An Investigation of Physical Participation Dissonance and Virtual Activity Participation in the United States

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ABSTRACT
Physical out-of-home (OH) activity accessibility has been studied extensively in the transportation sector, but the recent growth in virtual online activities highlights the need to consider the rich interplay between physical and virtual activity participation. In particular, telework and delivery services present opportunities for new modalities of activity access, potentially expanding activity opportunities for those with limited physical accessibility. In this paper, using data from the 2022 National Household Travel Survey in the United States, we investigate (a) the intensity (and heterogeneity across individuals in this intensity) of discord between how much individuals would like to partake in physical OH participation and how much they actually are able to (we refer to this discord as physical participation dissonance or PPD), (b) the subjective reasons for PPD (c) the intensity of, and heterogeneity across individuals in virtual participation (measured by the intensity of teleworking and home deliveries), and (d) whether or not virtual participation reduces or increases PPD, and by how much. Our results reveal that individuals from zero-worker households, households with fewer vehicles than drivers, low-income households, renting households, and households residing in rural areas all manifest a higher PPD, as do older individuals, racial minorities, non-drivers, and individuals with medical conditions. We find significant heterogeneity in the reasons for experiencing PPD and in virtual participation. Finally, virtual participation does seem to help reduce PPD for those in households with fewer vehicles than drivers, women, older adults, and individuals with medical conditions, but is not effective in reducing PPD for those in low-income, renting, and rural-residing households, as well as for racial minorities and non-drivers. These findings suggest a growing need to consider the relationship between physical and virtual participation, and provide insights for policymakers and transportation planners to improve overall activity accessibility (including expanding access to virtual opportunities) for disadvantaged populations.

Keywords: Perceived Accessibility, Physical and Virtual Activities, Dissonance, Transportation Needs, Social Exclusion

1. INTRODUCTION

Transportation accessibility plays an important role in an individual's ability to consume goods and services, as well as partake in out-of-home (OH) activities. In the early literature starting in the 1950s, it has been captured through objective measures, primarily in the form of highway travel time costs of reaching activity locations and the relative attractiveness of those locations (Hansen, 1959). More recently, transportation accessibility has grown into the concept of multi-modal perceived accessibility (MPA), a broader multidimensional concept based not simply on objective measures of reach to OH activities, but expanding to the consideration of the availability/quality of alternative transportation modes and individual perceptions of the transportation system (see Handy, 2020; Siddiq and Taylor, 2021). In particular, this broader notion of MPA includes subjective factors that account for an individual's abilities, personal experiences, travel attitudes, and perceptions of travel options (Tiznado-Aitken et al., 2020; De Vos et al., 2023). Examples include how an individual perceives safety from crashes, safety from crime, and cleanliness of different modal alternatives, based on the individual's own health/disability conditions and personal prior experiences (Martens, 2016; Allen and Farber, 2020). From a fairness perspective, it is important that these subjective factors be considered alongside objective measures of accessibility, since they can play a significant role in traveler behavior, travel constraints, and potential social exclusion (Lavieri et al., 2018; Pot et al., 2021).

In recent years, another important activity accessibility factor relates to virtual activity participation. The interplay between physical in-person OH activity participation (for ease, referred to simply as "physical participation" in the rest of this paper) and online virtual participation (for ease, referred to simply as "virtual participation" in the rest of this paper) did receive attention even before the onset of the pandemic (see, for example, Lyons et al., 2008; Lavieri et al., 2018). But this interplay has taken on new significance in the aftermath of the pandemic, because, during the pandemic, virtual participation became the norm for most individuals (see Morris et al., 2023). For many, it also was the first experience of ordering goods, food, and services online. In the after-COVID landscape, with opportunities for physical participation reopening, individuals and households appear to more seamlessly integrate physical and virtual participation. In this context, individuals with low levels of physical accessibility may have increasing opportunities to substitute/supplement physical participation with virtual activities to achieve better overall accessibility (Dias et al., 2020; Asmussen et al., 2024a; Shah et al., 2024). However, there are also wide variations in the level of virtual accessibility available to different people and in different areas.[1] A digital divide based on access to internet-enabled devices, spatial availability of delivery services, differential availability of telework opportunities, and individual proficiency with information and communications technologies all impact the extent to which virtual activities can be pursued (Lavieri et al., 2018; Budnitz and Tranos, 2022).

Motivated by the discussion above, our focus is on the extent to which virtual activities influence overall accessibility of individuals, and how physical and virtual participation modalities interact with each other. More specifically, we examine four separate dimensions of this interaction: (a) Is there a discord between how much individuals would like to partake in physical activities and how much they are actually able to, and does this discord vary across individuals? (b) What is the reason for the physical participation discord? (c) What is the intensity of virtual participation (measured in this paper by the intensity of teleworking and home deliveries) in the

[1] "Physical accessibility," as referred to in this paper, includes the holistic set of objective and subjective features of the transportation system that facilitate physical participation, while "virtual accessibility" refers to the objective and subjective factors that facilitate virtual participation.

after-COVID era, and how does this virtual participation vary across individuals? (d) Does virtual participation reduce or increase the intensity of discord in physical participation? Based on Festinger's theory of cognitive dissonance (1957), we also characterize the discord in physical participation as "physical participation dissonance" (PPD), which refers to instances where beliefs, desires, and attitudes (in our case about the need/desire to undertake out-of-home or OH activities) do not translate completely to travel behavior (actual participation in OH activities). In particular, Festinger's theory of cognitive dissonance characterizes situations where three conditions are met (see Festinger, 1957; Harmon-Jones and Mills, 2019). First, there must be a contradiction or opposition between beliefs or behaviors. In our characterization of PPD, we consider this opposition to arise due to trip suppression, when there is discord between planned OH activity participation (an indication of the desire to participate in OH activities) and an individual's actual OH activity participation.[2] Second, based on Festinger's theory, a second condition is that a desire that does not get manifested (in terms of not being able to attain the desired state) leads to adverse consequences, usually characterized by feelings of tension or stress as the individual attempts to reconcile the discord. In the case of PPD, it is certainly the case that individuals who plan to participate in desirable OH activities and are unable to participate in these activities experience negative consequences. As mentioned above, transportation accessibility has broad impacts on individual well-being in terms of social, economic, and health outcomes. Regarding trip suppression specifically, the inability to access key OH activity locations can prevent individuals from accessing critical services such as food and healthcare, cause increased stress and anxiety due to time-planning challenges and impacts on social relationships, and reduce overall life satisfaction (Mackett, 2021; Ettema et al., 2025). Finally, the third condition underlying Festinger's cognitive dissonance theory is that there is a conscious or subconscious effort by individuals to attempt to relieve dissonance by adapting to their situation. Individuals can attempt to relieve their dissonance either by adapting their behaviors to better correspond with their needs and beliefs (in this case finding ways to make the desired trips even when it is challenging), or by modifying their beliefs to align with their constraints (in this case, reducing their expectations about their ability to travel based on long-lasting constraints they experience in the transportation system). In the transportation arena, there is ample evidence demonstrating that individuals attempt to reduce PPD through adapting to their travel constraints by, among other things, choosing locations that are readily available (even if not the most desirable) and reducing their travel desires to be more compatible with their mobility constraints (see, for example, Martens, 2016; Dillahunt and Veinot, 2018; Landby, 2019). In addition, virtual participation presents a potential new avenue to adapt to these constraints and reduce PPD. This situation of PPD is depicted in Figure 1. In this case, an individual experiences dissonance because of a lack of access to OH activity-opportunity locations, but may attempt to reduce the dissonance by substituting/supplementing their physical participation with virtual participation.

In this paper, we use data from the 2022 NextGen National Household Travel Survey (Federal Highway Administration, 2023) to investigate the four dimensions of the interaction

[2] Our PPD characterization, admittedly, assumes that planned OH activities are desirable activities, so that the inability to partake in such OH activities creates a discord (negative feelings) between desire and behavior. It is certainly possible (and very likely) that some of the planned OH activities are not desirable activities, so that not partaking in such planned OH activities (for example, due to cancellation of an activity by someone else or being able to wiggle one's way out of an unpleasant activity) engenders positive emotions. However, as we discuss later in Section 3.1.1, the sample we use for the empirical analysis is such that the planned OH activities considered in our analysis may be much better characterized as desirable activities rather than unpleasant activities. Thus, in this paper, we will use PPD to refer to the discord between planned "desirable" activities and actual behavior.

between physical and virtual participation modalities, as just discussed. We specifically focus on the connection between physical and virtual participation to uncover the ways that virtual participation may provide an avenue to reduce PPD for some individuals, as well as identifying those individuals who may face both high PPD and low uptake of virtual activities. While our discussion references relevant literature from many other geographic, social, cultural, and temporal contexts to provide a comprehensive perspective of the relationship between PPD and virtual activity participation, the results from our analysis should be viewed in the strict context of the United States.

The rest of the paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 describes the sample used and the modeling methodology. Section 4 presents model estimation results and goodness of fit measures. Section 5 discusses the implications of this research for transportation policy. Finally, Section 6 summarizes important findings and identifies future research directions.

2. LITERATURE OVERVIEW AND THE CURRENT STUDY

2.1 Earlier Studies

There is a body of literature on physical accessibility that is relevant to the current study, as this literature reveals a wide range of barriers to physical participation. The most commonly used measures of objective physical accessibility are cumulative accessibility (CA) measures and gravity-based accessibility (GA) measures (Geurs and van Wee, 2004; Kapatsila et al., 2023). While the earliest CA and GA measures used a single highway network-based separation and did not differentiate based on individual characteristics/experiences, these measures may be easily extended to consider such variations. For instance, the number of OH activity locations for CA measures, and the attractiveness of OH activity locations for GA measures, can be varied across individuals based on such attributes as occupation (for instance, only counting jobs of a specific occupation as keyed to an individual's occupation). Alternatively, the thresholds for determining the number of OH points of interest for CA measures, and the separation representation for GA measures, can be varied across individuals based on such factors as modal availability. Some recent examples of these kinds of disaggregate physical participation accessibility measures include Dixit and Sivakumar (2020), Bills et al. (2022), Guzman et al. (2023), and Klein et al. (2023).

Of course, the ease of reach to OH activities is not only based on objective factors, but also on how these objective factors are perceived (De Vos et al., 2023). A wide range of studies have reported the effects of subjective perceptions on transportation outcomes, including trip-making and the use of specific modes. For instance, perceptions of travel time reliability have been shown to have a significant impact on transportation satisfaction and travel intentions (Taylor, 2013; Chen et al., 2017). Beyond the perception of travel time reliability, perceptions of safety are of critical importance, which may vary across individuals based on social norms and expectations. For instance, cyclists and pedestrians are likely to be concerned about crash-related safety (Ng et al., 2017), while public transit users may be more concerned about crime-related safety (Kim et al., 2007). These safety perceptions are also inherently individual specific, both because of differences in objective safety and because of perceived differences related to the personal backgrounds and experiences of individual users (Yavuz and Welch, 2010). For instance, women are more likely to experience harassment on public transit, and may tend to avoid transit, particularly when traveling alone (Currie et al., 2013; Stark and Meschik, 2018). Relatedly, while perceptions of crime may deter some users, excess security and policing may deter others. Thus, 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.” Finally, perceptions of health and cleanliness can also play a role. The COVID-19 pandemic provides a clear example. Fears of infection in public spaces and perceptions of cleanliness contributed to significant declines in public transportation, ridesharing, and other shared modes, while the use of individual active modes grew (Seabra et al., 2021; Javadinasr et al., 2022).

