Telework-to-Play or Play-to-Telework? Investigating the Directional Relationship Between Telework and Nonwork Travel

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ABSTRACT:
This study explores the intricate interrelationship between teleworking and weekly participation in two types of nonwork activities – maintenance episodes and leisure episodes. We employ a latent segmentation model to categorize the population into two segments: (1) those for whom nonwork activity participation influences telework frequency ("players"), and (2) those for whom telework frequency impacts nonwork activity participation ("workers"). Within each segment, to reduce any spurious association effects, we model teleworking and nonwork stop-making as a package by accommodating correlations in unobserved factors across the outcomes. The data for this analysis is drawn from a 2021-2022 weekly travel survey of Minnesotan workers in the Twin City region. The results reveal significant heterogeneity in the causal directionality of effect, with nonwork activity participation influencing telework intensity levels for about two-thirds of individuals (the "player" or NT segment), and telework levels influencing nonwork activity participation for the rest (the "worker" or TN segment). This result is in contrast to earlier studies that have predominantly assumed that all individuals belong to the TN or "worker" segment, which according to our analysis, is actually the case only for a minority of the population. Our analysis also indicates that, rather than asking the typical question of "does telework increase or decrease stop-making?", the more pertinent question is "how does the number of nonwork stops relate to the intensity of teleworking?". Our findings reveal an inverted U-shaped curve, with the highest number of nonstops occurring when individuals telework a few days a month or about one day per week. This, combined with the finding from the Asmussen et al. (2024a) study, indicates that low levels of teleworking (a day per week or less) actually increases both commute vehicle miles traveled (VMT) and nonwork VMT. Therefore, to achieve VMT reduction through teleworking, promoting moderate to high levels of telework appears important.

Keywords: Telework, maintenance travel, leisure travel, causal relationship, latent segments

1. INTRODUCTION

Technology has evolved at a tremendous pace over the past decade, permeating into our everyday existence and affecting literally every aspect of our lives. Our activity-travel choices have been no exception in this regard, as we make continuous and joint decisions about which activities we can and want to undertake (either in-person or virtually). Add to this the pandemic's upheaval of habits and behaviors, and there emerges a critical and renewed need to understand the activity-travel choices and decisions of individuals within a new landscape of transportation, technology, and pandemic-altered lifestyles.

Among the activity-travel changes brought on by the confluence of technology and the pandemic is a reshaping of telework activity. To be sure, advances in communication technology did facilitate telework even before the pandemic, but it was the telework experience of workers during the lockdown period at the height of the pandemic, combined with a surge in ubiquitous broadband communication technologies within homes and other non-office spaces during that period, that led to a dramatic telework shift. For example, in the United States, only six percent of workers primarily worked from a remote location (home or other) before the pandemic, while about three-quarters had never worked from a remote location (Coate, 2021).[1] This telework percentage reached its peak in 2020-2021 (Coate, 2021; Saad and Wigert, 2021), and has since fallen because of a combination of the ability to control the pandemic spread and renewed calls from many employers to return to the in-person workplace. Nonetheless, rates of never teleworking remain under 40%, with a sizeable percentage of the U.S. workforce having a hybrid work location arrangement (Flynn, 2023).

Not surprisingly, then, many post-COVID studies have examined the hybridization of the work location (we use the label "post-COVID" here to refer to the period after the wide availability of vaccinations in the U.S., which would be after Summer 2021).[2] This is not surprising because of the potential of telework to reduce morning and afternoon peak period traffic congestion, given that work travel, for many individuals, tends to have a regular weekday rhythm with a morning start at about 8 am and an evening return at about 5 pm. However, the confluence of technological and pandemic-caused shifts in activity-travel behavior has not been confined to work activity; it has had much broader impacts on nonwork activity pursuits too. In particular, the opportunity to pursue activities virtually and conveniently (rather than only in-person), along with businesses realizing the market potential opened up by virtual participations, has led to substantial impacts on nonwork in-person activity participations, including maintenance activities (such as grocery shopping, personal business, and medical appointments) and leisure activities (social-recreational pursuits, non-grocery shopping episodes, and dining experiences) (Murray, 2022). For example, focusing just on non-grocery shopping episodes, prior to the COVID-19 pandemic, the average person in the U.S. embarked on 0.84 trips per day. However, following the pandemic, this figure declined to 0.49 trips per day (Federal Highway Administration, 2017; Federal Highway Administration, 2022). Of course, some studies have also brought out the point that virtual (including telework) and in-person pursuits for nonwork activities are blending seamlessly in time

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

[2]According to CDC data, by July 4, 2021, approximately 67% of U.S. adults had received at least one dose of a COVID-19 vaccine (Nawas et al., 2022). By the end of that year, the percentage went up marginally to 73.3% of the total U.S. population (Nawas et al., 2022). These numbers reflect widespread national vaccine availability by the summer of 2021, even if a non-insignificant percentage of the U.S. population consciously decided not to get vaccinated.

and space in an increasingly e-commerce driven world (see Dias et al., 2020; Lavieri et al., 2018). These studies suggest that the package nature of decisions may be such that in-person outside-of-home nonwork pursuits may rise together with the increasing ubiquitousness of virtual participations, with the pandemic only appearing to have accelerated such tendencies. Interestingly, despite such potential disruptive changes in nonwork activity behavior, the post-COVID literature on nonwork activity participations has been relatively scant compared to the post-COVID literature on work activity participations.

In addition to the relatively less attention on post-COVID nonwork activity research, it is noteworthy that even the few studies that examine nonwork activity participations in the new landscape assume that telework influences nonwork activity participations through a strict one-directional causal pathway (see, for example, Haddad et al., 2023; Huang et al., 2023). One argument for such a pathway is that telework releases the time spent commuting and also leads to cost-savings, which can then potentially be appropriated for additional outside-of-home in-person (OHIP) maintenance and leisure activity episodes that may have been more difficult to schedule/undertake when commuting (Caldarola and Sorrell, 2022, Obeid et al., 2022, Huang et al., 2023). However, the relationship between telework and nonwork OHIP activity participation may be much more nuanced, because individuals who already partake (or desire to partake) in a high intensity of OHIP maintenance and leisure activities may consciously choose to telework more to facilitate their chosen (or desired) high outside-of-home activity intensity lifestyle (Lila and Anjaneyulu, 2013). This raises the question of the causal direction of effect: is telework the driver (or at least the facilitator) of more nonwork activity participation (which we refer to as the telework-to-play causal direction); or is telework the result of a desire for more nonwork activity participation in the first place (which we refer to as the play-to-telework causal direction; also, in the rest of this paper, any reference to maintenance/leisure episodes or nonwork activity participation will be in the context of OHIP episodes). This causal direction issue, to our knowledge, has not even been adequately recognized in the telework-nonwork activity-travel literature, let alone examined (in contrast, the causality direction question has been raised in the context of the telework-commute travel relationship, and has been extensively studied in a recent paper by Asmussen et al., 2024a). If the causal effect is from telework to nonwork activity participation, this may imply that telework would increase nonwork travel episodes, and may even offset any reduction in commute travel to the point that there is an overall increase in total travel (in terms of number of trips/vehicle miles of travel). On the other hand, if the causal effect is from nonwork activity participation to telework, this would imply that telework itself has no effect on the amount of nonwork travel, such that it has an overall positive benefit in terms of reducing traffic. It is also possible that the first causal direction holds for some individuals, while the second for other individuals.

Of course, any consideration of causality must also first accommodate the possibility that any relationship between telework and nonwork activity participation is a pure association between the two due to unobserved individual personality and lifestyle factors. Especially when trying to extract out causal effects from cross-sectional data, ignoring the jointness of the telework and nonwork activity decisions can lead to biased estimates of the causal direction of effects and their magnitudes. For instance, those who are relatively introverted may choose to telework more and make a conscious decision to engage in less maintenance and leisure activities (this would be an example of a negative unobserved correlation between telework tendency and nonwork activity generation, due to the intrinsic introverted nature of an individual). If ignored, this would underestimate any positive effect of telework on nonwork activity participation (if that is the causal direction of effect) and would also underestimate any positive effect of nonwork activity participation on telework choice (if the causal direction of effect is from nonwork activity participation to telework). Or, those who are socially extroverted may be the ones taking advantage of telework opportunities and also choosing to consciously participate in more maintenance and leisure activities (this would be an example of a positive unobserved correlation between telework tendency and nonwork activity participation, due to the intrinsic extroverted nature of an individual). If ignored, this would overestimate the positive effect of telework on nonwork activity participation (if that is the causal direction of effect) and would also overestimate the positive effect of nonwork activity participation on telework choice (if that is the causal direction of effect). Thus, it is important to consider telework intensities and nonwork activity participation as a joint package impacted by unobserved individual personality and lifestyle characteristics, and then examine causal directionality effects.

Motivated by the discussion above, in this study, we explore the causal direction/jointness issue underlying the interplay of teleworking choice and nonwork activity participation, within the context of the transportation, technology, and work environment landscape in the aftermath of the pandemic. In particular, we model the telework frequency, maintenance episode frequency, and leisure episode frequency decision-making process as a multivariate package choice to account for unobserved factors, as well as use a latent segmentation approach to recognize the two possible and distinct causal behavioral directions that may be at play. Through the latent segmentation model we characterize the population into two segments: (1) those for whom telework frequency impacts nonwork activity participation, and (2) those for whom nonwork activity participation influences telework frequency. The methodology combines an ordinal choice model for telework adoption/intensity with weekly count models (based on a generalized ordered-response model reformulation of count models; see Bhat et al., 2015) for the number of maintenance and leisure episodes. The data for the analysis is drawn from a 2021-2022 weekly travel diary and survey of Minnesotan workers.

Figure 1 provides an organizational framework of the paper, mapping different study elements to sections in the paper. Section 2 presents a concise overview of the pertinent literature, contextualizing the current research within the broader scholarly landscape. Section 3 details the survey administration process, data preparation steps, and the analytic framework. Section 4 discusses the methodology for both the multivariate package choice model and the latent segmentation framework, while Section 5 discusses the results of model estimation (which is organized into a discussion of the multivariate model first, followed by the characteristics, size, and profiles of the latent segments) and goodness of fit measures. Section 6 translates the estimation results to an evaluation of the impacts of teleworking on nonwork activity episodes (with subgroup analyses by demographic characteristics) and identifies policy implications. Finally, Section 7 concludes the paper by providing a summary discussion and identifying future research directions and study limitations.

2. OVERVIEW OF EARLIER RELEVANT LITERATURE

2.1. General Overview

Even prior to the pandemic, there was a significant body of literature exploring the impact of telework on overall (combined work and nonwork) activity-travel or on work-related travel specifically (see, for example, Nilles, 1991; Balepur et al., 1998; Mokhtarian et al., 2004; Helminen and Ristimäki, 2007; Ettema, 2010; Fu et al., 2012; de Abreu e Silva and Melo, 2018; Shabanpour et al., 2018; and DeVos et al., 2019). This study of telework effects on activity-travel characteristics has further intensified in the aftermath of the pandemic, especially in the context of work-related travel (see, for example, Kim and Long, 2022; de Abreu e Silva, 2022; Tahlyan et al., 2022; please refer to Asmussen et al., 2024a for an extensive review of such studies). In this regard, there has been relatively limited research exploring the relationship between telework and nonwork-related activity-travel. Furthermore, no study that we are aware of (before or after the pandemic) has examined the potential heterogeneity across individuals in the causal relationship between telework and nonwork-related travel. That is, previous telework-nonwork activity studies either consider nonwork activity-travel as affecting the adoption/intensity of teleworking for all individuals, or consider teleworking as affecting the planning/engagement of nonwork activity-travel for all individuals. For brevity, in the remainder of this paper, we will refer to the first causal direction of effect as NT (nonwork activity-travel first, teleworking next) and the second causal direction of effect as TN (teleworking first, nonwork activity-travel next).[3]

NT Studies

Within the category of NT studies, we are aware of only one study – that by Lila and Anjaneyulu (2013). The basic premise is that individuals who participate in increased nonwork activity-travel tend to appreciate their leisure time and value the freedom to partake in enjoyable activities beyond their homes. Consequently, they are more inclined to embrace telework, as it aligns with their preference for a flexible lifestyle. Lila and Anjaneyulu (2013) employed a multinomial logit (MNL) model to analyze telework frequency of workers based on an activity-travel survey conducted in Bengaluru, India, in 2013. They identified four nominal categories to represent weekly teleworking intensity: "never", "low" for those telework only occasionally, "medium" for those teleworking once a week, and "high" for those teleworking two days or more per week. They subsequently introduced "participate in nonwork activities" of the individual on the survey day (a typical weekday) as a singular exogenous variable, encompassing activities such as shopping, drop/pickup tasks, religious events, medical appointments, social meetings, movie outings, park visits, dining outside, bank visits, post office errands, or payment of bills. While not precisely specified, it appears that the "participate in nonwork activities" variable was introduced as a single dummy variable (did the individual participate in a nonwork activity or not during the reported travel weekday) in the analysis. Their findings revealed that individuals who participate in nonwork activities on the reported travel weekday are most predisposed to partake in low and high levels of teleworking, followed by medium levels of teleworking (with "never" teleworking being the base category).

TN Studies

Within the large group of TN studies, one set of studies has aggregated all non-work travel purposes into a single category (see, for example, Kim et al., 2015, Cerqueira et al., 2020, Caldarola and Sorrell, 2022, Obeid et al., 2020, and Wöhner, 2022; Asmussen et al., 2024a provides an exhaustive review). The general consensus among these studies is that that higher teleworking intensity tends to lead to higher levels of nonwork travel (sometimes referred to as a rebound effect), with the exception of Caldarola and Sorrell, 2022 who reported an inverted U-shaped effect of teleworking intensity, with medium-frequency teleworkers making the most

[3]As discussed earlier, any consideration of causality must at least attempt to first control for associative effects. In the rest of this section, when we classify earlier studies under the TN or NT categories, we are doing so based on the causal direction assumed in the studies, although all but two of these earlier studies ignore possible associative effects when teasing out causality.

nonwork trips and traveling longer for nonwork relative to those who never telework and those with a high telework frequency. In the rest of this section, and more relevant to the current study, we focus on a second set of TN studies that have examined the effect of teleworking on different types of nonwork travel, rather than collapsing all nonwork activity-travel into a single category.

Stiles and Smart (2021), using a repeated cross-sectional sample of U.S. knowledge workers from the American Time Use Survey (ATUS) between 2003-2017, found that teleworking by an individual on a given day from home (relative to working from the office) decreases nonwork travel time for both maintenance activity (by 35%) and leisure activity (by 12%), while any combination of work locations that includes in-person office on the work day increases maintenance and leisure travel time. Their disaggregation of nonwork travel aligns closely with our study's focus. The emphasis on times rather than distances or trips is a consequence of the use of the ATUS data for analysis.

Shah et al. (2024) also undertook their analysis at an individual level, but focused on tours rather than trips. They classified tours by the primary activity of the tour as "mandatory" (for work, school, pick up/drop off), "maintenance" (such as grocery shopping, personal business, appointments, errands), and discretionary (such as entertainment, social, recreational, religious activities, and mall shopping). However, these purpose-specific tour level variables themselves were considered as continuous latent variables, and represented as being manifested through indicators of total number of trips in all tours of the specific purpose, total travel time across all tours of the specific purpose, and percent of chained VMT. Using 2019 data from the Puget Sound region, they found a negative direct effect of telework duration (in weekly minutes) on (weekly) maintenance tours and a positive direct effect on discretionary tours. Similar to the approach in the Stiles and Smart (2021) study and our own, Shah et al. categorized nonwork into the two distinct groups of maintenance and leisure.

