

Intermediate Stop-Making During Commute Trips: An Analysis of Variations Across the Week

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ABSTRACT

Commute trips often include intermediate stops for non-work activities, adding trip segments that may contribute to peak-period travel demand. As hybrid work reshapes workplace commuting, an important question is whether the commute trips that remain become more complex. To address this question, the study examines how intermediate stop-making on home-to-work (H-to-W) and work-to-home (W-to-H) commute trips varies by telecommuting frequency and day of the week. The analysis uses Wave 2 of the Transportation Heartbeat of America Survey, conducted across the United States in 2026, and includes 2,409 full-time employees contributing 11,074 workplace commute-day observations. Intermediate stop-making in the two commute directions is jointly estimated using a panel bivariate binary probit model that accounts for repeated observations from the same individual and correlated unobserved influences across commute directions. The results show that intermediate stops are more common on W-to-H trips than on H-to-W trips. More importantly, telecommuting frequency is positively associated with stop-making in both directions, with progressively larger effects at higher telecommuting frequencies. However, this relationship is not uniform across the week. For W-to-H trips, the positive association is smaller on Thursday and Friday among low-frequency telecommuters and substantially smaller on Friday among medium-frequency telecommuters. Stop-making also varies by sociodemographic, household, commute, built-environment, and regional characteristics, with several relationships differing across the week. By providing a commute-direction-specific and day-specific analysis using contemporary national travel survey data, the study quantifies how stop-making on workplace commute days varies across telecommuting frequencies. The findings indicate that telecommuting is associated not only with fewer workplace commute days but also with greater commute-tour complexity on the days workers travel to the physical workplace. Accordingly, travel demand models and telecommuting impact assessments should account for telecommuting frequency, commute direction, and day-of-week variation rather than represent hybrid work as a homogenous behavioral phenomenon.

Keywords: Intermediate Stop, Commute Trip, Hybrid Work, Telecommuting, Panel Data, Joint Model

1. INTRODUCTION

Trip chaining is a central feature of daily activity-travel behavior. Rather than undertake each activity through a separate home-based trip, individuals frequently combine shopping, escorting, personal business, meals, and other activities within a single tour. The commute is especially important because travel to and from the workplace often serves as a structural anchor around which workers organize these activities (McGuckin and Srinivasan, 2005). Intermediate stops embedded within commute tours add trip segments and may alter departure times, routes, destinations, and travel distances. Because many such stops occur during morning and evening commute periods, they may also contribute to congestion when transportation networks are under the greatest stress (Wang, 2015). Commute trip chaining must therefore be represented adequately in travel demand forecasting models that seek to reproduce weekday activity-travel patterns.

Commute trip chains reflect how workers organize activities around spatial, temporal, and household constraints. Some stops are planned, while others are added opportunistically to tours anchored by higher-priority activities (Lee and McNally, 2006). Stop-making may also differ by commute direction. Travel from home to work (H-to-W) is commonly constrained by workplace arrival requirements, whereas travel from work to home (W-to-H) generally offers greater flexibility for shopping, personal business, chauffeuring, and social activities.

The widespread adoption of remote and hybrid work arrangements has added a new dimension to this behavior. The COVID-19 pandemic accelerated a structural shift in where and how often people commute to the workplace, and many workers did not return to full-time workplace attendance after offices reopened. Salon et al. (2022) found that 40-50 percent of workers expected to telecommute at least a few times per month after the pandemic, compared with 24 percent before COVID-19. Regional evidence from Southern California similarly indicates considerable interest in continuing hybrid work arrangements over the longer term (Ilogansen et al., 2024). Telecommuting has therefore become an enduring feature of the transportation landscape.

This shift raises questions beyond the mere elimination of commute trips on remote workdays. Hybrid workers may redistribute non-work activities between remote and workplace days, either consolidating them into fewer commute tours or completing them separately on remote work days. Stop-making may also vary across the week because workplace attendance and activity needs are not distributed uniformly by day. Recent evidence from the Atlanta region indicates that telecommuting is concentrated on Monday and Friday, while physical commuting peaks midweek (Atlanta Regional Commission, 2026).