While issues related to perceived travel time reliability, safety, and cleanliness, as just discussed, as well as other subjective considerations such as affordability, one’s own health status, and time availability, can influence an individual’s sense of physical accessibility, the ability to increasingly undertake activities virtually with communication technologies is another important factor today for assessing overall activity accessibility. This is evident in the large body of literature that has explored the ways that virtual activities (particularly telework and delivery services) can (1) substitute or replace existing physical participation, (2) increase physical participation that earlier was not easily pursued, (3) stimulate additional travel due to changes in activity patterns, and (4) redistribute trips for the same purpose to new physical locations (see Salomon, 1985; Mokhtarian and Salomon, 2002; Kenyon, 2006; Cochran, 2020; Elldér, 2020; Shukla and Raval, 2021; Le et al., 2022; Shao et al., 2022; Khaddar and Rahman Fatmi, 2024; Xu and Saphores, 2024). These virtual participation opportunities offer individuals with low physical accessibility the chance to increase their overall accessibility (Ozbilen et al., 2021; Vinella-Brusher et al., 2022). Those experiencing physical participation dissonance (PPD) may be particularly well suited to benefit from the growth of virtual activities, as they are individuals who desire a greater amount of activity participation than what they perceive as being possible through physical participation (Muhammad et al., 2008; Pot et al., 2025).

However, while virtual participation may seem to offer significant potential to enhance overall accessibility, it is conceivable that virtual participation actually increases PPD. In particular, given evidence that virtual activities can result in other changes to activity patterns (including stimulating additional trips) and lifestyles, those who adopt online activities may desire greater physical accessibility and experience more PPD (Lee et al., 2017). For instance, individuals who begin teleworking may experience greater PPD associated with OH leisure participation if they feel socially isolated working at home and are unable to compensate with an increase in physical participation to the extent they desire (Budnitz et al., 2020; Thulin et al., 2023). Another issue relates to fairness considerations. There is evidence that those with limited physical accessibility may be the same ones who face virtual accessibility challenges. After all, virtual accessibility requires access to technology, knowledge and availability of virtual opportunities to effectively replace specific physical activities, and the self-efficacy (or at least the perception of self-efficacy) to use technology to partake in remote activities (Chen et al., 2021; Cavallaro and Dianin, 2022). Individuals may also be constrained by the suitability of their physical environment to pursue virtual activities (such as loud home environments, making telework challenging) and the availability of social and technological support (Laumer and Maier, 2021; Squire, 2022). Thus, just as with physical accessibility, virtual opportunities and resources are not distributed evenly (van Wee, 2022; Pedreira Junior and Pitombo, 2024). Therefore, there is a need for a better understanding of the interplay between physical and virtual activity participation.

2.2 Study in Context

The current study examines the relationship between PPD and virtual participation, contributing to the literature in several ways. First, to our knowledge, the current study is the first to investigate dissonance in the context of trip making and accessibility. The theory of cognitive dissonance has been previously applied in other areas of transportation, such as to mode choice (De Vos, 2018; An et al., 2022), residential location choices (van de Coevering et al., 2018; De Vos and Singleton, 2020), sustainable travel decision making (Higham et al., 2013), and telework decisions (Anderson et al., 2024). However, to our knowledge, this social psychology theory has not been invoked in the context of activity participation. Second, we examine the subjective reasons for experiencing PPD, including perceived constraints of the transportation system, individual travel needs, and perceptions of health and safety (we will use the label "PPD reasons" to refer to these subjective reasons for PPD). As importantly, by modeling reported PPD experience jointly with PPD reasons, we account for any unobserved correlation that occurs between the PPD outcome and each PPD reason, allowing us to identify potential PPD reasons for any individual in the general population, regardless of whether an individual currently reports PPD or not. Third, we examine the propensity of individuals to participate in virtual activities (telework and online-based home deliveries) and whether (or not) virtual participation has the potential to reduce PPD. In investigating this issue, we control for unobserved factors that may impact both physical and virtual participation. Finally, we consider a detailed set of exogenous variables (including income, race, age, household composition, location, and vehicle access) to accommodate the heterogeneity (across individuals) in PPD experience, PPD reasons, and virtual participation. These results have implications for transportation policy, informing ways to better integrate physical and virtual systems to address disparities in access.

3. METHODOLOGY

3.1. Data Description

The data used for this study are drawn from the 2022 NextGen National Household Travel Survey (NHTS), administered by the US Department of Transportation between January 2022 and January 2023 (Federal Highway Administration, 2023). The 2022 NHTS is the first large-scale U.S. nationwide activity-travel survey to be collected since the onset of the pandemic, providing a unique opportunity to examine new transportation behaviors at a national level. A "random" sample was collected based on an address-based sampling frame from the US Postal Service. Participants were invited to participate in the survey online, with the option to request a paper survey. Respondents provided household socioeconomic and demographic information, mode use and commute data, and a one-day travel diary. The survey also included special topic questions covering the impacts of the COVID-19 pandemic, online work and shopping behaviors, the use of emerging modes, and concerns about transportation efficacy. Of particular interest here is a question in the transportation efficacy section asking whether individuals had taken fewer trips in the last 30 days than they had planned, and what the reasons were for suppressing these planned trips.

The 2022 NHTS is suited for our analysis of PPD experience, PPD reasons, and virtual participation, and their inter-relationships, for at least three reasons. First, the 2022 NHTS provides a relatively good sample size with representation across the United States. Second, it includes specific questions regarding whether or not individuals experienced PPD (in the context of suppression of trips in the 30 days prior to taking the survey), multiple possible reasons for PPD, virtual activity participation, and a broad range of individual/household-level demographics and built environments, all of which allow us to investigate how transport disadvantages and virtual activity participation opportunities are distributed among different demographic groups and different built environment contexts. Third, the survey was conducted at an opportune time in the aftermath of the COVID-19 pandemic, in the midst of rapid changes in the use of virtual activities even as many individuals were resuming pre-COVID in-person OH activity routines.

For the current analysis, we included only adults 18 years of age or over (individuals below the age of 18 years were not asked the transportation efficacy questions). We further focused on individuals who reported either not suppressing any planned trip in the past 30 days, or reported suppressing a planned trip for one of eight transportation-related reasons that could reasonably be construed as a sign of physical participation dissonance (PPD). This issue is discussed further in the next section. After cleaning and screening, the final sample included 12,469 individuals from the sampled households.

3.1.1 Endogenous Outcome Variables

Descriptive statistics of the endogenous outcome variables are shown in Table 1. The first outcome is a binary response indicating whether the individual took fewer trips than planned in the 30 days prior to taking the survey. Thus, because an individual needed to have some expectation of completing a trip to plan it in the first place, it is reasonable to view this suppression of planned trips as PPD, especially because, as we discuss below, the reasons for trip suppression provided by individuals in the sample used in our analysis all referenced transportation challenges or health concerns (implying that the trip suppression engendered negative emotions). Of the 12,469 individuals in the sample, 2,553 individuals (20.5%) indicated that they had suppressed at least one planned trip in the 30 days prior to the survey (that is, experienced PPD; see the first row-panel of Table 1).[3] This overall prevalence of PPD aligns well with findings from Gould-Werth et al. (2018) who found that just over 20% of sampled individuals in the United States had skipped going someplace because of a problem with transportation in the past 30 days as well as those of Murphy et al. (2022) who found that 24% of adults over 25 in the United States face some kind of transportation insecurity (using a combined index that included trip suppression).

The second set of outcomes consists of a set of eight PPD reasons. These include (with the shorter labels we will use in the rest of the paper in parenthesis):

1. Transportation did not feel safe (Not Safe)
2. Transportation did not feel clean or healthy (Not Clean)
3. Transportation was not reliable (Not Reliable)
4. Available transportation did not go where I need to go (Poor Destination Access)
5. Unable to afford available forms of transportation (Not Affordable)
6. Had health problems and unable to travel (Health Problems)
7. Did not have time to travel (No Time)
8. Concerns related to COVID-19 (COVID Concerns)

[3] An issue here is whether the time frame of the "past 30 days" is appropriate to capture information about trips not made. In this regard, Palm et al. (2024) find that a recall period of between a week and a month is appropriate because such a time frame balances the accuracy of identifying and recalling suppressed trips with the ability to capture any foregone trips even for typically important but infrequent OH activity participation desires. Besides, in the context of recalling past behaviors, the general survey literature (see, for example, Bell et al., 2019; te Braak et al., 2023) indicates that past summative behaviors (such as whether or not planned trips were suppressed at all or not over a long time period, as we use here) are more easily and accurately recalled relative to finer aspects of behaviors (such as the number of trips that were suppressed). We also note that the implication here is not that all trips are planned; there are of course, spur-of-the-moment trips. But the fundamental premise of travel demand modeling is that there is a high-level planning process at work that does influence our general trip-making patterns.

The results for the number of times each of the above PPD reasons was selected are shown in the second row-panel of Table 1.[4] Note that the entries in Table 1 are the percentages selecting one or more of the above eight PPD reasons out of the individuals who experienced PPD. Additionally, these entries do not add up to 100% (across the PPD reasons) because respondents could indicate multiple PPD reasons. The majority of respondents (73.0%) selected only a single PPD reason, while 17.3% selected two reasons and 9.7% selected three or more reasons. As can be observed from Table 1, the most common PPD reasons were “COVID concerns” (selected by 40.3% of those suppressing trips), “health problems” (selected by 28.7% of those suppressing trips), “no time” (selected by 25.2% of those suppressing trips), and “not affordable” (selected by 18.9% of those suppressing trips). The importance of time constraints to PPD aligns with findings of Singer and Martens (2023) who find that time constraints are the biggest factors causing trip suppression. In addition, they note that the importance of time has decreased after the onset of the COVID-19 pandemic, pointing to a similar importance of COVID-related challenges as well as improvements in mobility due to travel time reductions during the pandemic. The least common reasons were “not clean” (selected by 4.3% of those suppressing trips) and “not safe” (selected by 6.6% of those suppressing trips). While it may be surprising that safety concerns were so infrequent, this result mirrors findings of Gould-Werth et al. (2018) and may indicate that safety concerns fall into a different category of transport disadvantage, since individuals may reduce their PPD by lowering their aspirations for OH activity participation at time or locations where they do not feel they have safe transportation alternatives (see Palm et al., 2024 for additional discussion of how individuals alter their expectations in these ways). The most likely pairing (after controlling for total occurrence of each PPD reason) was “not safe” and “not clean.”

The final set of endogenous outcomes are those relating to virtual participation (shown in the bottom row-panel of Table 1). Participants indicated the frequency with which they telework and use delivery services (based on online activity), which were elicited in the survey on a four-point ordered-response scale. As far as telework, the telework outcome is only available for employed individuals, so is unavailable for 45.7% of the sample who were unemployed or retired. Most of the employed respondents (56.4% of those employed, and 30.6% of the overall sample) did not telework at all, while sizeable numbers of individuals teleworked at other frequency levels (especially “five or more days of the week”). A little more than a quarter of respondents did not have any deliveries in the 30 days prior to the survey, while the majority had between one and five deliveries (42.1%), and the remainder had six or more.

[4] The intent of the transportation efficacy section of the survey was to determine the extent of trip suppression due to transportation accessibility challenges, and whether this varied by population groups, which dovetails nicely with our study of PPD. But, in the survey, in addition to the eight reasons identified above, individuals could provide their response in an additional “other” reason category (for suppressing trips). We attempted to obtain the textual characterizations corresponding to this “other” reason but were informed that it would not be available. Given that this non-descriptive “other” category could be for a variety of reasons not related to PPD, such as “was ill” or “inclement weather during the past 30 days” or any of many other reasons for suppressing trips, we only included individuals who either did not suppress trips, or, if they suppressed trips, marked at least one of the eight reasons listed above. That is, with the sample as constituted, trip suppression becomes a much closer surrogate of PPD, as alluded to in the introduction section. One more issue here. An additional tenth PPD reason category in the survey was “I had more home deliveries instead of going to trips to stores.” While we could have used this as a metric for virtual activity, this PPD reason is available only for those who reported having PPD (and not for the vast number of other individuals in our sample who did not report PPD). Thus, we dropped individuals who reported this PPD reason (there were anyway very few individuals who chose this tenth reason exclusively). Instead, we used the actual reported number of deliveries as a separate virtual participation outcome, since this information is available for all individuals.