Asgari et al. (2016) investigated, at an individual level, the impact of telework hours in the day on activity time allocation on the workday, focusing on durations of time spent on nonmandatory activities such as shopping, maintenance, and discretionary pursuits. Using the 2010–2011 Regional Household Travel Survey (RHTS) from New York, their findings revealed that in an 8-hour workday, full-day telecommuters extended their outside-of-home shopping duration by approximately 11.52 minutes compared to a full-time commuter. Similarly, the time spent in maintenance and discretionary activities increased by about 16 and 47 min, respectively. Along similar lines, Zhu (2012) employed a linear regression model to analyze the effect of teleworking on the frequency of various nonwork trip purposes on a weekday. Nonwork trip purposes considered included a relatively disaggregate classification into shopping trips, family/personal business trips, school/church trips, medical/dental trips, visits to family/relatives, and other social/recreational outings. The sample for analysis was drawn from the 2001 and 2009 U.S. National Household Travel Surveys. Teleworking was defined as working from home at least once a week. The results revealed that teleworking had a positive impact on all nonwork trip purposes in terms of distance, duration, and frequency in the United States for both 2001 and 2009, with statistically significant impacts for "shopping" trips, "other family/personal business" trips, and social-recreational trips. This study was one of two studies that we are aware of that recognizes the potential endogeneity of teleworking, through the use of a two-stage instrumental variable approach.

Pabilonia and Vernon (2020) examined the time-use patterns of individuals using the 2017-2018 American Time Use Survey (ATUS) interview and one-day time diary, as well as the Leave and Job Flexibilities (ATUS-LV) module. In their analysis, they examined nonwork activity time-use stratified by gender using a linear regression model of time spent in each of several nonwork activities using weekday time diaries. In this weekday analysis of the effect of teleworking on nonwork time use, they combined the occasional and home-based teleworker categories into a single teleworker category. They found that office workers spent fewer minutes per day on non-commute trips (26 minutes for both male and female workers) compared to teleworkers working from home on the weekday diary day (31 minutes for both genders) and teleworkers working from the office on the weekday diary day (30 minutes for men and 29 minutes for women). In general, the results also indicate higher time allocations to food preparation, eating meals, caring for/spending time with family members and pets, and watching TV and computer activities for leisure among teleworkers relative to office workers, especially for teleworkers working from home on the diary day. In contrast, office workers and teleworkers who work from the office on the diary day spend more time socializing with coworkers than teleworkers working from home on the diary day.

Additional studies by Zhu and Mason (2014) in the U.S. regarding vehicle miles of travel for nonwork trips, He and Hu (2015) in the Chicago region of the U.S. with respect to nonwork trips, Budnitz et al. (2020) in England regarding number of nonwork trips, Bieser et al. (2021) in Stockholm with a focus on activity duration in nonwork activities, Wang and Akar (2020) in the U.S. related to the length of nonwork trips, and Huang et al. (2023) in Switzerland with regard to the number of nonwork trips found results generally consistent with Asgari et al. (2016), Zhu (2012), and Pabilonia and Vernon (2020) that teleworking increased the intensity in most/all types of nonwork activities in terms of nonwork activity participations.

2.2. A Summary of the Literature and the Current Paper in Context

The literature overview indicates that, from a causal direction viewpoint, all studies to date (except for one) consider teleworking to have a causal effect on nonwork activity-travel within the TN pathway effect. Also, except for Zhu (2012) and He and Hu (2015), all other TN studies consider teleworking to be predetermined (strictly exogenous) to nonwork activity-travel. That is, these TN studies do not control for potential associative effects when teasing out causality. Thus, associative effects of teleworking on nonwork travel are entirely comingled with "true" causal effects. Lila and Anjaneyulu (2013) is the only study that considers the reverse NT causal pathway, assuming nonwork activity participation is predetermined (exogenous) to telework decisions. Thus, again, the reported nonwork activity effect on telework choices comingles associative effects with a "true" causal effect. From the standpoint of characterizing telework and nonwork activity participation, most studies consider teleworking in binary or ordinal categories based on intensity of telework over a week or longer spans of time, though at least one study (Asgari et al., 2016) uses telework hours during the survey day. Nonwork activity-travel is captured through different dimensions, mostly focusing on nonwork trips and/or nonwork vehicle miles/kilometers of travel. However, some studies have also considered nonwork activity durations (Stiles and Smart, 2021 and Asgari et al., 2016) or nonwork tours (Shah et al., 2024). From a time unit analysis standpoint, most studies use a single day as the unit of analysis for nonwork travel, with fewer studies (see, for example, Cerqueira et al., 2020 and Caldarola and Sorrell, 2020) employing a week as the unit of analysis to accommodate natural variations (as well as variations across teleworking and non-teleworking days) across days in nonwork travel. From a nonwork purpose disaggregation standpoint, studies do show differences in the telework-nonwork relationship based on nonwork purpose, especially between maintenance activities and leisure activities. From a decision maker unit of analysis perspective, most studies consider an individual-level of analysis for nonwork activity, while a few studies (see Kim et al., 2015 and Kim, 2017) have considered nonwork activity of other household members too. However, important to note is that these latter studies do consider teleworking at an individual level rather than considering teleworking of all members of the household. For consistency in the decision maker unit across both teleworking and nonwork, in the current study, we maintain an individual-level analysis, leaving a household-level analysis along both dimensions for future research.

Overall, two overarching issues need to pointed out regarding the previous studies. First, they have all been undertaken based on data before the pandemic and/or well before any semblance of normality had returned after the worst of the pandemic (Obeid et al., 2022 is the only study that did have data from mid-2021; all other studies were based on data before the onset of the pandemic in early 2020 or during the height of the pandemic). In this regard, and while still evolving, there is little doubt that the extent of adoption and intensity of teleworking has seen a sea change from before the pandemic (see, for example, Asmussen et al., 2024b). Also, teleworking patterns and nonwork activity-travel patterns were still in transitory mode in 2020 and also early in 2021. Thus, there is a continuing need to study the telework-nonwork activity-travel relationship based on data in a new landscape when the worst of the pandemic was clearly in the rear view mirror. Second, all previous studies assume *a priori* a one directional causal pathway effect of relationship between telework and nonwork activity-travel, and all but two studies to our knowledge do not control for associative effects when teasing out causal effects. It is in these two broad contexts that we undertake the current study, which is based on data from the post-COVID time frame in late 2021 and early 2022 as well as presents a novel latent segmentation framework to explore the potential heterogeneity across individuals in the causal relationship between telework frequency and nonwork travel. In addition, our current research focuses on the number of nonwork stops as the activity-travel dimension of interest, as opposed to nonwork vehicle miles of travel or time spent traveling in the studies. The reason for our use of nonwork stops is that it constitutes an important first element of activity generation, with many other space-time travel considerations (including where to participate, how to insert stops into tours, travel mode, and duration of stops that determine travel distance, travel times, activity durations, and tour-making) of the stops typically decided in further downstream scheduling decisions (see Bhat and Koppelman, 1993; Goulias et al., 2011; Allahviranloo, 2016, Dianat et al., 2020). In this regard, our study has similarities with earlier studies such as Huang et al. (2023) and Obeid et al. (2022). However, we use a count approach appropriate for the discrete count of nonwork stops rather than descriptive or linear regression methods. We also disaggregate nonwork stops by maintenance and leisure purposes, based on evidence from earlier literature that the telework-nonwork relationship varies by these two broad nonwork activity purposes. But, while earlier studies that have distinguished between maintenance and leisure purposes have considered the purposes independently, we accommodate the potential jointness in decision-making across the two different types of nonwork activities. We accomplish this using a bivariate count model approach. In addition, we couple this bivariate count model with an ordinal model for telework frequency (to account for the package nature of telework and nonwork stops decisions) using a joint multivariate ordinal-count model system. Additionally, after accommodating jointness in decision-making, we explicitly recognize the possible presence of both causal directions (NT and TN), with some individuals having one direction of causality and others the other direction of causality. By using a latent segmentation approach, we are able to estimate the segment size of each direction of causality, as well as characterize the individuals who make decisions based on each direction of causality. Finally, we propose a methodology for calculating treatment effects within this innovative model framework and apply it to assess the net impact of telework on the generation of weekly maintenance and leisure stops.

3. DATA

3.1. The Survey

The primary data for the current study is obtained from the Travel Behavior Inventory (TBI) study, deployed between June 2021 and January 2022 across the greater Twin Cities area in Minnesota, U.S. The TBI was sponsored by the Minnesota Metropolitan Council in partnership with the Minnesota Department of Transportation and the Wisconsin Department of Transportation. The TBI is a two-part survey, including both an online questionnaire to gather individual/household sociodemographics, workplace location habits, and general travel behavior, and a week-long travel diary collected through the rMove app (Metropolitan Council, 2022). In this current study, we consider the weekday travel patterns (Monday through Friday) from the travel diaries of full-time workers. The sample includes 1,922 individuals, who recorded over 20,200 total maintenance and leisure stops over the course of the week.

Telework adoption and intensity information were collected in the survey as an ordinal variable reflecting general telework frequency, based on responses to the online questionnaire rather than the travel diary. Specifically, respondents were asked to indicate how often they telecommuted to their primary job by selecting from nine ordered categories: never, less than monthly, 1-3 days a month, 1 day every 2 weeks, 1 day a week, 2-3 days a week, 4 days a week, 5 days a week, and 6-7 days a week. The number of weekday stops for maintenance purposes, and separately for leisure purposes, on the other hand, were extracted from the week-long diary (importantly, the online questionnaire and week-long diary were administered and responded to in the same week, so it is not unreasonable to use the reported telework frequency and nonwork stops to investigate the package nature of these outcomes). We then defined a stop as the arrival to an outside-of-home destination, different than the trip's origin, with a purpose other than switching modes of transportation. While there were originally 26 distinct activity purposes for nonwork stops recorded in the TBI travel diary, we grouped nonwork stops into the two main categories of maintenance and leisure. Maintenance stops include those for errands such as grooming, pick-up/drop-off, medical appointments, and shopping. The survey did not distinguish between shopping for groceries and shopping for non-groceries, so all shopping stops are categorized under maintenance activity. Leisure stops include those for exercise outside of the home, eating out, visiting a friend's home, attending a family activity such as a child's sports game, a volunteering activity, or participating in a self-labeled social, entertainment, or cultural activity. Additional details of the mapping of the 26 distinct activity purposes into the two categories of maintenance and leisure are provided in Appendix A.

A host of exogenous variables are considered in the analysis, including (a) sociodemographic characteristics (age, gender, income, education level, race/ethnicity, and family lifecycle stage), (b) work-related attributes (including typical daily work duration), (c) dwelling unit attributes (such as housing tenure and single home versus apartment living), and (d) built environment (BE) variables characterizing the residence of the respondent. For the residential BE variables, respondents identified the zip code of their home, which was used to link built environment variables. In particular, activity density was computed as the ratio of the number of households units (HU) and employment establishments (EE) to unprotected acreage (i.e., excluding parks, water bodies, and other non-developable areas). Based on Ramsey and Bell (2014), zip codes with an activity density less than 0.5 HU + EE per unprotected acre of land are classified as low density or a rural neighborhood density type, while those with 6 or more HU + EE per unprotected acre of land are classified as high density, or urban. All other zip codes are classified as medium density or suburban. A number of other residential area BE variables corresponding to accessibility to nonwork activities (including proximity to grocery stores, clothing stores, home repair stores, as well as restaurants, bars, parks, and museums) were also developed by linking residential zip codes to the counts of business categories located within the same zip code, as defined by the North American Industry Classification System (U.S. Census Bureau, 2022). Among all of these, only the absence/presence of clothing/retail stores within an individual's residential zip code turned out to be statistically relevant in the final specification. Also, none of the dwelling-unit variables also were of any consequence. Thus, in the rest of this paper (including in our data description), we do not reference any dwelling-unit attributes and only reference the proximity to clothing/retail stores.

3.2. Data Description

Table 1 provides information on the individual and household characteristics of the 1,920 individuals used in our study. The sample is exclusively comprised of individuals who are employed on a full-time basis and either reside or work within the broader Twin Cities region in Minnesota, U.S. This demographic can be compared with gender, age, and income data from the Census Bureau's five-year American Community Survey (ACS) from 2022, though it is important to note that the ACS statistics encompass all workers, while our sample exclusively consists of full-time employees. Specifically, we conducted a comparison with ACS data for the 11 counties in the Twin City area, including Anoka, Carver, Chisago, Dakota, Hennepin, Isanti, Ramsey, Scott, Sherburne, Washington, and Wright. While the ACS offers Twin City worker-specific data on formal education level, presence of children (by age), and occupation split, it categorizes them differently than our survey, preventing a direct comparison of these descriptive statistics with those from our sample.

The comparison with the ACS data shows that our sample exhibits a slightly higher proportion of women in the workforce, and lower shares of those aged 18 to 24 years and those with a household annual income in the range of up to \$50K, relative to the Twin City region working population (U.S. Census Bureau, 2023). The age and income differences, in part, may be attributed to the difference between full-time workers (our sample) and all workers (the ACS data). As may be observed from Table 1, a little over one-third of sample respondents reside in an urban area and a similar percentage reside in a rural area, while a minority (26.5%) reside in suburban areas.

As indicated earlier, we are unable to compare many demographic/residential attributes with the population characteristics of full-time Twin City workers. However, we are able to examine the representativeness of our sample on work characteristics by comparing with the 2022 National Household Travel Survey (NHTS) data specifically for the Twin City Region (Federal Highway Administration, 2022), though, once again, the NHTS data provides statistics only for the combined set of full and part time workers. In terms of commute time, the NHTS data shows an average of 25.2 minutes, while our sample indicates a slightly shorter average of 24.3 minutes, demonstrating a relatively close alignment. Moreover, according to the NHTS data, 75.0% of employees have a commute time exceeding 15 minutes. Our sample closely mirrors this pattern with 74.1% of employees reporting a commute duration exceeding 15 minutes.

3.3. Description of Main Outcomes

There are three main outcomes in this study. The first outcome relates to telework frequency, and the second and third correspond to the number of maintenance and leisure stops across all weekdays in the survey week. While we can compare the binary distinction of being a full-time teleworker or not within our sample to the variable measured by the ACS in the Twin City region, we lack good information to compare the outcomes of telework frequency (at a more granular level) from our survey with the conditions on the ground in 2021 and 2022. Also, the ACS and NHTS data sets are based on one-day statistics of activity-travel (including both weekday and weekend days), and so the weekday counts of maintenance and leisure stops from our sample are not comparable to these other data sources.

The telework frequency (TF) outcome takes the form of an ordinal variable. As already discussed, the survey asked respondents to report their TF in one of nine ordinal categories. Due to the limited number of responses in the final ordinal category of "6-7 days a week" (1.0%), we merged this last ordered alternative with the preceding one to develop the telework frequency category labeled "≥ 5 days a week" (which implies that employees in this category teleworked on all weekdays of their work week). Further, because the "1-3 days a month" and "1 day every two weeks" categories clearly overlap (an obvious oversight in survey design), we collapsed these two into a single "1-3 days a month" category. The first numerical column of Table 2 presents the sample split across the final seven TF ordinal categories in this study. A little less than half (45.6%) of the full-time employees never telework, while 13.8% telework all days of their work week. This latter percentage closely mirrors the 13.7% percentage of workers who telework all days of the week, as documented in the 2022 ACS report for the Twin City region of Minnesota. Finally, in our sample, 40.2% of full-time employees telework at least once a week, while 14.2% telework at an intensity level that is less than once a week. There are no ACS statistics comparable to these TF splits for the Twin City region.

