

An Examination of the Adoption and Frequency of Part-Day and Full-Day Telework and the Impacts on Weekly Commute VMT

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ABSTRACT

Telework adoption has expanded rapidly in the aftermath of the COVID-19 pandemic, with many workers now engaging in flexible hybrid arrangements that include not only full-day telework but also part-day telework, in which work is split between in-person and remote locations within a single day. Despite the growing prevalence of part-day telework, most large-scale surveys and travel demand models fail to distinguish it from full-day telework, obscuring important differences in commute patterns, activity scheduling, and resulting vehicle miles traveled (VMT). This paper examines the adoption and frequency of part-day and full-day telework and quantifies their differential effects on weekly commute VMT, using multi-day travel diary data from the 2023 Puget Sound Regional Household Travel Survey. The analysis employs a joint modeling framework that represents telework adoption, the frequencies of part-day and full-day telework, and commute distance, while accounting for unobserved behavioral factors influencing these outcomes. The results reveal significant differences in preferences for part-day and full-day telework across individual demographics and location characteristics. Regarding travel impacts, part-day telework tends to be jointly chosen as a package along with living close to the physical out-of-home workplace (that is, shorter commute distances), while full-day telework is more commonly chosen as a package along with living farther from the physical out-of-home workplace. We also quantify the overall impacts of work arrangement choices on weekly commute VMT, revealing specific actionable insights for travel demand forecasting, transportation demand management, and employer telework policies.

Keywords: Part-Day Telework, Hybrid Work Arrangements, Commute VMT, Telework Frequency, Travel Demand Modeling

1. INTRODUCTION

A significant body of research has examined the adoption of telework and the impacts of telework choices on activity-travel behavior, particularly in the aftermath of the COVID-19 pandemic. During the height of the pandemic, more than 30% of workers in the United States moved to a work arrangement that consisted primarily of remote work (compared with less than 5% before the pandemic), while more than 60% of total working days were undertaken from home (Barrero et al., 2021; Rafiq et al., 2022; Olde Kalter et al., 2023). This rapid change was enabled by the growth of information and communications technologies that had already been influencing work arrangements for many years, as well as mandated changes to work arrangements due to strict lockdown policies enacted by local governments or internal company policies (Sweet and Scott, 2022; Wang et al., 2023). More recently, as the motivations for telework have continued to evolve, the landscape of remote work has become more complex. This evolution has included significant growth in flexible hybrid work arrangements, involving not only different work locations on different workdays, but also an increased ability to split time across multiple work locations *within a single day* (Kappler and de Abreu e Silva, 2025). Such part-day telework arrangements provide additional opportunities for worker flexibility, allowing those who have in-person work requirements on a particular day to also avail themselves of the many benefits of remote work on the same day, including being able to better balance personal/household needs with work needs or avoid commuting during peak hours (Asgari and Jin, 2018). In this sense, the post-pandemic growth of part-day telework may be viewed as a return to pre-pandemic telework practices, when part-day telework was more prevalent than full-day telework (see Elldér, 2020; Stiles and Smart, 2021).

Within this fast expanding post-pandemic landscape of part-day telework, it is important to recognize that part-day telework can have distinct impacts on commute patterns and overall activity-travel patterns compared with full-day telework (Elldér, 2020). In fact, several pre-pandemic studies found that part-day teleworkers tend to have a larger total VMT than non-teleworkers (due primarily to higher non-work VMT, particularly for maintenance trips during the morning peak period) as well as a larger VMT than full-day teleworkers (due primarily to higher commute VMT as part-day teleworkers still commute) (see Lachapelle et al., 2018; Asgari and Jin, 2018; Elldér, 2020; Stiles and Smart, 2021). In another post-pandemic study, Belloc et al. (2024) observed that part-day teleworking was associated with a decrease in overall daily travel time compared with in-person workers, but this effect was no longer significant when commute time was removed from the analysis. They suggest that part-day teleworkers may be able to reduce their travel time by shifting their commute to off-peak times but may replace this travel time with additional nonwork travel, a distinct mobility pattern compared with full-day teleworkers. Further, part-day telework may result in significantly different activity-scheduling patterns relative to full-day telework arrangements, including increased activity chaining outside of peak commute periods (Asgari and Jin, 2018; Elldér, 2020).

The differential travel-related impacts of full-day and part-day telework, as discussed above, underscore the importance of distinguishing between these two telework modalities in both empirical analyses and policy evaluations. Such distinctions, however, are only possible when data explicitly identify whether teleworking occurs on a full-day or part-day basis. Unfortunately, most large-scale surveys fail to do so, either equating telework to full-day telework or eliciting information using a single aggregate telework category. For instance, the American Community Survey (U.S. Census Bureau, 2024) identifies teleworkers by asking “How did you usually get to work last week?” and including “Worked from home” as an option, while the National Household Travel Survey (Federal Highway Administration, 2023) asks, “How often did you work only at home for an entire workday instead of traveling to a usual workplace?” Both questions focus exclusively on

whether the individual commuted at all, excluding part-day teleworkers from their definition of telework and focusing only on full-day telework that has no associated commute distance. In contrast, the Current Population Survey (U.S. Bureau of Labor Statistics, 2024) asks, “At any time (the week before last/last week), did you telework or work at home for pay?” This approach essentially combines the categories of part-day and full-day telework. Finally, many other surveys ask about the frequency or intensity of telework (either through revealed or stated preferences), while considering only a single work location on each day and leaving respondents to choose a single location for days on which they worked in multiple places (for just a few examples, see Nagata et al., 2021; Chauhan et al., 2022; Asmussen et al., 2023; Soler et al., 2023; Tokey and Alam, 2023). Thus, individuals working partially remotely may be inconsistently categorized as teleworkers or in-person workers when they do not fall neatly into these categories.

Motivated by the above discussion, and using a rather unique regional-level activity-travel diary data that enables us to distinguish between part-day and full-day telework, we examine the adoption and frequency of part-day telework alongside full-day telework, and quantify the total effects of telework on commute VMT. Specifically, we use the multi-day diary data (with three to five workdays in a single week from each respondent) collected in the 2023 Puget Sound Regional Household Travel Survey, which records the number of hours worked remotely on each day alongside a complete diary of work and non-work out-of-home activities. This allows us to classify each workday as (a) fully in-person, (b) fully remote, or (c) part-day telework, where work is split between in-person and remote locations. We then model this split of workplace choices, considering a binary outcome for whether each individual ever teleworks as well as the counts of part-day and full-day telework days. Jointly with these workplace location decisions, we model the worker’s commute distance, allowing us to determine the effect of commute distance on weekly work location choices, while simultaneously accounting for unobserved factors that may influence both commute distance and work arrangement preferences (for instance, an unobserved individual preference for schedule predictability and daily travel control may lead individuals to locate closer to employment centers while also favoring flexible work arrangements). After accounting for such unobserved factors, we then estimate a more “cleansed” structural causal relationship between commute distance and work arrangement. Finally, by jointly modeling workplace location choices alongside commute distance, we translate the results to quantify the impacts of the telework choices on aggregate commute VMT at a weekly level. This investigation has substantial importance for transportation planners, as the continued evolution of telework habits, including growing adoption of part-day telework, will influence the spatial and temporal distributions of travel demand, the future of residential choices and employment centers, and the structure of time-use and non-work travel decisions.

The remainder of this paper is organized as follows. The following section presents an overview of existing literature examining the adoption of part-day telework. Section 3 presents the details of the data used and the modeling methodology employed. The model results are presented in Section 4, while Section 5 presents the method used to quantify the effects of telework on commute VMT. Finally, Section 6 concludes the paper with a discussion of the major implications of the study.

2. LITERATURE OVERVIEW

While a large body of recent literature has examined the adoption of telework and the frequency of telework in general, we focus this review on the adoption of part-day telework, a work arrangement that has received less attention overall. Due to the changing trends in telework,

different ways of measuring working patterns over the last several years, and the relatively small number of studies examining part-day telework since the pandemic, we begin by briefly reviewing pre-pandemic literature on part-day telework, before turning to post-pandemic trends. In doing so, we focus on the dimensions relevant to the current paper, including only studies that have (a) expressly modeled part-day teleworking (either with full-day teleworking as another separate outcome or including part-day and full-day teleworking as one consolidated outcome), and (b) considered commute distance in the analysis. We do not dwell on studies that have considered part-day or full-day teleworking as predetermined and modeled travel behaviors as the outcome of these predetermined teleworking choices.¹

An overview of studies considering and analyzing part-day telework is presented in Table 1, providing (1) the study context (data source and location), (2) the elicitation method (retrospective responses or time-use/activity/travel diary) (3) the data resolution (the number of days used to identify telework arrangements; single day or multi-day), (4) the definition of part-day telework employed, and (5) the modeling approach. Within the modeling approach, we list multiple dimensions: (a) full-day telework modeled?, (b) part-day telework modeled?, (c) consideration of both full-day and part-day telework *frequencies*?, (d) telework adoption, full-day telework frequency, and part-day telework frequency all modeled jointly?, and (e) commute distance considered endogenous to telework arrangements? In part (d) above, note that there are four issues involved. The first is whether telework adoption is modeled jointly with the frequencies of part-day and full-day telework to accommodate common unobserved effects (through error correlations) that influence these propensities. For instance, unobserved individual preferences favoring sustained, uninterrupted remote work and stronger work-from-home self-efficacy may result in a stronger desire to adopt teleworking, but as complete work-from-home days rather than split-day arrangements. This would lead to a positive correlation between teleworking adoption and full-day telework frequency, but a negative correlation between telework adoption and part-day telework frequency (as we noticed in our own empirical analysis later). The second is whether part-day and full-day telework frequencies themselves are modeled jointly to accommodate common unobserved factors (again through error correlations, such as an introverted person avoiding contact with co-workers as much as possible while also wanting to show up occasionally at the workplace for professional visibility purposes). The third is whether intrinsic clustering effects among specific intensities of part-day and full-day telework, unrelated to individual-level employee effects, are accommodated. Such effects may originate because of unobserved employer policies that elevate or depress specific combinations of part-day and full-day telework intensities. For example, a certain fraction of employers may uniformly promote hybrid work arrangements, may have strict “in-person work” policies, or may not have a physical workspace available. The fourth is whether or not the basic identity that the number of part-day telework and full-day telework cannot exceed the total number of workdays is accommodated. In part (e) under modeling approach, the issue is whether commute distance is considered as an exogenous pre-determined variable or is modeled jointly with telework arrangements to account for unobserved factors that may influence both commute distance and work arrangement preferences (as discussed in the previous section).

¹The reader is referred to pre-pandemic data studies such as Lachapelle et al. (2018), Asgari and Jin (2018), Elldér (2020), Stiles and Smart (2021), and Abe et al. (2023), and post-pandemic studies such as Belloc et al. (2024), for research investigations that do not model telework per se, but do examine telework effects on travel behaviors (see also the second paragraph of the introduction section). Asmussen et al. (2026) provides a detailed review of earlier studies investigating telework effects on different types of travel behavior outcomes.

2.1 Studies of Part-Day Telework Before the Pandemic

The top panel of Table 1 shows two pre-pandemic studies of part-day telework. Haddad et al. (2009), in their study using a 2007 United Kingdom national multi-day survey, analyzed the number of full-day and part-day telework days reported during a one work-week reference period. They defined part-day telework as those who indicated that they had “worked at home and then at my workplace,” “worked at my workplace and then at home,” or “worked at home then my workplace then at home” (a 30-minute threshold work duration cut off was used to designate if a person worked from home on a workday), finding that 17.2% of respondents engaged in part-day telework. These part-day remote work arrangements were more prevalent than full-day telework, with only 9.8% of respondents teleworking at least one full day (full-day telework was defined as the response “worked at home only”). Additionally, part-day telework was undertaken at slightly higher frequencies, with an average of 2.02 days per week compared to an average of 1.96 days per week of full-day telework, among those who adopted each working modality. At a more disaggregate-level, they observed that being in a white collar occupation was the most important variable in explaining both full-day and part-day telework frequency, while commute distance and other demographic characteristics played little role. But full-day and part-day telework frequencies were modeled independently, without the constraint that the sum of the two frequencies cannot exceed the number of work days.

Deng et al. (2015) used a 2009 survey of commuters in Northern California to identify frequencies of full-day, part-day, and overtime telework in a typical month. They define full-day telework as “work at home for basically a full day without commuting at all that day,” part-day telework as “work at home and change the time you commute to or from work,” and overtime telework as “work at home for part of the day without changing your normal commute.” They then collapsed these three frequencies into a set of three binary outcomes for the adoption of each type of telework (those who indicated they used each mode at least “1-3 times a month”). They found overtime telework was the most commonly adopted form of telework (24.8% of respondents), followed by part-day telework (16.0% of respondents), with full-day telework being least commonly adopted (13.9% of respondents). They also examined adoption of these three telework modalities using a trivariate binary probit modeling system, finding strong positive correlations among the three dimensions (although they do not model an overall telework adoption dimension jointly with these three telework modalities, nor do they consider the actual frequencies of use of each telework option). They observed that higher levels of household income as well as college education were positively associated with adoption across all three telework types, while clerical occupations were consistently negatively associated with adoption, reinforcing the occupation-based findings of Haddad et al. (2009). They also found that attitudes (including orientation towards different levels of residential density) significantly influenced telework preferences, as well as finding that adoption of all three telework types was more common among those with longer commute distances (and particularly so for full-day telework; although they do not consider commute distance to be endogenous to telework choices).

2.2 Studies of Part-Day Telework After the Pandemic

Although we are aware of only two peer-reviewed published studies that have examined part-day telework with data collected during or since the pandemic (see the bottom panel of Table 1), there is a large body of evidence that telework behaviors in general have shifted significantly following the onset of the COVID-19 pandemic (see, for example, Asmussen et al., 2023; McNally et al.,

2023; Webber et al., 2023; Asmussen et al., 2024; Astroza et al., 2025; Anik and Habib, 2025; Asmussen et al., 2026).

