variables appearing in the nominal outcome model vary across alternatives, all elements of \mathbf{x}_j will be uniformly zero for a base alternative (in our analysis, we use PT use being the same as before the pandemic as the base alternative). $\boldsymbol{\gamma}$ is an $(A \times 1)$ column vector of coefficients corresponding to \mathbf{x}_j . We also assume that ξ_j is independent and identically distributed across individuals but allow a general covariance structure across alternatives for each individual. Specifically, let $\boldsymbol{\xi}$ be the $(J \times 1)$ vector $\boldsymbol{\xi} = (\xi_1, \xi_2, \dots, \xi_J)'$. Then, we assume $\boldsymbol{\xi} \sim MVN_J(0, \boldsymbol{\Lambda})$. Then, appropriate scale and level normalization must be imposed on $\boldsymbol{\Lambda}$ for identification. Since only utility differentials matter at each choice occasion, only the elements of the $((J - 1) \times (J - 1))$ covariance matrix $\tilde{\boldsymbol{\Lambda}}$ of the error differentials $\tilde{\xi}_j = \xi_j - \xi_1$ ($j \neq 1$) are estimable (with utility differentials taken with respect to the first alternative). Additionally, to account for scale invariance, the first diagonal element of $\tilde{\boldsymbol{\Lambda}}$ is set to 1. In our empirical analysis with $J=3$, $\tilde{\boldsymbol{\Lambda}}$ takes the following form:

$$\tilde{\boldsymbol{\Lambda}} = \begin{bmatrix} 1 & \lambda_{23} \\ \lambda_{23} & \lambda_3 \end{bmatrix}. \quad (2)$$

Next, consider the binary outcome representing the permanence of the change in public transit usage. Define a latent propensity y^* underlying this binary outcome. The latent propensity takes the following structure:

$$y^* = \boldsymbol{\beta}' \mathbf{z} + \varepsilon, \quad (3)$$

where $y = 1$ if $y^* > 0$ and $y = 0$ otherwise. In this case, \mathbf{z} is an $(L \times 1)$ vector of exogenous variables (including a constant), $\boldsymbol{\beta}$ is a corresponding $(L \times 1)$ vector of coefficients to be estimated, and ε is a random error term assumed to be standard normally distributed (the scale of y^* is not identified and so we arbitrarily, and without any loss of generality, set the variance of ε to one).

We now define the $(J \times A)$ matrix $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_J)'$ and the $(J \times 1)$ vector $\mathbf{U} = (U_1, U_2, \dots, U_J)'$ for the nominal variable. Also, define the $((J + 1) \times 1)$ vector $\mathbf{B} = \begin{bmatrix} \boldsymbol{\gamma}' \mathbf{x} \\ \boldsymbol{\beta}' \mathbf{z} \end{bmatrix}$ and

the $(J \times J)$ matrix $\Sigma = \begin{bmatrix} \tilde{\Lambda} & \boldsymbol{\sigma} \\ \boldsymbol{\sigma}' & 1 \end{bmatrix}$. In this matrix, $\boldsymbol{\sigma}$ is a $((J-1) \times 1)$ vector that captures the covariance between the nominal outcome utilities (in utility differenced form, with the difference taken with respect to the first alternative) and the binary outcome. In our case with $J = 3$,

$$\boldsymbol{\sigma} = \begin{bmatrix} \sigma_{24} \\ \sigma_{34} \end{bmatrix}, \text{ and } \Sigma = \begin{bmatrix} \tilde{\Lambda} & \boldsymbol{\sigma} \\ \boldsymbol{\sigma}' & 1 \end{bmatrix} = \begin{bmatrix} 1 & \lambda_{23} & \sigma_{24} \\ \lambda_{23} & \lambda_3 & \sigma_{34} \\ \sigma_{24} & \sigma_{34} & 1 \end{bmatrix} \quad (4)$$

For ease of presentation, we will present the case of estimation of the model for an individual for whom all outcomes are relevant. That is, they are either using public transit more or less than they did before the pandemic (but not the same as they did before the pandemic), so that they have a response to the permanence of this change. For an individual whose PT use has not changed through the pandemic, the procedure described below needs only to be modified slightly to obtain appropriate matrices marginalized to include only the nominal outcome utilities. For these individuals, we need only consider the nominal outcome variable as defined by equation (1), rather than the full joint likelihood considered for those individuals with a full set of outcome variables.