The second and third outcome variables correspond to the count of maintenance stops and the count of leisure stops across all weekdays (for ease, we will refer to these as weekly maintenance and weekly leisure stops, with the understanding that the reference is to stops across all weekdays within the week). Both these outcomes are represented as counts in our analysis framework. For both these outcomes, the count values ranged effectively from 0 to 15, with only about 2-3% of individuals reporting more than 15 stops for each of the two nonwork activity purposes. So we truncated the maximum number of stops in our count models to 15.

Table 2 captures the associative relationship of telework frequency as a function of nonwork stops in the spirit of a possible NT causal relationship by presenting the percentage splits across the different TF categories (across each row, the percentages sum to 100%) for individuals who make less than (and more than) the mean number of weekly stops in each nonwork category (the mean for maintenance stops is 3.86 and the mean for leisure stops is 5.31). Individuals with higher than the average number of maintenance stops are generally associated with never teleworking or substantial teleworking (four or more days per week), with 68.8% (46.5+7.9+14.4) of those with higher than average maintenance stops belonging to these low- and high-end teleworking categories relative to 66.5% (44.7+7.4+13.4) of those making lower than average maintenance stops). In contrast, the relationship between leisure stop-making and teleworking is monotonic, with those making more than average leisure stops associated with higher levels of teleworking (as may be observed from the drop in percentages at the lower ends of the telework frequency spectrum, and steady increase in the percentages toward the higher ends of the telework frequency spectrum, in the row labeled "more than average stops" for leisure in Table 3 relative to the row labeled "less than average stops" for leisure). Of course, these aggregate statistics and overall associative relationships do not account for heterogeneity across individuals and also comingle associative and "true" causal effects.

Table 3 examines the same associative relationship in reverse (that is, nonwork stops as a function of telework frequency in the spirit of a possible TN causal relationship). The second and third numeric columns of Table 3 indicate the highest maintenance and leisure stops being associated with those who telework "a few days a month". Besides this observation, no clear pattern of relationship between TF and maintenance/leisure stop-making is discernible from these statistics. The last row of Table 3 indicates a generally higher number of leisure stops in the week relative to maintenance stops (which also holds at every telework level). This is not surprising, given that maintenance stops tend to be scheduled from a time efficient utilitarian perspective, while leisure stops have more of eudemonic touch to them. But, again, as with the aggregate statistics in Table 2, those in Table 3 mask heterogeneity across individuals in the relationship as well as do not disentangle associative effects due to unobserved factors from "true" causal effects. The multivariate model system adopted in this paper will be able to better tease out relationships in this regard after controlling for a host of demographic, work-related, dwelling unit, and built environment attributes, as well as unobserved factors affecting the many dimensions and considering the causal directionality among the outcomes.

4. METHODOLOGY

4.1. Model Structure

The modeling framework in this study assumes that each individual follows one of two underlying causal pathways representing the relationship between teleworking and nonwork activity participation. However, the specific causal mechanism influencing each individual's behavior is not directly observable. To address this, a latent segmentation modeling approach is employed, which classifies individuals into one of the two causal segments (NT or TN) based on their individual-level attributes. A simplified depiction of the analytical framework is presented in Figure 2. In the first NT segment, nonwork activity participation is specified as a predictor of telework frequency, while in the second TN segment, telework frequency is modeled as a determinant of nonwork activity engagement. Within each of the two segments, the three main outcome variables are jointly modeled using a multivariate ordered response-count probit (MORCP) system of one ordered-response outcome (telework frequency) and two count outcomes (corresponding to the number of weekly maintenance and leisure stops). In addition, a latent segmentation approach is superimposed on this multivariate system to accommodate the two different causal directions (NT and TN) of effects. We are not aware of any formulation and application of such a latent segmentation MORCP model in the literature. A host of sociodemographic, household, and residential characteristics are introduced as exogenous variables. We first discuss the MORCP model system within each latent segment, and then discuss the overlay of the latent segmentation model.

4.2. Multivariate Ordered-Response Count Probit (MORCP) Model System

The MORCP model can be viewed as a multivariate generalized ordered-response probit model, based on the recasting of any count model in the form of a generalized ordered-response model. We begin by suppressing the index q for individuals for presentation ease. In the usual ordered-response form, let $\tilde{t}^*$ be the underlying teleworking propensity that is mapped to the ordinal teleworking outcome t as follows:

$$\tilde{t}^* = \boldsymbol{\beta}'\mathbf{x} + \varepsilon\,,\ t = k \ \text{if}\ \tilde{\psi}_{k-1} < \tilde{t}^* < \tilde{\psi}_k\,, \tag{1}$$

where $\mathbf{x}$ is a $(L \times 1)$ vector of exogenous variables (including a constant), $\boldsymbol{\beta}$ is a corresponding $(L \times 1)$ vector of coefficients to be estimated (some of whose elements can be zero), and ε is assumed to be a standard normal random error term (the standardization is innocuous because of the need for scale normalization). The vector $\mathbf{x}$ also includes variables corresponding to maintenance and leisure stop making for the NT segment, but these stop making variables do not appear for the TN segment. Additionally, k represents an ordinal value of t, and ranges from 1 to K (K=7 in the current paper). The thresholds $\tilde{\psi}_k$ satisfy the following condition; $\tilde{\psi}_0 = -\infty,\ \tilde{\psi}_1 = 0,\ 0 < \tilde{\psi}_2 < \ldots \tilde{\psi}_{K-1} < \tilde{\psi}_K = \infty)$ in the usual ordered-response fashion. Equation (1) may be rewritten as follows:

$$t^* = \varepsilon\,,\ t = k \ \text{if}\ \psi_{k-1} < t^* < \psi_k\,, \tag{2}$$

where $t^* = \tilde{t}^* - \boldsymbol{\beta}'\mathbf{x}$ and $\psi_k = \tilde{\psi}_k - \boldsymbol{\beta}'\mathbf{x}$. For later use, define a vector $\tilde{\boldsymbol{\psi}} = (\tilde{\psi}_2, \tilde{\psi}_{3,} \ldots, \tilde{\psi}_{K-1})$.

Consider C count outcomes for each individual, and let c be the index for the count variables ($c = 1,\ 2,\ \ldots,\ C; C = 2$ in our paper, representing the weekly counts of maintenance and leisure stops). Let the count index be r_c $(r_c = 0,\ 1,\ 2,\ \ldots, \infty)$ for the c^{th} count. Then, following the recasting of a count model in a generalized ordered-response probit formulation (see Castro et al., 2012 and Bhat et al., 2014), a generalized version of the Poisson count model may be written as:

$$y_c^* = \zeta_c,\ y_c = r_c \ \text{if}\ \theta_{c,r_c-1} < y_c^* < \theta_{c,r_c},\ \theta_{c,r_c} = f_{c,r_c}(\mathbf{z}) + \sum_{l=0}^{r_c} \alpha_{cl}\,, \tag{3}$$

where ζ_c is a standard normal random error term, θ_{c,r_c} represent thresholds that satisfy the ordering conditions $(\theta_{c,-1} = -\infty; -\infty < \theta_{c,0} < \theta_{c,1} < \theta_{c,2} < \ldots)$ in the usual ordered-response fashion, $f_{c,r_c}(\mathbf{z})$ is a non-linear function of a vector of individual exogenous variables ($\mathbf{z}$ includes a constant), and α_{cl} is a scalar similar to the thresholds in a standard ordered-response model $(\alpha_{c,-1} = -\infty;\ \alpha_{cM_c} = 0$ for identification, where M_c is the largest observed count value for count outcome c in the estimation sample; in our analysis, M_c =15 for both the maintenance and leisure count outcomes). The α_{cl} terms provide flexibility to accommodate high or low-probability masses for specific count values and can take values of zero for some count values. The non-linear function $f_{c,r_c}(\mathbf{z})$ takes the following form:

$$f_{c,r_c}(\mathbf{z}) = \Phi^{-1}\left(e^{-\lambda} \sum_{l=0}^{r_c} \frac{\lambda_c^l}{l!} \right),\ \text{with}\ \ \lambda_c = e^{\boldsymbol{\gamma}_c'\mathbf{x}}\,, \tag{4}$$

where Φ^{-1} is the inverse function of the univariate cumulative standard normal, and $\boldsymbol{\gamma}_c$ is a coefficient vector to be estimated. Some elements of $\boldsymbol{\gamma}_c$ will be zero, though not the coefficient on the constant in the vector $\mathbf{x}$ (for later use, we will refer to the coefficient in $\boldsymbol{\gamma}_c$ corresponding to the constant as the "gamma constant"; note also that the vector $\mathbf{x}$ in Equation (4) includes variables corresponding to telework intensity for the TN segment, but these variables do not appear for the NT segment). If $\alpha_{cl} = 0$ for all l, the set up in Equation (3) collapses to a traditional Poisson count model, as shown in Bhat (2014). Next, define $\boldsymbol{\alpha}_c = (\alpha_{c0}, \alpha_{c1}, \ldots, \alpha_{c,M_c-1})'$, $\boldsymbol{\theta}_c = (\theta_{c,0}, \theta_{c,1}, \theta_{c,2} \ldots)'$,

$\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_C)'$, $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, ..., \boldsymbol{\theta}_C)'$, and $\boldsymbol{\gamma} = (\boldsymbol{\gamma}_1', \boldsymbol{\gamma}_2', ..., \boldsymbol{\gamma}_C')'$. Also, stack the C latent variables y_c^* into a $(C \times 1)$ vector $\mathbf{y}^*$, and the C error terms ζ_c into another $(C \times 1)$ vector $\boldsymbol{\zeta}$. Note that the overall lower and upper threshold vectors ($\boldsymbol{\theta}_{low}$ and $\boldsymbol{\theta}_{high}$, respectively) for a specific individual depend on the collection of count values r_c for that individual, and are drawn appropriately from the threshold vector $\boldsymbol{\theta}$ for the individual. With these definitions, the latent propensity underlying the count outcomes may be written for a specific individual based on the vector of count values as:

$$\mathbf{y}^* = \boldsymbol{\zeta}, \quad \boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{up}. \tag{5}$$

Next, we allow correlations across the telework error term ε and the count error vector $\boldsymbol{\zeta}$ by specifying a standard multivariate normal distribution (SMVN). In our case, there are two count outcomes, and so the result is a standard three-dimensional normal distribution as follows:

$$\boldsymbol{\omega} = \begin{bmatrix} \varepsilon \\ \boldsymbol{\zeta} \end{bmatrix} = \begin{bmatrix} \varepsilon \\ \varsigma_m \\ \varsigma_l \end{bmatrix} \sim SMVN \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}; \begin{pmatrix} 1 & \rho_{tm} & \rho_{tl} \\ \rho_{tm} & 1 & \rho_{ml} \\ \rho_{tl} & \rho_{ml} & 1 \end{pmatrix} = SMVN[\mathbf{0}; \boldsymbol{\Xi}], \tag{6}$$

where ρ_{tm} is the correlation between telework propensity and maintenance stop making propensity, ρ_{tl} is the correlation between telework propensity and leisure stop making propensity, ρ_{ml} is the correlation between maintenance and leisure stop making propensities, $\mathbf{0}$ is a vector of zero elements, and $\boldsymbol{\Xi}$ is a correlation matrix as specified. Let $\mathbf{s}^* = \left(t^*, \mathbf{y}^{*\prime}\right)'$, $\tau_{low} = (\psi_{k-1}, \boldsymbol{\theta}_{low}')'$, and $\tau_{high} = (\psi_k, \boldsymbol{\theta}_{high}')'$. Then, for an individual with ordinal telework level k, and making r_1 maintenance stops and r_2 leisure stops, we have the following:

$$\mathbf{s}^* = \boldsymbol{\omega}, \quad \boldsymbol{\tau}_{low} < \mathbf{s}^* < \boldsymbol{\tau}_{up}. \tag{7}$$

The probability of this multivariate event may be written, given the parameter vector $\boldsymbol{\delta} = (\boldsymbol{\beta}', \boldsymbol{\gamma}', \boldsymbol{\alpha}', \tilde{\boldsymbol{\psi}}, \text{Vechup}(\boldsymbol{\Xi}))'$ (where Vechup($\boldsymbol{\Xi}$) stands for the upper diagonal elements of matrix $\boldsymbol{\Xi}$), as:

$$\Pr[k, r_1, r_2] \| \boldsymbol{\delta} = \Pr[\boldsymbol{\tau}_{low} < \boldsymbol{\omega} < \boldsymbol{\tau}_{up}] = \int_{D_{\boldsymbol{\omega}}} f_{C+1}(\boldsymbol{\omega} \mid \mathbf{0}, \boldsymbol{\Xi}) d\boldsymbol{\omega}, \tag{8}$$

where the integration domain $D_{\boldsymbol{\omega}} = \{\boldsymbol{\omega} : \boldsymbol{\tau}_{low} < \boldsymbol{\omega} < \boldsymbol{\tau}_{up}\}$ is simply the multivariate region (trivariate in our empirical case) of the $\boldsymbol{\omega}$ vector determined by the upper and lower thresholds. $f_{C+1}(\boldsymbol{\omega} \mid \mathbf{0}, \boldsymbol{\Xi})$ is the standard MVN density function of dimension C+1, with a correlation matrix $\boldsymbol{\Xi}$.

4.3. Latent Segmentation Model

As indicated earlier, one of two causal directions may be at play for any individual, after accommodating the association among the telework and nonwork stops decisions of an individual. The individual may have the NT causal pathway effect or the TN causal pathway effect. Thus, we use a latent segmentation approach in our analysis, in which we write the probability of the individual being in segment h (whether in the NT or TN segment) itself as a function of individual exogenous variables.[4] In this latent segmentation approach, the probability in Equation (8) will depend on the segment h (h=1 being the NT segment and h=2 being the TN segment) that an individual belongs to. Introducing the index q for individual now, we may write the probability in Equation (8), conditional on the individual belonging to segment h, as $\Pr_{qh}\left[k,r_1,r_2\right]\|\boldsymbol{\delta}_h$. Let $\pi_{qh}\ (h=1,2,\ldots,H; H=2 \text{ in our empirical analysis})$ denote the probability that individual q belongs to segment h. The conditions that $0 \le \pi_{qh} \le 1$ and $\sum_{h=1}^{H} \pi_{qh} = 1$ must be met. To enforce these restrictions, following Bhat (1997), the following logit link function is used:

$$\pi_{qh} = \frac{\exp(\boldsymbol{\mu}_h'\mathbf{a}_q)}{\sum_{j=1}^{H}\exp(\boldsymbol{\mu}_j'\mathbf{a}_q)}, \tag{9}$$

where $\mathbf{a}_q$ is a vector of individual attributes and $\boldsymbol{\mu}_h$ is a corresponding vector of parameters specific to segment h. $\boldsymbol{\mu}_H = \mathbf{0}$ serves as a vector identification condition. Defining $\boldsymbol{\varpi} = [\boldsymbol{\delta}_1',\ldots,\boldsymbol{\delta}_H';\boldsymbol{\mu}_1',\ldots,\boldsymbol{\mu}_H']'$, then the overall probability for an individual with telework level k, and r_1 maintenance stops and r_2 leisure stops, is

$$\Pr_q\left[k,r_1,r_2\right]\|\boldsymbol{\varpi} = \sum_{h=1}^{H}\left(\pi_{qh}\middle|\boldsymbol{\mu}_h\right)\times\left(\Pr_{qh}\left[k,r_1,r_2\right]\|\boldsymbol{\delta}_h\right) \tag{10}$$

A maximum likelihood inference procedure is then used to estimate the model parameters.