3.1.2 Exogenous Variables

The characteristics of the location of household residence, household demographics, and individual characteristics of respondents in the sample are provided in Table 2, along with data from the 2020 United States Census (U.S. Census Bureau, 2020). The sample, in the overall, reflects quite well the geographic distribution of households in the U.S. in terms of Census Division of household residence (the nine U.S. divisions were defined according to the Census groupings). The additional exogenous household location and built environment variables are included based on the household's Census block group of residence, classifying home location based on (1) a binary urban/rural classification based on population density, (2) the local road network density in terms of link-miles per square mile, (3) the employment density in terms of workers per square mile, (4) the walkability of the area (distinguished as "low" or "high" based on a National Walkability Index cutoff of 10; Chapman et al., 2021), and (5) public transit accessibility (where "Low" indicates that less than 10% of the working-age population has transit access and "High" indicates that 10% or more of the working-age population has transit access in the Census tract). The sample also exhibits an underrepresentation of single adult households (both with and without children) and low-income households, particularly those with incomes less than $25,000 (as a point of note, a child is defined in this study as an individual 17 years or younger). Conversely, there is a slight overrepresentation of owner households and households from rural locations. As far as individual characteristics, there is an overrepresentation of older, retired, and highly educated (in terms of formal degree attainment) respondents, and an underrepresentation of non-white and Hispanic respondents.

The skews in the exogenous variables observed in this sample compared with the national statistics imply that the descriptive statistics derived from this sample cannot be generalized to the entire U.S. population. However, since this study undertakes an individual-level analysis, there is no reason to believe that the causal relationships estimated would not apply to the population at large. The NHTS survey comprises a large sample that encompasses the entire nation, and presents substantial variation in the exogenous variables, allowing estimation of the effects of the exogenous variables on the endogenous outcomes of interest. Additionally, since the NHTS is based on a random address-based sample rather than on an endogenous sampling design, an unweighted approach is preferred to a weighted approach because it yields consistent and more efficient estimates (see Wooldridge, 1995; Solon et al., 2015).

3.2 Analytic Framework

The modeling framework consists of a multivariate ordered-response probit (MORP) model with eleven outcomes. The first is the binary PPD decision. The next eight outcomes correspond to binary responses for each of the eight possible PPD reasons. Each individual who reported experiencing PPD was able to select any combination of the PPD reasons, so these outcomes are not mutually exclusive and are jointly observed as eight binary responses. Finally, the last two outcomes correspond to the frequency of telework and frequency of deliveries, representing virtual participation outcomes, which are observed as ordered outcomes. The rest of this section describes the mathematical formulation of the MORP model (this is because binary responses can be viewed as ordered responses with two categories). Note that the MORP is presented assuming an individual with PPD. For an individual without PPD, the procedure requires a simple modification in estimation to marginalize over the PPD reasons such that only three outcomes are relevant (corresponding to the PPD outcome and the two virtual participation outcomes).

Let i be the index for each of the ordered outcomes $(i=1,2,...,I)$. In the current empirical context $I=11$. Let the number of ordered levels for each outcome be K_i such that each outcome is indexed by $(k_i=1,2,...,K_i)$. $K_i=2$ for the binary outcomes, and $K_i=4$ for the two virtual participation outcomes. In the following presentation, we suppress the index for individuals. Following the usual framework for ordered response variables, a latent propensity (y_i^*) can be defined for each outcome as a function of covariates that relates to the actual outcomes (y_i) through threshold bounds:

$$y_i^* = \boldsymbol{\beta}_i'\mathbf{x} + \varepsilon_i, y_i = k_i \text{ if } \theta_i^{k_i-1} < y_i^* < \theta_i^{k_i} \tag{1}$$

where $\mathbf{x}$ is an $(L\times 1)$ vector of exogenous variables (excluding a constant), $\boldsymbol{\beta}_i$ is a corresponding $(L\times 1)$ vector of coefficients to be estimated (some of whose coefficients can, and in general, will be zero), and ε_i is a standard normal error term assumed to be independent and identically distributed across all individuals. The threshold bounds satisfy the following conditions: $\theta_i^0=-\infty$, $\theta_i^{K_i}=+\infty$, and $\theta_i^0<\theta_i^1<\theta_i^2..<\theta_i^{K_i-1}<\theta_i^{K_i}$. Now stack the thresholds to be estimated for each outcome into a vector $\boldsymbol{\theta}_i=(\theta_i^1,\theta_i^2,...,\theta_i^{K_i-1})'$. Let $\mathbf{y}^*=(y_1^*,y_2^*,...,y_I^*)'$, $\boldsymbol{\theta}=(\boldsymbol{\theta}_1',\boldsymbol{\theta}_2',...,\boldsymbol{\theta}_I')'$, $\boldsymbol{\beta}=(\boldsymbol{\beta}_1,\boldsymbol{\beta}_2,...,\boldsymbol{\beta}_L)'$, and $\boldsymbol{\varepsilon}=(\varepsilon_1,\varepsilon_2,\varepsilon_3,\ldots,\varepsilon_I)'$. $\boldsymbol{\varepsilon}$ is multivariate normal distributed with a mean vector of zeros and a correlation matrix given by

$$\boldsymbol{\Sigma} = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1I} \\ \rho_{12} & 1 & \rho_{23} & \cdots & \rho_{2I} \\ \rho_{13} & \rho_{23} & 1 & \cdots & \rho_{3I} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{1I} & \rho_{2I} & \rho_{3I} & \cdots & 1 \end{pmatrix} \tag{2}$$

The off-diagonal terms of $\boldsymbol{\Sigma}$ capture error correlations among the underlying latent propensities of the endogenous outcomes, accommodating the presence of unobserved variables that jointly influence multiple outcomes. If all the correlation terms ρ_{ij} are zero, then this modeling system collapses to a series of independent ordered response models. Now, define a vector $\boldsymbol{\delta}$ that collects the parameters to be estimated: $\boldsymbol{\delta}=\left(\left[\text{Vech}(\boldsymbol{\beta})\right]',\boldsymbol{\theta}',\left[\text{Vechup}(\boldsymbol{\Sigma})\right]'\right)'$, where the operator "Vech(.)" row-vectorizes all the non-zero elements of the matrix/vector on which it operates, and the operator Vechup(.) row-vectorizes the upper diagonal elements of a matrix.

Let the individual under consideration select level m_i $(i=1,2,...,I)$. Stack the lower thresholds θ_{i,m_i-1} and the upper thresholds θ_{i,m_i} for the individual into $(I\times 1)$ vectors $\boldsymbol{\theta}_{low}$ and $\boldsymbol{\theta}_{high}$, respectively. Then, in matrix form, the latent propensities underlying the observed multivariate outcome for the individual should satisfy:

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

where $MVN_I(\boldsymbol{\beta}'\mathbf{x},\boldsymbol{\Sigma})$ stands for the multivariate normal distribution with mean $\boldsymbol{\beta}'\mathbf{x}$ and correlation matrix $\boldsymbol{\Sigma}$. The individual's likelihood function may be written as:

$$L(\boldsymbol{\delta}) = \Pr\left[\boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{high}\right],$$
$$= \int_{D_r} f_I(\boldsymbol{r} \mid \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma}) d\boldsymbol{r}, \tag{4}$$

where the integration domain $D_r = \{\boldsymbol{r} : \boldsymbol{\theta}_{low} < \boldsymbol{r} < \boldsymbol{\theta}_{high}\}$ is simply the multivariate region of the $\mathbf{y}^*$ vector truncated by the upper and lower thresholds. $f_I(\boldsymbol{r} \mid \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma})$ is the MVN density function of dimension I with a mean of $\boldsymbol{\beta}'\mathbf{x}$ and a correlation matrix $\boldsymbol{\Sigma}$. The log-likelihood function for a sample of Q decision-makers is the sum of the individual-level log-likelihood functions. The integral in Equation (4) involves up to a 11-dimensional integral, which is evaluated using recent matrix-based analytic approximation approaches (see Bhat, 2018).

As part of our joint system, and after controlling for unobserved correlation in the $\boldsymbol{\Sigma}$ matrix, we can also incorporate the direct effects of PPD/PPD reasons on virtual participation and virtual participation on PPD/PPD reasons. However, in joint limited dependent outcome models of the type estimated in the current paper, it is possible only to identify one-way recursive effects (see Bhat, 2015). In our empirical analysis, we tested both directionalities of effects; from PPD/PPD reasons to virtual participation and from virtual participation to PPD/PPD reasons; and selected the one that outperforms the other based on data fit considerations. In our final recursive configuration, both types of virtual participation (telework and deliveries) influenced PPD and PPD reasons (however, note that the PPD/PPD reasons and virtual participation outcomes are jointly modeled as a package because of the correlation in unobserved factors).

4. RESULTS

The final model specification was developed through an iterative process of including exogenous variables in various functional forms/combinations and testing the statistical fit. Categorical variables were initially included in their most disaggregate form and progressively combined based on statistical tests to yield a parsimonious specification. Additionally, in the model estimation process, variables were retained or removed based on a t-statistic threshold of 1.65 (corresponding to a 90% confidence level) for the PPD outcome and the two virtual participation outcomes. Due to the smaller number of participants with responses for the PPD reasons, and, in particular, the relatively small share of individuals picking some of the PPD reason categories (such as transportation did not feel "safe" or "reliable" or "clean" (see Section 3.1.1), a lower t-statistic threshold of 1.28 (corresponding to an 80% confidence level) was used for the PPD reason outcomes.[5]

[5] Some additional notes are in order here about our use of an 80% confidence level for the PPD reasons. In model specifications, the analyst needs to worry not only about including variables incorrectly (Type I error), but also rejecting variables incorrectly (Type II error). There is always a tradeoff between making the two different types of errors when selecting a confidence level. Further, as strongly endorsed by the American Statistical Association (ASA) (see Wasserstein and Lazar, 2016; Wasserstein et al., 2019), researchers have to make judgments specific to each empirical situation about the confidence level to use. In this regard, there is absolutely nothing magical or golden about the typically used 95% level of confidence (or 0.05 level of significance). In fact, as stated by the ASA studies, there is a dire need to get analysts out of this "p<0.05" mindset or any other specific p-level. In this context, in joint models with moderate samples, especially when some dependent outcomes are rather unbalanced in the choice shares (such as the safe/reliable/clean PPD reasons in our sample), we prefer to err more on allowing a slightly larger Type I error if it means identifying variables that are suggestive and that may help inform future specifications using larger sample sizes and/or more balanced shares in the PPD reasons. Finally, we must also note here that very few coefficients (only 22 of the 233 estimated coefficients, or less than 10% of all estimated coefficients) turned out to be statistically significant at the 80% level, but not at the 90% level; removing such coefficients had literally no effect on the signs

The model results are shown in Table 3 (a "--" entry in these tables indicates that the row exogenous variable does not have any statistically significant impact on the column outcome variable). The first row-panel of threshold values in Table 3 do not have any substantive interpretations and serve the sole (but important) purpose of translating the underlying latent propensities into actual observed ordinal values. The effects of the exogenous variables correspond to their impact on the underlying propensities of each endogenous outcome (these are the $\boldsymbol{\beta}$ matrix elements). For the binary PPD and PPD reasons, these effects also immediately carry over to the binary outcome probability effects. The parameters corresponding to "Census Division of Household Residence" (second row-panel of Table 3) accommodate for overall geographic variations in the endogenous outcomes and are included to account for sampling differences across geographic regions. As such, they are difficult to interpret, though they suggest an overall higher PPD (lower satisfaction with accessing OH activities) among households residing in the New England and Pacific Census divisions. The effects of other exogenous variables are discussed below. Also to be noted is that the effects of exogenous variables on PPD in Table 3 refer to the direct effects after accommodating the indirect effects through the endogenous telework/deliveries effects on PPD (we discuss this issue more in Section 5).