Although a growing body of research has examined telecommuting, non-work travel, and tour complexity, limited attention has been devoted to intermediate stops made specifically during workplace commute trips. Existing studies have not fully examined how stop-making differs between H-to-W and W-to-H travel, varies across telecommuting frequencies, and changes over the days of the week. These distinctions matter for activity-based travel demand models because they affect the number and sequencing of trip segments, the timing of travel, and the distribution of demand across the transportation network.

This study addresses these gaps using Wave 2 of the Transportation Heartbeat of America (THA) Survey that was conducted across the United States in early 2026. The analysis focuses on full-time employees who worked at least four days during the reported week and traveled to their primary workplace on at least one day. Workers are classified according to telecommuting frequency, ranging from no telecommuting to low-, medium-, and high-frequency telecommuting. For each workplace commute day, the survey identifies whether the respondent made at least one

intermediate stop while traveling from H-to-W and from W-to-H. The two outcomes are jointly analyzed using a panel bivariate binary probit model that accounts for repeated observations from the same individual (for multiple days of the week), shared unobserved influences across commute directions, and day-of-week heterogeneity.

The study makes three principal contributions. It provides a direction-specific analysis of commute stop-making, examines differences across telecommuting frequencies and days of the week, and uses recent national weekly travel data directly relevant to activity-based travel forecasting in the post-COVID era. The results clarify whether telecommuting simply reduces commute frequency or also changes the complexity of the commute trips that remain.

The remainder of this paper is organized as follows. The next section reviews the literature on commute trip chaining, telecommuting and non-work travel, and day-specific variations in workplace commuting. The subsequent sections describe the survey data and endogenous outcomes, present the methodological framework, and discuss the model estimation results and treatment effects. The paper concludes with a summary of key findings and implications for travel demand modeling and transportation planning.

2. COMMUTING AND STOP-MAKING IN THE NEW NORMAL

Trip chaining arises because individuals organize travel around activities rather than isolated trips. The workplace commute often serves as the principal weekday anchor, allowing workers to attach shopping, escorting, personal business, meals, and other activities to a tour with relatively fixed spatial and temporal commitments (McGuckin and Srinivasan, 2005). Tour formation may involve both deliberately planned and opportunistically added lower-priority activities (Lee and McNally, 2006).

Intermediate stops create additional trip segments and may affect departure time, route choice, destination choice, travel distance, and mode feasibility. They are especially relevant during peak travel periods (Wang, 2015). Direction also matters; H-to-W travel is generally governed by rigid workplace start times, whereas W-to-H travel may more readily accommodate shopping, errands, chauffeuring, dining, and social activities. Ignoring these directional patterns may cause travel demand models to misstate tour complexity and peak-period flows.

Telecommuting complicates these established patterns. It is often viewed as a travel demand management strategy because it removes the workplace commute on remote workdays and may reduce vehicle miles traveled (VMT) (Handy, 2025). The empirical literature, however, shows that its effects extend beyond avoided commute trips. Time saved by not commuting may be reallocated to other activities, while greater schedule flexibility may generate or redistribute non-work travel. A review by Speroni and Taylor (2023) concluded that telecommuting does not just produce a simple reduction in driving and may even be associated with greater overall travel.

Several studies document increased or reorganized non-work travel among telecommuters. Zhu (2012) found that telecommuting was associated with greater non-work trip frequency, distance, and duration across shopping, family and personal business, and social and recreational purposes. Obeid et al. (2024) reported that U.S. telecommuters made approximately one additional non-commute trip on telecommuting days relative to commute days. Although telecommuting reduced total weekly distance traveled in their analysis, the authors cautioned that its travel-reduction effects could be overstated if newly generated non-work trips were ignored. Jia et al. (2025) similarly found that telecommuting reduced total trips and VMT but increased maintenance and discretionary trip-making. Balbontin et al. (2024) associated more frequent work from home with greater shopping, personal business, social, and recreational travel, while Kothawala et al.

(2025) found that flexible work schedules were associated with greater social activity participation. Overall, these studies suggest that time savings and schedule flexibility may expand opportunities for non-work activities even when commute travel declines.