5. MODEL ESTIMATION RESULTS

The final model specification was developed through a systematic approach involving the testing of alternative functional forms and combinations of explanatory variables, with the exclusion of statistically insignificant ones. The estimation process employed codes and routines written by the research group in the GAUSS matrix programming language (Aptech, 2022). Exogenous variables, all gathered in categorical form, were treated as dummy variables in their most disaggregate form. These dummy variables were progressively aggregated based on statistical tests, resulting in parsimonious specifications. Although we tested several employment- and outside-of-home work-related factors (such as hours worked per day and per week, primary commute mode, parking availability at the workplace, and number of jobs held), none of these variables turned out to be statistically significant and were excluded from the final model. Additionally, we examined the influence of the count of both leisure and maintenance stops on telework frequency for the NT causal latent segment. This exploration involved the consideration of stop counts as such (resulting in a linear effect of the count on teleworking propensity) and as a series of dummy variables representing different ranges (allowing for non-linear effects). Throughout our extensive explorations, the dummy variable representation for nonwork stop counts (for the NT segment) consistently showed better performance compared to the "linear count-as-such" specification. Similarly, we investigated the impact of different telework frequency

[4] Please see Asmussen et al. (2024a) for a detailed discussion of the justification for the use of a latent segmentation approach (which is essentially an application of finite-mixture models) for cluster (or classification) analysis to represent different causal pathway effects. A similar approach to accommodate heterogeneity across individuals in the causal direction of effect has been employed in Waddell et al. (2007), Angueira et al. (2019), Astroza et al. (2019), Keya et al. (2021), and Batur et al. (2023).

groupings on both leisure and maintenance trips within the TN causal latent segment. This involved considering each of the seven ordinal categories individually and in various combinations, expressed as a series of dummy endogenous explanatory variables.

Several additional points regarding our estimation procedure and specification merit attention here. First, the objective of this study is to explore causal relationships at the individual level between exogenous variables and the targeted outcomes, as well as the causal relationships between the outcomes themselves. In conducting such a causal analysis, there is no specific need for the exogenous variable distribution to reflect that of the population of interest. For instance, variations in telework and nonwork travel across different age groups are accommodated through the inclusion of exogenous "age" category variables. Consequently, what is important is that there be adequate variation in the age variable within the sample to test different functional forms to capture the age effect. Moreover, our sampling strategy, while a convenience sample, is not based on targeting respondents based on whether they engage in telework or the frequency of their leisure or maintenance stops (that is, our sampling strategy corresponds to exogenous sampling, where the collection process is not contingent on the endogenous outcome values). Therefore, an unweighted estimation is appropriate, offering consistent and more efficient estimates compared to a weighted estimation procedure, as extensively discussed by Wooldridge (1995), Solon et al. (2015), and Robbennolt et al. (2026).

Second, we tested differential effects of exogenous variables on telework and nonwork stop counts across both the NT and TN latent segments. But none of these came out to be statistically significant. Further, we also did not see any substantial theoretical or conceptual rationale to anticipate differential effects of exogenous variables on telework and nonwork stops across segments, merely based on the direction of NT or TN causality. For example, there is no reason to assume that the inclination of those with graduate education to telework more than those with lower formal education should vary depending on the causal direction of effect. Similarly, there is no immediate reason to believe that a person's gender or age should differentially influence nonwork stop-making solely based on the causal direction at play. However, recognizing the potential for variation in the unobserved association between the telework and nonwork travel dimensions across the two segments, we permit the correlation elements across the dimensions to differ by segment. Additionally, since different causal directions of effects are present (introducing the nonwork count outcome in the telework propensity for the NT segment and the telework outcome in the nonwork stop propensities for the TN segment), we allow the constant/threshold coefficients for teleworking, the constant coefficient in the $\boldsymbol{\gamma}$ vector, and the elements of the $\boldsymbol{\alpha}$ vector to be freely estimated across the segments.

Third, we conducted a comprehensive examination of multiple interaction effects involving variables, particularly those associated with gendered life cycles, such as the interaction of gender with the presence of children and household structure. Additionally, we explored the interaction between telework decisions (nonwork stop-making choices) with demographic/residential neighborhood density dummy variables for the NT (TN) causal segments. None of these interactions turned out to be important. Important to note, however, is that the interaction effects of the endogenous effects of one outcome on another are still being implicitly captured through the sociodemographic and residential variables that appear in the latent segmentation model.

Fourth, we did use a lower confidence level (than the typical 95% confidence level) to reject the null hypothesis that a variable had no effect on the endogenous outcomes. That is, we were more liberal than usual in keeping variables in to explain the endogenous outcomes. In multidimensional models such as the one in the current paper (especially with latent segmentation), it is particularly important to maintain a delicate balance between including variables incorrectly (Type I error) and excluding variables incorrectly (Type II error). We decided to err a little more on the side of including variables incorrectly (a larger type I error) than on excluding variables incorrectly, and so used an 80% confidence level. However, we should mention that there were only a few effects that were not statistically significant at the 95% level, but significant at the more liberal 80% confidence level. Besides, removing these effects had little to no impact on the effects and statistical significance of other variables. Additionally, the effects that turned up to be significant only at the weaker 80% level had the same direction of effect and stayed at about the same magnitude over a whole variety of specifications, lending more credibility and validity in keeping these effects (Lu and White, 2014, Srivastava et al., 2018, and Brennan et al., 2021 suggest this kind of robustness testing).

Fifth, because estimation in latent class models can be somewhat challenging, we first estimated the MORCP parameters using a simple specification of exogenous variables and assuming the NT causal structure. Next, we similarly estimated the MORCP model separately assuming the TN causal structure. Using these as starting values for the MORCP component for the two latent segments, and maintaining only a constant in the first segment (with a small perturbation from zero for this constant), we subsequently estimated the MORCP model with latent segment membership. Once this simple specification for the proposed model was estimated and the estimates used as starting parameters, no estimation stability problems were encountered as we attempted a variety of different specifications for both the segment membership and the main MORCP model components. The final model specification was tested for both estimation robustness and numerical stability across multiple runs with slightly different starting values, but all these runs converged to the same log-likelihood value with the same parameter estimates.

Sixth, to reiterate two key points: (a) all respondents in the study are full-time employees, and (b) all maintenance and leisure trips documented took place on weekdays during the employees' work week.

With the above preliminaries, the results are presented in the following sequence. In Table 4, we present the effects of variables conditional on membership in the NT/TN segments. Note that a dash ("—") in Table 4 indicates that the corresponding variable was not statistically significant in the model, while "NA" denotes that the explanatory variable is not applicable to the given outcome variable. Additionally, in some cases the same coefficient (and t-statistic) appears across rows because formal tests of coefficient equality failed to reject the null hypothesis of parameter equivalence. Next, in Table 5, we present the effects of variables on the membership of the NT/TN segments, using the TN segment as the base. For quick identification, we label the two segments as follows: (a) the NT segment, wherein nonwork stop desires affect telework habits, is labeled as the "player" segment (that is, individuals in this segment prioritize "play" in nonwork activities and subsequently consider their telework options to conform to their nonwork desires), and (b) the TN segment, wherein telework frequency affects the number of leisure or maintenance stops, is labeled as the "worker" segment (that is, individuals in this segment generally prioritize their work arrangement, which then tends to affect their nonwork activity pursuits). This labeling is simply for ease in presentation; it has nothing to do with the level of commitment to work or play. Also, note that these effects represent causal pathway effects after considering unobserved associations due to unobserved factors. Thus, the model we present is a joint "package" model of telework frequency and nonwork stop-making.

5.1. Variable Effects

5.1.1. Gendered Lifecycle Characteristics

Several insights emerge from the analysis of variables related to gender, the presence of children, and living arrangements. In investigating the effects of these variables, we examined the variables individually but also as a collective to explore gendered lifecycle effects. As can be observed from Table 4, while identifying as a woman and the presence of children do not have main effects on teleworking propensity, the interaction of the two does. In particular, single mothers (relative to men, non-mothers, and non-single mothers) display a higher propensity to telework, while non-single mothers (relative to men, non-mothers, and single mothers) have a lower teleworking propensity than other individuals. Single mothers tend to be time-poor, and teleworking offers an avenue to reduce commute time, while also bringing in money through work and freeing up more time to spend with children (see Beckman, 2022 and Adisa et al., 2022).[5] In contrast, non-single mothers may prefer an office environment to compartmentalize their professional and home-based family/childcare responsibilities, especially given that mothers continue to shoulder a disproportionate share of the latter responsibilities relative to men and non-mothers (see Mondal and Bhat, 2021 and Del Boca et al., 2020). Of course, this result may also be potentially due to residence and work characteristics, such as commute distance and job type. For instance, non-single mothers tend to have shorter commute distances compared to other individuals (Hu, 2021; Asmussen et al., 2024a), which may spur less teleworking among non-single mothers.[6] Interestingly, our results also suggest that this increased home-based family/childcare responsibilities for non-single mothers does not necessarily extend to outside-of-home maintenance stops. However, women, regardless of their parental status, tend to make more maintenance stops than men. Of course, being the only adult in the home, it is not surprising that single mothers make more maintenance stops than other adults.

5.1.2. Age

Age significantly influences telework and nonwork travel behavior. Older individuals (55 years of age or older) have a lower telework propensity compared to their younger peers, a result that is one of the most consistent in the teleworking literature (see, for example, Raišienė et al., 2021, Nguyen, 2021, and Asmussen et al., 2024a). Insights from the human development literature suggest that older individuals tend to resist change, such as the shifts in workplace location imposed by COVID, because any kind of change in older individuals tends to lead to a sense of loss of control (and associated heightened feelings of angst and stress; Duque et al., 2019). Older adults also typically have more compact social networks, with the workplace being an important "social family" location (Bruine de Bruin et al., 2020; Tahlyan et al., 2022). Differently, younger individuals are drawn by the flexibility offered by telework, at least in part because of the comfort in using virtual technology tools and platforms (Mouratidis, 2018; Stickel, 2020; Kersting et al., 2021). Besides, younger individuals tend to have more expansive "external-to-work" socialization

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[5]Our dataset is based on a travel diary-based survey rather than a time-use diary and does not include questions that explicitly ask respondents whether they perceive themselves as time-poor. But, as already identified, there is substantial literature indicating that single mothers are more time-poor than other individuals.

[6]Including additional job-related characteristics (such as commute distance, occupation type, and company size) as exogenous variables would further help explain telework frequency, as evidenced in the earlier literature (see, for example, Mergener and Mansfeld, 2021, Adobati and Debernardi, 2022, and Asmussen et al., 2023). But to be noted here is that job-related characteristics, such as commute distance and telework frequency, may themselves be jointly determined, as reported by Asmussen et al. (2024a). In any case, the job-related characteristics identified above were not sought from respondents in the survey data used in the current research.

networks (see Asdecker, 2022, Raišienė et al., 2021, Nguyen, 2021) that adds to the appeal of teleworking because of the release of commute time that can be redirected for leisure. This is evidenced in the increasing leisure stop-making among those 54 years of age or younger (relative to those 55 years or older), with this increase particularly pronounced in the youngest age group (less than 35 years of age). The reduced engagement in outside-of-home leisure activities among the eldest group of employees may also be attributed to heightened mobility challenges. Further, time-use research (see for example, Paillard-Borg et al., 2009, Feller and Baker, 2021, U.S. Bureau of Labor Statistics, 2023) indicates that reading and other activities at home that involve some level of mental stimulation dominate the time-use of older adults. Finally, within age effects, middle-aged individuals (between 35 and 54 years old) tend to undertake more maintenance stops than both their younger and older counterparts, as also observed by Astroza et al. (2018) and Shah et al. (2024), presumably because of a confluence of multiple life-cycle-related biological and other consumption needs.

5.1.3. Race and Education

Our findings do not show any tangible effects of race on teleworking propensity or maintenance stop-making. However**,** compared to other racial groups, those who identify as Black engage less in leisure activity stops outside their homes, as also observed in leisure activity participation studies (see, for example, Misra and Bhat, 2000; Mallett and McGuckin, 2000; and Wang and Akar, 2023). This lower intensity of out-of-home leisure may be related to a stronger emphasis on in-home leisure activities among black families, stemming from a deeply rooted sense of community and support within extended family networks that often play a pivotal role in their social and cultural lives (Reed et al., 2023).

Employees with a graduate degree show an increased telework tendency, which may be tied to the increased employment in knowledge/information network-based occupations that are more conducive to teleworking. This may also be a consequence of more "power" in telework arrangement negotiations (see López-Igual and Rodríguez-Modroño, 2020, and Gaduena et al., 2022 for a similar education-based effect on telework frequency). Levels of formal education had no effect on maintenance or leisure travel in our empirical analysis.

5.1.4. Household Income Level and Vehicle Ownership

The household income effects in Table 4 reveal a clear trend of higher telework propensity with household income increases, consistent with many post-COVID studies (see, for example, Yasenov, 2020; Asmussen et al., 2023; Varvello et al., 2023). This is an expected result, because lower income occupations typically involve customer-facing, in-person service roles in sectors such as retailing and construction (Baker, 2020). Also, those in lower income brackets may prioritize physical presence at the workplace to enhance visibility and career advancement through face-to-face interactions with upper management (Jaff and Hamsa, 2021). With regard to nonwork travel, we did not find substantial variations across income groups until a household income of \$200,000. Table 4 indicates that those in the highest income group of \$200,000 and more make, in general, fewer maintenance stops relative to those in the lower income groups of \$200,000. This finding may be traced to the time and budget flexibility associated with high incomes, including the ability to subcontract out maintenance activities (such as hired help for housekeeping chores and childcare, and use of delivery services) (see Highfill and Franks, 2019, Parady et al., 2019, and Diaz-Gutierrez et al., 2023). Interestingly, income had no impact on leisure stop generation, in part because of the high correlation between income and vehicle ownership (discussed next).

Vehicle ownership plays a strong role in influencing telework propensity and nonwork stop-making. In particular, as may be observed from Table 4, individuals from households with fewer than three vehicles are more likely to telework than those from households with three or more vehicles, while those from households with zero vehicles are much less likely to pursue maintenance of leisure stops. These findings align with earlier telework studies (see, for example, Balbontin et al., 2021; de Abreu e Silva and Melo, 2018; Shah and Carrel, 2024) as well as earlier nonwork activity participation studies (Astroza et al., 2018; Guadamuz, 2020). Basically, these results reflect the reduced ability to reach outside-of-home activities when individuals have access to fewer vehicles in the household. Of course, we should also note here that we have assumed vehicle ownership to be exogenous to telework propensity and nonwork stop-making. All earlier NT and TN studies that we are aware of (including all the ones discussed in Section 2) also adopt this assumption or do not consider vehicle ownership as an exogenous variable at all. In reality, vehicle ownership decisions are likely to be made jointly with those involving employment/work arrangements (including teleworking) and nonwork stops. Indeed, it can be argued that even residential characteristics (and their built environment attributes) are jointly determined with employment/work arrangements and nonwork stops (see, for example, Bhat and Guo, 2007; Fatmi et al., 2017; Yu et al., 2017; Mondal and Bhat, 2023). However, we focus here on teleworking and nonwork stop decisions alone, leaving the additional joint modeling of decisions such as vehicle ownership and housing/employment choices to future efforts.[7]

5.1.5. Residential Characteristics

Surprisingly, our analysis did not reveal any statistical difference in telework frequency based on the residential area types of urban, suburban, or rural. Along the same lines, we did not find statistically significant variations across residential area types in the number of maintenance and leisure stops. But this may be partly explained by our consideration of various zip code-based built environmental variables, including proximity to grocery stores, clothing stores, home repair stores, as well as restaurants, bars, parks, and museums. But, even here, the sole variable that turned up to be of any consequence was the absence of clothing/retail stores within an individual's residential zip code, which reduced leisure stop-making (with no observable impact on either maintenance stop-making or telework frequency). When having to travel longer distances for errands at retail establishments, shoppers are likely to schedule the number of their recreational-shopping episodes more efficiently, consolidating the purchase of multiple items into a single outing. Again, as just discussed in the previous section, a caveat is that we are considering residential choice as an exogenous variable in the current analysis.