The matrix $\tilde{\Lambda}$ was presented above with error differences taken with respect to the first alternative. However, we need the covariance matrix corresponding to the error term differences taken with respect to the chosen nominal alternative. To achieve this, for each individual, let the chosen alternative for the nominal outcome be m . To obtain this covariance matrix, first define a matrix \mathbf{D} of size $((J+1) \times J)$. This matrix is constructed by first taking an identity matrix of size $(J \times J)$ and then supplementing it with an additional zero row vector of length $(1 \times J)$ in the first row. Next, define a matrix \mathbf{M} of size $(J \times (J+1))$. Fill this matrix with values of zero. Then, in the last row and column, insert the value of 1. Next, consider the first two rows and first three columns. Insert an identity matrix of size $(J-1)$ after supplementing with a column of '-1' values in column m .

Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = \left(\boldsymbol{\gamma}', \boldsymbol{\beta}', [\text{Vechup}(\Sigma)]' \right)'$, where the operator $\text{Vechup}(\cdot)$ row-vectorizes the non-zero upper diagonal elements of a matrix. Next, define a set of lower thresholds $\tilde{\Psi}_{low} = [-\infty_{J-1}, 0]'$ and a set of upper thresholds $\tilde{\Psi}_{high} = [0_{J-1}, \infty]'$. Then, the likelihood function may be written as

$$L(\boldsymbol{\delta}) = \int_{D_r} \phi(\mathbf{r} | \mathbf{MB}, \mathbf{MD}\Sigma\mathbf{D}'\mathbf{M}') d\mathbf{r}, \quad (5)$$

where $\phi(\cdot)$ refers to the standard multivariate normal density function, and the integration domain $D_r = \{\mathbf{r} : \tilde{\Psi}_{low} \leq \mathbf{r} \leq \tilde{\Psi}_{high}\}$ is simply the multivariate region of integration determined by the utility differences taken with respect to the utility of the chosen alternative for the multinomial outcome and the observed binary outcome. The likelihood function for the entire 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 this five-dimensional integral, we use Bhat's (2018) matrix-based approximation methods for the multivariate normal cumulative distribution to evaluate this integral.

MODEL RESULTS

The model specification is presented in Table 3 for both the impact of the COVID-19 pandemic on transit usage and the expected permanence of this change. The final specification was based on an iterative process of including exogenous variables in the model in different functional forms and testing the statistical fit of various combinations of exogenous variables. Categorical exogenous variables were included as dummy variables in the most disaggregate form available and then combined into more aggregate categories based on statistical tests. Each “—” entry within the table indicates that the exogenous variable lacks a statistically significant impact on the outcome. Furthermore, a t-statistic threshold of 1.65 was also used to either eliminate or retain variables, corresponding to a two-tailed confidence level of 90%¹.

Empirical Results

The results presented in this section pertain to the effects of exogenous variables on the utility of different alternatives in the nominal outcome (with the “Use PT the same as before” alternative as the base category), and on the latent propensity that the PT use change identified in the nominal outcome is permanent (with the “temporary change” alternative as the base category). The covariance between the nominal alternative utilities and the binary response latent propensity are also discussed. Table 3 presents the results with the base categories not appearing (effectively, all the coefficients for the many exogenous variables are set to zero for the base categories, which is needed for identification).

Individual-Level Demographic Effects

Among the individual-level demographic effects, which we discuss first, the results in Table 3 indicate that women (compared to men) and older individuals (relative to younger individuals) exhibit larger declines in PT use after the onset of the pandemic. These larger declines associated with PT use may be associated with the generally elevated health consciousness (and, thus, higher anxiety about contracting COVID on transit vehicles) among women (Čvirik et al., 2023; Feraco et al., 2024; Maslakçı and Sürücü, 2024), and the higher actual risk of contracting COVID among older adults (Navarrete-Hernandez et al., 2023). In the case of gender, another contributing factor may be the higher remote work among women post-COVID (see, for example, Astorquiza-Bustos and Quintero-Peña, 2023; Marcén and Morales, 2024). These declines should be of concern for future PT use on both the gender and age fronts. On the gender front, women were generally more likely to be PT users before the pandemic, a result which has been attributed to women’s higher green lifestyle tendencies, lesser access to household personal vehicles and gendered household car use dynamics (see Bloodhart and Swim, 2020; El Khoury et al., 2023; Palm et al., 2021; Soria et al., 2023). On the age front, older adults (65+) are the fastest-growing age group in the U.S, and are projected to account for 20% of the population by 2050 (Etu et al., 2023). On the positive side, women and older individuals appear to be as open as their peers to return to PT (note that gender and age do not affect the reported permanency of change), suggesting that customized PT use