Regarding specific part-day post-pandemic telework behavior studies as listed in Table 1, using data from the summer of 2021 across three major European cities, Kappler and de Abreu e Silva (2025) asked respondents to report, for each of 5 weekdays, whether they had teleworked for the full day, teleworked part-day in the morning, teleworked part-day in the afternoon, or not teleworked at all on that day (no specific duration thresholds were defined for telework). They observed that part-day telework had become significantly less prevalent than full-day telework, with the rate of part-day telework averaging between 0.25-0.60 days per week compared with a rate of full-day telework averaging between 2.14-3.38 days per week. While not modeling part-day and full-day telework behaviors jointly through unobserved error correlation effects, they do consider pre-determined individual attitudinal constructs of “reticence to engage in telework” and “positive to telework” as exogenous variables affecting the frequencies of part-day and full-day telework. They observe a strong state-dependence effect in that the pre-pandemic telework frequency in 2019 (undifferentiated between full-day and part-day telework) had a strong positive effect on both full-day and part-day post-pandemic telework frequencies. As with all other part-day-related studies we are aware of, Kappler and de Abreu e Silva (2025) also do not maintain the identity that the sum of part-day and full-day telework across the days of the week cannot exceed the total number of work days in the week. They also consider commute distance to be a predictor of telework choices, finding that those with short commutes have a greater propensity for part-day telework (they do not consider commute distance to be endogenous to telework choices).

In another recent study using data collected in 2023 and 2024 in Flanders, Belgium, Versigghel et al. (2025) found, in their descriptive analysis, that part-day telework was less prevalent than full-day telework, although they combined these categories into a single “telework” variable for their main modeling analysis. They found that longer commute durations reduced telework propensities, but did not separate this effect between part-day and full-day telework propensities, nor did they model commute distance as being endogenous to telework choices (see the “Modeling Approach” column of Table 1).

2.3 Study in Context

The current study examines the joint adoption of part-day and full-day telework as well as the relationship between these telework decisions and commute distance to quantify the impact of telework choices on weekly commute VMT. There are several salient aspects of the current study in the context of the extant literature. First, we consider the relationship between work arrangement choices and commute distance in the context of a major city in the United States (U.S.) several years after the pandemic. As discussed above, the consideration of part-day telework is rare in the post-pandemic literature on telework choices, with both the studies that have considered part-day telework being undertaken outside the U.S. Given evidence of significantly different mobility patterns between part-day teleworkers, full-day teleworkers and full-day in-person workers, the nature of these decisions needs additional study in a variety of geographic contexts. Second, unlike earlier studies, we model telework adoption (whether part-day or full-day), part-day telework frequency per week, and full-day telework frequency per week using an efficient joint trivariate ordered-response model system that simultaneously accommodates all the four considerations listed in the second paragraph of Section 2: (a) unobserved error correlation between telework adoption and the frequencies of part-day and full-day telework, (b) unobserved error correlations to accommodate unobserved employee preferences, (c) clustering effects in the combinations of

part-day and full-day telework through an innovative threshold-shifting strategy that allows specific combinations to be elevated or depressed (for example, because of employer-side considerations, as discussed in the paragraph just before Section 2.1), and (d) the integrity of the identity that weekly frequency of part-day and full-day telework days cannot exceed the number of workdays in the week (which also implicitly guarantees that the predicted number of days of in-person work cannot be negative) and cannot also both be equal to zero for teleworkers. Third, in addition to the joint modeling of telework adoption and the frequencies of part-day and full-day telework choices, we also model all these telework choices jointly with commute distance to accommodate the potential endogeneity of commute distance to telework choices. That is, we accommodate unobserved individual preferences such as for schedule predictability and daily travel control (see the penultimate paragraph of Section 1) that may simultaneously impact telework adoption, the frequency of participation in full-day or part-day telework, and commute distance. Finally, we use the model results to quantify the effects of telework choices on weekly commute VMT, accounting for the reduced frequency of commuting due to full-day telework (that do not occur for part-day telework) as well as commute distance differences for those with different levels of part-day and full-day telework adoption. These results reveal important implications from a policy standpoint, demonstrating how hybrid work arrangements influence travel demand and supporting more effective design of congestion mitigation strategies.

3. METHODOLOGY

3.1 Data Description

The primary data source used for this study is the 2023 Puget Sound Regional Household Travel Survey (Puget Sound Regional Council, 2024). The survey was administered between March and June 2023 using an address-based sampling approach. The sampling frame was stratified to oversample individuals living in census blocks with more racial and ethnic minorities and low-income individuals (see RSG, 2024 for additional details of the survey administration procedure). The study area was the Puget Sound (Greater Seattle, Washington) region, encompassing the King, Kitsap, Pierce, and Snohomish counties, a region including 82 cities and towns with a total population of over 1.6 million households. The survey elicited information about general travel behaviors and mobility choices, vehicle ownership and use, home location preferences, and detailed demographic and socioeconomic information about respondents. In addition, a travel diary was requested from each individual from each sampled household. Those completing the survey online or via the call center were asked to provide a one-day travel diary, while those completing the survey using the rMove smartphone app were asked to complete a travel diary for a period of up to seven days.

For the current study, we consider only employed individuals who worked on at least three weekdays during their reporting period. The consideration of individuals with multiple working days allows us to determine how they split their time between different working modalities across the week, providing frequencies of full-day and part-day telework adoption over a multi-day period rather than considering only the use of these work arrangements on a single day (as discussed in more detail in the following section). The resulting sample consists of 699 individuals (out of a total of 1218 individuals who completed the survey using the rMove smartphone app). The majority of the excluded individuals (75.3%) were unemployed, while the remaining 24.7% of the excluded individuals were employed but reported working less than three days during their travel diary.

3.1.1 Endogenous Outcome Variables

The main outcomes considered in the current study include the commute distance and the set of telework choices across the surveyed travel days. Descriptive statistics for these outcomes are shown in Table 2, based on the number of working days for each individual. The first outcome, commute distance, is considered as a continuous variable in our analysis. The mean one-way commute distance (between a respondent's home and primary out-of-home workplace) across all individuals in the dataset is 9.02 miles, and the median one-way commute distance is 6.15 miles (see the last row of the third main column of Table 2). Given the rightward skew and positivity of this outcome, we use the logarithm of the commute distance as the outcome in the model. Across the different numbers of workdays in the week, the mean/median commute distances do not vary too substantially, though these are lowest for individuals who work three days a week.

Regarding telework arrangements, we consider three aspects. First, we consider an overall adoption dimension (a binary outcome), indicating whether an individual teleworked at all during the reported period. Notably, the definition of telework used in the survey includes time spent working at home or remotely (anywhere besides the primary workplace) both during and outside regular business hours on each travel day. Further, to accommodate the fact that many individuals may undertake small work-related tasks on a regular basis outside of work hours that do not quite replace work tasks at the office, we do not consider an individual to have undertaken telework on any given day unless they spent more than 30 minutes working remotely on that day.² Second, for those who teleworked at all, we consider the frequency of full-day telework; that is, the number of days that the individual completed all of their work for the day remotely (using the same definition of telework), without any commute to their out-of-home workplace. Third, again for those who teleworked at all, we consider the frequency of part-day telework as the number of days that the individual completed a substantive portion of their work remotely (reported more than 30 minutes of telework) while also making a commute to their primary workplace during the same day. By identifying these two frequencies, the number of days that an individual works entirely from their primary workplace location without any telework is implicitly identified as the remaining reported working days.

As shown in Table 2, 71.8% of individuals (see the last row of the fourth main column) in the sample reported teleworking at least once during their reporting period, while the remaining 28.2% reported that they did not telework more than the 30 minute cutoff on any reported day from home (note that a teleworker is one for whom the sum of the number of days of full-day telework and part-day telework is more than zero). Not surprisingly, the rate of telework adoption increases substantially with the number of days worked, with only 49.5% of those working three days choosing telework at least once, while 81.2% of those working five days choose telework at least

²We should note that, similar to Haddad et al. (2009), we use this 30-minute cutoff to distinguish between substantive telework (where a significant portion of work is undertaken remotely) and incidental or marginal telework (such as checking email or performing brief tasks outside of working hours). Although many of the existing studies examining telework adoption do not make this distinction, there is evidence from literature in economics and organizational psychology that there are substantive differences in the motivations and behaviors of those undertaking relatively long-duration telework activities, compared with those supplementing their existing work routines with short-duration remote work activities (see Garrett and Danziger, 2007; Thompson et al., 2022). The need to make such a distinction was also highlighted by the work of Deng et al. (2015) who defined part-day teleworkers as those who “work at home and change the time you commute to or from work” and overtime teleworkers as those who “work at home for part of the day without changing your normal commute.” Thus, by applying a 30-minute cutoff, we aim to exclude incidental work that is unlikely to reflect a deliberate substitution of workplace presence. However, we recommend that future studies specifically collect information on, and examine the impacts of, the types of activities undertaken while teleworking and the duration of in-person and remote work on daily activity-travel patterns.

once. Descriptive statistics for the frequencies of full-day and part-day telework, among those who telework, are also presented in Table 2. Overall, there is wide variation in telework routines. In general, across all numbers of workdays, full-day telework is more common than part-day telework, with only 18.5% of teleworkers reporting zero full-day telework compared to 46.6% of teleworkers reporting zero part-day telework (see the last rows of the sub-columns corresponding to “0 days” in the full-day and part-day telework frequency columns). Additionally, it is relatively more common for individuals to work all of their working days as full-day telework, while it is more common to partake in part-day telework for only a single day or not at all (as may be observed in the percentages in the rows corresponding to each number of workdays in the telework frequency columns; for example, 34% of teleworkers with three working days telework fully remote on all three days). Also, consistent with the trend for overall telework adoption, full-day telework adoption and part-day telework adoption percentages are highest for those with five working days.

Table 3 proceeds to present the joint distribution of full-day and part-day telework. For conciseness and absorption ease, as well as to recognize that the joint distribution is constrained by the total number of work days, we present the distribution in seven discrete categories. The table highlights that among those who telework, the most common work arrangement is full-day telework on all workdays, followed by a combination of only full-day and part-day (with no days in the work week of only work at the primary workplace). The work arrangement selected least often corresponds to “part-day telework only,” which implies that the individual commutes every day to a physical workplace and supplements that with work at home on each of those days. It is also relatively less common to combine all three work modalities (full-day in-person, full-day telework, and part-day telework) across workdays.

Finally, Figure 1 presents the relationship between commute distance and work arrangement participation, indicating the proportion of individuals in each of four commute distance ranges who belong to each of the seven work arrangements listed in Table 3. Several observations may be drawn. First, as expected, the “full-day in-person only” (with no telework of any kind) arrangement is negatively associated with increasing commute distance, but only up to the distance of 15 miles. Beyond that distance, the percentage of respondents working only in-person reaches close to the percentage working only in-person in the distance range of less than five miles. In other words, the percentage of employees living very far away from their workplace who go into the office each and every workday is about the same as the percentage of employees living very close to their workplace who go into the office each and every day. This is a similar finding as in the study by Asmussen et al. (2024). Second, and in reverse, the percentage of employees engaging in full-day telework on all workdays (that is, work every workday fully from home) increases with commute distance, but only up to a commute distance of 15 miles, after which this percentage drops (though still markedly higher than for the commute distance of 10 miles or lower). Third, and similar to in-person work only, part-day teleworkers only (that is, individuals who commute to work every day and also work at home every day of the week) are the most highly represented among those who live very close to their workplace. And fourth, a clear trend is visible in the representation of individuals who have a combination of full-day and part-day telework (these are individuals who, across their workdays, work some days entirely from home and work other days at both the workplace and home). Such individuals are most represented in the pool of individuals who reside closest to their workplace, and this percentage progressively decreases with commute distance. Overall, it does seem that any amount of part-day telework is generally associated with short commute distances, while the reverse is the case with full-day

telework (at least until the commute distance of 15 miles). These variations demonstrate the importance of distinguishing between full-day and part-day telework arrangements, especially as the relationship with commute distance differs systematically between these two types of work arrangements. Of course, it is also important to note that the descriptive statistics in Tables 2 and 3 and Figure 1 do not provide any sense of heterogeneity across individuals in these preferences, or the nature of the joint relationship (whether the relationships observed are pure associations through unobserved individual-related factors, or structural causal effects).

3.1.2 Exogenous Variables

Descriptive statistics for individual demographics, household characteristics and location, and employment details are shown for the sample in Table 4, which also provides comparisons with data from the 2023 American Community Survey (ACS) for the Puget Sound region (U.S. Census Bureau, 2024). Although these statistics are not directly comparable for the demographic variables, as most ACS variables correspond to the entire population rather than employed individuals, they are presented to provide a sense of the representation of the survey in the region. The sample includes a relatively even split between men and women, while approximately 4.9% of respondents identify as non-binary (the ACS includes only two gender classifications). The majority of the sample is also made up of relatively young adults (65.5% of the sample is aged 25-44). The large share of younger adults compared to the ACS data is unsurprising, given that this is a sample of workers. Similarly, the fact that the sample includes a large share of individuals with high levels of educational attainment likely reflects the same sampling effect. Non-white individuals and individuals with disabilities that impact their travel are also underrepresented in the current sample compared with the overall ACS data for the region.

With regard to household demographics (see middle panel of Table 4), household composition and income mirror the overall distributions in the Puget Sound region, despite reflecting only the working population. In addition to the household-level variables included in the survey, several additional geographic variables were appended from the U.S. EPA Smart Location Database (Chapman et al., 2021) based on the census tract of respondents' home locations. Most respondents live in relatively high-density areas, with 77.0% of respondents living in areas with population densities of at least 2,000 people per square mile. Additionally, 70.7% of respondents live in areas where there is no employment in their census tract within 0.5 miles of a fixed-guideway transit stop, while the remainder have at least some access to employment via public transportation within their census tract. Further, most respondents live in areas with relatively high levels of walkability, with 52.1% of respondents living in areas with a National Walkability Index of 15 or greater (on a scale from 1 to 20).

Finally, in terms of employment variables (the bottom panel of Table 4), the vast majority of respondents are employed full-time. This is in part due to the requirement that only individuals with three or more working weekdays are included in the sample. Of the retained individuals, most individuals have a complete set of five working weekdays (15.3% have three working weekdays, 27.6% have four working weekdays, and 57.1% have a complete set of five working weekdays). However, despite the differences in the shares of full-time and part-time work, the distribution of workers across industry types matches the worker participation statistics for workers from the ACS closely. Finally, 41.1% of respondents report that their employer provides a free or subsidized transit pass and 36.9% report that their employer provides free or subsidized parking at work.

3.2 Modeling Framework

As mentioned in the previous section, the modeling framework consists of a continuous variable for the commute distance dimension (included as the logarithm of an individual’s one-way commute distance to their primary out of home workplace), a binary outcome (included as an ordinal response with two levels in the model formulation) indicating whether an individual teleworks at all, and two (additional) ordinal outcomes corresponding to the number of days that an individual teleworks either part-day or full-day for each weekday in their travel diary. This structure is depicted visually in Figure 2 (in the figure, the one-headed arrows indicate direct effects while the two headed arrows indicate correlations among the endogenous outcomes; the notations in the figure align with the mathematical formulation discussed in the following subsection).