Telecommuting also appears to alter the structure of daily activity-travel patterns. Su et al. (2021), using motif and sequence analysis of California travel data, found that telecommuters exhibited more diverse activity-travel structures than regular commuters. Hybrid workers who traveled on a workday made more trips and followed more complex schedules than workers with conventional commuting arrangements. Zubair et al. (2026) similarly found that hybrid workers had a greater likelihood of forming complex tours, although they formed fewer tours per day overall. These findings suggest that hybrid work may promote the consolidation of activities into more elaborate daily travel patterns.

These relationships may vary with telecommuting frequency. Asmussen et al. (2026) found a bidirectional association between non-work activity participation and telecommuting frequency, together with an inverted U-shaped pattern in which moderate telecommuters made more non-work stops than infrequent and high-frequency telecommuters. Caros et al. (2023) similarly found that hybrid workers made more non-work trips than fully remote and fully in-person workers. Caldarola and Sorrell (2022) reported that workers who telecommuted once or twice per week traveled farther overall than non-telecommuters. These findings indicate that telecommuters should not be treated as a homogeneous group.

Only a small number of studies have focused directly on telecommuting and commute trip chaining. Wang (2015) found that workers with access to work-from-home flexibility made approximately 12 percent more stops during their commute. Zhu and Guo (2022), using the 2009 and 2017 National Household Travel Surveys, found that telecommuting increased trip-chaining propensity, trip-chaining frequency, and tour complexity. Importantly, these relationships remained significant on days when telecommuters traveled to the workplace. Telecommuters therefore differed from non-telecommuters not only because they avoided commuting on remote days, but also because their travel patterns differed on the workplace days they retained.

Day-of-week variation has received even less attention. Hybrid workers may use remote days to complete errands near home, reducing the need for stops on subsequent commute days. Alternatively, they may consolidate non-work activities into the fewer days on which they travel to the workplace. These patterns may differ between the beginning, middle, and end of the week, especially as telecommuting tends to be concentrated on Monday and Friday (Atlanta Regional Commission, 2026). Commute stop-making should therefore be examined within a weekly framework rather than through an average weekday measure.

Several research gaps remain. Most prior studies examine total travel, non-work activity participation, VMT, or general tour complexity rather than stops embedded specifically within commute trips. Few distinguish between H-to-W and W-to-H stop-making, even though the two directions are subject to different temporal constraints. Telecommuters are also frequently treated as a single group despite evidence that travel behavior varies with telecommuting frequency. Much of the available evidence also relies on pre-pandemic data or observations collected during the transitional stages of the pandemic. Work arrangements have continued to evolve as employers and workers have settled into steady-state remote and hybrid practices. Contemporary national data are therefore needed to understand commute trip chaining under the work arrangements that characterize the post-COVID era.

The present study addresses these gaps by jointly modeling H-to-W and W-to-H stop-making across repeated commute days, differentiating workers by telecommuting frequency, and

explicitly accounting for day-of-week variation. In doing so, it provides a more behaviorally complete picture of how hybrid work is associated with the complexity of workplace commute tours and offers evidence needed to improve the treatment of trip chaining and weekly work arrangements in activity-based travel demand forecasting models.

3. DATA DESCRIPTION

This section presents an overview of the data used in the study, including the survey design, sample construction, and key characteristics of the final analysis sample.

3.1 Survey Overview and Sample Characteristics

The study uses data from the second wave of the Transportation Heartbeat of America (THA) Survey – a national survey administered in the United States between February and March 2026. The survey was fielded through an online panel assembled by a commercial survey firm. Quotas were imposed across a broad set of socioeconomic and demographic attributes to capture the variation observed in the general adult population and. The quota-based sampling design provided adequate representation across subgroups defined by race, age, gender, educational attainment, household income, area type of residence, and census division. Eligible participants were adults aged 18 years or older residing in the United States. Multiple attention checks and quality-control questions were embedded in the survey to ensure response reliability.

The survey collected detailed information on attitudes toward transportation, mobility, and urban living; current activity-travel patterns and mode use; safety experiences across travel modes; commuting behavior and telecommuting arrangements; online shopping and delivery practices; and knowledge and opinions regarding emerging transportation technologies and infrastructure investments. Residential built-environment attributes were appended to the survey records based on respondent ZIP code using data from the U.S. Environmental Protection Agency Smart Location Database (Chapman et al., 2021). These measures provide detailed information on the transportation and land-use context surrounding each respondent’s residence.