4.1 PPD Outcome

The results for the PPD outcome are shown in the first numeric column of Table 3, followed in the next immediate eight columns by the PPD reasons. The discussion below should be interpreted as general (average) tendencies; deviations from these general tendencies will always be present. Those living in rural locations exhibit higher PPD relative to those residing in urban areas, primarily due to lack of affordability, which is not an unsurprising result given the longer trip distances in low-density areas (McGrail et al., 2015). In urban areas, individuals suppress trips (even though not at the same intensity as rural residents) due to concerns of safety, cleanliness, and health, most possibly because of the higher population densities, and the higher shares of travel by public transit and active modes (essentially, tight spaces and high occupancy travel compared to rural areas). While employment density does not seem to impact experience of PPD overall, those living in areas with high employment density are more likely to experience PPD due to concerns of safety, cleanliness, destination access, and lack of time. As expected, those living in more walkable neighborhoods tend to have lower PPD relative to those in less walkable neighborhoods, primarily due to reduced safety concerns and fewer concerns about time. However, these individuals are also more likely to say that their transportation is unreliable. This finding highlights the importance of developing safe and walkable neighborhood environments that encourage the use of walking as an alternative to other modes but highlights that overreliance on walking may lead to challenges since it may not be physically available to everyone and may not always be considered reliable. Finally, those living in areas with high transit accessibility report experiencing higher levels of PPD, largely due to safety concerns, although transit accessibility seems to alleviate health-related concerns. This finding presumably reflects that, although public transit offers an additional transportation mode, many individuals living in these areas may be more constrained to using transit despite any accessibility or safety-related concerns they have. This finding may also reflect that individuals who use transit tend to have higher expectations for

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and magnitudes of other model parameter estimates or the model fit. At the same time, the few variables that had an impact only at the 80% confidence level saw little movement in their estimated effect sizes across a range of different specifications we tested. These observations demonstrate the robustness of the results (Lu and White, 2014; Srivastava et al., 2018; Brennan et al., 2021 suggest this kind of robustness testing), and bolster their consideration and inclusion.

accessibility than they are actually able to realize on transit, leading to a mismatch between their plans and behaviors that is less likely to reduce over time.

Single adults have a higher PPD relative to households with 2+ adults, attributable to poorer destination access, though single adults also appear to be less COVID-concerned. The latter result presumably reflects potential contagion concerns in multi-adult households. There is no PPD disparity based on the presence of children, though individuals in households with children are generally more concerned with affordability of physical travel, and much less with reliability or the ability to reach specific destinations of interest. This result is intuitive, as individuals with children face particular economic challenges, though they are generally less deterred by activity-reach problems in their quest to facilitate OH activity participation of their children (see Lee et al., 2007; Mackett, 2013). Individuals from worker-households (households in which at least one individual works) do not show any differences from those in zero-worker households in terms of PPD, but those from two or three-worker households are more likely to cite poor reliability and poor destination access of the transportation system as PPD reasons, potentially due to the narrower space-time windows to pursue joint OH activities outside of the work schedules of the multiple workers (Gliebe and Koppelman, 2005; Neutens et al., 2012).

As expected, vehicle-constrained households (those with fewer vehicles than drivers) experience higher PPD relative to other households (that is households with equal or more vehicles than drivers) (see Blumenberg et al., 2020). Vehicle-constrained households tend to suppress trips due to concerns of safety, destination access, and COVID contagion, reflecting the unease commonly associated with shared modes such as public transportation. Similarly, PPD is much more common among individuals in lower income households relative to individuals in higher income households, particularly due to concerns of reliability, destination access, and affordability. These results are aligned with a large body of existing literature showing that low-income households have less access to affordable and reliable transportation (Lovejoy and Handy, 2008; Makarewicz et al., 2020; Tiznado-Aitken et al., 2022). Higher-income households, however, are more likely to suppress trips due to health problems; however, these income effects on "health problems" are statistically significant at only the 85% significance level.

Compared with homeowners, renters exhibit a higher PPD tendency (more likely to suppress planned trips), largely due to concerns of safety, reliability, destination access, and affordability. This is consistent with findings suggesting that renters, particularly lower-income renters, have challenges finding affordable housing in areas that also have high levels of accessible and affordable transportation (see Makarewicz et al., 2020). Renters seem less concerned about time considerations relative to homeowners, though this effect is statistically significant at only the 81% level).

As far as individual level characteristics, women experience more PPD than do men, particularly due to health problems and COVID concerns. The COVID concern is consistent with findings suggesting that women tend to be more health-conscious (Feraco et al., 2024; Maslakçı and Sürücü, 2024). Men, in contrast, seem to be more concerned with affordability relative to women, perhaps a reflection of the fact that women generally face more economic disadvantage and have less control over household finances; so they may adapt more to the conditions surrounding their physical participation, including greater use of shared and less expensive modes (Kunieda and Gauthier, 2007; Priya Uteng and Turner, 2019). On the other hand, men, who have more financial control, may perceive greater lack of affordability because of higher expectations of what they believe the transportation system should provide to accommodate their more expensive travel "needs," including the use of private vehicles for much of their travel. Older individuals also tend to experience more PPD, due in large part to health problems and concerns about COVID. This may be explained by their increasing physical frailty and their higher likelihood of actually contracting contagious illnesses (Roe et al., 2021). Reliability and time-related considerations are less of an issue for older adults, particularly individuals 55+ years of age.

While those employed are no different than those retired or unemployed in terms of experiencing PPD, employed individuals are more likely to identify "no time" as a reason for PPD, presumably due to space-time constraints from work schedules. Retired individuals, not surprisingly, are less concerned about reliability, though report experiencing PPD due to "health problems," likely due to physical mobility constraints limiting their travel alternatives (Dabelko-Schoeny et al., 2021). In terms of race effects, individuals identifying as non-white report more PPD than those identifying as white, attributing the PPD to transportation unreliability, poor destination access, and COVID concerns. These results align with the existing literature showing that minority racial groups, particularly Black Americans, face significantly more economic and temporal constraints, live in areas with less developed transportation infrastructure, are more likely to use public transportation, and have increased safety concerns largely related to discrimination and policing (Barajas, 2021; Haddad et al., 2023). As far as educational attainment, those with higher levels of formal education are predisposed more to PPD, largely due to transportation systems being "not clean," having "no time," and being COVID contagion concerned. These PPD reasons reflect broad trends of greater health concern and more time constraints among those with high formal education (Jacobs and Burch, 2021). At the same time, this result contrasts with existing research (Brown, 2017; Xiao et al., 2018) observing that individuals with lower levels of formal educational attainment face more significant transportation challenges compared to those with higher levels of formal educational attainment. Taken together, our result suggests that individuals with lower levels of educational attainment reduce their travel expectations due to travel constraints, thus reducing their PPD even if they experience more transportation challenges (Har-Tal and Martens, 2025).

Finally, individuals without a driver's license, and those who have medical conditions that hinder their travel, experience more PPD, reflecting the burdens of the travel constraints these groups face. Respondents without a driver's license are less likely to attribute PPD to health factors, instead citing time constraints. These individuals are more reliant on rides from others, active modes, and public transportation, all of which are typically more time consuming (than driving) (Haustein and Siren, 2014). The reverse holds for respondents with medical conditions, who appear to experience PPD less due to time constraints, but more to health problems.

4.2 Virtual Accessibility

While the results in the previous section focused on PPD, the final set of results (presented in the last two columns of Table 3) center on virtual participation, including the propensity to telework and use delivery services. Individuals living in rural areas (rather than urban areas) have a lower propensity to use both telework and delivery services. The urban effect may be attributed to broader internet access, greater suitability of jobs for telework, and more delivery services with lower costs in urban areas (Kaplan et al., 2023). Similarly, individuals living in areas with higher levels of employment density also seem to get delivery services more often, suggesting that there is a close connection between physical and virtual access to these types of services that may represent a complementary rather than substitution effect. Conversely, those living in areas with high road network density, high levels of walkability, and better transit accessibility seem to utilize delivery services at lower rates. This indicates that those individuals living in areas with better overall levels of objective physical neighborhood accessibility are more likely to shop in-store rather than online, at least within the broader geographic context that determines the availability of these services.

Individuals in households with two or more adults (relative to sole-adult individuals) and those with children in the household (relative to those without children) have a lower propensity to telework, perhaps due to the greater number of household distractions among larger families (Pabilonia and Vernon, 2022). Those with children in the home also appear to have a higher tendency to have deliveries (possibly a mechanism to reduce time spent on OH shopping; Spurlock et al., 2020), while those with a large number of workers are inclined to have fewer deliveries (possibly because these workers tend to combine OH shopping activities with the commutes of one or more workers; Dirks et al., 2022). Other effects of household characteristics are as follows: (a) Individuals in vehicle-constrained households have a higher predilection to be teleworkers, but also a lower inclination for package deliveries, (b) As household income increases the propensity of teleworking and receiving deliveries both increase. These results have been found in many recent studies (see, for example, Kaplan et al., 2023; Asmussen et al., 2024b).

As far as individual characteristics, women utilize delivery services more than men, perhaps representing women's higher level of time consciousness and responsibilities for home maintenance activities (Young et al., 2022). Younger individuals are less predisposed to telework (presumably reflecting greater preferences for sociability and opportunities for advancement in physical offices; Tagliaro and Migliore, 2021), while older individuals have a lower propensity to use delivery services (potentially reflecting less technology-savviness and greater concerns that delivery services will fulfill their needs; see Erjavec and Manfreda, 2022). Similarly, retired individuals, unemployed individuals, and those identifying as non-white have a lower generic tendency for deliveries. The latter result may be associated with inequities in delivery service provision, wherein delivery providers, driven by profit maximization associated with the amount of consumption of consumer goods, locate themselves to serve geographic areas with white majority populations (Saphores and Xu, 2021; Hicks et al., 2022).

Individuals with higher levels of formal education attainment show a higher predilection for telework and use of delivery services. This result is intuitive given that jobs most suitable for telework are associated with higher educational attainment (see, for example, Nguyen, 2021). Marketing of delivery services also tends to be oriented towards concerns that resonate more with well-educated population groups, including convenience for students and young professionals, diverse food options aligning with the preferences of those with more exposure to diverse cuisines, and health and wellness efforts appealing to those who are more nutrition and wellness aware (Shah et al., 2021; Keeble et al., 2022). Finally, those with a medical condition tend to have higher propensities for telework and deliveries, suggesting that virtual participation may be helping alleviate OH accessibility challenges.

4.3 Correlations and Endogenous Effects

The estimated correlation parameters and their t-statistics are shown at the bottom of Table 3. Sixteen correlation terms are significant at the 80% confidence level or above and are retained in the model. These significant correlation terms indicate the presence of unobserved effects that jointly impact several of the endogenous outcomes. Importantly, the PPD reasons are only observable if a person reports PPD. To generalize the perceived physical participation barriers due to the transportation system (which is what the PPD reasons represent) to all individuals, the resulting sample selection in the observed data needs to be accounted for. In our estimations, though, these correlations did not turn out to be statistically significant. However, there is substantial correlation across the PPD reasons, with positive correlations among the PPD reasons of (a) "not safe," "not clean," "not reliable," and "poor destination access" and (b) "not affordable," "not "reliable," and "poor destination access." These positive correlations suggest that intrinsic (unobserved) individual factors as well as unobserved location factors may lead to a common set of transportation barriers. Additionally, positive correlations between the PPD reasons of "COVID concerns" with "not safe" and "not clean" suggest the "not safe" and "not clean" perceptions may decline as pandemic effects subside. The correlations between "health problems" and "safety," and "COVID concerns" and "no time," are rather weak and barely significant at the 80% confidence level.