5.1.6. Endogenous Effects

In our latent segmentation model framework, nonwork stops influence telework propensity within the NT or "player" segment. To assess this impact, we examined weekly counts of leisure and maintenance travel using a variety of functional forms. These included a continuous form, different combinations of grouped nonwork frequency forms, and interactions with sociodemographic

[7]To further evaluate any potential consequence of ignoring the endogeneity of vehicle ownership on the results of other exogenous variables and, importantly, the intensity of the endogenous effects among outcomes, the model was re-estimated without the effects of vehicle ownership. The elimination of vehicle ownership led to a very similar set of results in our analysis, with the vehicle ownership effects essentially being transferred to income effects. But the removal of the vehicle ownership variable had little impact on the magnitude of other exogenous effects or the endogenous effects between outcomes.

characteristics and built environment variables, including gender, household structure, presence of household vehicles, population density of residence, and residence proximity to retail store. Ultimately, only a single, non-interacted variable of nonwork travel frequency yielded the best data fit. This variable, pertaining to leisure stops, categorizes weekly occurrences into (i) fewer than four, and (ii) four or more. Specifically, the findings from Table 4 indicate that it is leisure stop-making rather than maintenance stop-making that influences telework intensity. Specifically, within the NT ("player") segment, those making more than four leisure stops tend to have a higher telework propensity, which is intuitive because teleworking opens up the time and the freedom to engage in the desire to make leisure stops. Besides, employees who enjoy leisure may telework more often because it enables the ability to work from different locations, such as working from vacation spots or exploring new places while maintaining job responsibilities. While it is unclear why it is the threshold of four weekly leisure stops that matters, our analysis emphasizes the importance of distinguishing between maintenance and leisure stops (in their effects on telework frequency). This may be because of the relative ease of chaining maintenance stops rather than leisure stops during the commute, because leisure stops tend to be much longer in duration and more in social-recreational settings with others (Zhen, 2015; Xing et al., 2020; Gebhardt et al., 2021).

The second latent segment in our model corresponds to the TN ("worker") segment. The causal pathway effect among individuals in this segment is from teleworking to nonwork stop-making. In investigating such an effect, again we considered telework frequency in many functional forms. Following a series of specification trials, the final specification model was defined by a set of grouped categories, which include, (i) does not telework or does so less than weekly, (ii) teleworks once to three time a week, and (iii) teleworks at least four times a week. The results in Table 4 indicate that individuals who engage in a weekly hybrid workplace location arrangement; teleworking at least once a week but no more than three days a week; are likely to make fewer maintenance stops compared to both low and high-frequency teleworkers. Those who rarely telework (commute frequently) may find it quite easy to make maintenance stops during their commutes, while those who telework frequently have less of a need to consolidate their maintenance stops because they have the luxury of time. Interestingly, we tested the effect of telework frequency (in direct linear as well as non-linear dummy variable forms) on leisure stops too, but this effect was statistically insignificant at even the 60% confidence level in all our specification trials. That is, in the TN segment, the time released through teleworking influences maintenance activity pursuits but not leisure activity pursuits. Additional investigations on this issue would be a fruitful direction for future research.

One more point here. It is often assumed that work-related decisions are made in a long-term context and serve as fixed anchors for shorter-term nonwork activity decisions. However, there is considerable theoretical and empirical evidence that individuals do make conscious and deliberate choices regarding work-related decisions based on nonwork stop-making desires, even if work-related decisions may not be changed easily in the short-term. From a <u>theoretical</u> perspective, since the 1920s, economists have recognized that the time spent on mandatory work activities is not based solely on effort expenditure and income associated with such activities, but also with the relative attraction for other nonwork activities (Robertson, 1921; Prasch, 2000; Jara-Díaz and Contreras, 2024). In fact, a variety of time assignment models have been developed that treat work, maintenance, and leisure activities as a joint package choice, maximizing the total utility of participation in all activities rather than treating these activities in a hierarchical manner (see Jara-Díaz et al., 2008; Hössinger et al., 2020; Hensher et al., 2022). From an <u>empirical</u>

perspective, and even well before the COVID pandemic, Doherty and Mohammadian (2011) noted in their analysis of activity planning decision processes that less than 50% of mandatory activities were planned first in out-of-home activity tours, and that individuals actively consider the temporal allocation of the full set of nonwork and work activities in their daily activity planning/scheduling. Further, more recently, there is mounting evidence of increasing job mobility, because of individuals being more selective than in the past in their choice of job opportunities to ensure that work responsibilities are commensurate with broader lifecycle, leisure, and lifestyle aspirations (He et al., 2021; Lyttelton et al., 2023; Tessema et al., 2022; Reiffer et al., 2023; Smite et al., 2023; Kaur, 2024; St-Denis and Hollister, 2024). Even on a daily basis, and building on the findings of Doherty and Mohammadian (2011), Zhang et al. (2024) point out that the typical way of defining anchors using home and work schedules in activity-based travel models is increasingly problematic as many individuals prioritize maintenance and leisure activities in daily activity planning and scheduling. As we discuss in Section 5.3, our study lends further support to the notion of nonwork activities affecting job characteristics (specifically telework in the current research) by estimating that more individuals fall within the NT causal structure segment than the TN causal structure segment.

5.1.7. Thresholds

The constant and the thresholds within the ordinal model component for telework, along with the gamma constant and threshold shifters in the count model for both dimensions of nonwork travel, do not hold any substantive behavioral interpretations. They simply provide the optimal data fit, accounting for the impacts of exogenous variables. While it might be tempting to infer telework and nonwork travel differences between the two latent segments based on the relative magnitudes of the constants across segments, especially considering that the effects of all exogenous variables are consistent across the two segments (as discussed earlier), and the variances of the error terms are identical, it is important to note that the composition of the two segments is inherently different. As a result, the ranges of exogenous variables in the two segments differ. Consequently, making conclusions based on a relative comparison of constant values across segments is not advisable.

5.1.8. Correlation Matrix

The two final broad rows of Table 4 present the correlation matrix among the three dimensions of telework frequency, maintenance stops and leisure stops for each of the two segments. Across both segments, the sole significant correlation is a positive relationship between maintenance and leisure stops for only the NT segment. Possibly explained by the direction of causality in the NT segment, "players" have a stronger connection to maintenance and leisure activities compared to those in the "worker" segment. Importantly, the endogenous effects in each latent segment, as discussed in Section 5.1.6, represent influences among the three main outcomes after controlling for unobserved factors (including omitted variables such as commute distance, occupation type, and company size) that may lead to associative effects, as discussed in the first section of this paper. In this regard, the model estimated in the current paper provides endogenous effects that are closer to "true" causal effects than would be obtained from a model that ignores error correlations. Nevertheless, being able to explain the three main outcomes in this paper using additional explanatory variables would further improve the estimation of the causal effects.

5.2. Characteristics of Latent Segments

The results in Table 5 reveal that single parents are more likely to belong to the TN ("worker") segment compared to partnered parents or employees without children. Given the inherent time pressures of being solely responsible for raising their child, single parents often need to arrange their errands and recreational activities around their work schedules.

In terms of age, middle-aged employees (between 35 and 44 years old) are more likely to be in the NT ("player") segment relative to their younger and older peers (who fall more within the TN or "worker" segment compared to the middle-aged employees). Younger adults (under 35 years) may find themselves at the early stages of their careers, where the allure of the "new thing" is significant, shaping their socialization and errands around their work commitments. This age group is often in a life phase with a high priority on career growth and advancement. Conversely, older adults (45 and above) generally have already established their careers, having navigated the pre-COVID era predominantly through in-person work. Their well-established routines, both within and outside of work, make them less likely to alter their nonwork habits in response to newfound post-COVID workplace flexibilities. Individuals in the middle age bracket (35-44 years) likely possess established careers but may be balancing family commitments with careers.

Next, individuals from zero-vehicle households are likely to be affiliated with the NT ("player") segment. Without a car, a person must base their travel decisions on others or specific services, such as public transportation or micro-mobility options. Therefore, they may attempt to arrange their work location flexibly around their nonwork pursuits. Finally, individuals from rural households are also more likely to fall within the NT ("player") segment, presumably because of the need to carefully plan and schedule "less-easy to-access" nonwork activities. This contrasts with urban and suburban residents, who typically have easier access to leisure and maintenance activities, allowing for a more seamless integration of nonwork participations around telework choices.

The constant reported toward the end of Table 5 lacks a substantive, interpretable meaning but serves as an adjustment factor. Despite its lack of interpretability, the positive value implies a larger segment size for the NT ("player") segment in comparison to the TN ("worker") segment, as detailed below. It is crucial to highlight that the causal direction at play—i.e., the segment to which an individual belongs—is unaffected by any employment characteristics, such as the number of work hours, workdays per week, occupation sector, or company size. This is evident from the absence of any employment attribute in Table 5. The implication is that whether an individual falls into the "player" or "worker" category is more strongly influenced by basic lifecycle and related demographic attributes than by employment-related factors.

5.3. Latent Segment Sizes and Profiles

Utilizing the latent class assignment for each individual, we ascertain the size of each segment employing the methodology devised by Bhat (1997). The final row of Table 5 presents the proportions reflecting the size of the latent segments; 64.8% of the sample is estimated to fall within the NT ("player") segment, while 35.2% is estimated to be in the TN ("worker") segment. In contrast to previous studies that assume a single causal direction, our research indicates heterogeneity in the population regarding the causal direction of the effect.

Table 6 presents a comprehensive breakdown of the variations of the two segments based on demographic attributes, utilizing actual percentages calculated with the procedure outlined by Bhat (1997). In the primary numeric column labeled "Percent (%) within segment," the variable distribution is illustrated within each segment. For instance, in the first segment where nonwork travel influences telework frequency (NT), 48.5% are women, and 51.5% are men. In the second segment where telework habits influences nonwork travel frequency (TN), the corresponding split between women and men is 49.1% and 50.9%, respectively.

An alternative characterization of the segments is found in the entries corresponding to the column titled "Percent within attribute." These columns outline the binary split between the two segments for each individual variable (or attribute). Notably, 64.6% of women belong to segment one (compared to 65.1% of men), while 35.4% of women belong to segment two (compared to 34.9% of men). These percentages closely align with the segment size distributions at the bottom of Table 5, where 64.8% of the sample is part of segment one, and 35.2% is likely a member of segment two. This consistency indicates little variation within the gender attribute across the two segments.

Similar interpretations can be extended to other entries in the table related to various exogenous variables. The percentages of sociodemographic split "within segment" and "within attribute" align with the results in Table 5. As expected, the most significant shifts and variations occur for sociodemographic variables that proved to be significant in the membership model (specifically, single parents, age, vehicle ownership, and residential location), while other sociodemographic attributes exhibit minimal variation across the segments.

5.4. Data Fit Measures

The goodness of fit for our proposed joint latent segmentation model can be assessed through comparison to other more restrictive models to gauge the improvement in data fit. Specifically, we evaluate the data fit at both the disaggregate and aggregate levels.

5.4.1. Disaggregate Data Fit Measures

At the disaggregate level, we compare the data fit provided by our proposed model relative to two non-nested versions: (i) a joint model that assumes a strict NT "player" causality direction, and (ii) a joint model that assumes a strict TN "player" causality direction. Note that, in both these non-nested versions, we still consider the jointness originating from the correlation in unobserved factors across the dimensions. As indicated in Section 2, all earlier studies have exclusively considered one specific direction of causality (without also considering the jointness). These non-nested versions can be compared against our proposed model using the Bayesian Information Criteria (BIC) statistic $\left[= -L(\hat{\boldsymbol{\varpi}}) + 0.5 \times \left(\#\text{ of model parameter}\right) \times \log\left(\text{sample size}\right)\right]$ as well as a non-nested likelihood ratio test. For the latter, we first compute the adjusted likelihood ratio index $\bar{\rho}^2$ for each of the models as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\boldsymbol{\varpi}}) - M}{L(c)}, \tag{11}$$

where $L(c)$ denotes the log-likelihood function considering only the thresholds/constants in the three equations, and M represents the number of parameters estimated in the proposed model without including the thresholds/constants. Let the adjusted likelihood ratio index for our proposed model be $\bar{\rho}^2_{\text{proposed}}$ and for the other two models be $\bar{\rho}^2_{\text{NT,player}}$ and $\bar{\rho}^2_{\text{TN,worker}}$, respectively. Considering the NT "player" model as an example, if the difference in the indices is $(\bar{\rho}^2_{\text{proposed}} - \bar{\rho}^2_{\text{NT,player}}) = \tau$, then the probability that this difference could have occurred by chance is no larger than

$\Phi\{-[-2\tau L(c)+(M_{\text{proposed}}-M_{\text{NT,player}})]^{0.5}\}$. The lower this probability, the more confidence that the proposed model provides a superior data fit.

5.4.2. Aggregate Data Fit Measures

At the aggregate level, we evaluate the data fit of our proposed model with the two other models by comparing predicted and observed shares of individuals across various combinations of telework frequency and weekly maintenance and leisure stops. To achieve this, the model predicts a multivariate probability for each of the 1792 possible combinations of the three outcomes (7 telework options, 16 maintenance stop options, and 16 leisure stop options) for all individuals. While we could aggregate individual predictions to these 1792 [7×16×16] levels, it would be cumbersome and encounter many empty bins with no observed data. Instead, for clarity and to address potential sparsity issues, we aggregate individuals into 36 bins based on coarser categorizations: four telework bins (never, less than monthly to 1 day/week, 2-3 days/week, and 4+ days/week), three bins for maintenance stops (0-2, 3-5, and 6+), and three bins for leisure stops (0-2, 3-5, 6+). The model's performance is then evaluated by comparing the observed and predicted number of individuals in each of these bins, using a weighted absolute percentage error (WAPE) metric. The weighting in WAPE calculation is based on the actual observed share of individuals in each combination bin.

Table 7 summarizes the model evaluation results. The top panel of the table provides the disaggregate fit measures, while the bottom panel provides the aggregate data fit measures. The disaggregate fit measures clearly reveal the superior fit of our model, with the probability of chance occurrence of the superior fit being almost non-existent based on the non-nested likelihood ratio tests. The same result is clear in the aggregate data fit measures too for each of the 36 combination bins, with the WAPE for our proposed model turning out to be 11.5% relative to 51.1% for the NT player model and 95.1% for the TN worker model. Similar differences are seen in the APE values for average telework frequency, maintenance stops, and leisure stops by segment. These substantial improvements in predictive accuracy highlight the importance of accounting for population heterogeneity through latent segmentation, as well as underscores the potential for misleading causal inference conclusions when such segmentation is ignored.