Standard data-cleaning procedures were applied to remove records with missing or clearly erroneous information, yielding an initial cleaned sample of 8,567 respondents. Because this study focuses on intermediate stops made during commute trips, the sample was restricted to respondents who were employed full time, worked at least four days during the reported week, and traveled to their primary workplace on at least one of those days, reducing the sample to 2,525 respondents. An additional 116 respondents were excluded because their residential location could not be matched to the EPA Smart Location Database, resulting in a final sample of 2,409 individuals.

These respondents contributed a total of 11,074 workplace commute-day observations. Each observed commute day yielded one H-to-W trip and one W-to-H trip, yielding 11,074 H-to-W and 11,074 W-to-H stop-making outcomes. The resulting panel dataset therefore contains repeated commute-day observations for each worker and supports analysis of both cross-sectional differences and within-person variation across the week.

The demographic, household, geographic, and built-environment characteristics of the final analysis sample are presented in Table 1. The sample includes a somewhat larger share of men than women, at 62.3 and 37.7 percent, respectively. Respondents are concentrated in the prime working-age categories, with 38.1 percent aged 35-44 years and 21.1 percent aged 45-54 years. Educational attainment is relatively high with 22.4 percent holding a bachelor’s degree and 34.3 percent holding a graduate degree. The sample is also economically diverse, although it is

weighted toward middle- and higher-income households. About 30 percent of respondents fall into each of the \$50,000-\$99,999 and \$100,000-\$149,999 annual household income categories.

Table 1: Socio-Economic and Demographic Characteristics of the Sample

<i>Individual Attributes (N = 2,409)</i>		<i>Household Attributes (N = 2,409)</i>	
Variable	%	Variable	%
Gender		Household annual income	
Woman	37.7	Less than \$25,000	3.2
Man	62.3	\$25,000 to \$49,999	12.8
Age category		\$50,000 to \$99,999	29.0
18 to 24 years	8.1	\$100,000 to \$149,999	30.0
25 to 34 years	15.9	\$150,000 to \$199,999	17.5
35 to 44 years	38.1	\$200,000 or more	7.5
45 to 54 years	21.1	Household size	
55 to 64 years	11.9	One person	12.8
65 years or older	4.9	Two persons	19.8
Education attainment		Three or more persons	67.4
High school or less	19.6	Housing unit type	
Some college or technical school	23.7	Stand-alone home	77.2
Bachelor's degree(s)	22.4	Attached home/apartment	21.2
Graduate degree(s)	34.3	Other	1.6
Race		Home ownership	
Asian or Pacific Islander	6.0	Own	72.1
Black	17.2	Rent	26.7
White	67.1	Other	1.2
Other	9.7	Vehicle ownership	
Ethnicity		No vehicle	2.7
Hispanic	25.9	One vehicle	42.1
Non-Hispanic	74.1	Two vehicles	41.7
Number of telecommuting days in the last week		Three or more vehicles	13.5
0 days	65.3	Location	
1-2 days	21.9	Urban	51.1
3-4 days	10.3	Suburban or small town	40.3
5-6 days	2.5	Rural	8.6
<i>Built-environment Characteristics of Respondent Zip Code</i>			
Variable	Description	Mean	Std Dev
No-vehicle households	Share of households with no motor vehicles	0.12	0.15
One-vehicle households	Share of households with one motor vehicle	0.34	0.10
Two-or-more-vehicle households	Share of households with two or more motor vehicles	0.53	0.19
Low-wage workers	Share of zip-code workers earning low-tier wages	0.23	0.05
Population density	Persons per acre	15.63	28.33
Jobs-to-household ratio	Ratio of jobs to households	2.87	13.43
Auto network density	Auto-oriented links facility-miles per square mile	1.45	2.18
Multimodal network density	Multimodal links facility-miles per square mile	4.09	4.97
Pedestrian network density	Pedestrian-oriented links facility-miles per square mile	13.35	7.04
Intersection density	Street intersections per square mile	95.76	70.58
Auto intersection density	Auto-oriented intersections per square mile	4.39	11.38
Job accessibility	Jobs reachable within 45 minutes by automobile	153,058	185,999
Working-age population	Share of population aged 18 to 64 years	0.61	0.06
Road density	Total facility miles of road-network links per square mile	18.88	10.12