¹In addition to the variables in the final specification of Table 3, additional variables were tested in the model and found not to be statistically significant at the 90% confidence level (or even at much lower confidence levels in most cases). These included the level of educational attainment, individual employment status, and household location variables based on the U.S. Census Division classification. Additionally, endogenous effects among the outcomes were tested (after accounting for jointness due to error correlation effects), but no such endogenous effects turned out to be statistically significant.

promotion strategies directed toward women and older adults may attract back some of these individuals to public transportation (as discussed later).

Race and ethnicity also have a bearing on PT use change through the pandemic. Compared with non-Hispanic individuals, Hispanic respondents report a higher propensity to either take public transit less often than before the pandemic or more often, with a correspondingly lower propensity to maintain the same level of use. A similar trend is evident for Black and Asian respondents relative to their white peers. These results suggest that the pandemic caused a much larger disruption to the transportation habits of minority ethnic/racial groups. Also, important to note is that individuals belonging to all these minority groups are more likely to report a decline in PT use rather than an increase in PT use (note the higher magnitudes of the parameters on these variables in the “less often than before” column compared to the “more often than before” column). This net decline in PT use among minority groups post-COVID may be attributable to public transport service cuts after the onset of the pandemic, but also may be due to the perceived vulnerability among minority groups in interactions with police when in relatively less-crowded PT spaces during and after the pandemic (He et al., 2022). Again, though, these minority groups do not indicate that the decline in their PT use is any more permanent than their peers. In fact, Black individuals specifically indicate that their PT use changes are only temporary. Taken together, and as with gender and age, these results again suggest ample scope for reviving PT patronage among minority groups, especially given that a higher share of individuals in these groups generally do not have personal vehicles in their households.

Finally, individuals without a driver’s license have a higher tendency relative to their peers to increase their PT use, and these changes tend to be permanent. These individuals are likely to have used PT services through the pandemic and may have learned strategies to maintain their safety and security. Clearly, initiatives to provide good PT services to this group of riders can help reduce overall traffic congestion and carbon emissions, while also providing equitable transportation services.

Household Level Effects

Moving on to the household-level characteristics, the results in Table 3 reveal that individuals with more adults in the household and those in households from “ $\geq 75k$ ” annual income are unlikely to increase their PT use relative to their peers. This is to be expected, as individuals in large households must be more aware of infection concerns affecting the entire family, and individuals in higher income households may have elevated teleworking rates in the post-COVID period (see Iogansen et al., 2024). Individuals in the highest income bracket ($>150k$ annually) also state that their move away from PT use is permanent. On the other hand, individuals with children in the household are most likely to remain at their before-COVID state, using public transportation to the same extent as they did before the pandemic (notice the negative coefficients for the “less often than before” and “more often than before” alternatives in Table 3, relative to the base category of “same as before”). This last result may be explained by the relatively consistent transit dependency over time of individuals in households with children, due to the variety in travel needs of both children and parents, making travel mode changes less likely (Barthelmes et al., 2023).

Table 3 also indicates that those living in urban areas and in vehicle-constrained households (fewer vehicles than number of drivers) have increased PT use in the post-COVID period, with this change being more permanent for vehicle-constrained households. In regard to urban residency, service declines were much smaller in urban areas, where larger transit services were better able to accommodate ridership declines and were more likely to maintain services to support

essential workers. A greater pre-pandemic reliance on transit for some urban PT users also may have left some individuals located in urban areas with few other mobility alternatives, particularly at the onset of the pandemic (Molina et al., 2021; Speroni et al., 2023). Similarly, vehicle-constrained households may have been more likely to increase their ridership during the pandemic because their existing limited mobility gave them few alternatives to adapt to pandemic-era conditions and these households are most likely to be essential workers who had to maintain higher levels of travel throughout the pandemic (Harrington and Hadjiconstantinou, 2022; Tahlyan et al., 2022).