In addition, as a complement to the above analysis, we compute the average predicted values of telework frequency and nonwork stop-making by segment and across the overall sample as follows. For telework frequency, we first predict the probability that each individual will belong to the NT segment and choose each of the four (aggregated) ordinal categories of telework frequency. Next, we map the four ordinal categories to expected days of telework per week as follows: 0 for never telework, 0.5 for "less than monthly" to 1 day/week, 2.5 for 2-3 days/week, and 5 for 4+ days/week. Subsequently, we compute the predicted number of telework days per week for each individual if the individual belonged to the NT segment, then multiply this probability with the predicted probability of the individual belonging to the NT segment, and compute an average across individuals to predict the average telework frequency for the NT segment. We then adopt the same procedure to obtain the predicted average telework frequency for the TN segment. The overall predicted average telework frequency (in days per week) for the entire sample may be obtained as the weighted (by the size of the NT and TN segments) sum of the predicted average telework frequency in each segment. A similar procedure is adopted to determine the predicted average by segment for maintenance and leisure stops, as well as the overall predicted average for the entire sample for maintenance and leisure stops (in these computations, we assign cardinal values as follows: 1 for 0-2 stops, 4 for 3-5 stops, and 6 for 6+ stops). The results are as follows:

- Average telework frequency per week: NT segment prediction (1.45); TN segment prediction (1.61); Predicted sample count (1.51); Observed sample count (1.51).
- Average number of maintenance stops per week: NT segment prediction (3.32); TN segment prediction (4.82); Predicted sample count (3.84); Observed sample count (3.84)[8].
- Average number of leisure stops per week: NT segment prediction (3.06); TN segment prediction (9.33); Predicted sample count (5.27); Observed sample count (5.34).

The results above for each outcome (in a marginal sense) indicate that all the three outcomes of telework frequency, maintenance stops, and leisure stops are higher, on average, in the TN segment relative to the NT segment. These results are consistent with the numbers in Table 7. For example, from Table 7, the prediction is that 47.1% of those in the NT segment never telework, while 42.2% of those in the TN segment never telework. On the other end, the prediction is that 20.5% of those in the NT segment telework 4 days or more per week relative to 23.3% of those in the TN segment. These results drive up the average telework frequency in the TN segment compared to the NT segment. Similar correspondences may be observed between Table 6 and the average number of stops for maintenance and leisure.

6. IMPLICATIONS

The estimation results in the previous section do not directly reveal the impacts of variables on teleworking and nonwork stop-making. In fact, even the signs associated with the coefficients of the exogenous variables do not necessarily indicate the directional impact on the outcomes of interest. This is because of the non-linearity of the model stemming from the unobserved correlation effects, endogenous effects, and latent segmentation assignment, which makes quantifying the effects of variables challenging. Yet, for practical applications, policy makers need a more accessible interpretation of how flexible work arrangements influence individuals' errand and leisure stop counts. To address this, we leverage our findings to estimate the expected number of maintenance and leisure stops individuals make under various telework arrangements. While the actual outcome effects will vary across individuals due to the non-linear nature of our model, we can compute average treatment effects (ATEs) to determine the average impact of variable changes on weekly stop counts for each nonwork activity type (see Angrist and Imbens, 1991 and Heckman and Vytlacil, 2000).

The ATE computation procedure starts with computing, for each individual, the multivariate predictions for each of the 1792 combinations of possible outcomes for the three outcome variables. We then calculate the expected number of maintenance and leisure stops for a particular remote work scenario. To formulate this mathematically, as in Equation (8), for a given individual q, let $\Pr_q\left[k, r_1, r_2\right]$ be the predicted multivariate probability of telework arrangement k, maintenance stop count r_1, and leisure stop count r_2. Then, the marginal probabilities of

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[8]The observed sample count for maintenance stops per week here (3.84) is slightly lower than the actual sample count average in Table 2 (3.86) because the average stop counts here are computed based on collapsing the original range of 0-15 stops into three aggregate categories. Similarly, the observed sample count for leisure stops per week here (5.34) is slightly higher than the actual sample count average in Table 2 (5.31) for a similar reason.

maintenance and stop counts, conditional on teleworking arrangement k, may be computed as follows:

$$\Pr_q\left[y_{Maint.}=r_1 \mid (t=k)\right]=\frac{\sum_{r_2=0}^{15}\Pr_q(t=k, y_{Maint.}=r_1, y_{Leis.}=r_2)}{\sum_{r_2=0}^{15}\Pr_q(t=k, y_{Leis.}=r_2)} \tag{12}$$

$$\Pr_q\left[y_{Leis.}=r_2 \mid (t=k)\right]=\frac{\sum_{r_1=0}^{15}\Pr_q(t=k, y_{Maint.}=r_1, y_{Leis.}=r_2)}{\sum_{r_1=0}^{15}\Pr_q(t=k, y_{Maint.}=r_1)} \tag{13}$$

The expected value for the number of maintenance and leisure stops for individual q, conditional on telework arrangement level k, is:

$$\overline{f}_{q,Maint.} \mid (t=k)=\sum_{r_1=0}^{15} r_1 \times \left[\frac{\Pr_q\left[y_{Maint.}=r_1 \mid (t=k)\right]}{\sum_{\tilde{r}_1}\Pr_q\left[y_{Maint.}=\tilde{r}_1 \mid (t=k)\right]}\right] \tag{14}$$

$$\overline{f}_{q,Leis.} \mid (t=k)=\sum_{r_2=0}^{15} r_2 \times \left[\frac{\Pr_q\left[y_{Leis.}=r_2 \mid (t=k)\right]}{\sum_{\tilde{r}_2}\Pr_q\left[y_{Leis.}=\tilde{r}_2 \mid (t=k)\right]}\right] \tag{15}$$

We apply this procedure to calculate the predicted value of nonwork stops, conditional on each telework level, for a specific state A for each exogenous variable (say age < 35 years for the age variable) for individual q (regardless of the actual age of the individual in the sample, but maintaining all other exogenous variables at the observed values in the sample). An average of the predicted values of nonwork stops, conditional on each telework level, across all individuals is then computed. Then, the state for the exogenous variable under consideration is changed to another state B (say age 55+ for the age variable), and the same procedure as above for state A is applied.

The results are presented in Table 8 for selected exogenous variables. Thus, for age (see the second row panel of Table 8), the numeric value of "3.65" under "expected number of stops" for "Maintenance stops" in the "Age < 35 years" column indicates that, if younger than 35 years and never teleworking, individuals would make, on average, 3.65 weekly maintenance stops. On the other hand, if younger than 35 years and teleworking but less than once a month, individuals would make, on average, 3.58 weekly maintenance stops (a drop of 2% from the "never" teleworking level). Similarly, the numeric value of "4.08" under "expected number of stops" for "Maintenance stops" in the "Age 35-54 years" column indicates that, if aged 35-54 years and never teleworking, individuals would make, on average, 4.08 weekly maintenance stops and, if aged 35-54 years and teleworking but less than once a month, would make 4.00 weekly maintenance stops (a drop of 2% again). Other entries may be similarly interpreted. Assuming that the distance traveled to nonwork stops is not dependent on the number of stops, the percentage changes also correspond to changes in vehicle miles traveled (VMT).

The results generally align with the discussion in Section 4, but enable us to better understand the effects of different teleworking levels for different population subgroups. We highlight key observations from the tables and discuss their implications under five broad topics: (1) The Inverted U-Shape of Teleworks' Impact on Nonwork Travel, (2) Maintenance Stop Effects, (3) Leisure Pursuits: Teleworkers are Playing, (4) Challenges for Single Mothers, and (5) Employees in Zero-Vehicle Households.

The Inverted U-Shape of Teleworks' Impact on Nonwork Travel

Based on Table 8, it is evident that telework does not show a straightforward monotonic effect on either maintenance or leisure stops. Thus, rather than asking whether telework increases or decreases stop-making, as is posed in much scientific literature, the more pertinent question appears to be how the number of nonwork stops varies with teleworking intensity. In this study, we observe an inverted U-shaped curve in the effect of telework intensity, with the highest number of stops occurring when individuals telework at an intensity of 1-3 days a month or one day per week (this result is similar to that of Caldarola and Sorrell, 2022). However, there is also a secondary peak, especially for leisure stops, at 4 days per week of teleworking. These results have implications for both a traffic perspective as well as a broader quality of life perspective. From a traffic perspective, the results suggest that, for every population subgroup, low levels of telework (one day per week or less, but at least once a month) can be expected to increase nonwork stop-making, which may in turn contribute to higher VMT, more so than not teleworking at all or teleworking at high intensity levels. Although VMT is not directly modeled in this study, this inference builds on the observed stop-making patterns and prior research. For example, Asmussen et al. (2024a) find that individuals who telework once a week or less accrue higher monthly commute-related VMT compared to those teleworking more frequently. This implies a compounding (commute plus non-commute) travel effect at lower telework intensities, cautioning against the consideration of low levels of telework as a tool for VMT reduction. While it is likely that a good fraction of this increase in stop-making and VMT will occur during non-peak periods of the day, the net result will be higher wear and tear on the infrastructure (increasing maintenance costs) as well as higher mobile-source emissions (exacerbating air pollution problems). In contrast, 2-3 days of telework or five or more days of teleworking result in slightly lower nonwork stop-making and reduced commute-related VMT (Asmussen et al., 2024a). This suggests that moderate to high levels of home-based teleworking have the potential to effectively reduce overall travel demand. Consequently, transportation planning agencies should consider incentivizing higher telework frequencies whenever feasible. Conversely, cities and state or federal labor agencies may find it beneficial to discourage employers from offering telework options that involve only a few days per month, as such limited teleworking can worsen congestion and increase VMT. From a quality-of-life perspective, though, if one interprets more leisure participation as a positive, the suggestion is that allowing for some, even if limited, teleworking at levels of once a month or more enable employees to balance in-person work, remote work, and outside-of-home activities better, enhancing work-life balance without significantly reducing social or leisure engagements. Implementing such flexible work policies that allow for weekly or biweekly telework can reduce commuting stress, increase personal time, and promote active lifestyles. This balance can benefit individual mental and physical health, contributing to a healthier and happier workforce.

Maintenance Stop Effects

The analysis of activity patterns among different demographic groups reveals distinct trends in maintenance stops by teleworking intensity. Across all teleworking groups, single mothers, particularly those teleworking multiple times a month, demonstrate the highest frequency of maintenance stops during the week, ranging from 5.43 to 5.72 per week (nearly 1.5 more trips per week compared to the nearest stop generating group). On the other hand, those making the fewest number of maintenance stops are individuals from zero-vehicle households, regardless of the telework pattern (ranging from 2.14 to 2.25 maintenance trips), who make 1 or more fewer trips per week as compared to any other demographic group.

Regarding relative percent increases in maintenance stops during the work week compared to never teleworking, the most significant change across all teleworking groups occurs when transitioning from never teleworking to teleworking 1-3 days a month. The largest shift here is a 3.5% increase for households with three or more vehicles. To highlight the highest percent changes across each teleworking group, the overall most notable shifts, regardless of direction, are as follows:

- < Monthly: zero-vehicle households (-2.1%)
- 1-3 days/month: Employees from household with 3 or more vehicles and those aged 55+ (3.5%)
- 1 day/week: Single mothers (1.7%)
- 2-3 days/week: Employees from vehicle-less households (-0.7%)
- 4 days/week: Single mothers (1.5%)
- 5 days/week: Employees from vehicle-less households (-1.5%)

Overall, though, there is not too much shift in maintenance stops conditional on telework intensity. Further, the shifts show rises and drops in stops for different telework intensities, suggesting that, in general, the relatively small effects on maintenance stops based on teleworking intensity gets even more tempered. Therefore, unless a substantial number of employees shift to a single teleworking intensity level, it may be challenging to predict whether there will be a net increase or decrease in outside-of-home errands or appointments. This uncertainty complicates efforts to plan for infrastructure needs and traffic management, as planners cannot reliably forecast changes in travel behavior. To address this, planners might consider monitoring teleworking trends closely and developing flexible strategies that can adapt to varying levels of telework adoption.

<u>Leisure Pursuits: Teleworkers are Playing</u>

Leisure travel, on the other hand, reveals much higher generation rates across teleworking groups with at least one day per month of teleworking relative to never teleworking, and also shows much larger fluctuations across teleworking levels, as compared to maintenance travel. Similar to maintenance travel, single mothers make the highest number of leisure trips per week, ranging from 5.78 to 6.75 during the work week. The increase in teleworking is especially pronounced for single mothers teleworking 1-3 days a month compared to any other demographic group. Across all telework groups, single mothers make nearly one more trip per week than the next closest demographic. This trend suggests that single mothers likely use leisure trips to access their support networks or for their children's activities. Following single mothers, the youngest employees (< 35 years of age) have the next highest rates of leisure stop generation, ranging from 5.19 to 6.09 trips during the work week.

On the other hand, zero-vehicle households make the fewest number of workweek leisure stops, ranging from 2.80 to 3.41 weekday trips. This is expected, as individuals without a vehicle have less independent mobility. Following this group are employees older than 55 and Black employees, who, while making fewer leisure stops than other groups, still average nearly two more weekly trips than households without vehicles.

In terms of relative percent increases in leisure travel during the workweek compared to never teleworking, the most significant change across all teleworking groups is seen when shifting from never teleworking to teleworking 1-3 days a month. The largest shift here is a 16.2% increase in leisure trip generation for households without vehicles. To highlight the highest percent changes across each teleworking group, the most notable overall shifts, regardless of direction, are as follows:

- < Monthly: Single mothers (-4.9%)
- 1-3 days/month: Employees from zero-vehicle households (16.2%)
- 1 day/week: Employees from zero-vehicle households (9.4%)
- 2-3 days/week: Employees from zero-vehicle households (3.9%)
- 4 days/week: Employees from zero-vehicle households (9.7%)
- 5 days/week: Employees from zero-vehicle households (5.1%)

The percent increases for leisure travel when employees shift from never teleworking to any teleworking level of one or more days per month are nearly ten times as large as the increases for maintenance travel. It is evident that the number of leisure stops, conditional on teleworking level, reaches its peak at teleworking 1-3 days a month or more. This shift in work and travel behavior suggests that teleworking, at low levels per month in particular, supports work-life balance and encourages higher levels of leisure engagement. Teleworking provides greater control over schedules, enabling seamless integration of leisure activities into weekdays. To reduce the resulting nonwork traffic engendered by teleworking, urban planners can implement neighborhood redesigns featuring mixed-use developments that seamlessly integrate residential, commercial, and recreational spaces. These live-work-play areas hold particular appeal for younger employees (under 34 years old), who are substantially engaged in leisure activities, as well as individuals in zero-vehicle households who prefer closer proximity to various establishments. Moreover, supplementing/retrofitting residential areas with amenities such as parks, fitness centers, and social spaces supports teleworkers in spending more time locally. This is especially beneficial for employees without a car, as they can easily access these facilities on foot. Such a comprehensive urban planning strategy can not only foster sustainability and livability, but also alleviate traffic congestion.

Challenges for Single Mothers

Single mothers show the highest overall number of both maintenance and leisure stops during the week compared to any other demographic group. But these trends become more nuanced when examining the percent changes in nonwork stops between "never teleworking" single mothers and other single mothers, presumably arising from the unique responsibilities single mothers face in providing, caring for, and entertaining their children. For instance, single mothers show the highest percentage increase in maintenance stop generation when transitioning from no telework to anywhere from 1 day a week to 4 days a week, relative to non-mothers and men. But single mothers also exhibit the smallest percentage change in leisure stops when transitioning from not teleworking to any telework frequency level of one day per month or more, compared to the other two gendered lifecycle groups.