Household characteristics also exhibit considerable variation. About two-thirds of respondents reside in households with three or more persons, while 12.8 percent live alone. Most respondents live in stand-alone homes and own their residence, at 77.2 and 72.1 percent, respectively. Vehicle availability is generally high, although not universal with 42.1 percent of respondents living in one-vehicle households, 41.7 percent in two-vehicle households, and 2.7 percent in households without a vehicle. The sample spans a range of residential contexts, with 51.1 percent of respondents living in urban areas, 40.3 percent in suburban areas or small towns, and 8.6 percent in rural areas. Telecommuting frequency also varies meaningfully. While 65.3 percent did not telecommute during the reported week, 21.9 percent telecommuted one or two days, 10.3 percent telecommuted three or four days, and 2.5 percent telecommuted five or six days.

The appended built-environment measures further demonstrate substantial variation in the residential contexts represented in the sample. For example, the mean population density is 15.63 persons per acre, with a standard deviation of 28.33, indicating considerable dispersion across respondents' residential ZIP codes. Similar heterogeneity is evident in the jobs-to-household ratio, network density measures, intersection density, and automobile job accessibility. Mean job accessibility is approximately 153,000 jobs reachable within 45 minutes by automobile, but the large standard deviation of about 186,000 reflects wide variation in regional accessibility. Overall, the sample spans a broad range of individual, household, telecommuting, geographic, and built-environment conditions. This variation renders the dataset well suited to the bivariate panel modeling exercise undertaken in this study.

3.2 Endogenous Outcomes

Commute trip chaining characteristics are captured in the survey by asking respondents, for each day on which they traveled to their primary workplace, whether they made at least one intermediate stop while traveling H-to-W and whether they made at least one intermediate stop while returning W-to-H. The survey did not collect information on the number or purpose of stops. Accordingly, two binary endogenous outcomes are defined. The H-to-W stop-making outcome equals one if at least one intermediate stop was made between home and the workplace and zero otherwise. The W-to-H outcome is defined analogously. Because these outcomes are observed for each reported workplace commute day, the data provide repeated daily observations for each respondent, permitting analysis of both differences across workers and within-worker variation over the week.

Table 2 presents the percentage of commute trips that included an intermediate stop by commute direction, telecommuting frequency, and day of the week. Several clear patterns emerge. First, stop-making is more common on the return journey from work than on the trip to work. Across all 11,074 commute-day observations, 18.1 percent of H-to-W trips included an intermediate stop, compared with 24.1 percent of W-to-H trips. This directional difference is evident on every day of the week in the full sample. For example, the corresponding rates are 18.7 and 24.7 percent on Monday, 18.0 and 28.5 percent on Friday, and 25.0 and 32.6 percent on Saturday. The pattern is behaviorally intuitive because the trip to work is generally constrained by workplace arrival requirements, whereas the return journey offers greater flexibility to accommodate shopping, errands, chauffeuring, and other non-work activities.

Second, stop-making increases markedly with telecommuting frequency. Among workers who did not telecommute, 14.0 percent of H-to-W trips and 20.2 percent of W-to-H trips included a stop. These rates rise to 26.5 and 32.0 percent among workers who telecommuted one or two days during the week and to 33.8 and 39.4 percent among those who telecommuted three or four days. The highest-frequency telecommuting group exhibits stop-making rates of 77.2 percent in

both directions. Although this final segment is based on only 101 commute-day observations and should therefore be interpreted cautiously, the broader progression across telecommuting categories is striking. The descriptive evidence suggests that workers who telecommute more frequently are more likely to incorporate non-work activities into the workplace commute trips they make. This may reflect greater schedule flexibility, a tendency to consolidate activities into fewer workplace days, or other differences between telecommuters and workers who commute every workday. The descriptive statistics alone cannot distinguish among these explanations.

Third, the table reveals meaningful day-of-week variation. In the full sample, stop-making is generally lowest during the middle of the workweek and higher on Friday and Saturday. H-to-W stop-making declines to 16.4 percent on Thursday before rising to 18.0 percent on Friday and 25.0 percent on Saturday. W-to-H stop-making follows a similar pattern, declining to 20.8 percent on Thursday and then increasing to 28.5 percent on Friday and 32.6 percent on Saturday. Among workers who did not telecommute, the W-to-H stop-making rate rises from 18.1 percent on Thursday to 25.9 percent on Friday and 27.4 percent on Saturday. Similar end-of-week increases appear among workers telecommuting one or two days, for whom W-to-H stop-making reaches 36.2 percent on Friday and 45.3 percent on Saturday.