In addition to the correlations among the PPD reasons, a positive correlation between COVID concerns and telework is unsurprising, indicating that those with more intrinsic pandemic concern have a higher propensity to telework. Similarly, a positive correlation between the use of telework and delivery services indicates that unobserved factors, such as technological savviness or access to technology, impact the use of both virtual services. Finally, both virtual activities are positively correlated with PPD. Notably, these correlations between PPD and virtual participation outcomes take the opposite sign of the endogenous effects discussed next, indicating that, if these correlations were ignored, the impact of virtual participation on PPD would be underestimated, incorrectly discounting the potential of virtual participation to reduce PPD and enhance overall accessibility.

Finally, we arrive at the endogenous causal effects. Higher levels (relative to lower levels) of telework and deliveries lead to statistically significant reductions in PPD, as we hypothesized earlier. This overall PPD reduction is explained to a large extent by a reduction in "poor destination access" and "no time" perceptions. Thus, virtual participation opportunities do appear to have the beneficial effect of elevating overall (physical and virtual) accessibility.

4.4 Model Fit

Although the statistically significant correlations mentioned in the previous section already motivate the use of a joint modeling approach, we compare the proposed joint model to an independent ordered probit model to assess the overall model fit. The independent model assumes that the errors among the endogenous outcomes are all independent, maintaining a correlation structure with zeros for all off-diagonal terms in Equation (2). A series of disaggregate and aggregate statistics are shown in Table 4 to compare the joint and independent models. First, comparing the disaggregate measures, the log-likelihood at convergence and adjusted likelihood ratio index for the full model are both larger than that of the independent model, while the Bayesian Information Criterion (BIC) statistic shows a lower value for the joint model relative to the independent model. Since the independent model is a nested form of the full model, the two can be compared with a formal likelihood ratio test. The likelihood ratio test statistic is 458.86, which is much higher than the chi-squared value with 16 degrees of freedom at any reasonable level of significance, indicating a statistically significant superior fit for the proposed model. Finally, the models can be intuitively compared based on the average probability of correct predication, which is computed using the multivariate predictions for all available outcomes for each individual (note that the average probability of correct prediction is low for both models due to the large number of possible combinations for the complete outcome set, amounting to 4096 possible combinations for those reporting PPD and 16 possible combinations for those not reporting PPD.

The models can also be compared based on aggregate fit. To do so, the share of individuals selecting each combination of outcomes is compared with the predicted shares based on each model. Since the total number of outcome combinations for the full set of 11 dimensions is very large, we limit this aggregate comparison to the PPD dimension and the two virtual accessibility dimensions, resulting in 40 possible combinations (including combinations that do not include the telework dimension for non-workers). For each combination of these three outcomes, the absolute percent error (APE) between the predicted share and the observed share in the dataset is computed for each model. Then, the weighted average percent error (WAPE) is computed by weighing these APEs by the observed shares. The weighted average percent error is smaller for the proposed model (5.89) than the independent model (8.89). Overall, based on a variety of data fit metrics at both the disaggregate and aggregate data fit measures, our joint model outperforms the independent model.

5. IMPLICATIONS

5.1 ATE Computations

The model results presented in the previous section provide important insights into the underlying propensities associated with PPD, PPD reasons, and virtual participation. But, as such, they do not provide the magnitude of effect on the actual binary PPD and PPD reasons, and the ordinal virtual participation outcomes. This is especially so for the PPD outcome because the exogenous variable effects in Table 3 represent direct effects not overall effects that include indirect effects through the virtual participation outcomes. For this, we use Average Treatment Effects (ATEs), which represent the impact of a change of state of an antecedent variable on the endogenous outcomes of interest. While we can compute such effects for each of the eleven dimensions in our analysis, here we focus on exogenous variable effects on the PPD outcome and the two virtual participation outcomes. We begin by computing, for each individual, the tri-variate probability predictions for each of the 32 combination outcomes of the PPD, telework, and deliveries outcomes (total possible combinations $=2\times4\times4=32$, including counterfactual outcomes) for the base level of an exogenous variable. Then, by marginalizing over the combinations, we can obtain the probability of "yes" and "no" for the PPD outcome for each individual. For the telework frequency and delivery frequency outcomes, we obtain the probabilities for each ordinal level and compute an expected value by assigning the mid-point frequency value of each level (so, we assume 1-2 days per week represents 1.5 days a week and so on for telework, and assume 1-5 deliveries in the last 30 days corresponds to 2.5 deliveries in the last 30 days and so on for deliveries). The share of individuals with "yes" and "no" for the PPD dimensions can be computed as the average probability of each of the two PPD categories across all individuals, and the average teleworking days and monthly deliveries can be computed similarly by averaging the expected value across individuals. The same procedure is adopted for the treatment level of the exogenous variable. For example, consider the treatment effect of presence of children. We set all individuals in the dataset to "no presence of children" and compute the share (in percentage terms) of "yes" for PPD, as just discussed. Then, all individuals are assigned to the treatment level of "presence of children," and we get the share again (in percentage terms) of "yes" for PPD. The change in the "yes" shares (in percentage terms) provides the magnitude and direction of the total ATE of the "presence of children" variable on PPD. The ATE effect for the telework and deliveries dimensions are computed as the difference in the average teleworking days and monthly deliveries between the base and treatment levels. For the sake of presentation simplicity, for exogenous variables with more than two levels (such as income), we compute the ATEs for a change between only the highest and lowest levels.

An additional issue here is that there are endogenous outcome effects of telework and deliveries on PPD. This implies that the total ATE effect of an exogenous variable is a combination of mediating effects through the telework/deliveries outcomes (indirect effects) as well as a direct effect of the variable on PPD. To distinguish between the two types of effects, we compute the direct effect of an exogenous variable on PPD by maintaining the values of all other exogenous variables (as well as the telework/deliveries endogenous outcomes affecting PPD) as they are in the data. The treatment effect corresponding to this computation is the direct ATE effect of the exogenous variable. By subtracting the direct effect from the total ATE, we obtain the indirect effect. As an example, the effect of presence of children on PPD, based on the estimation results from Table 3, is purely an indirect effect through telework and deliveries (note that "presence of children" has no direct effect on PPD). The presence of children has a negative effect on telework propensity, but a positive effect on the propensity of having deliveries. Both telework propensity and propensity of deliveries have a negative PPD effect, which implies that individuals with children in the household will have an indirect positive effect on PPD (through telework) and an indirect negative effect on PPD (through deliveries). The total ATE effect will be the net combination of the two effects.

The final ATE effects (including direct and indirect effects on PPD) are shown in Table 5. We order the endogenous outcomes differently from that in Table 3 because the causal pathway starts from telework and deliveries, and both these affect PPD. Also, for easy interpretation, we take the treatment level as the one that leads to a higher overall PPD relative to the base level (so the base level in Table 5 may be different from the base level in Table 3). The exogenous variable effects on weekly teleworking days and monthly deliveries are straightforward and represent direct effects (that also represent total effects). For example, the entry of "-0.92" under the "Telework ATE" column for "Income" indicates that individuals in households with low income (<50K annually), on average, telework about one fewer day per week than individuals from households with high income (>200K annually). The entry of "-1.75" in the "Monthly Deliveries ATE" column for "Income" indicates that individuals in low-income households, on average, have 1.75 fewer monthly deliveries than individuals in high-income households. The PPD column has four sub-columns. The entry of "13.14" in the last sub-column for income indicates that, in a pool of 100 individuals from low-income households, one may expect about 13 more individuals to experience PPD relative to in a pool of 100 individuals from high-income households. The three immediate sub-columns to the left of the "Total ATE" column provide the percentage splits of the total effect as originating from an indirect telework effect, from an indirect deliveries effect, and from a direct effect. Thus, for income, the increased PPD among individuals from low-income households may be attributed to a 6% effect through the reduced ability to telework, an 11% effect through the reduced ability to order deliveries, and an 83% direct PPD effect. The sign associated with each contribution illustrates whether the corresponding effect increases the total PPD ATE (+) or decreases the total PPD ATE (-). For example, the total PPD ATE for "presence of children" may be attributable to an increase in PPD due to the reduced ability to telework (contributing 57% to the total PPD) and a decrease in PPD due to increase delivery services (contributing 43% to the total PPD). There is no direct effect on PPD based on the presence or absence of children. Note also that the relative magnitudes of the indirect and direct effects are computed to total 100%. All other entries in Table 5 may be similarly interpreted.

Toward the bottom of the table, we also compute the ATE effects of telework and deliveries on PPD. These endogenous ATE effects on PPD add value to policy development and insights. For these effects, we consider a change from the base level of "5+ days per week" to the treatment level of “0 days per week” (for telework) and from the base level of “more than 10 deliveries in the past 30 days” to “0 deliveries in the past 30 days” (for deliveries). The corresponding ATEs indicate the substantial PPD-alleviating impacts of virtual participation.

In the rest of this section, we discuss the implications of our results based on the ATE results from Table 5, combined with the PPD reason results in Table 3. The focus of our discussions will be on the indirect and direct ATE effects on the PPD outcome, though we invoke other results from Table 3 and Table 5 as appropriate in our discussions.

5.2 Who is Teleworking and Who Receives Home Deliveries?

Our results provide insights based on demographic variations in telework and home delivery preferences; telework frequency is higher for single adults without children, individuals from vehicle-constrained households and high-income households in urban areas, older adults, those with more formal education, and individuals with medical conditions. These findings have important implications for cities, developers, and urban planners as they design developments appropriate for telework and consider the impacts of changing commuting patterns. Strategies such as providing local community workspaces in residential areas could be beneficial to promote telework among those who do not have suitable spaces at home and provide mechanisms to help teleworkers maintain social connections while working remotely (Ciccarelli and Mariotti, 2024). At the same time, the low telework among individuals with children, along with the higher overall PPD among individuals with children, reveals a need to promote telework opportunities for this population group, which already faces a high level of mobility-related social exclusion due to time poverty and work-family conflict issues (see Bernardo et al., 2015). Work-friendly telework and flexible work policies directed toward parents, as well as establishing third workplace facilities in communities with a sizeable share of households with children, may be beneficial in addressing PPD among parents.

The results in Table 3 also have implications for employers as they rethink telework policies to align with their own needs and the preferences of their employees. For instance, telework seems to have been particularly helpful at reducing PPD (and particularly the adverse effects of COVID-19, as per the results of PPD reason in Table 3) for older adults, allowing them to retain spatial separation while working. Telework opportunities allow older adults to continue to participate in the workforce for longer, enabling them to be engaged in productive income-generating activities. Doing so has been tied to feelings of less social exclusion, especially in the post-COVID era, while also providing a sense of self-empowerment and continued self-efficacy among older adults (Nagarajan and Sixsmith, 2023; Yuan and Wang, 2023). Thus, it is important for employers to consider retaining telework opportunities for aging employees, provide training in the use of online services, and communicate these options to their workforce.

The frequency of home deliveries is higher among individuals in households with children, without workers, with more vehicles and high incomes, and living in urban areas, areas with higher employment densities, and lower physical accessibility (in terms of road network density, walkability, and transit access), as also among women, younger employed individuals, white individuals, those with more formal education, and individuals with medical conditions. These variations in delivery frequency have implications for businesses and service providers, who can tailor their services and marketing to specific population segments. For instance, younger individuals who value the flexibility afforded by delivery services may prefer more rapid service times (such as same day or 2-hour deliveries) and may make smaller but more frequent purchases. Beyond providing customized services to specific population groups, from a broader societal standpoint, the results highlight inequities in delivery services, underscoring a need to better serve low-income and minority population groups (virtual participation inequities are further discussed in Section 5.4). Regarding geographic location, the results suggest that delivery services should prioritize expanding access in areas with lower levels of physical accessibility, as those living in neighborhoods with lower road network density, reduced walkability, and poor transit access will be more likely to adopt these services and use them frequently. Notably, delivery platforms may have opportunities to take advantage of order bundling and consolidation strategies, which can reduce the costs of delivery in these areas which may also be harder for delivery providers to reach, but which may have high adoption rates. The results also highlight the importance of accommodating the impacts of delivery services in travel demand models; the growth in delivery services may lead to reductions in personal travel for maintenance activities that then increase other OH activity participation over potentially a more expansive spatial area, as well as an increased number of delivery trips serving these orders (see Dias et al., 2020; Xu and Saphores, 2024). In this context, a better integration between individual-level travel demand models and commercial vehicle movement is needed. Relatedly, there is an increasing need to collect detailed information in activity-travel surveys on home-based deliveries.