Within the ordinal modeling framework for the number of days of part-day and full-day telework, we incorporate threshold shifters to address the strong interdependence between the number of full-day and part-day telework days. These shifters adjust the threshold for part-day telework propensity based on the chosen discrete category for full-day telework, after controlling for the error correlation across the part-day and full-day telework propensities. This accounts for factors that elevate or depress specific combination levels of full-day and part-day telework frequencies, such as employer policies that promote all forms of telework (or discourage all forms of telework) and specific combination preferences among certain demographic groups. Figure 3 provides an example of such shifter effects, with the upper panel showing the baseline case of an individual selecting zero days of full-day telework and the lower panel showing the shift effects based on selecting a single day of full-day telework. In the figure, the blue lines show the latent propensity for full-day telework. In both the upper and lower panels, this formulation takes the same structure, with identical thresholds (labeled $\tilde{\psi}_{2,1}$ through $\tilde{\psi}_{2,5}$ to align with the notation in the following section). However, the part-day telework propensity (shown with black lines in the figure) is discretized with a different set of thresholds based on the number of full-day telework days selected. When zero days of full-day telework are selected (upper panel) the thresholds that discretize the latent propensity for part-day telework take a set of baseline values (labeled $\psi_{3,1}$ through $\psi_{3,5}$). Then, threshold shifters are defined that adjust these thresholds when other values of full-day telework are selected. Thus, as shown in the lower panel of Figure 3, three shifters are defined ($\delta_{3,2}$ through $\delta_{3,4}$) when a single day of full-day telework is selected that shift the thresholds for the part-day telework propensity. For instance, if there is a particularly large concentration of individuals selecting a single day of full-day telework *and* three days of part-day telework, with relatively fewer individuals selecting a single day of full-day telework *and* one or four days of part-day telework, the thresholds would shift as shown in the lower panel of Figure 3 (widening the region for three days of part-day telework while shrinking the area for one and four days, when a single day of full-day telework is selected). These shifter terms can also be a function of exogenous variables and commute distance to accommodate behavioral heterogeneity in the frequency choice combinations of full-day and part-day teleworking.

This brings up another issue, which is that not all combinations of ordered outcomes (with a range of each ordinal variable between zero and five) are possible for a five-day reporting period (and some individuals report fewer than five working weekdays). Specifically, given that an individual is categorized as a teleworker, it is impossible for them to report zero days of both full-day and part-day telework, and it is impossible for the sum of their days of full-day and part-day telework to exceed the total number of workdays. For instance, see in Figure 3 that an individual

who selects zero days of full-day telework is not able to also select zero days of part-day telework and that an individual who selects one day of full-day telework is not also able to select five days of part-day telework (these regions of the respective latent propensities are shown in red in the figure). Thus, an additional normalization is needed to account for these specific impossible combinations of outcomes. To accommodate this, we calculate the likelihood of each individual selecting their chosen combination of alternatives from among all combinations of alternatives (including those that are infeasible), then divide this by the likelihood of each individual selecting any feasible alternative from among all combinations of alternatives. This normalization gives the individual's likelihood of selecting their chosen alternative given that only a subset of possible outcome combinations are available to them. The mathematical formulation of the model, including this normalization, is discussed next.

3.2.1 Mathematical Formulation

To begin, consider the continuous outcome (representing the logarithm of commute distance; see the central portion of Figure 2). For ease in presentation, we will suppress the index for decision-makers and assume that all error terms are independent and identically distributed across decision-makers. For the continuous outcome, we can write, in the usual form of linear regression:

$$y = \beta'x + \varepsilon, \quad (1)$$

where x is an $(A \times 1)$ vector of exogenous variables (including a constant) and β is an $(A \times 1)$ column vector of the coefficients associated with x . ε represents a normally distributed error term centered at zero with scale σ .

Next, consider the three ordinal outcomes (the binary outcome and two count outcomes are all included here as ordinal outcomes as discussed above; see the right side of Figure 2). Let n be the index for the ordinal outcomes ($n = 1, 2, \dots, N$), with $N = 3$ in our empirical application representing the overall telework adoption dimension, the count of full-day telework days, and the count of part-day telework days. As mentioned above, we consider these counts in the form of a standard ordered response probit framework. To do so, let J_n be the number of categories for the n^{th} ordinal outcome (in our case $J_1 = 2$ for the binary telework adoption dimension and $J_2 = J_3 = 6$ for the count of full-day telework days and count of part-day telework days corresponding to counts from zero to five) and let the corresponding index be j_n ($j_n = 1, 2, \dots, J_n$). Then, for these ordinal variables we can write the underlying latent propensity $\tilde{y}_n^*$ in the usual ordered response formulation, as:

$$\tilde{y}_n^* = \tilde{\beta}_n'z + \tilde{\varepsilon}_n \quad (2)$$

where z is a $(C \times 1)$ vector of exogenous variables (excluding a constant but potentially including the values of commute distance), $\tilde{\beta}_n$ is a corresponding vector of coefficients to be estimated, and $\tilde{\varepsilon}_n$ is the standard normal random error for the n^{th} ordinal outcome. Also, for each ordinal outcome, define the thresholds $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \dots < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$, where $\tilde{\psi}_{n,0} = -\infty$ and $\tilde{\psi}_{n,J_n} = +\infty$. Assume that the individual under consideration chooses the a_n^{th} ordinal category. Then each individual can be assumed to select $\tilde{y}_n = a_n$ if $\tilde{\psi}_{n,a_n-1} < \tilde{y}_n^* < \tilde{\psi}_{n,a_n}$.

As discussed in Section 3.2, we also allow the thresholds for the ordinal outcomes to be shifted based on the values of other exogenous and endogenous variables. To do so, we define each of the thresholds using a series of shift effects so that each threshold is defined as:

$$\tilde{\psi}_{n,i_n} = \psi_{n,i_n} + \delta_{n,i_n} \text{ for } (i_n = 1, \dots, J_n - 1) \quad (3)$$

where ψ_{n,i_n} represents a baseline (unshifted) threshold level and δ_{n,i_n} is the total shift effect. This total shift effect may be defined as:

$$\delta_{n,i_n} = \lambda'_{n,i_n} \mathbf{z} + \sum_{b=1}^{J_2} (\tilde{\gamma}_{i_n,b} + \gamma'_{i_n,b} \mathbf{z}) \mathbf{I}(a_2 = b, n = 3) \quad (4)$$

where λ_{n,i_n} is a $(C \times 1)$ vector of shift effects corresponding to the vector $\mathbf{z}$ of exogenous variables (and including the individual's commute distance). Thus, the first term refers to direct effects of exogenous variables and commute distance on the thresholds for each telework frequency outcome. Of course, an identification restriction is needed such that variables already appearing in the latent propensity equation for each ordinal outcome n may have $J_n - 2$ additional direct threshold shift effects (immediately implying that no shift effects are defined for the overall telework adoption dimension). The next term in equation (4) refers to shift effects activated by the specific levels of other ordinal outcomes. As described in Section 3.2 we consider the selected level of full-day telework frequency to impact the thresholds for part-day telework frequency. Thus, for identification, these terms are set to zero for the first and second ordinal outcomes and only cause shifts for the part-day telework frequency thresholds. In this second term, $\mathbf{I}(a_2 = b, n = 3)$ is an indicator function that takes the value 1 when the selected category for full-day telework is equal to the level b and the threshold of interest applies to the part-day telework outcome (and takes the value zero otherwise), $\tilde{\gamma}_{i_n,b}$ represents the direct shift effect to the threshold i_n based on the selected category of full-day telework, and $\gamma_{i_n,b}$ is a $(C \times 1)$ vector of moderating effects based on the values of other exogenous variables. Again, an identification restriction is needed to account for the constraint that not all combinations of full-day and part-day telework are possible (as discussed more next, we use another normalization later to eliminate these infeasible outcome combinations, so threshold shifts cannot be defined among these infeasible outcome combinations). Specifically, no shift effects are defined based on combinations of outcomes that lead to more than five days of total work or zero days of both full-day and part-day telework (which is separately accounted for by the binary outcome).

For later use, stack the lower thresholds for each decision maker into an $(N \times 1)$ vector $\tilde{\psi}_{low} = (\tilde{\psi}_{1,a_1-1}, \tilde{\psi}_{2,a_2-1}, \dots, \tilde{\psi}_{N,a_N-1})$ and the upper thresholds for each decision maker into a second $(N \times 1)$ vector $\tilde{\psi}_{up} = (\tilde{\psi}_{1,a_1}, \tilde{\psi}_{2,a_2}, \dots, \tilde{\psi}_{N,a_N})$. Then, stack the set of fixed threshold components for each outcome as $\psi_n = (\psi_{n,1}, \psi_{n,2}, \dots, \psi_{n,J_n-1})'$ and define the set of fixed thresholds as $\psi = (\psi'_1, \psi'_2, \dots, \psi'_N)'$. Also, stack the coefficients for the direct shift effects of exogenous variables into the matrix $\lambda = (\lambda_{2,1}, \lambda_{2,2}, \dots, \lambda_{2,J_2-1}, \lambda_{3,1}, \lambda_{3,2}, \dots, \lambda_{3,J_3-1})'$, the coefficients for the shift effects based on the number of days of full-day telework into the vector $\tilde{\gamma} = (\tilde{\gamma}_{1,1}, \tilde{\gamma}_{1,2}, \dots, \tilde{\gamma}_{1,J_2}, \tilde{\gamma}_{2,1}, \dots, \tilde{\gamma}_{J_3-1,J_2})'$ and the moderating effects of exogenous variables into the matrix $\gamma = (\gamma_{1,1}, \gamma_{1,2}, \dots, \gamma_{1,J_2}, \gamma_{2,1}, \dots, \gamma_{J_3-1,J_2})'$.

Finally, stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{\mathbf{y}}^*$ and the N error terms $\tilde{\varepsilon}_n$ into another $(N \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$, and define the $(N \times C)$ matrix $\tilde{\boldsymbol{\beta}} = (\tilde{\boldsymbol{\beta}}_1, \tilde{\boldsymbol{\beta}}_2, \dots, \tilde{\boldsymbol{\beta}}_N)'$. To accommodate the correlations between the ordinal variables, the error vector $\tilde{\boldsymbol{\varepsilon}}$ is assumed to be multivariate normally distributed with a mean vector of zeros and a general correlation matrix given by:

$$\boldsymbol{\Sigma} = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1N} \\ \rho_{12} & 1 & \cdots & \rho_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1N} & \rho_{2N} & \cdots & 1 \end{pmatrix} \quad (5)$$

where the off-diagonal terms ρ_{ij} capture error correlations among the underlying latent propensities for the ordinal outcomes. These correlations accommodate the presence of unobserved variables that jointly influence multiple ordered outcomes. Note that, for estimation, each of these stacked vectors must be marginalized for all individuals without a complete set of outcomes. Specifically, those individuals indicating that they never telework do not have responses to the two count outcomes. These individuals will only have the single overall telework adoption dimension (along with the continuous commute distance dimension), rather than the complete set of three ordinal outcomes.

Next, to accommodate the joint nature of the model between the continuous outcome and ordinal outcomes, we can define $\tilde{\mathbf{y}} = \left(y, [\tilde{\mathbf{y}}^*]' \right)'$ which contains the complete set of outcomes for an individual. Similarly, we can define $\tilde{\boldsymbol{\beta}} = (\boldsymbol{\beta}, \tilde{\boldsymbol{\beta}}')'$ and $\tilde{\boldsymbol{\varepsilon}} = (\varepsilon, \tilde{\boldsymbol{\varepsilon}})'$. The covariance matrix of $\tilde{\boldsymbol{\varepsilon}}$ is given by $\tilde{\boldsymbol{\Sigma}} = \begin{pmatrix} \sigma & \boldsymbol{\Omega}' \\ \boldsymbol{\Omega} & \boldsymbol{\Sigma} \end{pmatrix}$, where $\boldsymbol{\Omega}$ is an $(N \times 1)$ vector of covariance terms between the continuous outcome and each ordinal outcome. These covariance terms accommodate unobserved factors that jointly influence the continuous outcome and ordinal outcomes. Then, for the complete model system, we have $\tilde{\mathbf{y}} \sim MVN_{N+1}(\tilde{\mathbf{B}}, \tilde{\boldsymbol{\Sigma}})$, which is the $(N+1)$ -dimensional multivariate normal distribution with mean $\tilde{\mathbf{B}} = \begin{bmatrix} \boldsymbol{\beta}'\mathbf{x} \\ \tilde{\boldsymbol{\beta}}'\mathbf{z} \end{bmatrix}$ and covariance matrix $\tilde{\boldsymbol{\Sigma}}$. Let $\boldsymbol{\alpha}$ be the collection of parameters to be estimated: $\boldsymbol{\alpha} = [\text{Vechup}(\tilde{\boldsymbol{\Sigma}}), \text{Vech}(\tilde{\boldsymbol{\beta}}), \text{Vech}(\boldsymbol{\psi}), \text{Vech}(\boldsymbol{\lambda}), \tilde{\gamma}, \text{Vech}(\boldsymbol{\gamma})]$, where the operator "Vech(.)" vectorizes all the non-zero elements of the matrix/vector on which it operates and the operator "Vechup(.)" vectorizes all the upper-diagonal non-zero elements of the matrix.