Table 2: Percent of Commute Trips with Intermediate Stops by Telecommuting Frequency and Day of the Week

Segment	Trip purpose	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Weekly
0 days telecommute	H-to-W	13.0	13.6	14.4	13.4	14.2	19.3	14.2	14.0
	W-to-H	18.4	17.3	19.4	18.1	25.9	27.4	21.7	20.2
	<i>Sample size</i>	1,506	1,538	1,524	1,507	1,470	424	254	8,223
1-2 days telecommute	H-to-W	25.5	24.7	27.5	23.9	28.6	41.3	32.0	26.5
	W-to-H	34.3	30.4	32.0	25.4	36.2	45.3	32.0	32.0
	<i>Sample size</i>	466	441	425	402	304	75	25	2,138
3-4 days telecommute	H-to-W	38.0	28.6	31.7	25.0	35.0	61.5	48.0	33.8
	W-to-H	44.7	37.8	32.7	37.0	35.0	69.2	36.0	39.4
	<i>Sample size</i>	150	119	104	108	80	26	25	612
5-6 days telecommute	H-to-W	91.4	87.5	53.8	88.9	68.4	50.0	77.8	77.2
	W-to-H	82.9	62.5	76.9	77.8	78.9	75.0	66.7	77.2
	<i>Sample size</i>	35	8	13	9	19	8	9	101
ALL	H-to-W	18.7	17.0	18.2	16.4	18.0	25.0	20.1	18.1
	W-to-H	24.7	21.4	23.0	20.8	28.5	32.6	24.9	24.1
	<i>Sample size</i>	2,157	2,106	2,066	2,026	1,873	533	313	11,074

Note: The table is color-coded according to percentage values, with a gradient ranging from red (lowest percentages) through orange and yellow (intermediate percentages) to green (highest percentages).

The day-specific patterns are not entirely uniform across telecommuting segments. Workers telecommuting three or four days exhibit relatively high stop-making rates on Monday as well as on the weekend, while the highest-frequency group displays considerable variation from one day to another. However, the sample sizes become progressively smaller as telecommuting frequency increases, particularly for weekend commute days. For example, the three-to-four-day telecommuting segment contributes only 26 Saturday and 25 Sunday observations, while the five-to-six-day segment contributes fewer than 20 observations on every day except Monday. Estimates for these cells should therefore be viewed as descriptive signals with appropriate caution (rather than statistically precise estimates).

Overall, Table 2 indicates that commute stop-making varies systematically by direction, telecommuting frequency, and day of the week. W-to-H trips are generally more likely to include a stop, stop-making rises with telecommuting frequency, and end-of-week commute days tend to exhibit greater tour complexity. At the same time, the differences across days are not uniform across worker groups. These patterns motivate the use of a panel bivariate modeling framework that can jointly analyze the two commute directions, account for repeated observations from the same worker, and identify whether telecommuting and day-of-week differences persist after controlling for individual, household, commute, geographic, and built environment characteristics.

4. MODEL STRUCTURE

This section presents an overview of the analytical framework adopted to examine intermediate stop-making during commute trips. Figure 1 provides a simplified representation of the model structure. The two binary endogenous outcomes, indicating whether a respondent made at least one intermediate stop on the H-to-W and W-to-H commute trips, are modeled jointly using a bivariate binary probit model for panel data.