Covariance Terms

The covariance matrix terms for the multinomial outcome corresponding to the change in PT use were estimated based on the error differences from the baseline outcome of using public transit the same as before the pandemic. Due to the possibility of many non-differenced matrices yielding identical differenced matrices, the elements of the covariance matrix are not interpretable except if some untestable assumptions are placed. Specifically, we assume here that the error term for the “use public transit the same as before the pandemic” alternative (the base category for the nominal outcome) has small variance and is uncorrelated with the other error terms. With this assumption, the utility variance for the “use public transit more than before the pandemic” alternative is relatively large (λ_3 in Equation (4) = 5.087), indicating the presence of unobserved factors impacting this alternative to a greater extent than the other PT use change alternatives. This is intuitive, given the very small share of individuals reporting higher PT use in the after-COVID period relative to the before-COVID period). The covariance between the decreased public transit use and increased public transit use utilities turned out to be negative (λ_{23} in Equation (4) = -0.648), as would be expected. The covariance between “reduced PT use” utility and the “permanence” dimension is negative (σ_{24} in Equation (4) = -0.361), signifying the presence of common unobserved factors that make any PT use reductions in the after-COVID period stay rather temporary. This is in contrast to the positive covariance between “increased PT use” utility and the “permanence” dimension (σ_{34} in Equation (4) = 0.186), indicating the presence of intrinsic individual factors that make permanent any elevated use of PT in the after-COVID period.

Table 3: COVID-era Impacts on Public Transit Use

| Exogenous Variables (base category) | Use Less Often Than Before | | Use More Often Than Before | | Permanence of Change | |
|---|----------------------------|--------|----------------------------|--------|----------------------|--------|
| | Coeff. | T-Stat | Coeff. | T-Stat | Coeff. | T-Stat |
| <i>Individual-Level Demographics</i> | | | | | | |
| Gender (male) | | | | | | |
| Female | 0.339 | 1.883 | -- | -- | -- | -- |
| Age (18-34) | | | | | | |
| 35-64 | 0.550 | 2.108 | -- | -- | -- | -- |
| 65+ | 1.767 | 2.929 | -- | -- | -- | -- |
| Ethnicity (non-Hispanic) | | | | | | |
| Hispanic | 1.014 | 2.243 | 0.158 | 2.350 | -- | -- |
| Race (white) | | | | | | |
| Black or African American | 2.278 | 2.892 | 0.534 | 6.742 | -0.316 | -3.286 |
| Asian | 1.851 | 2.735 | 0.421 | 5.336 | -- | -- |
| Driver Status (driver) | | | | | | |
| Non-Driver | -- | -- | 0.264 | 4.050 | 0.214 | 2.705 |
| <i>Household-Level Demographics</i> | | | | | | |
| Number of Adults (1 adult) | | | | | | |
| 2 | -- | -- | -0.166 | -3.718 | -- | -- |
| 3+ | -- | -- | -0.224 | -4.006 | -- | -- |
| Household Income (<\$75,000) | | | | | | |
| \$75,000-\$99,000 | -- | -- | -0.234 | -3.986 | -- | -- |
| \$100,000-\$149,999 | -- | -- | -0.150 | -3.179 | -- | -- |
| ≥\$150,000 | -- | -- | -0.217 | -4.274 | 0.242 | 4.155 |
| Presence of Children (no children) | | | | | | |
| Children | -1.221 | -2.771 | -0.285 | -5.546 | -- | -- |
| Resident Location (rural) | | | | | | |
| Urban | -- | -- | 0.217 | 3.867 | -- | -- |
| Number of Vehicles < Drivers (no) | | | | | | |
| Yes | -- | -- | 0.307 | 5.173 | 0.125 | 2.015 |
| Constant | -2.062 | -3.271 | -1.062 | -5.064 | 0.165 | 1.144 |

Model Fit

We assessed the proposed joint model by comparing it to a model that maintains independence across the utility errors of the three PT use change alternatives, and also assumes that the covariances between the utility errors of the PT use change alternatives and the “permanency of change” outcome error are zero. At the disaggregate level, we evaluate these two models based on several likelihood-based metrics as well as the average probability of correct prediction, as shown in Table 4. On all these metrics, our model clearly outperforms the model that assumes independence. For further evaluation, we examine the aggregate data fit statistic results (see Table 5). To do so, we compare the predicted aggregate shares of individuals selecting each of the five

combinations of outcomes to the corresponding observed shares. An absolute percent error (APE) is computed for each of the five combinations, and a Weighted Absolute Percent Error (WAPE) is calculated based on the observed shares. The WAPE is smaller for the proposed joint model (9.1%) compared to the independent model (10.6%), indicating again that the proposed model outperforms the independent model. That is, there is a package nature to the responses of individuals to the PT use change category and the permanency of change.