5.3 How has Virtual Participation Reduced PPD?

The endogenous ATE effects (of both telework and deliveries) on PPD, shown at the bottom of Table 5, indicate that virtual activities can serve to alleviate PPD. In particular, virtual participation has the effect of reducing PPD for individuals from households with fewer vehicles than drivers, women, older adults, those with more formal educational attainment, and individuals with medical conditions. For women (particularly those with children), the PPD reduction through virtual participation is through increased home deliveries, which is not surprising given the continued disproportionate household maintenance activity responsibility of women (Wang and Cheng, 2024). Online shopping can save time, allowing women to allocate more time to other activities, such as education, career advancement, or leisure, potentially leading to a more balanced lifestyle (of course, we do not mean this at the necessary exclusion of more general society-wide efforts to reduce the gender identity-based asymmetry in household responsibilities). In addition to releasing time pressures, online shopping can enable women, especially those with limited mobility and in male-dominated societies, to make purchases independently, fostering financial autonomy (Roper and Alkhalifah, 2020; Liu et al., 2023). Therefore, continuing to promote delivery services for basic household products and expanding the reach of food and grocery delivery services (including through strategies mentioned in the previous section) should help promote gender accessibility.

Individuals with medical conditions that make travel difficult also appear to be able to leverage virtual participation (both in the form of telework and delivery services) to alleviate dissonance (reducing overall PPD by about 8%). However, after accounting for the benefits of virtual participation, PPD is still 15.79% higher among those with a medical condition (compared to those without). Thus, there is still substantial potential to expand virtual participation access for this population group. This can include ensuring that delivery personnel leave packages in designated and easy to reach drop-off locations (Lee et al., 2020), and designing apps and websites that embed screen readers, voice commands, and large font sizes, especially for those with visual impairments (see Kaufman-Scarborough and Childers, 2009; Leporini et al., 2023). Finally, building inclusive user-centered virtual participation systems that involve individuals with medical conditions in the design process from the get-go will help increase virtual participation and further alleviate PPD in this population group.

5.4 For Whom Has Virtual Participation Not Reduced PPD?

While virtual participation has alleviated PPD for some groups, this has not been universal. In terms of geographic variation, it is evident that individuals in rural areas have lower levels of virtual participation and that those in areas with lower employment density tend to get fewer deliveries, contributing further to the already existing physical accessibility gap between those living in urban and rural areas. This virtual participation disparity is a result of several interrelated factors associated with urban areas, including (a) the higher concentration of telework-conducive knowledge-based jobs, (b) higher quality of internet and telecommunications infrastructure, (c) greater demand for flexible work arrangements to alleviate peak-hour traffic congestion, and (d) higher density of delivery services and concentration of consumers (Dannenberg et al., 2020; Asmussen et al., 2024a). Expanding high-speed internet access, including through traditional broadband services as well as cellular and satellite networks, and providing greater access to technological resources and public working spaces will help the growth of virtual participation in rural areas. In terms of home deliveries, there is a growing need to ensure that rural areas are provided with adequate coverage and service quality, and at affordable prices (note from Table 3 that "not affordable" is a common PPD reason in rural areas). This includes maintaining local and regional delivery hubs that serve as locations to collect and dispatch deliveries to rural areas. In addition, collaboration with local businesses (in a community-centered approach that is customizable to the needs of local residents) is especially important in lower-density areas; local businesses can serve as pick-up and drop-off points for deliveries, can assist in last-mile delivery, and can provide reliable and cost-effective service fulfillment by minimizing shipping distances and costs (Sousa et al., 2020; Wu et al., 2022).

In addition to geographic disparities, demographic disparities in virtual participation exist based on income and race; virtual participation is less common among individuals from low-income households and racial minorities, population groups that already face high PPD. Telework promotion strategies among these population segments can include diverse hiring initiatives and financial assistance to cover upfront telework-related expenses such as internet bills, utility costs, and office supplies. For deliveries, hubs located near underserved communities to increase reliability and reduce costs, as well as the provision of access to a full range of products through online ordering platforms, can be beneficial. In contrast, today, many food and grocery delivery platforms customize their delivery options (in both the variety of the product line and the time/cost of delivery) based on profit-maximizing margins, essentially exacerbating existing disparities in physical accessibility. Fairness considerations need to be brought to the fore, through government incentives for businesses in underserved markets and the creation of shared delivery hubs to improve the affordability of delivery services (see Haider et al., 2022; Buettner et al., 2023).

These findings also highlight that efforts to expand the reach of delivery services should be carefully balanced with the ways that these services may change the availability of physical services. If the growth of delivery services reduces the availability of physical stores, then overall levels of PPD may rise (Gauri et al., 2021; Tong et al., 2025). This also aligns with our findings that individuals living in areas with higher levels of road network density, walkability, and transit accessibility get fewer deliveries, but the effects on PPD due to deliveries are relatively small compared with the direct effects of these physical accessibility changes. Thus, if an expansion of access to delivery services resulted in a loss of access to physical shopping locations, the total impact would likely cause an increase in overall PPD. Conversely, if expanded access to delivery services incorporated support for local businesses or investment by online retailers in physical store locations (see Gauri et al., 2021) to prevent any reduction in physical accessibility, then an expansion of delivery services would likely help to reduce overall PPD. Given these results, a focus on maintaining and improving physical accessibility, even with growth in virtual activity participation, is critical for reducing PPD, as discussed next.

5.5 How Can Physical Infrastructure Improvement Reduce PPD?

While virtual participation can play an important role in reducing PPD, it is (as of yet) not doing much for those in low-income, renting, and rural-residing households, as well as for racial minorities and non-drivers. In addition, as mentioned above, the direct effects of walkability and transit accessibility on PPD seem to significantly outweigh any effects through virtual activity participation, suggesting that physical neighborhood characteristics are key in experience of PPD. Many of these population groups cite "not reliable" and "poor destination access" as PPD reasons (see Table 3), which underscores the need not to lose sight of more traditional physical infrastructure improvements to alleviate PPD. Some specific strategies include expanding access to public transportation by (a) designing routes that connect low-income residential areas to key points of interest (including employment centers, educational institutions, healthcare facilities, grocery stores, and recreational facilities), (b) improving last-mile connectivity both through the use of bike-sharing and scooter programs and good provision of sidewalks/bike lanes, and (c) provision of reliable public transportation services by establishing dedicated bus lanes, increasing frequency during peak hours, and implementing real-time tracking systems so that users can efficiently navigate schedules and delays (see, for example, Al-Hawari et al., 2020; Beale et al., 2023). The fact that individuals in areas with better transit access report higher levels of PPD indicates that transit services should continue to be improved to reduce PPD. Given that PPD represents the gap between the expected level of access to physical participation and the actual level of accessibility achieved, the high PPD among those who are more reliant on transit indicates that there is a continued mismatch between expectations about accessibility provided by transit and actual transit outcomes. As mentioned above, improving transit reliability and better aligning transit routes with the needs of riders are important ways to reduce this gap. Affordability is another common concern for rural-residing residents as well as renters and low-income individuals. Providing discounted or free public transportation ridership, partnering with ride-sharing companies to offer subsidized rides, and implementing income-based fare structures may all be effective ways of addressing affordability concerns. Additionally, investing in demand-responsive transit may be effective in rural areas as it can offer a cost-effective and flexible transportation alternative in areas without enough demand to support fixed-route public transportation (Vansteenwegen et al., 2022). In addition to expanding and improving transit accessibility, improving pedestrian accessibility and neighborhood walkability is an important step towards reducing PPD. We find that individuals in more walkable neighborhoods have significantly reduced PPD, and improving pedestrian access can be particularly beneficial at addressing safety and affordability concerns expressed by these groups with high PPD. Specific steps include developing mixed-use neighborhood that put stores and services at walkable distances relative to homes and apartments (as well as workplaces), expanding footpath connectivity, ensuring that signalized intersections are equipped with accessible pedestrian signals and that crossing times are sufficient for those with low mobility, and ensuring that walking paths are safe, separated from traffic, and provide a pleasant walking experience (see Cerin et al., 2020; De Vos et al., 2023). Prioritizing these types of physical transportation infrastructure improvements is particularly important given the substantial direct PPD effect for these population groups, as evidenced in Table 5.

6. CONCLUSIONS

In the current study, using data from the 2022 National Household Travel Survey, we investigate the dissonance that exists between how much individuals would like to participate in in-person OH activities and how much they are actually able to (PPD), as well as the extent to which virtual participation can alleviate this dissonance. Our results reveal that low-income individuals, racial minorities, older individuals, those without driver's licenses, and individuals with medical conditions (that limit their ability to travel) are more likely to experience PPD than their peers. We also find significant heterogeneity in the PPD reasons across different population groups; low-income individuals and racial minorities tend to attribute PPD to infrastructure-related factors (such as "poor destination access," "not reliable," and "not affordable"), while older individuals and those with medical conditions tend to attribute dissonance to health problems and COVID concerns. Finally, virtual participation appears to help reduce PPD for those with medical conditions, women, older adults, and vehicle-constrained households, but not for those living in rural areas, low-income individuals, and racial minorities. These results have important implications, suggesting a growing need to incorporate both physical and virtual participation modalities into measures of accessibility and activity-based travel demand modeling. In terms of employment accessibility, telework has significantly changed the need for physical access, potentially expanding the reach of many people with limited mobility. Similarly, delivery services should be carefully considered when evaluating access to healthy food, as these services may provide a greater range of options than individuals can access on their own. At the same time, however, we find that some existing disparities in physical accessibility are replicated and exacerbated by disparities in virtual accessibility, highlighting the need to carefully consider the interplay between physical and virtual participation from an overall accessibility as well as fairness standpoint.

As with any research, there are several avenues to extend this research. While we provide evidence of the potential of virtual participation to reduce PPD from an activity accessibility standpoint, we have not examined the broader social aspects of the two different activity participation channels. For instance, delivery services may provide better access to healthy food, but obviously do not provide the same level of social interactions that are possible at the neighborhood grocery store. There is a need to consider activity participation at this broader level of fulfilment, satisfaction, and quality of life, beyond simply subjective perceptions of access to activity opportunities afforded by the transportation system. Further, while we examine the extent of participation in virtual activities here, a broader and more comprehensive examination of the barriers to virtual participation (including, for example, the feasibility of telework), and the discord between expected and actual uptake of virtual activities (that is, a measure of virtual participation dissonance in parallel to PPD as studied in the current paper) would be valuable. Future studies also can expand the consideration of virtual participation to include other online activities such as telemedicine and telesocial activities. Further, consistent with an activity-based travel modeling approach, future data collection should focus on OH activities and not trips and should be more specific regarding suppression of OH activities that were expressly desired to be participated in (and not just planned). In doing so, it would be valuable to collect the measure of suppressed desired OH activities not simply as a singular binary variable, but disaggregated by activity purpose, along with an expanded set of activity purpose-specific reasons for not being able to participate in desired OH activities. In this regard, a customized and specialized data collection effort should be able to provide an improved database to more rigorously study the relationship between PPD (as we have defined it) and PPD reasons, as well as the effects of virtual participation on PPD/PPD reasons. Of course, as we go into more specific measures for capturing PPD, one needs to also consider the time frame for capturing PPD, as discussed in Section 3.1.1. Finally, future research can consider a more complete range of built environment factors as well as other variables, such as attitudes toward technology, different facets of employment arrangements, frequency and quality of internet access, and the availability and quality of delivery services. In summary, the rich and nuanced interplay between physical and virtual participation within the context of different types of activity participation needs and desires offers a range of future research opportunities, especially at a time of rapid technological development.