For model estimation, let the observed value of the continuous outcome for the individual be g . Then, the conditional distribution of $\tilde{\mathbf{y}}^*$ for the ordinal outcomes, given $y = g$ is multivariate normally distributed with mean $\tilde{\mathbf{B}} = \tilde{\boldsymbol{\beta}}'\mathbf{z} + \boldsymbol{\Omega}\sigma^{-1}(g - \boldsymbol{\beta}'\mathbf{x})$ and variance $\tilde{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma} - \boldsymbol{\Omega}\sigma^{-1}\boldsymbol{\Omega}'$. Also, let the number of working days for an individual be d ($3 \leq d \leq 5$). Finally, as discussed above, not all combinations of frequencies of part-day and full-day telework are possible. Thus, given the number of working days, we can define the set of threshold level combinations that are infeasible for the individual as:

$$\tilde{\psi}^{\text{inf}} = \left\{ \left[\tilde{\psi}_{\text{low}}^{\text{inf}} = \begin{pmatrix} \tilde{\psi}_{1,1} \\ \tilde{\psi}_{2,i} \\ \tilde{\psi}_{3,j} \end{pmatrix}, \tilde{\psi}_{\text{up}}^{\text{inf}} = \begin{pmatrix} \tilde{\psi}_{1,1+1} \\ \tilde{\psi}_{2,i+1} \\ \tilde{\psi}_{3,j+1} \end{pmatrix} : (i+j=0) \mid (i+j > d) \right] \right\} \quad (6)$$

where $\tilde{\psi}^{\text{inf}}$ is the set of all infeasible threshold combinations (with $\tilde{\psi}_{\text{low}}^{\text{inf}}$ and $\tilde{\psi}_{\text{up}}^{\text{inf}}$ being the vectors of lower and upper thresholds, respectively, for each element in this set). Specifically, it is impossible that an individual who engages in telework during the week also has zero days of part-day telework and zero days of full-day telework and impossible that the sum of days with part-day telework and full day telework is greater than the number of reported days (d). This set of infeasible outcome combinations include those where an individual reports telework but has zero teleworking days ($i+j=0$) or reports more days of telework than days of work ($i+j > d$). As noted in the previous section, this set of outcomes is infeasible and the likelihood for each individual must be normalized to account for the fact that not all outcome combinations are available. Thus, the joint likelihood function may be written as:

$$L(\mathbf{a}) = \frac{f(y=g \mid \beta'x, \sigma) \times \Pr \left[\tilde{\psi}_{\text{low}} \leq \tilde{y}^* \leq \tilde{\psi}_{\text{up}} \mid y=g \right]}{\left(1 - \sum_{[\tilde{\psi}_{\text{low}}^{\text{inf}}, \tilde{\psi}_{\text{up}}^{\text{inf}}] \in \tilde{\psi}^{\text{inf}}} \Pr \left[\tilde{\psi}_{\text{low}}^{\text{inf}} \leq \tilde{y}^* \leq \tilde{\psi}_{\text{up}}^{\text{inf}} \mid y=g \right] \right)} \quad (7)$$

where $f(y=g \mid \beta'x, \sigma)$ is the normal density function with a mean of $\beta'x$ and scale σ evaluated at the chosen continuous outcome g . The probability in the numerator of equation (7) is the conditional likelihood of selecting the chosen combination of ordinal outcomes given the chosen continuous outcome and assuming that all combinations of ordinal outcomes are available. The denominator normalizes the likelihood function to account for the fact that not all combinations of ordinal outcomes are possible. Then, using the conditional distribution of $\tilde{y}^*$, the likelihood function can be written as:

$$L(\mathbf{a}) = \frac{f(y=g \mid \beta'x, \sigma) \times \int_{\tilde{\psi}_{\text{low}}}^{\tilde{\psi}_{\text{up}}} f_N(\mathbf{r} \mid \tilde{\mathbf{B}}, \tilde{\Sigma}) d\mathbf{r}}{\left(1 - \sum_{[\tilde{\psi}_{\text{low}}^{\text{inf}}, \tilde{\psi}_{\text{up}}^{\text{inf}}] \in \tilde{\psi}^{\text{inf}}} \int_{\tilde{\psi}_{\text{low}}^{\text{inf}}}^{\tilde{\psi}_{\text{up}}^{\text{inf}}} f_N(\mathbf{r} \mid \tilde{\mathbf{B}}, \tilde{\Sigma}) d\mathbf{r} \right)} \quad (8)$$

where the integration domain in the numerator is simply the multivariate region of the elements of the $\tilde{y}^*$ vector determined by the observed ordinal outcomes and the integration domain denominator is simply the multivariate region of elements of the $\tilde{y}^*$ vector determined by the specific infeasible outcomes. $f_N(\mathbf{r} \mid \tilde{\mathbf{B}}, \tilde{\Sigma})$ is the MVN density function of dimension N with a mean of $\tilde{\mathbf{B}}$ and a covariance of $\tilde{\Sigma}$, and evaluated at $\mathbf{r}$. The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions.

4. RESULTS

The final model specification is presented in Table 5. The specification was developed using an iterative process of including exogenous variables in various forms and testing alternative

combinations of explanatory variables based on existing theoretical interpretations and statistical fit. The categorical variables were considered as dummy variables in the most disaggregate form available and progressively combined based on statistical tests to yield parsimonious specifications. Several continuous variables were also considered (including the endogenous effect of commute distance on the telework outcomes), but in each case the best representation among those tested was in the form of dummy variables. In the model estimation process, we used a t-statistic threshold of 1.28 (corresponding to a 0.2 level of significance or 80% confidence level) to retain variables. This threshold was selected based on the relatively small sample size of 699 respondents and the potential of variables included in this specification (even if at a slightly lower confidence level) to inform future research with larger sample sizes.³

The remainder of this section presents the model estimation results. The results for the effects of individual demographics are discussed first in Section 4.1, followed by the discussion of the effects of household characteristics and location in Section 4.2 and employment-related effects in Section 4.3. Then, Section 4.4 presents the covariance elements among the outcomes as well as the endogenous effects of commute distance on telework choices and Section 4.5 presents the constant, baseline thresholds, and threshold shifter effects. Finally, Section 4.6 presents model fit in comparison with several restricted alternate formulations.

4.1 Effects of Individual Demographics

The model results indicate that gender influences both commute distance and telework adoption. Specifically, women exhibit shorter commute distances compared to men, consistent with earlier studies linking women's residential and employment choices to greater household and caregiving responsibilities (Axisa et al., 2012; Hu, 2021; Casado-Díaz et al., 2023; Asmussen et al., 2024). Women also have a greater propensity to adopt telework. This pattern, while differing from some recent studies, is consistent with pre-pandemic evidence (Deng et al., 2015), and may reflect the flexibility telework offers for balancing work and home responsibilities (Wang et al., 2023). In contrast, nonbinary individuals are less likely to adopt telework, potentially reflecting lower workplace flexibility and greater concerns regarding workplace visibility or bias (Bai et al., 2025; Lagos et al., 2026).

Age exhibits a pronounced nonlinear relationship with both commute distance and telework preferences. Individuals aged 25-54 commute farther than younger adults, likely reflecting residential preferences for larger homes or quieter neighborhoods farther from employment centers (Asmussen et al., 2024). Telework adoption, however, is highest among the youngest (ages 18-24) and oldest (55+) workers, supporting previous research that young individuals are more likely to have positive attitudes towards telework (de Abreu e Silva and Melo,

³We should also note here that our decision to adopt an 80% confidence level threshold for including variables rests on several important considerations. Choosing a confidence threshold necessarily requires balancing competing risks between the possibility of making Type I errors (incorrectly treating irrelevant variables as significant) and making Type II errors (mistakenly discarding variables and missing genuine relationships). The American Statistical Association (ASA) has stressed (see Wasserstein and Lazar, 2016; Wasserstein et al., 2019) that researchers should apply judgment suited to their specific context when determining appropriate thresholds, rather than defaulting reflexively to the conventional 95% confidence level (or any other arbitrary confidence level). Given our relatively small sample of 699 individuals, and the added complexity of jointly identifying the combined frequencies of full-day and part-day telework (while accounting for unobserved effects influencing the propensities of each and interdependencies between these two frequencies), we chose to place greater weight on minimizing Type II errors than a standard 0.05 significance level would allow. This approach lets us flag variables that appear meaningfully related to telework adoption and frequency within our present data and can guide future model specifications drawing on larger samples of workers, even though it comes at the cost of a somewhat elevated risk of Type I errors.

2018; Nguyen, 2021; Kappler and de Abreu e Silva, 2025) and older individuals may be less concerned with in-person visibility as a vehicle for advancement opportunities (Rudolph et al., 2021; Asmussen et al., 2024; Mahmoud et al., 2024). This trend is mirrored in the frequency of full-day telework, with the youngest workers having the highest propensity for full-day telework, and the oldest workers having a higher propensity for full-day telework than middle aged workers (those aged 25-54). In contrast, middle-aged workers exhibit the strongest propensity for part-day telework, suggesting a preference for balancing the flexibility of remote work with the continued benefits of workplace presence, perhaps reflecting the need to coordinate work with family responsibilities while maintaining in-person visibility (Haddad et al., 2009; Chung and van der Lippe, 2020; Rudolph et al., 2021).

Educational attainment serves primarily to distinguish between the two telework modalities. Individuals with graduate degrees have a higher propensity to engage in full-day telework but less so to engage in part-day telework, compared with those with lower levels of educational attainment. This pattern likely reflects the greater workplace autonomy enjoyed by highly educated workers, enabling them to consolidate in-person responsibilities onto specific office days while conducting other work entirely remotely (López-Igual and Rodríguez-Modroño, 2020; Golden and Gajendran, 2019; Gaduena et al., 2022; Asmussen et al., 2024).

Race and ethnicity play a more limited role. While overall telework adoption does not vary significantly across racial groups, non-white individuals have a lower propensity for part-day telework than white respondents, perhaps reflecting persistent disparities in workplace flexibility or a greater need for in-person visibility among non-white individuals (Asfaw, 2022; Lewis et al., 2024; Patole et al., 2026). Hispanic respondents, meanwhile, exhibit shorter commute distances and a greater propensity for full-day telework, consistent with previous evidence regarding residential location patterns and telework participation among Hispanic workers (Angrisani et al., 2023; Robbennolt et al., 2024).

Finally, individuals with disabilities that affect travel are more likely to adopt telework, and exhibit a greater propensity for full-day telework. This result is consistent with a growing literature demonstrating that telework improves employment accessibility by eliminating the commute burden faced by many workers with mobility impairments (Schur et al., 2020).

4.2 Effects of Household Characteristics and Location

In terms of household composition, individuals with children tend to have longer commute distances than those without children, likely reflecting residential preferences for better schools, larger homes, and safer neighborhoods at the expense of workplace proximity (Baker et al., 2016; DeLuca and Jang–Trettien, 2020; Robbennolt et al., 2024). Further, single parents are less likely to adopt telework, perhaps because of a need for greater separation between work and home responsibilities (Dunatchik et al., 2021; Clar-Novak, 2025). Similarly, adults in nuclear families tend to have a lower propensity for full-day telework, reflecting similar challenges in balancing work and childcare responsibilities. Finally, compared with single adults, couples without children exhibit a lower propensity for both part-day and full-day telework. These individuals, who have fewer competing demands than those with children and more household resources than single adults, may be better able to prioritize a consistent in-person workplace presence while treating telework as an occasional arrangement (Wang et al., 2024).

Income primarily differentiates both commute distance and telework participation. Higher-income households exhibit shorter commute distances and greater telework participation. While the shorter commute distances contrast with much of the existing literature, they may reflect the

Seattle context, where high-income professionals increasingly reside in gentrifying neighborhoods located close to major employment centers (Long, 2021; Couture et al., 2024). At the same time, higher-income workers are more likely to engage in both full-day and part-day telework, consistent with the greater flexibility and telework compatibility of higher-paying jobs, as well as the ability of higher-income workers to negotiate remote arrangements (Astroza et al., 2020; Dingel and Neiman, 2020; Asmussen et al., 2024).

Regarding household location, individuals living in high population density neighborhoods tend to have shorter commutes and show a higher propensity for part-day telework. This is not at all surprising, as these individuals tend to live nearer to employment centers, have relatively easy access to both work-related and non-work activities, and may be more inclined to utilize part-day telework as a strategy to shift their commutes outside of peak hours, saving time in dense, congested areas (Asgari and Jin, 2018). Individuals with good access to public transportation also tend to have shorter commutes but appear to prefer full-day telework to part-day telework. The latter result perhaps is a reflection of their dependence on public transportation that typically does not have good service during off-peak periods, which reduces the appeal of shifting the timing of commute travel through part-day telework. Finally, individuals living in locations that are more walkable tend to have shorter commutes, are more likely to adopt telework, and display a high propensity for both full-day and part-day telework. The higher telework rates observed in more walkable neighborhoods may reflect lifestyle self-selection, whereby individuals who prefer urban, walkable environments are also more likely to hold occupations compatible with flexible work arrangements (Zhao et al., 2023).

4.3 Employment-Related Effects

Employment characteristics also shape both commute distance and telework patterns. Part-time workers (those working less than 35 hours per week) exhibit shorter commute distances than full-time workers (those working 35 hours per week or more), consistent with evidence that lower earnings reduce the incentive to accept long commutes (Axisa et al., 2012; Sen et al., 2021; Asmussen et al., 2024). They are also more likely to engage in full-day telework, perhaps because shorter work schedules and the growth of fully remote part-time positions make complete remote work easier to accommodate (Deng et al., 2015; Katz and Krueger, 2019; Asmussen et al., 2024). Similarly, self-employed individuals are less likely to engage in part-day telework, likely because greater autonomy allows them to organize fully remote workdays rather than split work between home and the workplace. Not surprisingly, individuals working more days each week are more likely to adopt telework, particularly full-day telework, reflecting the greater benefits of reducing commuting over a larger number of workdays.

Employer-provided transportation subsidies also influence employees' telework decisions. The provision of a free or subsidized transit pass results in a lower propensity for part-day telework, consistent with the limited benefit of shifting the timing of the commute (as discussed in the previous section). Likewise, employer-provided free or subsidized parking reduces the propensity for full-day telework, supporting previous findings that lower commuting costs encourage workplace attendance (Shoup, 2005).

Finally, employment sector strongly differentiates telework behavior. Workers in the health sector and in construction/manufacturing have shorter commute distances, likely because employment in these sectors is more geographically dispersed than concentrated in a few major employment centers. As expected, workers in health care, construction/manufacturing, and education/social work are generally less likely to telework because of greater in-person job

requirements. An interesting exception is that health-sector workers exhibit a higher propensity for part-day telework, suggesting that remote work is increasingly used for administrative and documentation tasks while patient care remains in person (Jones et al., 2023). In contrast, workers in the information/finance and technology sectors are more predisposed to full-day telework, while those in public administration prefer part-day to full-day telework, perhaps reflecting a balance between workplace accountability and scheduling flexibility (Mele et al., 2023).

4.4 Covariance Elements and Endogenous Effects

Table 5 provides the elements of the covariance matrix, reflecting the presence of unobserved factors that jointly influence commute distance and work arrangement choices. First, two elements of Ω are statistically significant, including a positive correlation between commute distance and the propensity for telework adoption and a negative correlation between commute distance and the propensity for part-day telework frequency. For instance, the first result may reflect the preference of more introverted individuals to live farther away from their workplace to avoid running into coworkers at non-work locations as well as the preference of these same more introverted individuals to avoid coworker interactions at their workplace by adopting telework. In contrast, more extroverted individuals may prefer to live closer to their workplace to maximize time for social interactions inside and outside of their workplace, explaining the negative correlation between commute distance and the propensity for part-day telework. Second, we find that all three elements of Σ are also statistically significant, with a positive correlation between telework adoption and full-day telework propensity but negative correlations between part-day telework propensity and both overall telework adoption and full-day telework propensity. These could be due, for instance, to unobserved preferences for maintaining consistent, uninterrupted routines. If some individuals prefer to avoid workplace distractions and avoid work disruptions they may be more likely to choose telework overall, spend more time on full-day telework and be less likely to choose part-day telework that would entail a mid-day disruption to their workday. The negative correlation between full-day and part-day telework likely also reflects substitution effects suggesting that many individuals may primarily lean towards one telework modality rather than choosing a mix of both.