Table 4: Disaggregate Model Fit

| Summary Statistics | Joint Model | Independent Model |
|---|--|-------------------|
| Log-likelihood at Convergence | -7388.55 | -7405.88 |
| Log-Likelihood at Constants | -7586.18 | -7586.18 |
| Number of Parameters | 30 | 26 |
| Adjusted Likelihood Ratio Index | 0.022 | 0.021 |
| BIC | 7446.294 | 7455.93 |
| Average Probability of Correct Prediction | 0.255 | 0.231 |
| Likelihood Ratio Test | 334.66 (>Chi-squared table value with 4 degrees of freedom at even the 99.999999% level) | |

Table 5: Aggregate Model Fit

| Change in Public Transit Use | Permanence of Change | Observed | | Proposed Model | | Independent Model | |
|--|----------------------|----------|-----------|----------------|---------|-------------------|---------|
| | | Number | Share (%) | Predicted (%) | APE (%) | Predicted (%) | APE (%) |
| More | Permanent | 241 | 3.4 | 2.9 | 15.0 | 2.4 | 30.6 |
| More | Temporary | 87 | 1.2 | 1.9 | 53.8 | 2.2 | 86.7 |
| Same | -- | 3,762 | 53.2 | 52.8 | 0.8 | 53.1 | 0.2 |
| Less | Permanent | 1,865 | 26.4 | 22.7 | 13.7 | 22.2 | 15.8 |
| Less | Temporary | 1,121 | 15.8 | 19.7 | 24.4 | 20.1 | 26.7 |
| Weighted Absolute Percent Error (%) | | | | 9.1 | | 10.6 | |

IMPLICATIONS

The results presented in the previous section provide the exogenous variable effects on the utilities of the alternatives characterizing PT use change and on the propensity of permanency of the use change. But they do not provide the magnitude of the effects of each of the exogenous variables on PT use change behavior and permanency. To do so, we compute the average treatment effects (ATEs) (Angrist and Imbens, 1991; Heckman and Vytlačil, 2000). Essentially, we set each exogenous variable to a base state for each individual (while keeping the values of all other variables to be the same for each individual). Next, we compute the probabilities of the five combinations of use change and permanency at the individual level and aggregate across individuals to get predicted shares of each combination. The above procedure is then repeated by changing the exogenous variable from the base state to a “treatment” state. This is then followed by the computation of the change from the base share (in percentage terms) to the treatment share (in percentage terms). Such ATEs can be computed for a change of an exogenous variable from any base state to any treatment state, though we will focus here on changes corresponding to only one selected pair when there are multiple states characterizing an exogenous variable. These ATE effects are presented in Table 6. For instance, consider the entry of “5.9” for the “use public transit less often” and “permanent” column for the age variable. This entry indicates that, in a group of 100 individuals aged 65 years or more, one can expect about six more individuals to use public transit less after the pandemic relative to in a group of 100 individuals who are younger than 35 years. Other ATEs may be similarly interpreted. Further, to calculate standard errors for the average treatment effects, we take bootstrap draws from the multivariate sampling distribution of the estimator for the model parameters and compute the ATE for each draw (using the same procedure described above). The standard errors presented in parentheses in Table 6 are the standard deviations of the ATE calculations across these bootstrap draws. As may be observed from Table 6, almost all the ATE effects are different from zero at the 90% confidence level or higher. The remainder of this section will discuss these ATEs selectively, focusing on implications for government policies, public transit services, and travel demand modeling.

Gender and PT Use

As shown in Table 6, women are more likely than men to have reduced their PT use through the pandemic, although this decline is fairly evenly split between those who say this change is temporary and those who say it is permanent. This result has important implications for public transit ridership as well as for more general trends in gendered mobility and lifestyle patterns, particularly so because women were more likely to be PT riders before the pandemic. While our study does not uncover the reasons for the decline among women in PT use, this may be tied to heightened health and safety concerns. While health-related anxiety concerns appear to have eased over time, safety concerns remain. Specifically, there has been evidence of an increase in violence and harassment on public transit during and after the worst of the pandemic, much of which is directed toward women (Federal Transit Administration, 2023; Ashour et al., 2024). This may be related, in part, to supply-side issues with public transit provision during the pandemic, which led to reduced service (leading to higher waiting times) and overcrowding (Qi et al., 2023). Thus, the intention to return to public transit after the pandemic for women may be closely tied to their expectations regarding future improvements in service quality and whether the public transit provision disruptions, experienced during the pandemic, are perceived as being permanent.