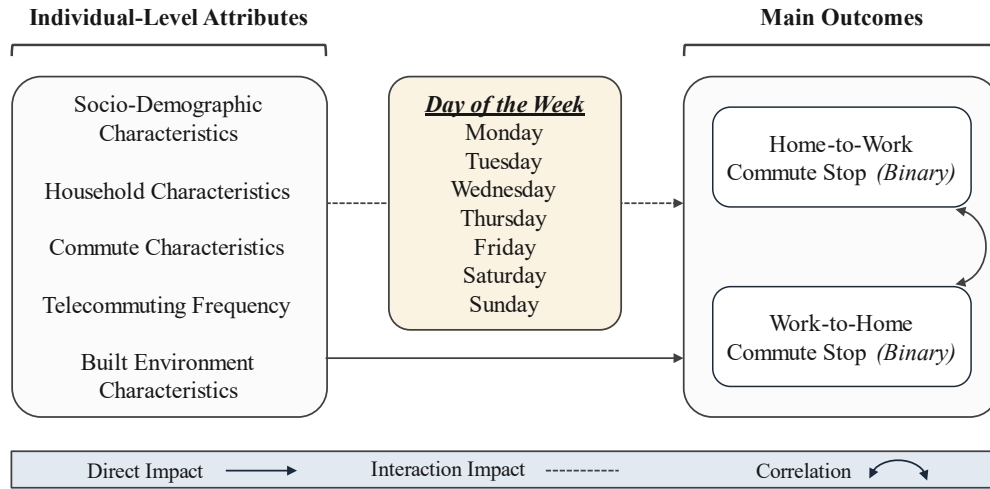


Figure 1: Model Framework

The explanatory variables shown on the left-hand side of Figure 1 include individual socioeconomic and demographic attributes, household characteristics, commute characteristics, telecommuting frequency, and built-environment measures. Telecommuting frequency is included explicitly among these individual-level exogenous attributes and constitutes a central explanatory variable in the analysis. It captures differences between workers who did not telecommute and those who telecommuted at low, medium, or high frequencies during the reported week. The direct arrows from the explanatory variables to the two stop-making outcomes represent their potential effects on the propensity to make an intermediate stop in each commute direction.

Day of the week enters the framework as an additional source of variation in stop-making behavior. In addition to its direct effect, day of the week is interacted with selected socioeconomic, commute, and work-arrangement attributes, including telecommuting frequency. These interaction effects allow the influence of worker and commute characteristics to vary across days of the week. This formulation is particularly important for hybrid workers, who may not organize non-work activities consistently across all workplace commute days. For example, the association between telecommuting frequency and stop-making may be different on Monday or Friday than during the middle of the week.

The panel structure is also central to the model specification. Each respondent may contribute multiple commute-day observations and stop-making reported by the same individual across days is unlikely to be statistically independent. Time-invariant unobserved characteristics, such as a general inclination to combine activities within commute tours, may influence stop-making across all observed commute days for the same worker. The panel formulation accounts for this repeated-observation structure through respondent-specific unobserved effects through a common error term with a scale that generates a covariance across the H-to-W direction of stop-making across all workdays of an individual, and another common error term with a scale that generates a covariance across the W-to-H direction of stop-making across all workdays of an individual.

Finally, the bivariate structure permits the unobserved factors affecting H-to-W and W-to-H stop-making to be correlated for each day of the week. Workers who exhibit an unobserved tendency to make stops on the way to work may also be more inclined to make stops while returning home. Jointly estimating the two outcomes therefore provides a more behaviorally realistic representation than estimating separate independent binary models. Overall, the framework captures differences across workers, variation within workers over the week, heterogeneity by day of week, and dependence between the two commute directions for each day.

In the interest of brevity, the detailed mathematical formulation and estimation procedure are not presented here. But the structure corresponds to a panel bivariate probit model, which is a straightforward extension of a traditional bivariate probit model (see, for example, Greene, 2003) with two additional layers of mixing (integration over the real line) over the common error terms for the H-to-W direction and the W-to-H direction.

5. MODEL ESTIMATION RESULTS

This section presents a detailed description of the model estimation results.

5.1 Main Estimation Results

Table 3 presents the estimation results for the H-to-W and W-to-H stop-making outcomes. Positive coefficients indicate a greater latent propensity to make at least one intermediate stop, while negative coefficients indicate a lower propensity, relative to the applicable reference category. Because the estimates are probit coefficients, they should be interpreted in terms of direction and statistical significance rather than as direct changes in stop-making probability. The magnitudes of key relationships are examined subsequently through the treatment-effect estimates.

The standalone day-of-week indicators were not statistically significant in either equation and were therefore omitted from the final specification. With Monday serving as the reference day, this finding indicates that there are no uniform differences in stop-making propensity between Monday and the other days of the week for respondents in the relevant reference categories. This does not imply that stop-making is invariant across the week. Several statistically significant interactions between day of week and individual, commute, and telecommuting characteristics indicate that weekday differences are heterogeneous across population segments and travel circumstances.