The results above indicate that teleworking single mothers, in general, appear to invest the time savings from teleworking more to managing household tasks and errands (relative to other demographic groups), but invest less of the saved time on leisure pursuits. This disparity highlights socio-economic and lifestyle challenges unique to single mothers, who face time and financial constraints that limit their ability to engage in leisure travel, with potentially downstream mental fatigue and reduced job satisfaction effects. Additionally, the inability to engage in leisure activities may diminish their sense of fulfillment and happiness in parenting, as they may feel unable to adequately recharge and balance their responsibilities. Addressing these challenges with supportive teleworking policies and resources tailored to single mothers' needs would be helpful, including offering increased access to college savings plans and programs, incentivizing policies that provide more paid time off, and providing corporate discounts for childcare services.

Employees in Zero-Vehicle Households

Employees in zero-vehicle households experience the highest increase in leisure pursuits conditional on teleworking at a level of at least once a month (relative to employees who never telework). However, since these households lack cars, their leisure stops are likely undertaken by foot or by bike, through carpooling with family and friends, or by using ride-sharing services. Thus, encouraging more households to become zero-car households can alleviate traffic congestion on roads and improve overall traffic conditions, while also opening up active leisure opportunities for individuals, fostering more frequent social interactions, and contributing to overall happiness and well-being, as indicated by (Deka, 2017; Goetzke and Rave, 2015; Morris et al., 2020). Municipalities can support this transition by investing in infrastructure that supports alternative transportation, implementing policies that create livable, walkable communities with access to amenities and recreational spaces, incentivize car-free living, and promoting public awareness campaigns about the benefits of reducing car dependency.

The demographic groups with the lowest amount of leisure travel include individuals aged over 55 and black employees, suggesting increased social exclusion in these groups. The combination of (1) encouraging these individuals to transition to zero-car households, (2) providing more flexibility to telework at low levels per month, and (3) incentivizing relocation to areas where amenities and errands are easily accessible by foot could potentially increase leisure opportunities for these population groups and enhance quality of life.

7. CONCLUSION

The rapid technological advancements of the past decade, along with the new habits/experiences from the pandemic, have profoundly influenced our daily lives, including our choices regarding activity and travel. This study explores the intricate interrelationship between teleworking and weekly participation in two types of nonwork activities – maintenance episodes and leisure episodes. We employ a latent segmentation model to categorize the population into two segments: (1) those for whom nonwork activity participation influences telework frequency ("players"), and (2) those for whom telework frequency impacts nonwork activity participation ("workers"). Within each segment, to reduce any spurious association effects, we model teleworking and nonwork stop-making as a package by accommodating correlations in unobserved factors across the outcomes. Our methodology integrates an ordinal choice model for telecommuting adoption/intensity with count models to analyze the frequency of maintenance and leisure episodes. The data for this analysis is drawn from a 2021-2022 weekly travel survey of Minnesotan workers in the Twin City region.

Our analysis reveals significant heterogeneity in the causal directionality of effect, with nonwork activity participation influencing telework intensity levels for about two-thirds of individuals (the "player" or NT segment) and telework levels influencing nonwork activity participation for the rest (the "worker" or TN segment). This result is in contrast to earlier studies that have predominantly assumed that all individuals belong to the TN or "worker" segment, which according to our analysis, is actually the case only for a minority of the population. Data fit measures at the disaggregate and aggregate levels clearly illustrate the superior performance of our proposed model relative to ones that *a priori* impose a single causal direction of effect across all individuals. Employees who are not single parents, those between 35 and 44 years old, individuals who are from zero-car households, and rural dwellers are more likely to feature in the NT segment, highlighting a lifestyle-driven approach where personal preferences and activities tend to dictate teleworking patterns. Conversely, single parents, younger-aged employees (younger than 35 years old), those who are not in zero-car households, and urban and suburban dwellers, tend to be more likely to belong to the TN segment, suggesting a lifestyle where professional and personal spheres are intricately linked.

Finally, through ATE calculations, our study reveals that there is no monotonic effect of telework on the number of stops made. The typical question of whether telework increases or decreases stop-making oversimplifies the issue. Instead, our study underscores the need to investigate how the number of nonwork stops relates to the intensity of teleworking. Our findings reveal an inverted U-shaped curve, with the highest number of nonwork stops occurring when individuals telework 1-3 days a month or one day per week. Assuming that the travel length to nonwork stops is independent of the number of nonwork stops made, the percentage changes observed also reflect changes in VMT. This, combined with the finding from the Asmussen et al. (2024a) study, suggests that low levels of telework (a day per week or less) actually increases both commute VMT and nonwork VMT. Therefore, to achieve VMT reduction through teleworking, promoting moderate to high levels of telework appears important.

While this study offers new insights into the bidirectional relationship between telework intensity and nonwork activity engagement, it is subject to a few important limitations that suggest directions for future research. First, due to data constraints, we were unable to incorporate characteristics of respondents' outside-of-home workplaces and employer/company (such as commute distance/duration, workplace density, job industry, or company size) which have been identified in prior research as significant determinants of telework adoption and frequency. These employment-related attributes likely influence both telework engagement and activity-travel behavior. Incorporating such variables would be a valuable direction for future research using specialized survey instruments. Second, while we included transportation-related variables such as vehicle ownership and residential location characteristics as exogenous controls, future research could take a more integrated modeling approach. Specifically, variables such as mode choice, vehicle availability, and urban residential preferences could be treated as endogenous outcomes within a joint framework of telework engagement, residential location, and travel behavior. Such an approach would allow for a better understanding of how transportation access and constraints co-evolve with decisions about where people live, how they travel, and how frequently they telework. Modeling these interdependencies explicitly would enhance the behavioral realism of future models and offer stronger support for transportation and land use policy decisions. In conclusion, this study contributes to the growing body of literature on telework by providing an updated, post-COVID detailed analysis of the intricate relationship between telework and nonwork activity participation. As teleworking continues to evolve, it will be essential for policymakers, urban planners, and transportation researchers to track teleworking intensity levels and the changing patterns of work and nonwork participation behavior. Of course, additional empirical investigations using both cross-sectional and longitudinal data are needed to examine the external validity (spatial and temporal transferability) of our results, as well as to extend our investigation to include more detailed spatial-temporal dimensions of nonwork (and work) activity participation behaviors in a continually evolving landscape of hybrid work arrangements and virtual technologies.

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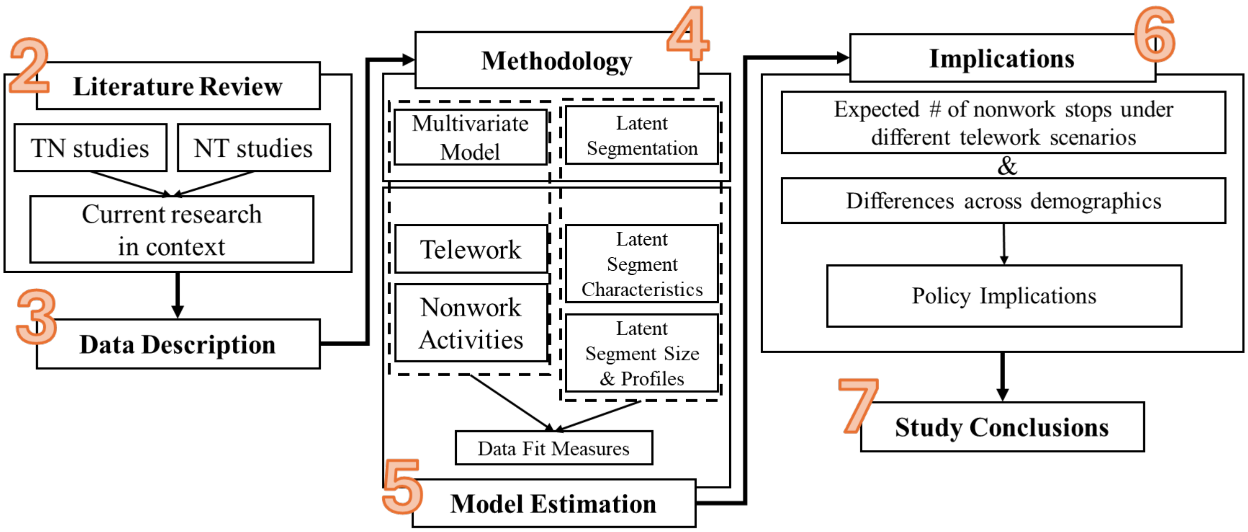

Figure 1. Study Organization

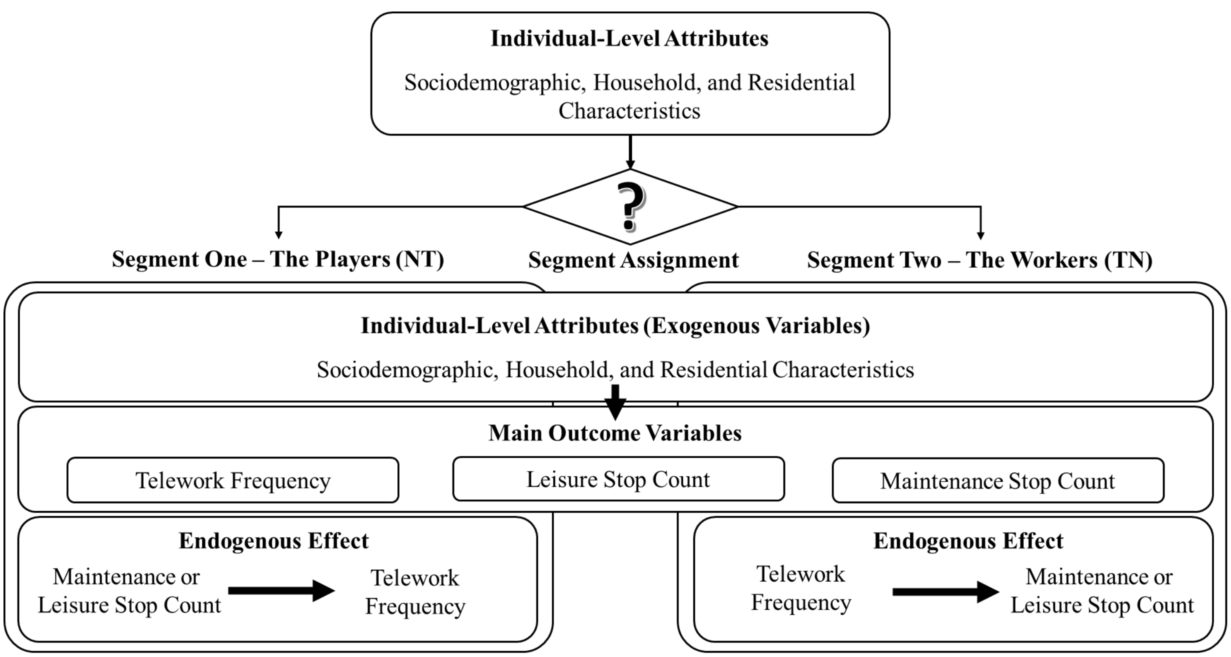

Figure 2. Model Framework

Table 1. Sample Distribution of Exogenous Variables (N=1920)

Variable	Count	%	MN%
Individual Demographics			
Gender			
Female	935	48.7	43.6
Male	920	47.9	56.4
Non-Binary	65	3.4	
Age			
18 to 24	115	6.0	24.0
25 to 34	621	32.3	23.2
35 to 44	543	28.3	21.1
45 to 54	312	16.3	14.2
55 to 64	285	14.8	10.2
65 or older	44	2.3	5.3
Race			
White	1655	86.2	—
Black	71	3.7	—
Neither White or Black	194	10.1	—
Formal Education Level			
Less than a Bachelor’s degree	564	29.4	—
Bachelor’s degree	799	41.6	—
Graduate degree	557	29.0	—
Residential Attributes			
Neighborhood Density Type			
Rural	684	35.6	
Suburban	509	26.5	—
Urban	727	37.9	—
Proximity to Clothing/Retail Stores			
At least one within home zip code	1295	67.4	—
None within home zip code	625	32.6	—

Variable	Count	%	MN%
Household Demographics			
Presence of Children (including ages)			
No children	1407	73.3	—
One child	215	11.2	—
Two children	198	10.3	—
Three children	81	4.2	—
Four or more children	19	1.0	—
Household structure			
Lives alone	623	32.4	—
Does not live alone and has no kids	784	40.8	—
Does not live with partner and has kids (single parent)	82	4.3	—
Single Mom	57	3.0	—
Single Dad	25	1.3	—
Lives with partner and has kids	431	22.4	—
Female and has a kid	236	12.3	
Household Annual Income			
Less than $25,000	84	4.4	18.3
$25,000 to $49,999	319	16.6	21.2
$50,000 to $74,999	380	19.8	17.6
$75,000 to $99,999	319	16.6	12.5
$100,000 to $149,999	410	21.4	15.6
$150,000 to $199,999	281	14.6	7.0
$200,000 or more	127	6.6	7.8
Number of Vehicles			
Zero	104	5.4	—
One or Two	1594	83.0	—
Three or more	222	11.6	—

“—” indicates that census comparisons are not available on the employed population of the Twin City region of Minnesota.

Table 2. Nonwork Stops as a Function of Telework (N=1920)

Telework Frequency (TF)	Portion of the Sample		Average # of Weekly Maintenance Stops*	Average # of Weekly Leisure Stops*	Average # of Total Nonwork Stops
	Count	%			
Never	875	45.6	3.92	5.06	8.98
Less than Monthly	146	7.6	3.72	5.08	8.80
1-3 Days a Month	127	6.6	4.20	6.06	10.26
1 Day a Week	101	5.3	3.51	5.80	9.31
2 to 3 Days a Week	258	13.4	3.50	5.33	8.83
4 Days a Week	147	7.7	3.85	5.80	9.65
≥ 5 Days a Week	266	13.8	4.03	5.44	9.47
Average # of Stops Over Entire Sample			3.86	5.31	9.17

*Only stops performed on weekdays where the employee has worked are reported here.

Table 3. Telework Frequency as a Function of Nonwork Stops

Telework Frequency (TF)		Never		Less than Monthly		1-3 Days a Month		1 Day a Week		2 to 3 Days a Week		4 Days a Week		≥ 5 Days a Week		Sum
		Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	
Maintenance Travel* (N=1920)	Less than 3.86 stops per week	457	44.7	83	8.1	65	6.4	59	5.8	145	14.2	76	7.4	137	13.4	1022 100%
	More than 3.86 stops per week	418	46.5	63	7.0	62	6.9	42	4.7	113	12.6	71	7.9	129	14.4	898 100%
Leisure Travel** (N=1920)	Less than 5.31 stops per week	542	47.4	91	8.0	66	5.8	55	4.8	152	13.3	81	7.1	156	13.6	1143 100%
	More than 5.31 stops per week	333	42.9	55	7.1	61	7.9	46	5.9	106	13.6	66	8.5	110	14.2	777 100%

* The average number of maintenance stops per week is 3.86 stops
** The average number of leisure stops per week is 5.31 stops.