Policies and strategies that increase the personal safety and security for all PT riders, but women in particular, can help bring back women to the PT fold and even increase overall PT

ridership. Some of these actions may include (a) providing general bystander intervention training, and raising awareness about “street harassment” and its substantial societal costs, through public-facing information and education campaigns, (b) coaching public transit staff on how to address harassment “on the spot”, and (c) designing convenient online harassment reporting systems with a guarantee of prompt response and action, along with extending public support services to those who report. Further, increased policing has also been shown to be effective in making women feel safer on public transportation (Gardner et al., 2017). Several other recent studies (see, for example, Chavan et al., 2023; Kacharo et al., 2022; Suneel et al., 2024) have also recommended real-time passenger tracking (including smart ticketing systems and facial recognition technology) for overcrowding detection and occupancy limitations on city buses to allow only for seated passengers, especially during peak hours and late evenings (overcrowding is when sexual harassment is most likely to occur; see Kacharo et al., 2022). Additional improvements, such as improved lighting around bus stops can also help women (and all) riders feel safer (Greer Cowan, 2023). At the same time, it is important to consider how PT use changes have impacted gendered lifestyles and household dynamics. Women have generally had less access to household vehicles, and their mobility options may have gotten more limited post-pandemic because of reduced PT availability and use. Future studies should examine the extent to which PT use changes may have affected women’s participation in out-of-home activities and what these changes mean for gender equity in transportation provision.

Age and PT Use

The effect of age on PT use in Table 6 also indicates a strong decline in public transit use for those over the age of 65. The increased contact with strangers and more confined spaces within PT vehicles present health-related concerns to older individuals, many of whom resorted to an increased reliance on family members for transport during the pandemic (Sureshbabu et al., 2022). While this result has important implications for transit agencies in terms of ridership levels and fare-box revenues, the declining ridership of older individuals can have much broader deleterious effects from a quality-of-life standpoint. In particular, research suggests that PT use provides important cognitive, physical, and social benefits to older individuals, through the acts of memorizing routes and schedules, walking to and from stations, and interaction with other riders, all of which help to maintain good physical and cognitive abilities for many older adults (Etu et al., 2023). Thus, even beyond the immediate issue of PT revenues, it is important to address older adult concerns and ensure that PT continues to be an inclusive mode available for all. In this context, a critical concern for older adults relates to fear of contagion in crowded spaces. There is a need, without underplaying the health concerns of older adults, to provide objective information directed toward older adults on contagion risk, which has been established to be not very different on public vehicles/facilities compared to everyday interactions at offices and other routine social gatherings (Tirachini and Cats, 2020; Taylor and Ding, 2021; Calderón Peralvo et al., 2022). Similarly, communicating the safety and continued benefits of the PT modes to older individuals would be an effective way to help draw back some older riders (Downey et al., 2022). Improvements in the convenience of the boarding/deboarding process, which presents challenges for many individuals with physical impairments, may also be helpful and effective. For instance, bus drivers could be provided additional training on ways to physically assist elderly individuals, and bus stops and vehicles themselves can be designed to eliminate challenges in the boarding process (such as the ability to “kneel” buses to reduce the need to climb steep stairs; see Ravensbergen et al., 2021). Finally, in partnership with voluntary community organizations, transit

agencies can perhaps provide assisted transportation (that is, a volunteer who stays with the older adult throughout the trip) for the first few PT experiences, as a way to ease older adults into longer-term PT use by themselves.