As part of the joint modeling of commute distance and telework choices, and after controlling for unobserved elements, we are able to estimate the structural causal effects of commute distance on telework choices. The results for the effect of commute distance on telework in Table 5 indicates that commute distances greater than five miles (compared to commutes of less than five miles) and increased telework adoption go hand-in-hand, a finding consistent with prior studies that highlight telework as a strategy to manage time and costs associated with lengthy commutes (Mokhtarian et al., 2004; de Abreu e Silva and Melo, 2018; Kappler and de Abreu e Silva, 2025). However, commute distances greater than 15 miles are associated with a correspondingly lower telework propensity than those between 10 and 15 miles. This non-monotonic relationship with commute distance suggests that those with the longest commutes are disproportionately associated with occupations requiring regular physical presence, while workers with moderately long commutes are more likely to hold telework-compatible professional positions for which avoiding the commute provides substantial benefit (see also Asmussen et al., 2024 for a similar result).

However, while there is a clear jointness between lower telework adoption and the longest commute distances, the propensity for full-day telework and part-day telework among those who decide to adopt telework shows a consistent relationship with commute distance. Thus, individuals

with longer commutes who telework tend to also favor full-day telework over part-day telework, while the propensity for part-day telework is closely aligned with short commute distances (reinforcing the direction of the covariance effect between commute distance and full-day and part-day telework propensities). The first result is rather intuitive, while a likely explanation for the second result is that part-day telework still requires a commute to the workplace, but provides only part of the workday in return. As commute distances increase, this tradeoff becomes progressively less attractive. Consequently, workers with shorter commutes may find this tradeoff acceptable, while those with longer commutes are more likely to prefer spending the entire workday in a single location, either fully in the office or fully remote.

Importantly, note that our model considers commute distance, telework adoption, and full-day and part-day telework frequencies as a joint package decision, even if the structural causal effect shows a directional effect from commute distance to telework arrangements. That is, our results show that the choices of long commute distances and high rates of full-day telework are made as a package decision, as are the choices of short commute distances and high rates of part-day telework. The import of this result will become clearer in Section 5.

4.5 Constant, Thresholds, and Threshold Shifters

Finally, the lower panel of Table 5 shows the constant for the continuous commute distance dimension, the threshold for the binary telework adoption dimension (note that no constant is included in the telework adoption equation, which then shows up as a threshold estimate), and the baseline thresholds as well as the threshold shifters for the ordinal full-day and part-day telework frequency outcomes. Although the constants and baseline thresholds do not have substantially meaningful interpretations, it is notable that the baseline thresholds for part-day telework are much higher overall than those for full-day telework. This mirrors the aggregate finding (discussed in Section 3.1.1) that part-day telework does seem to be adopted at relatively lower rates than full-day telework.

The first two threshold shifters are based on the effects of commute distance on specific thresholds for full-day and part-day telework propensities beyond the overall endogenous effects discussed in the previous subsection. In particular, individuals with commute distances of 10 miles or more (compared to those with commute distances of less than 10 miles) have a positive shift to $\tilde{\psi}_{2,2}$ (the threshold demarcating the counts of one and two full-day telework days) and slightly larger positive shift to all higher thresholds for full-day telework. This indicates that individuals with higher commute distance are less likely to work all days from home relative to what is estimated based purely on the structural positive effect of commute distance on full-day teleworking propensity, as discussed in the previous section (we explore this pattern in additional detail in the following section). In contrast, we find a negative shift effect for those with a commute distance of 10 miles or more on $\tilde{\psi}_{3,2}$ (the threshold demarcating the counts of two and three part-day telework days), suggesting that these individuals with long commute distances tend to have a higher preference for two days of part-day telework than as determined purely by the structural causal effect of commute distance.

The next set of threshold shifters relate the counts of full-day and part-day telework directly. All of these threshold shifters are found to be significant and negative, suggesting that higher levels of part-day telework are generally selected when more full-day telework is also chosen. As noted in Section 3.1.1, it is more common for individuals to choose a combination of two or fewer work modalities (of full-day in-person, full-day telework, and part-day telework) rather than choosing all three. Therefore it is not surprising that the shifters for part-day telework

generally make the highest available category of part-day telework more common based on the number of days of full-day telework, shifting the thresholds so that the combination of all three work modalities is generally less common. These patterns may reflect employer policies related to telework, as discussed earlier in Section 2. Further, two interaction effects with exogenous variables are also significant. First, individuals aged 25-44 who choose a single day of full-day telework have a positive shift to threshold $\tilde{\psi}_{3,2}$ (the threshold demarcating the counts of two and three part-day telework days) and all higher part-day telework thresholds, indicating an elevated preference for the combination of one day of full-day telework and one-day of part-day telework (perhaps due to a desire for a high degree of flexibility and varying work routine throughout the week given the lifecycle stage they are in). Finally, individuals in households with children who choose at least one day of full-day telework have a positive shift in all thresholds for part-day telework. This result suggests that parents may be particularly inclined to prefer some stability in their work routine, avoiding part-day telework if they have at least one day of full-day telework per week. This is consistent with expectations and may reflect a balance between the need for dedicated, distraction free, work time while also balancing the needs of household maintenance responsibilities through full-day telework.

4.6 Model Fit

The performance of the proposed model is assessed compared with several restricted models. First, the proposed model is compared with two restricted models that assume a more limited amount of dependency between the outcomes. These comparisons are shown in the upper part of Table 6, comparing the proposed model to a model that excludes the shifter effects as well as an independent model that disregards the shifters and the correlations among the outcomes (the independent model assumes that the covariance matrix $\tilde{\Sigma}$ is diagonal). Several disaggregate and aggregate measures of fit are presented in Table 6 to compare the two models. First, at a disaggregate level, the adjusted likelihood ratio index is computed as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\delta}) - M}{L(c)}, \quad (9)$$

where $L(\hat{\delta})$ is the log-likelihood value at convergence, $L(c)$ is the log-likelihood value for a constants-only model, and M is the number of parameters estimated in the model, excluding constants. The higher value for the adjusted likelihood ratio index for the proposed model indicates that it provides a better fit compared with either restricted model.

Next, the Bayesian Information Criterion (BIC) is calculated as:

$$BIC = -L(\hat{\delta}) + 0.5(\# \text{ of model parameters}) \log(\text{sample size}). \quad (10)$$

The model with the lower BIC value is preferred, again indicating the superior performance of the proposed model. Finally, the two restricted models may be compared with the proposed model using a formal likelihood ratio test. The test statistics for the likelihood ratio tests are much larger than the associated chi-square critical values (with 14 and 19 degrees of freedom, respectively) also highlighting the better performance of the proposed model.

Finally, the models may be compared at an aggregate level using two measures. First, we compare the predicted number of individuals selecting each possible workplace arrangement combination to the total observed share selecting each combination. We then compute the percentage error for each combination and the weighted average percentage error (WAPE) based

on the actual share selecting each combination. This value is reported in Table 6 as the “Work Arrangement WAPE.” Next, we compute the expected commute distance as estimated across all respondents, and again compute the absolute percentage error (APE) compared with the average commute distance in the sample. This second value is reported as the “Commute Distance APE” in Table 6. Both of these values are smaller for the proposed model compared with either restricted model (although the commute distance APE values are similar in magnitude across the three models). Collectively, these model fit metrics, at a disaggregate and aggregate level, demonstrate the superior performance of the proposed joint model, highlighting the importance of capturing the observed and unobserved dependencies among the telework and commute outcomes.

An alternative modeling approach would be to consider a breakdown of work arrangements into the seven categories shown in Table 3 (and discussed in Section 3.1.1 at the aggregate level). Then, ordinal equations could be specified for each of these unordered outcomes to determine the appropriate number of full-day and part-day telework days. That is, while the proposed model implicitly identifies the combinations of adoption of full-day telework, part-day telework, and full-day in-person work based on the two ordered frequencies, these could be separated directly in an unordered choice model (with seven unordered choices corresponding to the combinations of adoption of each of these three working modalities) and linked to separate ordinal outcomes for full-day and part-day telework. This alternative formulation would explicitly identify individuals with positive participation in each work arrangement type but would entail a significant increase in the number of parameters to estimate the counts of telework of each type. But, we may compare the predictive power of such a discrete unordered multinomial probit (MNP) model based on the identification of these seven unordered categories to the implicit predictions from the proposed model. To do so we estimate a joint model of commute distance and workplace location using the unordered framework just described (ignoring the actual counts of work and just focusing on participation in each telework type). Then, because the model is not nested with the proposed model, we compare the two in the lower panel of Table 6 based on several predictive fit metrics. First, we present the predictive log-likelihood at convergence for the commute distance and work arrangement (in terms of the seven unordered categories) using each model. Then, we compute the predictive adjusted likelihood index and BIC (using the formulas in equations (9) and (10)). The unordered model has the better log-likelihood at convergence. But, after accounting for the increase in the number of parameters to estimate preferences across the seven unordered outcome combinations, the adjusted likelihood ratio index of the unordered model is lower than that of the proposed model and the BIC is higher, indicating that the proposed model has a better fit after accounting for the number of parameters. The two may also be compared using an informal non-nested likelihood ratio test. For this test, the probability that the improved predictive adjusted likelihood ratio index of the proposed model over the unordered model could have occurred by chance is no larger than

$$\Phi\{-[2(\bar{\rho}_{proposed}^2 - \bar{\rho}_{unordered}^2)L(c) + (M_{proposed} - M_{unordered})]^{0.5}\} \quad (11)$$

The negligible value of this probability for the non-nested test indicates that although the unordered model outperforms the proposed model in terms of the raw log-likelihood at convergence, the proposed model does come out significantly better in terms of data fit after accounting for the number of parameters. Further, while the proposed model performs well for these tests, it also provides the ability to get the exact counts of full-day and part-day telework, which would entail the addition of ordered response outcomes to the current unordered formulation and the addition of a large number of extra parameters. Overall, this set of tests confirms that the

proposed model performs better than an alternative unordered approach for overall work arrangements.

5. WORK ARRANGEMENT PREFERENCES AND WEEKLY COMMUTE VMT

While the discussion in the previous section highlights specific exogenous variable effects on the underlying propensities for each of the outcomes, it does not reveal the total magnitude of effects or the overall relationship between work arrangement and weekly commute VMT. This is particularly so due to the combination of direct effects, threshold shifter effects, and correlations that lead to interdependencies among the outcomes. To better illustrate these relationships, we translate the results in two ways. First, we quantify the overall relationship between work arrangement and commute VMT by estimating the expected one-way daily commute VMT conditional on work arrangement (the number of days of full-day telework and part-day telework) as well as the expected total weekly VMT conditional on work arrangement. We can estimate this conditional relationship even though the structural causal effect shows a directional effect from commute distance to telework arrangements because commute distance, telework adoption, and full-day and part-day telework frequencies are modeled as a joint package decision. To translate the model results in this way, we first compute the expected value of the logarithm of the one-way commute distance conditional on the set of work arrangement choices:

$$E[y | \tilde{y}] = \int_{-\infty}^{\infty} v[f_y(v | \tilde{y})]dv, \quad (12)$$

where $f_y(v | \tilde{y})$ denotes the density function of y (the logarithm of one-way commute distance) at a specific value v given the specified values of the work arrangement variables $\tilde{y}$ (this can be done for each combination of full-day and part-day telework days). The variance of the logarithm of the one-way commute distance may be similarly calculated as:

$$VAR[y | \tilde{y}] = \left(\int_{-\infty}^{\infty} v^2[f_y(v | \tilde{y})]dv \right) - \left(\int_{-\infty}^{\infty} v[f_y(v | \tilde{y})]dv \right)^2. \quad (13)$$

Then, the expected one-way commute distance for an individual with the specified work arrangement is:

$$E[\text{Commute Distance} | \tilde{y}] = \exp \left(E[y | \tilde{y}] + \frac{1}{2} VAR[y | \tilde{y}] \right). \quad (14)$$

To translate this expected one-way daily commute distance to an expected weekly commute distance, we simply multiply by the sum of the number of fully in-person days and the number of part-day telework days implied by the selected work arrangement combination. These values are computed for each individual in the sample, and the averages are reported in Figure 4 and Figure 5 respectively for the expected one-way daily commute VMT and expected total weekly VMT. For instance, the value of 7.1 in the top left cell in Figure 4 indicates that the expected one-way commute distance for an individual who works all five days as part-day telework (with no fully in-person days or full-day telework days) is 7.1 miles. The corresponding value of 71.1 in the top left cell in Figure 5 indicates that the expected weekly commute VMT for an individual who works all five days as part-day telework (with no fully in-person days or full-day telework days) is 71.1 miles.

Second, we examine the effects of exogenous variables on work arrangement preferences and on overall commute VMT. To do so, for each exogenous variable of interest, we set the value for each individual in the dataset equal to a base value of interest (for instance, we start by setting each individual in the dataset to “Male” without changing the values of any other exogenous variables). We then compute the probability of each individual choosing each feasible combination of full-day and part-day telework days and the expected commute distance (both the one-way commute distance and weekly commute distance) conditional on that selected work arrangement (using the same procedure just described). We next compute the expected number of days of full-day telework and the expected number of days of part-day telework (implicitly defining also the expected number of days of fully in-person work) based on the probabilities for each combination of working days and the overall expected one-way and weekly commute VMT based on weighted averages of the expected conditional commute distance. We also calculate the portion of the weekly commute VMT that is expected to take place on part-day teleworking days. Finally, we set the value of the exogenous variable in the dataset to a treatment level (for instance, by setting each individual in the dataset to “Female” without changing the values of any other exogenous variables) and calculate the same set of quantities for the treatment level. The percent difference (in the average of these values across all individuals in the dataset) between the base and the treatment level is then reported in Table 7 as the total effect. For instance, the values in the first numeric row and column of Table 7 indicate that, on average, women have 7.53% more full-day telework days than men each week and 13.10% more part-day telework days than men each week. Women also have an average commute distance that is 19.34% lower than for men, leading to a 21.69% lower weekly commute VMT (due to the combination of lower commute distance and more full-day telework). Finally, the portion of their weekly commute VMT that comes from part-day telework is 15.41% higher for women than for men (this last value is meaningful because part-day telework is more likely to involve off-peak commutes, so a higher share of VMT coming from part-day telework days suggests that the commute-related driving distance of women may be more concentrated in off-peak conditions compared to that of men).