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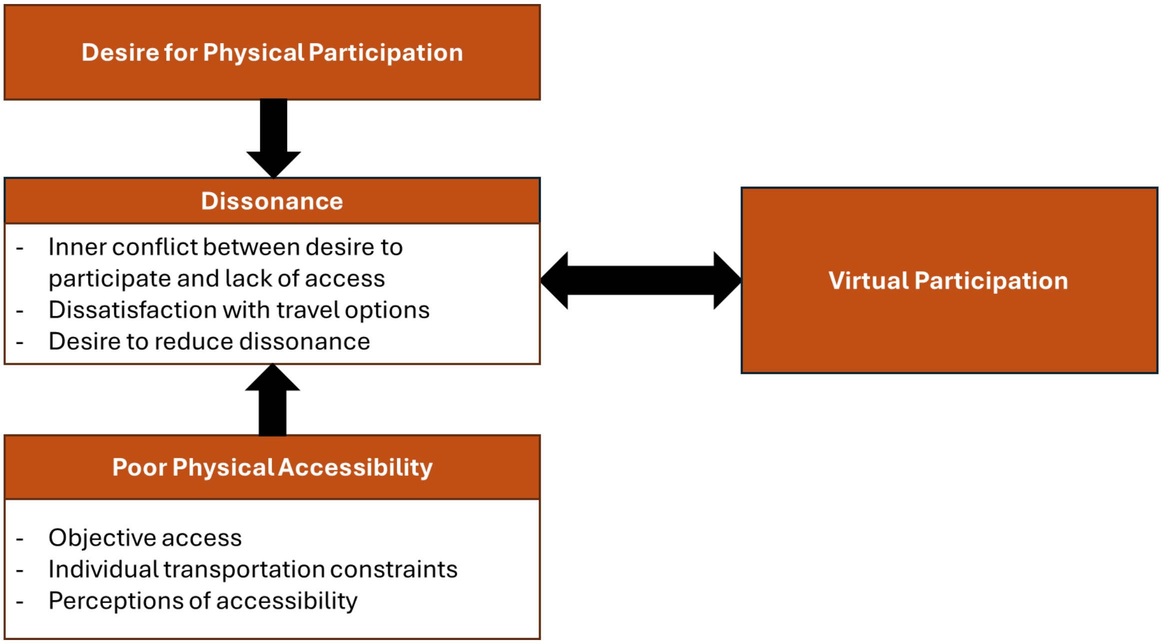

Figure 1 Framework of Physical Participation Dissonance (PPD)

Table 1 Descriptive Statistics of Outcomes

Physical Participation Dissonance (PPD)	Number	Percent
Suppressed trips in the last 30 days	2553	20.5
No suppressed trips in the last 30 days	9916	79.5
PPD Reasons	**Times Selected**	**Percent**
Transportation did not feel safe	169	6.6
Transportation did not feel clean or healthy	109	4.3
Transportation was not reliable	234	9.2
Available transportation did not go where I need to go	199	7.8
Unable to afford available forms of transportation	482	18.9
Had health problems and unable to travel	732	28.7
Did not have time to travel	643	25.2
Concerns related to COVID-19	1028	40.3
Virtual Participation	**Number**	**Percent**
Work from home		
NA (unemployed or retired)	5693	45.7
0 days per week	3821	30.6
1 – 2 days per week	961	7.7
3 – 4 days per week	536	4.3
5 or more days per week	1458	11.7
Number of deliveries in the last 30 days		
0	3125	25.1
1 – 5	5245	42.1
6 – 10	2323	18.6
More than 10	1776	14.2

Table 2 Descriptive Statistics of Exogenous Variables

Variable	% in Sample	% in Census	Variable	% in Sample	% in Census
Household Location					
Census division of household residence			**Road network density**		
New England	5.9	4.6	0 – 9 link-miles per square mile	40.0	
Middle Atlantic	11.8	12.8	10 – 19 link-miles per square mile	32.2	
East North Central	16.0	14.3	20 or more link-miles per square mile	27.8	
West North Central	7.2	6.5	**Employment density**		
South Atlantic	19.9	19.9	0 – 999 workers per square mile	47.1	--
East South Central	5.6	5.9	1,000 – 1,999 workers per square mile	19.1	--
West South Central	11.1	12.3	2,000 or more workers per square mile	33.8	--
Mountain	7.8	7.5	**Walkability**		
Pacific	14.7	16.2	Low walkability	61.5	--
Household location type			High walkability	38.5	--
Rural	28.5	21.2	**Transit accessibility**		
Urban	71.5	78.8	Low transit accessibility	85.2	--
			High transit accessibility	14.8	--
Household Demographics					
Household composition			**Household income**		
One adult, no children	14.7	27.6	Less than $50,000	24.4	33.8
Two or more adults, no children	52.9	42.0	$50,000 – $99,999	31.6	28.9
Single parent	3.2	6.8	$100,000 – $149,999	22.0	17.1
Two or more adults with children	29.2	23.6	$150,000 – $199,999	9.2	8.8
Number of workers			$200,000 or more	12.8	11.4
0	28.8	--	**Vehicles per driver**		
1	31.1	--	More vehicles than drivers	15.6	--
2	31.9	--	Equal vehicles and drivers	64.5	--
3 or more	8.2	--	Fewer vehicles than drivers	19.9	--
Household ownership					
Own	78.4	63.1			
Rent	21.6	36.9			
Individual Characteristics					
Gender			**Race**		
Male	48.7	49.1	White	83.5	61.6
Female	51.3	50.9	Black	6.9	12.4
Age			Asian	5.8	6.0
18 – 25	9.9	12.0	Other	3.8	20.0
25 – 34	14.3	17.4	**Ethnicity**		
35 – 44	14.8	16.4	Not Hispanic	90.9	81.3
45 – 54	14.0	15.8	Hispanic	9.1	18.7
55 – 64	18.0	16.8	**Education**		
65 or older	29.0	21.6	Less than high school diploma	6.8	19.6
Employment			High school diploma	15.4	28.6
Unemployed (and not retired)	19.0	21.9	Some college	28.8	27.4
Retired	26.7	18.4	Bachelor's degree	27.9	15.5
Employed	54.3	59.7	Graduate degree	21.1	8.9
Medical condition that makes travel difficult			**Driver status**		
Yes	8.5	--	Driver	90.7	--
No	91.5	--	Non-driver	9.3	--

Table 3 Main Estimation Results (1/3)

Thresholds/Variables (base)	PPD		PPD Reasons																Virtual Participation			
			Not Safe		Not Clean		Not Reliable		Poor Destination Access		Not Affordable		Health Problems		No Time		COVID Concerns		Telework		Deliveries	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Thresholds																						
Threshold 0|1	0.86	8.77	1.88	18.96	2.18	15.82	1.15	10.54	1.15	4.53	0.52	5.45	1.28	6.44	0.59	2.72	0.97	10.07	1.10	11.92	0.16	2.34
Threshold 1|2	--		--		--		--		--		--		--		--		--		1.53	16.64	1.38	20.00
Threshold 2|3	--		--		--		--		--		--		--		--		--		1.80	19.51	2.06	29.62
Household Location																						
Census Division (New England)																						
Middle Atlantic	-0.15	-3.01	--		--		--		--		--		0.26	2.43	0.20	1.90	0.36	3.78	--		--	
East North Central	-0.21	-4.49	--		--		--		0.18	1.59	0.37	3.99	0.15	1.54	--		0.20	2.24	--		--	
West North Central	-0.28	-4.66	--		--		--		--		--		0.28	2.22	0.32	3.44	--		--		-0.09	-2.16
South Atlantic	-0.21	-4.80	--		--		--		0.17	1.59	0.21	2.43	--		0.22	1.62	0.15	1.86	--		0.05	1.99
East South Central	-0.21	-3.21	--		--		--		--		--		0.27	2.07	0.33	3.02	--		-0.14	-2.14	-0.10	-2.33
West South Central	-0.24	-4.72	--		--		--		--		--		0.25	2.34	0.25	1.97	--		-0.08	-1.70	-0.07	-2.26
Mountain	-0.15	-2.61	--		--		--		--		--		--		0.23	2.22	0.18	1.68	0.14	2.44	--	
Pacific	--		--		--		--		0.16	1.36	--		0.14	1.44	0.32	3.44	0.42	4.84	--		--	
Household Location Type (Urban)																						
Rural	0.05	1.70	-0.22	-1.91	-0.27	-1.85	--		--		0.11	1.65	-0.14	-2.00	--		--		-0.18	-5.10	-0.09	-3.00
Road Network Density (0 – 9)																						
10 – 19	--		--		--		--		--		--		--		--		--		--		-0.07	-1.81
20 or more	--		--		--		--		--		--		--		--		--		--		-0.12	-2.19
Employment Density (0 – 999)																						
1,000 – 1,999	--		--		--		--		--		--		--		--		--		--		0.07	1.77
2,000 or more	--		0.24	2.26	0.39	3.36	--		0.14	1.58	--		--		0.17	2.11	--		--		0.12	2.26
Walkability (Low)																						
High	-0.08	-2.36	-0.27	-2.41	--		0.16	1.97	--		--		--		-0.16	-2.07	--		--		-0.08	-1.86
Transit Accessibility (Low)																						
High	0.08	1.82	0.24	1.89	--		--		--		--		-0.17	-1.77	--		--		--		-0.07	-1.67
Household Demographics																						
Composition																						
Single adult (2+ adults)	0.11	3.13	--		--		--		0.22	2.25	--		--		--		-0.13	-2.10	0.09	2.26	--	
Presence of children (≤17 yrs)	--		--		--		-0.13	-1.32	-0.19	-1.86	0.14	1.96	--		--		--		-0.10	-3.03	0.07	2.83
Number of Workers (0 workers)																						
1 worker	--		--		--		--		--		--		--		--		--		--		-0.09	-2.69
2 workers	--		--		--		--		0.32	2.95	--		--		--		--		--		-0.28	-6.64
3+ workers	--		--		--		0.23	1.50	0.32	2.95	--		--		--		--		--		-0.46	-8.62

Table 3 Main Estimation Results (cont. 2/3)