Ethnicity/Race and PT Use

Public transit use changes based on ethnicity and race are more nuanced than based on gender and age. Compared to individuals of white race, individuals of Hispanic ethnicity, and individuals of Black/Asian origin, are more likely to (a) have changed their public transit use, either using PT less or PT more after-COVID relative to before-COVID (though the decline in PT use is clearly more dominant), and (b) state that the PT changes are temporary. These results indicate that minority groups were more significantly impacted by pandemic effects, but also seem to be more willing to return to pre-COVID PT use (consistent with the findings from Qiang and McKenzie, 2024). This is a rather reassuring result, given the large share of racial minority riders using PT before the pandemic. To leverage this result, policies and services that focus on equity and creating a safe environment for minority individuals is essential, both from a PT ridership standpoint as well as the broader need to address systematic transportation access inequities that were only further exacerbated by the pandemic. Black households are more likely to be vehicle-constrained and 76% of Black households were burdened by transportation costs during the pandemic, highlighting the importance of public transportation for this group (Molloy et al., 2024). Additionally, during the pandemic, Black and Hispanic individuals experienced more income loss compared to white individuals, adding to constraints faced by these individuals during the pandemic, and emphasizing the need to provide PT services (Huang, 2024). One specific suggestion is to recognize and accommodate the ways that safety is conceptualized by minority racial groups. Although security and policing have been mentioned earlier as a possible mechanism to reduce harassment on public transportation for women, there is significant evidence that widespread policing can alienate and cause increased safety concerns for many minority racial groups (He et al., 2022). This is not without reason; Black riders are stopped more often than white riders, are overrepresented in “code of conduct” violation citations when on transit vehicles, and, not infrequently, even violently attacked by police for the simplest of infractions (Spieler, 2020). As Spieler (2020) puts it, “White riders are likely to see a police officer on a train as a comforting presence, while many Black riders justifiably will perceive them as a potential threat.” In this context, and as we come out of the pandemic, there is a golden opportunity to, among other changes, (a) acknowledge and address head-on structural racism elements deeply embedded in PT route, schedule, comfort, fare, and policing considerations, (b) co-design PT offerings collaboratively with communities and end-users by “going to end-users”, rather than simply holding public meetings and expecting the diversity of the public to show up for input, and (c) ensure that PT leadership teams represent the diversity of riders and society at large.

Individuals with Fewer Travel Mode Options and PT Use

Individuals without driver’s licenses and those who live in households with fewer vehicles than adults are generally more likely than others to take transit more often than before the pandemic. Interestingly, these individuals also view the change as being permanent. This increasing reliance on PT among those with vehicle constraints is an important area of focus for public transportation planners. At the same time, some of these vehicle-constrained individuals also reveal declines in PT use, which they again identify as being permanent. It is possible that PT service cutbacks during the pandemic may have required much larger lifestyle changes for those with mobility constraints

compared to those with more readily available alternatives. This is a plausible explanation for why, while some mobility-constrained individuals became more reliant on transit during the pandemic, others had little choice but to lower their PT dependency. Accordingly, it is important for transit agencies to carefully consider the needs of these mobility-constrained riders and ensure the continuation of providing services to meet their needs. Taking steps to collaborate with employers to develop flextime and staggered work schedules, as well as reducing overcrowding and provide more travel schedule flexibility, will likely help keep transit attractive for those who have made pandemic-era increases in their ridership (Kapatsila, Bogdan, 2024) as well as recapture the ridership of those who reduced their PT dependency in the after-COVID period. This includes emphasizing the impacts of PT on environmental consequences, equity, and congestion (Beaudoin et al., 2015). Since these riders were PT users in the past, awareness campaigns directly targeted at recovering riders may be effective. For instance, providing more awareness of the congestion reductions caused by public transit may attract those who have growing preferences for sustainable travel choices since the pandemic (see Anwar et al., 2023). Further, given that intention to return to higher levels of PT use are likely to be closely associated with expectations about future PT service provision and quality, PT agencies should proactively communicate their plans for service improvements to their existing user base. Even individuals who currently view their reduced transit use as permanent (due to low expectations of future service provisions) may reconsider if they see clear efforts to restore service quality and reliability.

Income and Public Transit Use

Low-income households (<75K annual income) are more likely to have increased their PT use during the pandemic, or to be more willing to return to transit in the future if they reduced their PT use, compared to high-income households (>150K annual income). Lower-income groups tend to face more challenges associated with transportation affordability and accessibility (Tiznado-Aitken et al., 2022) and are more likely to be required to work in-person, making them ideal candidates for public transit ridership recovery efforts. Thus, providing incentives and economically friendly improvements to public transit are good steps to increase ridership for low-income individuals. Specifically, fare optimization policies and dynamic pricing provide an emerging method of addressing equity and ensuring access for low-income individuals. This approach customizes PT service provision to riders' personal needs, and then provides discounts and loyalty points to frequent commuters based on the personalized analysis (Vemuri et al., 2024). Other general strategies such as the provision of free rides, reduced fares for specific low-income or disadvantaged population segments, and improved services and connectivity between low-income residential areas and low-income jobs centers are important to consider as well (Saphores et al., 2020; Bull et al., 2021). PT provides critical services for many low-income individuals, and these policies have the potential to increase ridership by incentivizing renewed use by those who are most interested and to improve equity for these vulnerable groups.