These overall effects of exogenous variables on work arrangement and weekly commute VMT are discussed in detail in the remainder of this section, with a specific focus on the policy and modeling implications of these results.

5.1 Full-Day and Part-Day Telework as Distinct Avenues for Commute VMT Reduction

A central finding emerging from the results shown in Figures 4 and 5 is that full-day and part-day telework exert fundamentally distinct effects on weekly commute VMT, and that conflating these two behaviors in demand management policies or travel demand modeling is likely to produce materially inaccurate forecasts. Full-day telework reduces weekly commute VMT primarily through trip elimination. That is, despite the fact that one-way commute distances are actually highest for those choosing full-day telework once per week (see Figure 4), there is a consistent pattern of reduction in overall weekly commute VMT with each additional day of full-day telework (moving from left to right in Figure 5). In contrast, part-day telework retains the commute and therefore reduces weekly VMT only to the extent that it is associated with shorter commute distances. For instance, in Figure 5, adding a single day of part-day telework consistently reduces weekly commute distances for a fixed number of full-day commuting days because it is packaged with shorter commute distances. Further, it is the combination of full-day and part-day telework that appears to provide the biggest gains in terms of commute VMT reduction. The longest one-way commute distance is for those working a single day of full-day telework and no part-day

telework, while the commute distance drops dramatically when a single day of part-day telework is introduced. This is a critical distinction from a policy perspective. Encouraging low levels of full-day telework does not yield any meaningful improvements in terms of VMT reduction compared to those who do not telework, because it is packaged with a longer commute distance. Instead, encouraging those with lower levels of telework to undertake telework at a higher frequency, and particularly encouraging a combination of full-day and part-day telework would have a much more substantial impact.

These results demonstrate that the aggregation of part-day and full-day telework into a single “telework” category is not innocuous; part-day and full-day telework are adopted by systematically different groups, have different relationships with commute distance, and produce different VMT outcomes. As noted in Section 1, major national data systems either exclude part-day telework from their definitions of telework entirely or collapse part-day and full-day telework into a single category. Thus, our findings about the different preferences for part-day and full-day telework and the different implications for commute VMT suggest that such aggregations will misrepresent both the level and composition of telework-related demand reductions. Further, given that there is substantial variation in the intensity of use of both part-day and full-day telework, and the fact that the relationship between the use of each type of telework and commute distance is nonlinear, the collection of multi-day travel diary data to assess the impacts of these telework behaviors is critical. Therefore, surveys should cover several workdays to capture the weekly distribution of work arrangements, as a single diary day will frequently misclassify hybrid workers.

The distinction between the two telework modalities is also demonstrated by the exogenous variable effects on weekly commute VMT, shown in Table 7, revealing how specific preferences for different work arrangements, alongside residential location preferences, lead to overall VMT impacts. For instance, individuals with disabilities have a 9.72% lower weekly commute VMT (compared with those without disabilities) despite having virtually no different daily commute distance. Thus, this difference in commute VMT comes exclusively from the reduced number of commutes due to their increased use of full-day telework. In contrast, despite a minor reduction in the number of days of full-day telework, those living in high density areas (compared with those living in low density areas) also have a lower weekly commute VMT. Thus, these workers instead choose to live closer to their employment in general and adopt part-day telework (potentially shifting more of their commutes to off-peak times), yielding VMT benefits despite having nearly identical numbers of commute trips per week. Finally, individuals in more walkable neighborhoods have much stronger telework preferences than those in less walkable neighborhoods, teleworking 41.04% more full-days and 32.57% more part-days compared to those in less walkable areas. When combined with a lower average one-way commute distance, the result is a reduction in weekly commute VMT of over 50%. This result both points to a key way to promote VMT reductions, by supporting walkability and the development of mixed-use neighborhoods, and demonstrates the crucial role of part-day telework in reducing peak period demand, as these individuals spend a much greater portion of their weekly commute VMT on trips for part-day telework.

5.2 Implications for Travel Demand Modeling

The results reveal several direct implications for the structure and specification of activity-based travel demand models used by metropolitan planning organizations (MPOs) and state departments of transportation. As noted above, our findings demonstrate that treating part-day and full-day telework as a single aggregate behavior (or, more commonly, ignoring part-day telework entirely)

introduces meaningful errors in the prediction of both commute trip frequency and weekly commute VMT. As shown in Figures 4 and 5, the predicted one-way commute distance and weekly VMT vary substantially across work arrangement combinations, and this variation is not simply monotonic with respect to the total number of telework days. For instance, individuals who mix part-day and full-day telework have systematically different VMT profiles than those who engage in only one type, a distinction that is entirely lost when part-day telework is either excluded or folded into a single telework frequency variable.

The results also reveal key variations in work arrangement preferences that should be included in such forecasts. For example, industry-based segmentation of telework propensities is critical given the variation in telework availability across fields and our findings about the different telework preferences across different sectors. Part-day telework, while generating smaller aggregate VMT reductions, may serve as an important complementary strategy for workers who cannot adopt full-day telework due to in-person work requirements, including many health workers (who display a 10.91% decrease in full-day telework days relative to those without such requirements) and public administration workers (who display a 46.27% increase in part-day telework days relative to hospitality workers). Similarly, the large walkability-based differences in part-day telework adoption (36.48% more part-day telework days for workers in walkability index 10–14.9 areas relative to low-walkability areas) suggest that built environment segmentation of telework and separating these telework preferences based on full-day telework and part-day telework can have meaningful impacts.

5.3 Implications for Transportation System Operations and Congestion Management

The findings also carry implications for the timing and spatial distribution of commute demand, which are central to congestion management and infrastructure investment decisions. The distinction between full-day and part-day telework is particularly relevant here, as these two behaviors affect peak-period demand in fundamentally different ways. Full-day telework eliminates commute trips on remote days, providing the most direct form of demand relief. Part-day telework, in contrast, retains a commute but may shift its timing, with evidence from prior research suggesting that part-day teleworkers tend to commute outside traditional peak windows (see, for example, Asgari and Jin, 2018; Lachapelle et al., 2018; Stiles and Smart, 2021). The current findings, which confirm that part-day telework is jointly packaged with the choice of living in dense, highly walkable areas with short commute distances, suggest that the peak-spreading effects of part-day telework are likely to be concentrated in urban cores where congestion is most acute. This suggests that part-day telework policies may play a critical role in demand management through peak spreading even if it has a much smaller impact on total commute VMT.

Income-based differences in VMT impacts also have implications for the distributional effects of congestion pricing and other demand management instruments. Workers earning \$100,000–\$199,999 or more than \$200,000 per year undertake substantially more part-day telework (18.25% and 22.30% more days, respectively) and more full-day telework (18.33% and 17.21% more days, respectively) than workers earning less than \$50,000. When combined with their already lower commute distances, the result is a weekly VMT reduction of 28.50% and 25.08%, respectively, for these high-income groups. Further, the part-day share of commute VMT is substantially increased for high-income workers (39.06% and 43.10% higher, respectively) compared to low-income workers. The net result is that demand management policies targeting peak-period commuting trips will disproportionately impact lower-income travelers who have less access to telework flexibility. Thus, from an equity perspective, this income-based disparity in

telework access means that the monetary and time-saving benefits of reduced weekly VMT are disproportionately accrued to higher-income workers, suggesting that policies promoting telework among low-wage jobs may be necessary to ensure more equitable distribution of these benefits. Further, in terms of aligning demand management strategies with actual user behaviors, congestion pricing programs should be designed with the relatively lower income of peak period commuters in mind. Such congestion pricing programs should be paired with targeted telework support or trip reduction incentives for lower-income workers to achieve equitable distribution of both the demand management benefits and the financial burden of peak-period pricing.

5.4 Implications for Work Arrangement and Employer Policies

A final set of implications concerns actual employer policies for work arrangements and telework adoption. Employers should recognize the far-reaching implications of such policies, including on the commuting behaviors of their employees. For instance, female workers relative to male workers undertake 13.10% more part-day telework days and 7.53% more full-day telework days, resulting in a 21.69% reduction in weekly commute VMT and an increase in the part-day share of commute VMT of 15.41%. This pattern is consistent with prior evidence linking women's telework adoption to the management of household and caregiving responsibilities (Wang et al., 2023; Chung and van der Lippe, 2020), but the much larger increase in part-day relative to full-day telework suggests that women may be using part-day telework specifically to shift commute timing around household obligations rather than to eliminate commutes entirely. In contrast, nonbinary workers undertake 18.10% fewer part-day telework days and 12.12% fewer full-day telework days relative to male workers, resulting in 11.87% higher weekly commute VMT. This result is consistent with concerns about workplace scrutiny and visibility pressures faced by nonbinary workers (Bai et al., 2025; Lagos et al., 2026), and points to a need for explicit employer policies that support equitable access to flexible work arrangements across gender identities. Employers should recognize these particular needs of women and nonbinary employees and (a) institutionalize telework options (including both full-day and part-day telework options) to provide access to all employees (including all gender identities, but also availability across all racial groups, ages, and abilities, as discussed below), (b) offer women and nonbinary individuals more control over daily work timing and location to accommodate caregiving-related schedule variability, and (c) ensure that employees working more time remotely are given sufficient visibility, access to resources, and opportunities for advancement. Further, employers should also consider allowing for shifted hours or work-timing flexibility even when full-day in-person work is required, as these individuals who undertake fewer days of part-day telework are otherwise more likely to be constrained to peak-period commutes.

Racial and ethnic differences in telework outcomes similarly reflect ongoing inequities in workplace flexibility. Non-white workers undertake 18.30% fewer part-day telework days than white workers (with only a limited difference in full-day telework). This pattern suggests that the equity gap in access to part-day telework arrangements documented by Lewis et al. (2024) and Asfaw (2022) persists in the post-pandemic period in the Puget Sound region. Policies aimed at addressing this gap, including explicit employer commitments to equitable telework eligibility and transparent criteria for remote work approvals, are important both for worker well-being and for ensuring that the travel demand benefits of part-day telework are broadly accessible. The results for workers with disabilities that impact travel are also noteworthy. These workers undertake 12.81% more full-day telework days and 8.01% more part-day telework days relative to workers without such disabilities, resulting in a 9.72% reduction in weekly commute VMT. These results

highlight the importance of work location flexibility for these individuals who face additional commuting challenges. Employer policies that explicitly accommodate disability-related telework needs, including support for both full-day and part-day arrangements depending on individual circumstances, are important for both equity and efficiency.

Finally, age-related patterns impacting weekly commute VMT point to important shifts in the composition of commute VMT over time. Middle-aged workers (ages 25-44 and 45-54) undertake substantially more part-day telework and fewer full-day telework days relative to the youngest workers (ages 18-24), and have substantially higher weekly VMT. For workers aged 45-54, weekly VMT is 70.15% higher than for those aged 18-24, driven in part by a 54.05% longer one-way commute distance and an increased number of fully in-person work days. As this middle-aged cohort continues to dominate the workforce in coming decades, and given that they tend to reside further from employment centers, the aggregate VMT implications of their telework patterns will be particularly significant. Employers and policymakers seeking to maximize the individual-level time savings and overall demand management benefits of telework should give particular attention to increasing full-day telework opportunities for middle-aged workers, for whom the VMT savings per eliminated trip are greatest.

6. CONCLUSIONS

The current study employs multi-day travel diary data from the 2023 Puget Sound Regional Household Travel Survey to examine the adoption and frequency of part-day and full-day telework and the implications for commute VMT. We find that frequent part-day teleworkers constitute a distinct group from full-day teleworkers, being adopted more commonly among women, middle-aged individuals, those with lower levels of educational attainment, those with disabilities that impact travel, individuals living in higher income households and in areas with higher densities and better walkability, and among full-time employed individuals working in the public administration sector. Regarding travel implications, part-day telework and shorter commute distances (living closer to the physical work place) have a high probability of being chosen together as a package, while full-day telework and longer commute distances (living farther away from the work place) similarly have a high probability of being chosen as a package. These differences underscore that part-day and full-day telework serve different roles in the travel landscape and should not be conflated, as they have very different implications for overall commute VMT.

Beyond the specific empirical findings, the study highlights broader implications for transportation planning as well as employer policies. The results demonstrate that large-scale travel surveys, which generally either exclude part-day telework from their definitions of telework or collapse it with full-day telework, may systematically misrepresent the composition and magnitude of telework-related demand reductions. Activity-based travel demand models used by metropolitan planning organizations should incorporate the distinct VMT impacts of each telework modality, and should be segmented by industry, built environment context, and worker demographics to reflect the heterogeneity in telework preferences documented here. Further, significant heterogeneity in the adoption and modality of telework have important implications for demand reduction strategies, impacting the spatial and temporal distribution of commute trips as well as the populations impacted by demand management programs. For instance, the income-based disparities in telework access, with high-income workers capturing the greatest VMT savings, suggest that congestion pricing programs should be designed with an awareness of who remains at peak periods, and should be paired with telework support or trip-reduction incentives for lower-wage workers to achieve effective and equitable outcomes.

Finally, there are several promising directions for future research to build on these findings. First, and as noted in our analysis, this study focused exclusively on commute VMT and did not account for potential increases in non-work travel associated with part-day telework arrangements. As several existing studies (primarily in the pre-pandemic era) have found that part-day teleworkers may generate more out-of-home maintenance trips, future work should examine how the two telework modalities jointly shape non-work travel and total daily VMT. Second, the 30-minute threshold used here to distinguish substantive telework from incidental remote work tasks serves to distinguish some workers performing marginal telework activities but not substituting for actual out-of-home travel. Still, future studies should continue to investigate the broad range of work patterns to better classify workers across the range of work arrangements and routines. This also includes the finer-grained distinctions of whether remote work occurs before or after the commute to the out-of-home workplace as well as the extent to which part-day telework routines reflect deliberate and routine schedule shifts or ad hoc responses to daily demands. Third, while the current study used multi-day diary data to capture weekly telework routines, the sample was drawn from a single metropolitan area in 2023, and replication across diverse regional contexts and economic conditions would strengthen the generalizability of these findings. Finally, the role of employer policies (including desk-sharing arrangements, flexible parking schemes, and meeting scheduling practices that facilitate mid-day commutes) in shaping the feasibility of part-day telework merits direct empirical investigation, both for understanding current adoption patterns and for designing workplace strategies that can redirect commute demand away from peak periods.