Thresholds/Variables (base)	PPD		PPD Reasons																Virtual Participation			
			Not Safe		Not Clean		Not Reliable		Poor Destination Access		Not Affordable		Health Problems		No Time		COVID Concerns		Telework		Deliveries	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Vehicles per Driver (Fewer)																						
Equal vehicles and drivers	-0.06	-1.66	--		--		--		-0.16	-1.60	--		--		--		--		-0.37	-8.21	0.09	3.33
More vehicles than drivers	-0.10	-2.08	-0.17	-1.40	--		--		-0.18	-1.38	--		--		--		-0.09	-1.30	-0.48	-8.87	0.18	5.33
Household Income (< $50,000)																						
$50,000 - $99,999	-0.19	-4.98	--		--		-0.29	-3.05	-0.24	-1.59	-0.29	-3.73	--		--		--		0.10	2.03	0.22	7.52
$100,000 - $149,999	-0.33	-7.34	--		--		-0.39	-3.09	-0.28	-2.43	-0.39	-3.98	0.15	1.79	--		--		0.27	5.23	0.30	8.97
$150,000 - $199,999	-0.37	-5.93	--		--		-0.49	-3.51	-0.28	-2.43	-0.65	-3.90	0.16	1.70	--		--		0.44	7.23	0.43	10.08
$200,000+	-0.39	-6.49	--		--		-0.49	-3.51	-0.28	-2.43	-0.78	-4.62	0.16	1.70	--		--		0.51	8.57	0.53	13.34
Home Ownership (Own home)																						
Rent	0.09	2.49	0.22	2.45	--		0.24	2.66	0.26	2.73	0.20	2.63	--		-0.16	-2.09	--		--		--	
Individual Characteristics																						
Gender (Male)																						
Female	0.10	3.63	--		--		--		--		-0.11	-1.75	0.13	2.03	--		0.09	1.70	--		0.26	13.05
Age (18-24)																						
25-34	0.20	3.17	--		--		--		--		--		0.32	1.88	-0.19	-1.50	--		0.43	6.26	--	
35-44	0.23	4.17	--		--		--		--		--		0.43	2.68	-0.19	-1.50	--		0.51	8.07	--	
45-54	0.23	4.17	--		--		--		--		--		0.43	2.68	-0.32	-2.26	0.17	1.99	0.51	8.07	--	
55-64	0.23	4.17	--		--		-0.33	-2.97	--		--		0.43	2.68	-0.45	-3.35	0.30	3.86	0.51	8.07	-0.10	-3.48
65+	0.23	4.17	--		--		-0.33	-2.97	--		--		0.51	2.85	-0.45	-3.35	0.56	7.82	0.59	7.68	-0.23	-6.11
Employment Status (Employed)																						
Retired	--		--		-0.36	-2.96	-0.20	-1.60	--		-0.38	-4.86	0.34	3.78	-0.60	-4.29	--		--		-0.31	-7.16
Unemployed	--		--		--		--		--		--		--		-0.34	-2.70	--		--		-0.46	-13.68
Race (White)																						
Black	0.26	4.91	--		--		0.36	3.20	0.26	1.97	--		-0.25	-2.22	--		0.35	3.82	--		-0.15	-3.66
Asian	0.20	3.42	--		--		0.21	1.49	0.50	3.47	-0.30	-1.93	--		--		0.36	3.31	--		-0.25	-5.67
Other	0.15	2.24	0.51	3.74	0.35	2.21	0.24	1.51	0.29	1.60	-0.31	-1.91	--		--		--		--		-0.23	-4.28
Education (No diploma)																						
High school diploma	0.14	2.16	--		--		--		--		--		-0.19	-1.34	--		--		--		0.44	9.34
Some college	0.24	3.81	--		--		--		--		--		-0.21	-1.41	0.29	2.92	--		0.37	7.54	0.83	18.66
Bachelor's degree	0.24	3.81	--		0.17	1.70	--		--		--		-0.23	-1.65	0.29	2.92	0.16	2.79	0.74	15.42	0.97	20.89
Graduate degree	0.34	4.72	--		0.17	1.70	--		--		-0.19	-2.04	-0.24	-1.76	0.29	2.92	0.16	2.79	0.74	15.42	1.06	21.56
Driver Status (Driver)																						
Not a driver	0.18	3.80	--		--		--		--		--		-0.23	-2.12	0.35	2.82	--		--		--	
Medical Condition (No)																						
Yes	0.66	14.37	--		--		--		--		--		1.25	15.67	-0.41	-3.93	--		0.45	4.87	0.07	1.93

Table 3 Main Estimation Results (cont. 3/3)

Thresholds/Variables (base)	PPD		PPD Reasons																Virtual Participation			
			Not Safe		Not Clean		Not Reliable		Poor Destination Access		Not Affordable		Health Problems		No Time		COVID Concerns		Telework		Deliveries	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Endogenous Effects																						
Telework (none)																						
1 – 2 days per week	-0.10	-1.96	--		--		--		--		--		--		-0.17	-2.09	--		--		--	
3 – 4 days per week	-0.18	-3.07	--		--		--		-0.21	-1.89	--		--		-0.24	-2.51	--		--		--	
5 or more days per week	-0.18	-3.07	--		--		--		-0.23	-1.81	--		--		-0.28	-2.00	--		--		--	
Deliveries (none)																						
1 – 5	--		--		--		--		-0.18	-1.58	--		--		-0.14	-1.99	--		--		--	
6 – 10	-0.30	-6.40	--		--		--		-0.23	-1.29	--		--		-0.18	-1.49	--		--		--	
More than 10	-0.35	-4.99	--		--		--		-0.38	-1.49	--		--		-0.24	-1.32	--		--		--	
Correlations																						
PPD	1.00	--	--		--		--		--		--		--		--		--		--		--	
Not Safe	0.00	--	1.00	--	--		--		--		--		--		--		--		--		--	
Not Clean	0.00	--	0.58	6.51	1.00	--	--		--		--		--		--		--		--		--	
Not Reliable	0.00	--	0.26	2.94	0.31	2.18	1.00	--	--		--		--		--		--		--		--	
Poor Destination Access	0.00	--	0.14	1.87	0.29	2.13	0.33	3.66	1.00	--	--		--		--		--		--		--	
Not Affordable	0.00	--	0.00	--	0.00	--	0.12	1.99	0.17	2.85	1.00	--	--		--		--		--		--	
Health Problems	0.00	--	-0.36	-3.25	0.00	--	0.00	--	0.00	--	0.00	--	1.00	--	--		--		--		--	
No Time	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	1.00	--	--		--		--	
COVID Concerns	0.00	--	0.17	1.42	0.28	2.55	0.00	--	0.00	--	0.00	--	0.00	--	-0.23	-1.91	1.00	--	--		--	
Telework	0.17	3.59	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.21	2.51	1.00	--	--	
Deliveries	0.13	3.73	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.00	--	0.18	3.15	1.00	--

Table 4 Model Fit

Disaggregate Fit Measures		
Metric	**Proposed Model**	**Independent Model**
Log-Likelihood at Convergence	-35898.38	-36127.81
Log-Likelihood at Constants	-39260.02	-39260.02
Number of Parameters	233	217
Adjusted Likelihood Ratio Index	0.080	0.075
Bayesian Information Criterion	36375.54	36572.20
Average Probability of a Correct Prediction	0.169	0.165
Likelihood Ratio Test	458.86	

Aggregate Fit Measures								
Outcome Combinations			**Observed**		**Proposed Model**		**Independent Model**	
Suppressed Trips	Telework Frequency	Delivery Frequency	Count	Share (%)	Share (%)	APE	Share (%)	APE
No	N/A	0	1476	11.84	11.96	1.01	11.69	1.23
No	N/A	1-5	1788	14.34	14.21	0.89	14.96	4.40
No	N/A	6-10	648	5.20	5.00	3.75	5.37	3.33
No	N/A	More than 10	434	3.48	2.98	14.32	3.46	0.39
No	0 days	0	783	6.28	6.62	5.45	5.26	16.31
No	0 days	1-5	1405	11.27	11.22	0.43	10.42	7.49
No	0 days	6-10	602	4.83	4.84	0.31	5.07	4.96
No	0 days	More than 10	438	3.51	3.39	3.54	4.41	25.44
No	1-2 days	0	86	0.69	1.05	52.14	1.01	46.72
No	1-2 days	1-5	307	2.46	2.63	6.81	2.42	1.91
No	1-2 days	6-10	212	1.70	1.44	15.31	1.31	23.16
No	1-2 days	More than 10	182	1.46	1.24	15.14	1.24	15.27
No	3-4 days	0	40	0.32	0.48	48.45	0.56	74.30
No	3-4 days	1-5	182	1.46	1.32	9.79	1.39	4.43
No	3-4 days	6-10	88	0.71	0.77	9.14	0.77	9.53
No	3-4 days	More than 10	103	0.83	0.71	14.32	0.75	9.69
No	5+ days	0	139	1.11	0.98	12.18	1.39	24.52
No	5+ days	1-5	469	3.76	3.22	14.33	3.74	0.49
No	5+ days	6-10	273	2.19	2.14	2.34	2.16	1.23
No	5+ days	More than 10	261	2.09	2.26	8.04	2.16	3.15
Yes	N/A	0	426	3.42	3.34	2.38	3.50	2.58
Yes	N/A	1-5	561	4.50	4.89	8.76	4.29	4.70
Yes	N/A	6-10	225	1.80	1.96	8.63	1.47	18.72
Yes	N/A	More than 10	135	1.08	1.32	21.51	0.90	16.90
Yes	0 days	0	127	1.02	1.06	4.35	1.27	24.67
Yes	0 days	1-5	261	2.09	2.10	0.33	2.44	16.37
Yes	0 days	6-10	119	0.95	1.01	6.11	1.16	21.39
Yes	0 days	More than 10	86	0.69	0.79	15.09	0.99	42.84
Yes	1-2 days	0	16	0.13	0.22	73.19	0.25	96.50
Yes	1-2 days	1-5	83	0.67	0.61	7.77	0.57	14.01
Yes	1-2 days	6-10	40	0.32	0.37	14.21	0.30	6.39
Yes	1-2 days	More than 10	35	0.28	0.35	24.53	0.28	1.51
Yes	3-4 days	0	6	0.05	0.11	124.28	0.14	190.91
Yes	3-4 days	1-5	54	0.43	0.33	24.20	0.33	23.53
Yes	3-4 days	6-10	37	0.30	0.21	29.49	0.18	40.08
Yes	3-4 days	More than 10	26	0.21	0.21	2.49	0.17	20.02
Yes	5+ days	0	26	0.21	0.25	21.07	0.35	68.04
Yes	5+ days	1-5	135	1.08	0.92	14.57	0.89	17.52
Yes	5+ days	6-10	79	0.63	0.68	6.58	0.50	21.16
Yes	5+ days	More than 10	76	0.61	0.81	32.58	0.48	20.43
Weighted Average Percent Error (WAPE)					**5.89**		**8.89**	

Table 5 Average Treatment Effects (ATEs)

Variable	Base Level	Treatment Level	Telework ATE	Monthly Deliveries ATE	PPD ATE: Percent Contribution Through Telework	PPD ATE: Percent Contribution Through Deliveries	PPD ATE: Percent Direct Effect	PPD ATE: Total ATE
Household Location								
Household Location Type	Urban	Rural	-0.31	-0.28	14	12	74	1.98
Road Network Density	0 – 9	20 or more	0.00	-0.39	0	100	0	0.34
Employment Density	2,000 or more	0 – 999	0.00	-0.39	0	100	0	0.33
Walkability	High	Low	0.00	0.27	0	-9	91	2.01
Transit Accessibility	Low	High	0.00	-0.23	0	8	92	2.35
Household Demographics								
Number of Adults	Two or More	Single Adult	0.17	0.00	-4	0	96	3.04
Presence of Children	No Children	Children	-0.17	0.23	57	-43	0	0.05
Number of Workers	No Workers	3+ Workers	0.00	-1.44	0	100	0	1.21
Vehicle Ownership	More Vehicles than Drivers	Fewer Vehicles than Drivers	0.88	-0.60	-19	13	68	2.53
Income	$200,000+	< $50,000	-0.92	-1.75	6	11	83	13.14
Home Ownership	Owner	Renter	0.00	0.00	0	0	100	2.49
Individual Characteristics								
Gender	Male	Female	0.00	0.86	0	-21	79	1.97
Age	18-24	65 or Older	0.93	-0.74	-12	9	79	5.57
Employment	Employed	Retired	0.00	-1.02	0	100	0	0.88
Employment	Employed	Unemployed	0.00	-1.48	0	100	0	1.25
Race	White	Black	0.00	-0.47	0	5	95	7.87
Race	White	Asian	0.00	-0.80	0	11	89	6.35
Race	White	Other	0.00	-0.73	0	13	87	4.83
Educational Attainment	No Diploma	Graduate Degree	1.25	3.08	-9	-20	71	5.05
Driver Status	Driver	Non-Driver	0.00	0.00	0	0	100	4.62
Medical Condition	No Medical Condition	Medical Condition	0.85	0.23	-3	-1	96	20.77
Endogenous Effects								
Telework	5+ Days per Week	None	--	--	--	--	100	4.72
Deliveries	More than 10	None	--	--	--	--	100	8.98