Table 4. Estimation Results for Endogenous Variables Within Each Segment

Exogenous Variables	Telework		Maintenance Stops		Leisure Stops	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Individual Level Characteristics						
Gendered Lifecyle Characteristics						
Female	—		0.043	3.69	—	
Single Mother	0.348	2.22	0.098	3.14	—	
Non-single Mother	-0.184	-1.95	—		—	
Age (younger than 35)						
35 to 54	—		0.039	3.17	-0.014	-0.59
55 or older	-0.223	-3.27	—		-0.148	-5.07
Race (not black)						
Black	—		—		-0.105	-2.19
Formal Education (less than graduate degree)						
Graduate degree	0.148	2.47	—		—	
Household Level Characteristics						
Annual Income Level (less than $50,000)						
$50,000 to $74,999	0.252	3.15	—		—	
$75,000 to $99,999	0.312	3.65	—		—	
$100,000 to $199,999	0.506	7.02	—		—	
Over $200,000	0.782	6.28	-0.065	-2.82	—	
Number of Vehicles (three or more vehicles)						
Zero	0.311	3.60	-0.172	-5.16	-0.207	-3.14
One or two	0.311	3.60	—		—	
Residential Characteristic						
Proximity of Residential Location						
No clothing/retail stores within zip code	—		—		-0.081	-3.88
Endogenous Effects						
Frequency of Leisure Stops per Week (less than 4)						
4 or more leisure stops (specific to NT segment)	0.231	2.24	—		—	
Telework Frequency (Maintenance: teleworks less than once or more than three times a week)						
Teleworks one to three days a week (specific to TN segment)	—		-0.059	-1.99	—	
Thresholds: NT or Player Segment						
Constant coefficient for teleworking/Gamma coefficient for nonwork stop-making	0.593	5.02	3.190	28.77	2.960	17.46
Threshold 2	0.811	6.84	NA		NA	
Threshold 3	0.966	8.10	NA		NA	
Threshold 4	1.102	9.19	NA		NA	
Threshold 5	1.521	12.51	NA		NA	
Threshold 6	1.807	14.64	NA		NA	
Thresholds: TN or Worker Segment						
Constant coefficient for teleworking/Gamma coefficient for nonwork stop-making	0.404	3.35	3.390	23.24	2.730	8.35
Threshold 2	0.574	4.78	NA		NA	
Threshold 3	0.793	6.58	NA		NA	
Threshold 4	0.953	7.87	NA		NA	
Threshold 5	1.363	11.07	NA		NA	
Threshold 6	1.691	13.33	NA		NA	

Exogenous Variables	Telework		Maintenance Stops		Leisure Stops	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Threshold Shifters for NT or Player Segment						
0|1	NA		5.571	13.12	4.453	7.96
Threshold Shifters for TN or Worker Segment						
0|1	NA		5.820	8.82	1.378	1.12
Kernel (NT or Player Segment)						
Telework	1.000		-0.015	-0.39	0.013	0.20
Maintenance Stops			1.000		0.136	2.99
Leisure Stops					1.000	
Kernel (TN or Worker Segment)						
Telework	1.000		-0.013	-0.25	-0.057	-0.78
Maintenance Stops			1.000		0.009	0.15
Leisure Stops					1.000	

Table 5. Latent Segmentation Assignment Model

Explanatory Variables (base category)	NT Segment "Players"		TN Segment "Workers" (base)
	Coeff.	t-stat	
Individual and Household-level Characteristics			
Lifecycle Variables			
Single Parent	-0.665	-2.16	—
Age (younger than 35 and older than 44)			
35 to 44 years old	0.423	2.51	—
Number of Vehicles (at least one vehicle)			
Zero	0.684	1.28	—
Residential Location (urban or suburban)			
Rural	0.253	1.37	—
Constant	0.459	3.05	—
Segment Size	64.8		35.2

Table 6. Profiles of the Two Latent Market Segments

Attributes		Percent (%) within segment		Percent (%) within attribute		Overall Sample (%)
		The Players NT NW→TW	The Workers TN TW→NW	The Players NT NW→TW	The Workers TN TW→NW	
Individual and Household-level Characteristics						
Gender	Female	48.5	49.1	64.6	35.4	48.7
	Male*	51.5	50.9	65.1	34.9	51.3
Household children	No children present (regardless of age)	73.4	73.2	64.9	35.1	73.3
	Children present (regardless of age)	26.6	26.8	64.8	35.2	26.7
Household structure	Single Mother	2.4	4.0	52.0	48.0	3.0
	Single Father	0.8	1.5	51.6	48.4	1.3
	Parent who lives with partner	22.8	20.4	67.4	32.6	22.4
	Others**	74.0	74.1	64.8	35.2	73.3
Age	18 to 34	37.0	40.7	62.6	37.4	38.3
	35 to 44	30.9	23.4	71.0	29.0	28.3
	45 to 54	15.6	17.7	61.7	38.3	16.3
	55 or older	16.5	18.2	62.7	37.3	17.1
Race	Black	4.3	4.1	65.3	34.7	3.7
	Not Black	95.7	95.9	64.8	35.2	96.3
Education level	Less than a graduate degree	70.9	70.9	64.9	35.1	71.0
	Graduate degree	29.1	29.1	64.8	35.2	29.0
Household income	Up to $50,000	21.1	20.6	65.3	34.7	21.0
	$50,000 to $74,999	19.7	20.1	64.3	35.7	19.8
	$75,000 to $99,999	16.5	16.9	64.4	35.6	16.6
	$100,000 to $199,999	36.0	35.9	65.0	35.0	36.0
	$200,000 or more	6.7	6.5	65.5	34.5	6.6
Number of vehicles	Zero	6.5	3.4	77.6	22.4	5.4
	One or two	81.9	84.8	64.1	35.9	83.0
	Three or more	11.6	11.8	64.5	35.5	11.6
Residential Characteristics						
Population density	Rural	15.6	13.2	68.8	31.2	14.7
	Suburban or Urban	84.4	86.8	64.2	35.8	85.3
Proximity to retail store	Within zip code	67.2	67.9	64.5	35.5	67.4
	Not within zip code	32.8	32.1	65.5	34.5	32.6
Segment size		**Percent (%)**		**64.8**	**35.2**	**100.0**
		N		**1246**	**676**	**1920**

NW: Nonwork Travel; TW: Telework Frequency

*We include non-binary individuals in the male category, as the combination was used for the base relative to female workers in our model

**We did not include the individual segment profiles for all household structures, as the ones excluded were all fairly equivalent to the overall sample and segment size across all metrics (as the "lives with a partner" structure is). Household structures under the term "other" include: lives with partner with no children, live with parents, lives alone, and live with unrelated roommates.

Table 7. Goodness-of-Fit Statistics

Metric	Proposed Joint Model	NT “Player” Model	TN “Worker” Model
Disaggregate Fit Measures			
Log likelihood at convergence	-12633.753	-12681.830	-12682.368
No. of non-constant/threshold parameters	33	24	24
Log likelihood at constants/thresholds only	-12902.342	-12902.342	-12902.342
Adjusted rho-squared value	0.0183	0.0153	0.0153
Non-nested likelihood ratio test: Proposed model versus NT “Player” Segment	$\Phi(-9.30) \lll 0.0001$		
Non-nested likelihood ratio test: Proposed model versus TN “Worker” Segment	$\Phi(-9.30) \lll 0.0001$		

Aggregate Fit Measures

Combination Counts			Observed Count	Proposed Joint Model	NT “Player” Model	TN “Worker” Model
Telework (Days/wk)	**Maint. Stop Count**	**Leisure Stop Count**				
Never	0-2	0-2	8.2	7.2	11.0	0.2
Never	0-2	3-5	4.2	5.0	7.1	1.2
Never	0-2	≥6	5.1	4.7	2.4	9.2
Never	3-5	0-2	5.5	5.3	8.0	0.2
Never	3-5	3-5	5.4	4.9	6.7	1.6
Never	3-5	≥6	5.6	6.7	2.8	13.8
Never	≥6	0-2	2.2	2.4	3.6	0.1
Never	≥6	3-5	2.8	2.9	3.7	1.6
Never	≥6	≥6	6.7	6.3	1.8	14.3
< Monthly to 1 day/week	0-2	0-2	2.8	2.8	4.3	0.1
< Monthly to 1 day/week	0-2	3-5	2.3	2.1	2.9	0.6
< Monthly to 1 day/week	0-2	≥6	2.2	2.3	1.0	4.6
< Monthly to 1 day/week	3-5	0-2	1.6	2.1	3.2	0.1
< Monthly to 1 day/week	3-5	3-5	2.3	2.1	2.8	0.8
< Monthly to 1 day/week	3-5	≥6	3.8	3.2	1.2	6.8
< Monthly to 1 day/week	≥6	0-2	0.7	0.9	1.4	0.1
< Monthly to 1 day/week	≥6	3-5	1.3	1.2	1.5	0.8
< Monthly to 1 day/week	≥6	≥6	2.4	3.0	0.8	7.0
2-3 days per week	0-2	0-2	2.4	2.0	3.0	0.0
2-3 days per week	0-2	3-5	1.4	1.5	2.1	0.4
2-3 days per week	0-2	≥6	1.6	1.5	0.7	3.0
2-3 days per week	3-5	0-2	1.5	1.4	2.3	0.1
2-3 days per week	3-5	3-5	1.7	1.4	1.9	0.6
2-3 days per week	3-5	≥6	2.2	2.1	0.8	4.5
2-3 days per week	≥6	0-2	0.5	0.6	1.0	0.0
2-3 days per week	≥6	3-5	0.5	0.9	1.0	0.5
2-3 days per week	≥6	≥6	1.8	2.0	0.5	4.5
4 or more days per week	0-2	0-2	2.6	3.0	4.5	0.1
4 or more days per week	0-2	3-5	2.4	2.4	3.3	0.7
4 or more days per week	0-2	≥6	2.9	2.6	1.2	5.1
4 or more days per week	3-5	0-2	1.9	2.2	3.3	0.1
4 or more days per week	3-5	3-5	2.4	2.3	3.0	1.0
4 or more days per week	3-5	≥6	3.4	3.4	1.3	7.6
4 or more days per week	≥6	0-2	0.9	1.0	1.4	0.1
4 or more days per week	≥6	3-5	2.1	1.4	1.6	1.0
4 or more days per week	≥6	≥6	2.8	3.2	0.9	7.6
Weighted Absolute Percentage Error (WAPE)				11.5	51.1	95.1

Table 8. Effect of Telework Arrangement on Nonwork Stop-Making

Variable Category	Categories	Female, non-mother				Single mother				Male			
	Nonwork Purpose	Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops	
		Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking
Gendered Lifecycle	Never	4.03	—	5.11	—	5.54	—	6.08	—	3.58	—	5.15	—
	< Monthly	3.95	-2.0	4.90	-4.2	5.43	-1.9	5.78	-4.9	3.51	-2.0	4.93	-4.2
	1-3 days/mo.	4.17	3.4	5.78	13.0	5.72	3.2	6.75	10.9	3.70	3.4	5.82	12.9
	1 day/wk.	4.10	1.5	5.50	7.5	5.63	1.7	6.48	6.5	3.63	1.6	5.54	7.5
	2-3 days/wk.	4.03	-0.1	5.26	2.9	5.55	0.2	6.22	2.3	3.57	-0.1	5.30	2.9
	4 days/wk.	4.08	1.2	5.50	7.6	5.62	1.5	6.47	6.4	3.62	1.1	5.54	7.5
	≥ 5 days/wk.	4.01	-0.5	5.30	3.6	5.54	0.0	6.25	2.7	3.56	-0.6	5.34	3.6
Age	Categories	Age < 35 years				Age 35-54 years				Age 55+ years			
	Nonwork Purpose	Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops	
		Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking
	Never	3.65	—	5.42	—	4.08	—	5.29	—	3.65	—	4.22	—
	< Monthly	3.58	-2.0	5.19	-4.1	4.00	-2.0	5.07	-4.2	3.58	-2.0	4.02	-4.6
	1-3 days/mo.	3.78	3.4	6.09	12.5	4.22	3.4	5.96	12.7	3.78	3.5	4.85	15.1
	1 day/wk.	3.71	1.6	5.81	7.3	4.15	1.6	5.68	7.4	3.71	1.5	4.58	8.5
	2-3 days/wk.	3.65	-0.1	5.57	2.9	4.08	-0.1	5.44	2.9	3.65	-0.2	4.35	3.2
	4 days/wk.	3.70	1.2	5.81	7.3	4.13	1.2	5.68	7.4	3.69	1.1	4.57	8.3
	≥ 5 days/wk.	3.63	-0.6	5.61	3.6	4.06	-0.5	5.48	3.6	3.63	-0.7	4.37	3.6

Table 8. (CONTD): Effect of Telework Arrangement on Nonwork Stop-Making

Variable Category		Black				Not Black			
	Categories								
	Nonwork Purpose	Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops	
		Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	% Change from "Never" Teleworking
Race	Never	3.84	—	4.33	—	3.84	—	5.19	—
	< Monthly	3.77	-2.0	4.12	-4.8	3.77	-2.0	4.97	-4.2
	1-3 days/mo.	3.97	3.4	4.96	14.5	3.97	3.4	5.86	12.9
	1 day/wk.	3.90	1.6	4.70	8.4	3.90	1.6	5.58	7.5
	2-3 days/wk.	3.84	-0.1	4.47	3.2	3.84	-0.1	5.34	2.9
	4 days/wk.	3.89	1.2	4.69	8.3	3.89	1.2	5.58	7.5
	≥ 5 days/wk.	3.82	-0.6	4.50	3.8	3.82	-0.6	5.37	3.6

Variable Category	Categories	0 vehicles				1 or 2 vehicles				3 or more vehicles			
	Nonwork Purpose	Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops		Maintenance Stops		Leisure Stops	
		Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops	Expected Number of Stops	% Change from "Never" Teleworking	Expected Number of Stops
Number of Vehicles	Never	2.19	—	2.93	—	3.94	—	5.28	—	3.94	—	5.31	—
	< Monthly	2.14	-2.1	2.80	-4.7	3.86	-2.0	5.05	-4.3	3.86	-1.9	5.11	-3.8
	1-3 days/mo.	2.25	2.8	3.41	16.2	4.07	3.4	5.95	12.8	4.08	3.5	6.00	13.2
	1 day/wk.	2.21	0.9	3.21	9.4	4.00	1.6	5.67	7.4	4.00	1.6	5.70	7.5
	2-3 days/wk.	2.17	-0.7	3.05	3.9	3.94	-0.1	5.43	2.9	3.93	-0.1	5.46	2.9
	4 days/wk.	2.20	0.3	3.22	9.7	3.99	1.2	5.67	7.5	3.98	1.1	5.69	7.3
	≥ 5 days/wk.	2.16	-1.5	3.08	5.1	3.92	-0.5	5.47	3.6	3.91	-0.6	5.48	3.2

Appendix A

The comprehensive breakdowns of activity purposes, categorized from the travel diary within the TBI dataset, are outlined below:

Maintenance Activities:

1. Errand without appointment (e.g., post office)
2. Grocery shopping
3. Other routine shopping (e.g., pharmacy)
4. Medical visit (e.g., doctor, dentist)
5. Drop someone off
6. Pick someone up
7. BOTH pick up AND drop off
8. Accompany someone only (e.g., go along for the ride)
9. Got gas
10. Errand with appointment (e.g., haircut)
11. Other shopping or errand (e.g., pharmacy, post office)
12. Shopping for major item (e.g., furniture, car)
13. Other activity only (e.g., attend meeting, pick-up or drop-off item)
14. Changed or transferred mode (e.g., waited for bus, drove onto ferry)

Leisure Activities:

1. Exercise or recreation (e.g., gym, jog, bike, walk dog)
2. Social activity (e.g., visit friends/relatives)
3. Dined out, got coffee or take-out
4. Leisure/entertainment/cultural (e.g., cinema, museum, park)
5. Volunteering
6. Went to another residence (e.g., someone else's home, second home)
7. Religious/civic/volunteer activity
8. Went to temporary lodging (e.g., hotel, vacation rental)
9. Attend other type of class (e.g., cooking classes)
10. Other leisure activity
11. Attend vocational education class
12. Family activity (e.g., watch child's game)