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Table 1: Summary of Literature on Part-Day Telework

Reference	Study Context	Elicitation Method	Data Resolution	Definition of Part-Day Telework	Modeling Approach				
					Full-day Telework Modeled?	Part-Day Telework Modeled?	Consideration of both full-day and part-day telework frequencies?	Telework adoption, full-day telework, and part-day telework all modeled jointly?	Commute distance considered endogenous?
Pre-Pandemic Studies									
Haddad et al. (2009)	United Kingdom national survey in 2007	Retrospective responses of behavior in previous week	Five-day reference week	Part-day telework consists of (1) worked at home and then at my workplace, (2) worked at my workplace and then at home, or (3) worked at home then my workplace then at home; “worked at home” itself is flagged based on working from home for a duration of at least 30 minutes.	Modeled as ordered frequency	Modeled as ordered frequency	Yes	No	No
Deng et al. (2015)	Survey of I-5 commuters in Northern California, United States in 2008	Retrospective responses of typical telework frequencies per month	Typical monthly frequencies were treated as binary to focus on adoption	Part-day telework is defined as “work at home and change the time you commute to or from work” and is differentiated from overtime telework, defined as “work at home for part of the day without changing your normal commute.” Monthly part-day telework frequency was collected and considered as a binary outcome indicating whether the individual chose part-day telework at a frequency of “1-3 times a month” or greater.	Modeled as binary	Modeled as binary	No	No	No
Post-Pandemic Studies									
Kappler & de Abreu e Silva (2025)	Online survey in 2021 in the Lisbon, Istanbul, and Porto Alegre Metropolitan Areas	Travel–telework diary	Five-day diary	Part-day telework refers working at home or another remote location for part of the day without eliminating the commute on that day. No specific duration thresholds were defined.	Modeled as ordered frequency	Modeled as ordered frequency	Yes	No	No
Versigghel et al. (2025)	Online survey in 2023 in East Flanders, Belgium	Retrospective responses of typical telework choices on each day of the week	Seven-day reference week	Part-day telework was defined as performing paid work from home during work hours while also traveling to the workplace on the same day. No thresholds were defined but informal after-hours work was excluded (part- and full-day telework were combined into a total weekly telework frequency category for the main analysis).	Part-day and full-day telework combined and modeled as total frequency		No	No	No
The Current Study	Puget Sound, United States Regional Household Travel Survey, 2023	Travel diary	Five-day diary	Respondents are classified as engaging in part-day telework if they completed at least 30 minutes of telework (at home or a remote location) while also making a commute to their primary out-of-home workplace.	Modeled as ordered frequency	Modeled as ordered frequency	Yes	Yes	Yes

Table 2: Frequency of Full-Day and Part-Day Telework Participation

Number of Working Days	Number of Respondents	Commute Distance		Percent Teleworking at least once	Percent (of Teleworkers) Choosing Full-Day Telework for:						Percent (of Teleworkers) Choosing Part-Day Telework for:					
		Mean	Median		0 Days	1 Day	2 Days	3 Days	4 Days	5 Days	0 Days	1 Day	2 Days	3 Days	4 Days	5 Days
3	107	8.53	5.87	49.5	30.2	22.6	13.2	34.0	--	--	47.2	34.0	7.5	11.3	--	--
4	193	9.31	6.11	64.8	18.4	18.4	15.2	13.6	34.4	--	53.6	20.8	10.4	8.8	6.4	--
5	399	9.01	6.28	81.2	16.7	11.7	16.0	13.0	14.2	28.4	43.8	20.4	14.8	9.9	5.5	5.6
All Individuals	699	9.02	6.15	71.8	18.5	14.6	15.6	15.3	17.7	18.3	46.6	21.9	12.9	9.8	5.2	3.6

Table 3: Joint Distribution of Full-Day and Part-Day Telework Days

Work Arrangement Combination	Number	Percent
Full-day in-person only	197	28.18
Full-day telework only	153	21.89
Part-day telework only	32	4.58
Full-day in-person and full-day telework	81	11.59
Full-day in-person and part-day telework	61	8.73
Full-day telework and part-day telework	127	18.17
Full-day in-person, full-day telework, and part-day telework	48	6.87

Table 4: Descriptive Statistics of Exogenous Variables

Variable	Sample	ACS	Variable	Sample	ACS
<i>Individual Demographics</i>					
Gender			Education		
Male	49.3	50.6	Less than bachelor's degree	20.8	52.0
Female	45.8	49.4	Bachelor's degree	39.9	28.5
Nonbinary	4.9	--	Graduate degree	39.3	19.5
Age			Race		
18-24	5.6	10.1	White	67.4	59.2
25-34	35.6	20.9	Non-white	32.6	40.8
35-44	29.9	19.8	Ethnicity		
45-54	12.7	15.6	Hispanic	15.0	11.7
55-64	11.9	14.5	Not Hispanic	85.0	88.3
65+	4.3	19.1	Disability that Impacts Travel		
			Yes	5.6	12.0
			No	94.4	88.0
<i>Household Characteristics and Location</i>					
Household Composition			Population Density (people per square mile)		
Single adult	39.9	38.8	Less than 2,000	23.0	--
Single parent	2.1	4.5	2,000 - 3,999	28.3	--
Nuclear	16.5	19.8	4,000 - 5,999	15.6	--
Couple	37.9	28.4	6,000 or more	33.1	--
Other	3.6	8.5	Employment Within 0.5 Miles of Transit Stop		
Household Income			No transit accessibility	70.7	--
Less than \$50,000	17.3	21.1	Any transit accessibility	29.3	--
\$50,000 - \$99,999	26.5	24.2	National Walkability Index		
\$100,000 - \$199,999	32.3	31.6	Less than 10	12.9	--
\$200,000 or more	23.9	23.1	10 - 14.9	35.0	--
Household Type			15 or more	52.1	--
Single family home	37.3	56.3			
Multi-family dwelling	62.7	43.7			
<i>Employment Details</i>					
Employment			Free or subsidized parking		
Full-time	82.2	--	Yes	36.9	--
Part-time	9.2	--	No	63.1	--
Self-employed	8.6	--	Industry		
Number of Working Days			Health	11.2	21.0
3	15.3	--	Education or social work	14.2	15.7
4	27.6	--	Construction and manufacturing	10.1	9.3
5	57.1	--	Information and finance	20.9	18.2
Free or subsidized transit pass			Technology	7.3	10.0
Yes	41.1	--	Public administration	8.7	8.4
No	58.9	--	Hospitality	14.9	17.4
			Other		

Table 5: Main Estimation Results

Variables (base)	Commute Distance		Telework Adoption		Full-Day Frequency		Part-Day Frequency	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Individual Demographics								
Gender (male)								
Female	-0.19	-2.11	0.17	1.49	--		--	
Nonbinary	--		-0.22	-1.34	--		--	
Age (18-24)								
25-44	0.23	1.95	-0.17	-1.30	-0.23	-1.52	0.26	1.91
45-54	0.47	3.06	-0.38	-2.01	-0.42	-1.86	0.36	1.73
55+	--		--		-0.17	-1.56	--	
Education (bachelor's or less)								
Graduate degree	--		--		0.20	1.85	-0.31	-2.87
Race (white)								
Non-white	--		--		--		-0.12	-1.37
Ethnicity (not Hispanic)								
Hispanic	-0.25	-1.79	--		0.17	1.31	--	
Disability that Impacts Travel (no)								
Yes	--		0.35	1.72	0.26	1.67	--	
Household Characteristics and Location								
Household Composition (single adult)								
Single Parent	0.17	1.43	-0.38	-1.36	--		--	
Nuclear	0.17	1.43	--		-0.11	-1.35	--	
Couple	--		--		-0.16	-1.45	-0.15	-1.28
Income (Less than \$50,000)								
\$50,000 - \$99,999	-0.33	-2.25	--		0.23	1.44	--	
\$100,000 - \$199,999	-0.33	-2.25	0.20	1.80	0.25	1.48	0.18	1.39
\$200,000 or more	-0.39	-3.05	0.20	1.80	0.25	1.48	0.23	1.53
Population Density (< 4,000)								
4,000-5,999	-0.30	-2.04	--		--		0.15	1.41
6,000+	-0.42	-3.13	--		--		0.15	1.41
Employment Within 0.5 Miles of Transit Stop (none)								
Any transit accessibility	-0.40	-3.70	--		0.12	1.48	--	
National Walkability Index (< 10)								
10-14.9	-0.61	-3.57	0.26	1.52	0.17	1.38	0.20	1.37
15+	-0.82	-4.40	0.42	2.25	0.37	1.70	0.20	1.37
Employment Details								
Employment (Full-Time)								
Part-Time	-0.34	-2.23	--		0.37	1.98	-0.22	-1.44
Self-Employed	--		--		--		-0.11	-1.50
Number of Working Days (3)								
4	--		0.45	2.95	0.15	1.61	--	
5	--		0.79	5.34	0.50	2.01	--	
Employer Subsidies (none)								
Free or subsidized transit pass	--		--		--		-0.12	-1.40
Free or subsidized parking	--		--		-0.13	-1.30	--	
Industry (hospitality)								
Health	-0.18	-1.57	-0.17	-1.41	--		0.22	1.36
Construction and Manufacturing	-0.34	-2.47	-0.28	-1.87	-0.18	-1.32	--	
Education or Social work	--		-0.22	-1.48	--		--	
Information and Finance	--		--		0.25	1.55	--	
Technology	--		--		0.12	1.49	--	
Public Administration	--		--		-0.33	-1.69	0.38	1.93

Variables (base)	Commute Distance		Telework Adoption		Full-Day Frequency		Part-Day Frequency	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
<i>Covariance Elements</i>								
Commute Distance	1.07	40.44						
Telework Adoption	0.12	1.31	1.00	--				
Full-Day Frequency	0.00	--	0.70	3.05	1.00	--		
Part-Day Frequency	-0.17	-2.03	-0.61	-2.25	-0.59	-5.80	1.00	--
<i>Endogenous Effects</i>								
Commute Distance (<5)								
5-10	--		0.12	1.69	0.29	2.11	-0.12	-1.42
10-15	--		0.53	2.36	0.68	3.96	-0.37	-2.50
15+	--		0.25	1.77	0.70	3.69	-0.42	-2.69
<i>Constant and Thresholds</i>								
Baseline Constant and Thresholds								
Constant	2.93	13.77	--		--		--	
Threshold between zero days and one day	--		0.27	1.03	-0.25	-0.51	0.53	1.90
Threshold between one day and two days	--		--		0.20	0.40	1.45	5.77
Threshold between two days and three days	--		--		0.60	1.14	1.67	6.81
Threshold between three days and four days	--		--		0.99	1.80	1.95	8.18
Threshold between four days and five days	--		--		1.55	2.62	2.34	9.16
Threshold Shifters								
Commute 10+ miles on the threshold between one day and two days	--		--		0.13	1.43	-0.16	-1.92
Commute 10+ miles on the threshold between two days and three days and all higher thresholds	--		--		0.19	1.55	--	
One day full-day telework on the threshold between one day and two days	--		--		--		-0.61	-3.26
One day full-day telework on the threshold between two days and three days	--		--		--		-0.56	-2.93
One day full-day telework on the threshold between three days and four days	--		--		--		-0.46	-2.22
Two days full-day telework on the threshold between zero days and one day	--		--		--		-0.54	-2.99
Two days full-day telework on the threshold between one day and two days	--		--		--		-0.93	-5.63
Two days full-day telework on the threshold between two days and three days	--		--		--		-0.82	-5.21
Three days full-day telework on the threshold between zero days and one day	--		--		--		-0.42	-2.32
Three days full-day telework on the threshold between one day and two days	--		--		--		-0.88	-5.15
Four days full-day telework on the threshold between zero days and one day	--		--		--		-0.21	-1.29
One day full-day telework * Age 25-44 on the threshold between one day and two days and all higher thresholds	--		--		--		0.13	1.40
One or more days full-day telework * Presence of children on the threshold between zero days and one day and all higher thresholds	--		--		--		0.30	1.72

Table 6: Model Fit

Comparisons with Restricted (Nested) Models			
Metric	Proposed Model	Model Without Shift Effects	Independent Model
<i>Disaggregate Measures</i>			
Log-Likelihood at Convergence	-2805.70	-2896.64	-3026.23
Log-Likelihood at Constants	-3162.37	-3162.37	-3162.37
Number of Parameters	105	91	86
Adjusted Likelihood Ratio Index	0.083	0.059	0.020
Bayesian Information Criterion	3149.55	3194.65	3307.86
Likelihood Ratio Test Statistic	--	181.89	441.07
<i>Aggregate Measures</i>			
Work Arrangement WAPE	13.21	19.59	26.66
Commute Distance APE	9.28	10.44	10.75
Comparisons with Unordered (Non-Nested) Model			
Metric	Proposed Model	Unordered Model	
<i>Disaggregate Measures</i>			
Log-Likelihood at Convergence	-2187.73	-2114.34	
Log-Likelihood at Constants	-2368.86	-2368.86	
Number of Parameters	105	181	
Adjusted Likelihood Ratio Index	0.037	0.035	
Bayesian Information Criterion	2531.59	2707.09	
Informal Non-Nested Likelihood Ratio Test	--	$\Phi(-7.860) \ll 0.000$	

Table 7: Exogenous Variable Effects on Weekly Commute VMT

Variable	Base	Treatment	Percent Change in:				
			Number of Days of Full-Day Telework	Number of Days of Part-Day Telework	Average One-Way Commute Distance	Average Weekly (two-way) Commute	Portion of Commute for Part-Day Work
Gender	Male	Female	7.53	13.10	-19.34	-21.69	15.41
	Male	Nonbinary	-12.12	-18.10	8.63	11.87	-26.27
Age	18-24	25-44	-22.24	26.67	29.24	35.05	-3.65
	18-24	45-54	-41.20	36.98	54.05	70.15	-23.58
	18-24	55+	-7.24	8.47	-3.89	-1.20	8.08
Race	White	Non-White	4.62	-18.30	-8.16	-4.77	-19.13
Ethnicity	Not Hispanic	Hispanic	9.59	-8.80	-14.69	-18.45	-5.98
Disability	No	Yes	12.81	8.01	0.04	-9.72	18.97
Income	Less than \$50,000	\$50,000 - \$99,999	11.33	-8.35	-23.67	-26.23	2.16
	Less than \$50,000	\$100,000 - \$199,999	18.33	18.25	-21.30	-28.50	39.06
	Less than \$50,000	\$200,000+	17.21	22.30	-21.99	-25.08	43.10
Population Density	<4,000	4,000 - 5,999	-3.10	13.72	-19.87	-23.68	-1.91
	<4,000	6,000+	-3.10	13.72	-26.53	-30.48	-4.55
Walkability Index	<10	10 - 14.9	23.08	36.48	-41.28	-46.55	92.78
	<10	15+	41.04	32.57	-48.25	-54.98	113.24
Industry	Hospitality	Health	-10.91	7.73	-3.47	-6.83	-13.49
	Hospitality	Construction/manufacturing	-20.29	-9.56	-23.61	-21.03	-40.08
	Hospitality	Education/social work	-8.65	-11.34	6.25	8.34	-18.24
	Hospitality	Information/finance	12.57	-11.69	9.16	5.00	6.58
	Hospitality	Technology	6.39	-5.68	5.41	3.52	4.81
	Hospitality	Public administration	-22.65	46.27	-5.89	-8.03	-14.44