Table 6: Average Treatment Effects

| Variable | Base Level | Treatment Level | Use PT Less Often | | Use PT the Same | Use PT More Often | |
|----------------------|--------------|-----------------|-------------------|-----------------|------------------|-------------------|-----------------|
| | | | Permanent | Temporary | | Permanent | Temporary |
| Gender | Male | Female | 1.13 (0.64) | 1.28 (0.60) | -2.03 (1.07) | -0.22 (0.14) | -0.16 (0.05) |
| Age | <35 | 65+ | 5.90 (0.97) | 6.70 (1.08) | -10.65 (1.59) | -1.14 (0.37) | -0.81 (0.07) |
| Ethnicity | Not Hispanic | Hispanic | 3.29 (1.24) | 3.78 (1.18) | -7.39 (2.04) | 0.17 (0.48) | 0.15 (0.13) |
| Race | White | Black | 0.56 (1.89) | 15.15 (3.11) | -18.21 (2.87) | 0.51 (0.65) | 1.99 (0.33) |
| Race | White | Asian | 6.04 (1.38) | 6.77 (1.43) | -14.74 (2.48) | 1.08 (0.63) | 0.85 (0.14) |
| Driver Status | Driver | Not Driver | 3.37 (1.37) | -3.71 (1.36) | -2.56 (0.48) | 2.21 (0.55) | 0.69 (0.09) |
| Number of Adults | Single Adult | 3+ Adults | 0.15 (0.12) | 0.11 (0.02) | 1.96 (0.40) | -1.27 (0.43) | -0.95 (0.09) |
| Income | >\$150,000 | <\$75,000 | -4.21 (1.19) | 3.96 (1.19) | -1.82 (0.33) | 0.80 (0.36) | 1.27 (0.14) |
| Presence of Children | No | Yes | -3.84 (0.84) | -4.44 (0.86) | 9.61 (1.47) | -0.76 (0.33) | -0.57 (0.12) |
| Location | Urban | Rural | -0.12 (0.13) | -0.09 (0.04) | -1.61 (0.27) | 1.05 (0.31) | 0.77 (0.12) |
| Vehicles per Adult | More | Fewer | 1.85 (1.10) | -2.25 (1.08) | -2.94 (0.52) | 2.22 (0.51) | 1.12 (0.14) |

CONCLUSIONS

This study presents an exploration of the impacts of the pandemic on public transit usage and identifies the demographic groups exhibiting an increase, decrease, or no change in their transit use following the pandemic. This research highlights significant racial, gender, and age disparities in public transit usage during the pandemic, pointing to significant equity issues that should be addressed as public transit continues to adapt to a post-pandemic world. There are numerous ways that public transit agencies can adapt to provide a safer and cleaner environment for riders that would promote usage and potentially regain previous ridership levels for older and female individuals. In addition, given that significant changes to mobility patterns have particularly impacted racial minorities, policies that focus on maintaining and further improving the PT environment will elevate their experiences. At the same time, many of the changes impacting transit stem from lifestyle changes, such as telework, which have impacted these groups differently, and need to be better understood to adequately respond to these continuously evolving conditions. Further investigation is needed to analyze racial effects on telework to further understand the extent of impact this has on public transit usage. In the same vein, while the impacts of household location found in this study were small, additional research that better analyzes these dynamics across various locations and with more specific features of different neighborhoods (beyond the simple urban/rural categorization) would be beneficial.

There are several other opportunities as well for future research in this area. While our study examines the changes during the COVID-19 pandemic, studies of impacts to public transit from other major disruptions would help to generalize these results to help with forecasting and the development of more detailed policy and service interventions. Additionally, a deeper investigation into the behaviors and choices of individuals who do not have driver's license and live in vehicle constrained households would be valuable. We find significant differences in the behaviors of these individuals, pointing to the need for additional careful consideration of the behaviors of these individuals as well as further support for these groups through infrastructure investment (i.e. more bus stops and route adjustments). This can be achieved through collaboration between transit services and top employers to create more flexible work schedules, reducing overcrowding (a key concern mentioned among riders). Finally, examining the motivations for these changes during the pandemic and reasons for returning to public transit over the next few years would be extremely valuable. This deeper understanding of the dynamics at play would help to narrow the service and infrastructure improvements needed to attract and retain current riders.

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