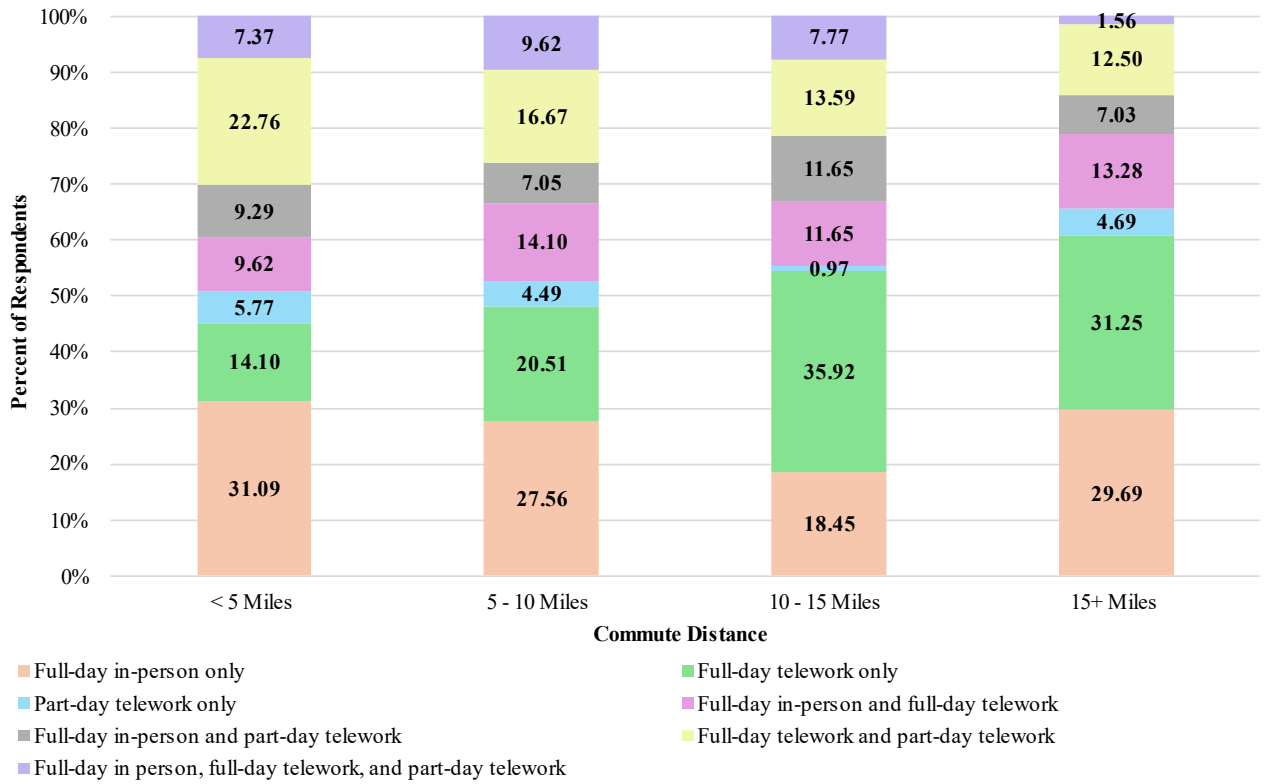


Figure 1: Relationship Between Commute Distance and Work Arrangement Participation

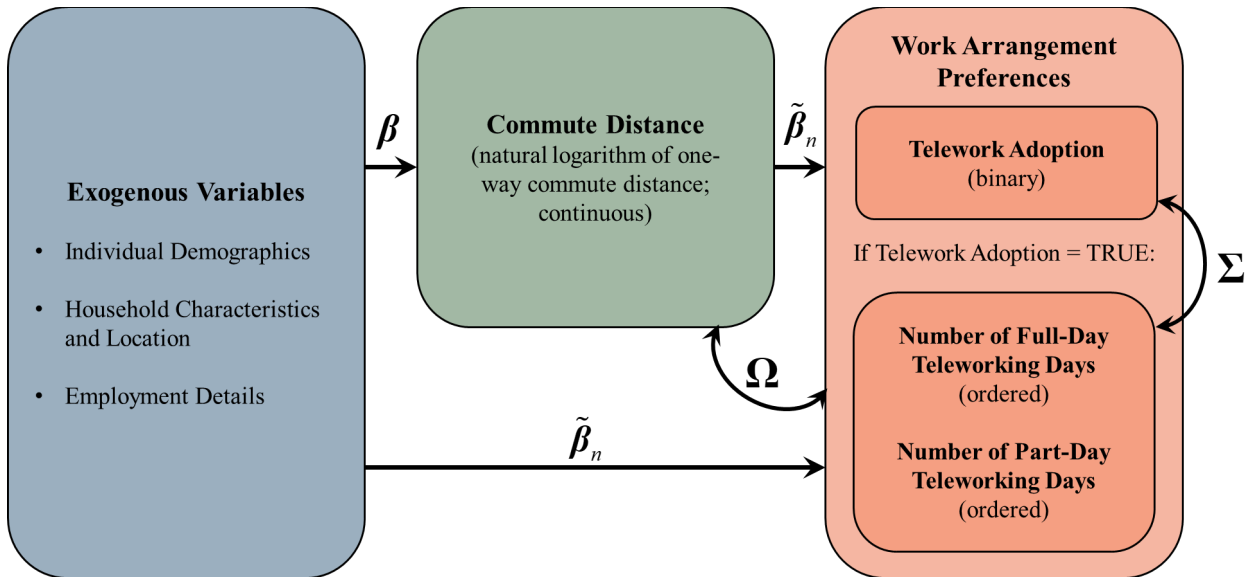


Figure 2: Framework for Joint Model of Commute Distance and Work Arrangements

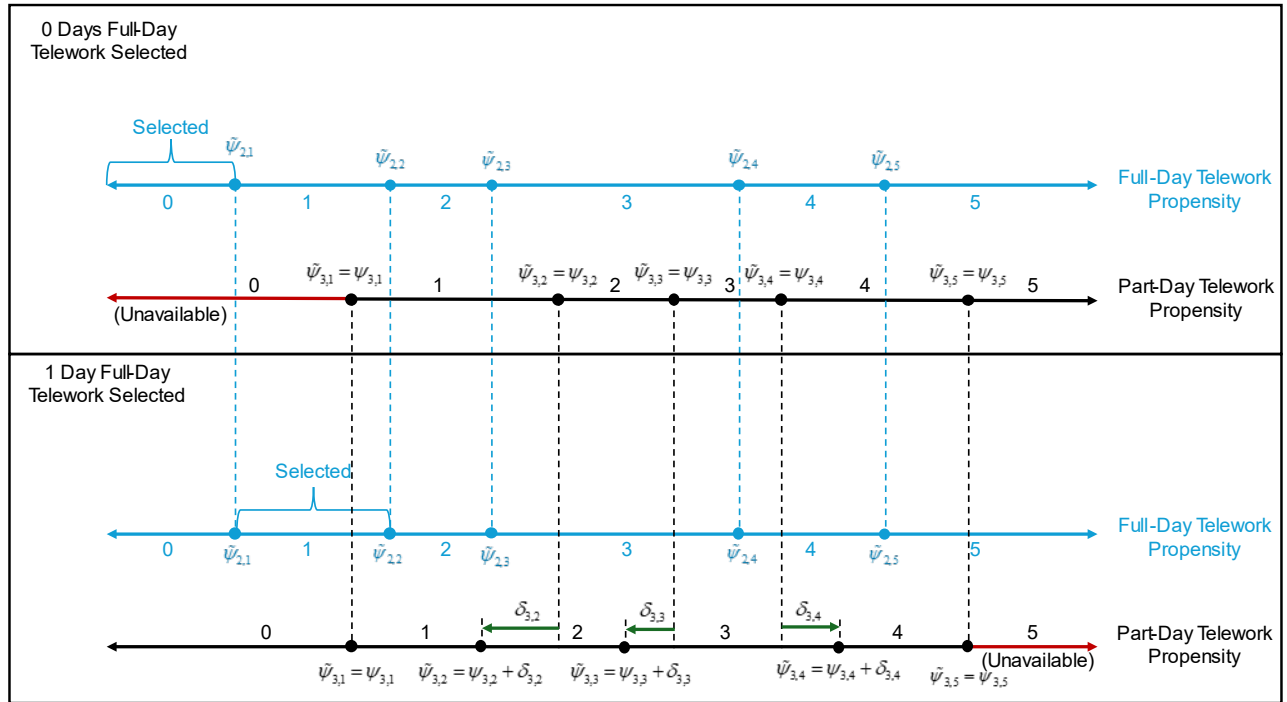


Figure 3: Conceptual Diagram of Effects of Threshold Shifters

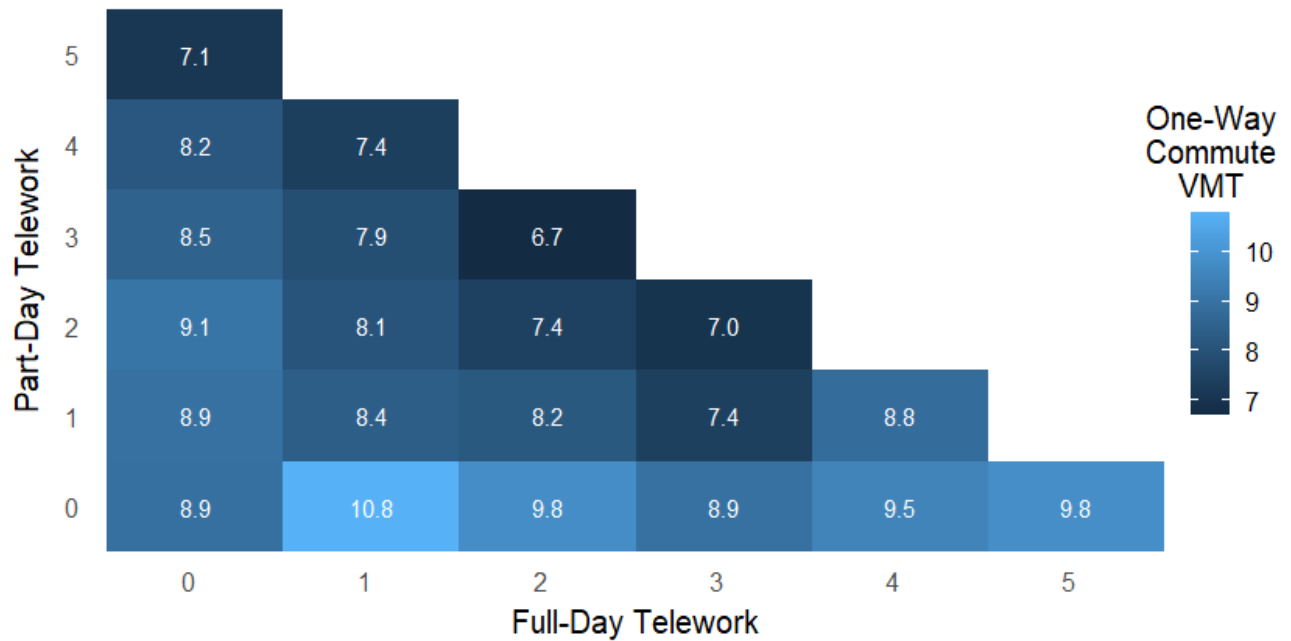


Figure 4: Predicted One-Way Commute Distance Conditional on Work Arrangement Combination

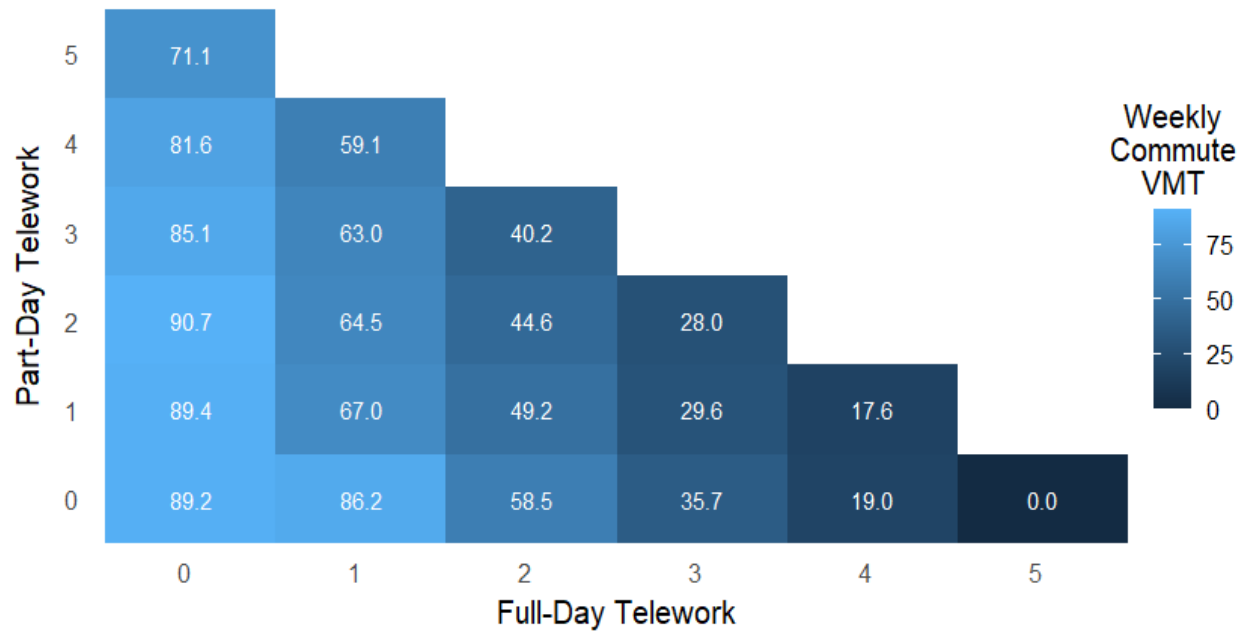


Figure 5: Predicted Weekly Two-Way Commute VMT Conditional on Work Arrangement Combination