A number of individual characteristics are associated with stop-making. Women exhibit a lower propensity than men to make intermediate stops on the W-to-H journey, while no statistically significant gender difference is evident for H-to-W travel. Age differences are confined to the H-to-W direction. Relative to workers aged 18-54 years, those aged 55-64 years are less likely to make an intermediate stop, and the negative association is even larger among workers aged 65

years or older. This finding is broadly consistent with evidence that older adults form less complex work-related tours than middle-aged workers (Yang et al., 2019).

Table 1: Estimation Results of the Main Outcome Model Components (N = 11,074)

Explanatory variables (base category)		Home-to-work commute stop		Work-to-home commute stop	
		Binary: Yes, No (base)			
		Coef.	t-stat	Coef.	t-stat
Constant		2.685	16.58	2.091	16.04
Individual Characteristics					
Gender (male)	Female	—	—	-0.173	-1.98
Age (18 to 54 years)	55 to 64 years	-0.729	-3.81	—	—
	65 years or older	-1.466	-4.63	—	—
Education (< bachelor's degree)	Bachelor's degree(s) or higher	—	—	0.337	3.35
Race (not Black)	Black	0.311	4.13	0.311	4.13
Interaction terms (*)	Hispanic × Saturday	0.346	2.02	—	—
	Some college/technical school × Friday	0.413	3.28	0.599	6.44
	Bachelor's degree(s) or higher × Friday	—	—	0.539	7.08
	Black × Thursday	—	—	-0.305	-2.44
Household Characteristics					
Presence of children (none)	One or more	0.652	4.83	0.407	3.82
Number of household workers (1 or 3+)	Two	-0.369	-3.30	—	—
Housing tenure type (not owned)	Own	—	—	-0.243	-2.29
Commute Characteristics					
Commute distance in 100-mile units		0.790	1.90	—	—
Commute travel mode (all others)	Public transit	-0.233	-3.05	-0.233	-3.05
Telecommuting frequency (No, zero days)	Low (1-2 days)	0.763	4.27	0.547	3.98
	Medium (3-4 days)	1.279	5.18	1.095	5.70
	High (5-6 days)	4.152	6.46	2.993	5.70
Interaction terms (*)	Private vehicle × Saturday	—	—	0.404	4.00
	Low (1-2 days) × Thursday	—	—	-0.306	-2.66
	Low (1-2 days) × Friday	—	—	-0.263	-2.04
	Medium (3-4 days) × Friday	—	—	-0.839	-3.50
Built-environment Characteristics					
Auto network density (<1.305)	High (≥ 1.305)	—	—	0.293	3.27
Multimodal network density (< 3.351)	High (≥ 3.351)	-0.249	-1.97	—	—
Working age population (*)	Medium (≥ 0.589, < 0.624)	—	—	0.185	2.04
	High (≥ 0.624)	-0.253	-1.96	—	—
Census division (all others)	Middle Atlantic	0.445	2.80	—	—
Correlation					
Work-to-home commute stop		0.318	11.54	—	—
Scale of respondent-specific unobserved effect		2.391	56.93	1.782	49.18
Model Fit Measures					
Log-likelihood at convergence		-7699.952			
Log-likelihood at constants		-8012.903			
Log-likelihood at zero		-15351.824			
Adjusted likelihood ratio index (relative to the constants-only model)		0.035			
Adjusted likelihood ratio index (relative to equal-probability model)		0.496			
Bayesian information criterion		15680.235			
Likelihood ratio test		625.902			

Note: Coef. = coefficient; “—” = not applicable; (*) Base category is not identical across the model equations and corresponds to all omitted categories.

Education-related differences are particularly evident on Friday. Respondents with some college or technical-school education exhibit an additional positive Friday effect in both commute directions (see the row labeled “interaction terms” under individual characteristics). Respondents with a bachelor’s degree or higher also have a greater overall propensity to make W-to-H stops, and this difference becomes even larger on Friday. These patterns may reflect differences in occupation, schedule flexibility, or end-of-week activity planning. Workers with greater educational attainment may have more control over their work schedules and may be more inclined to combine shopping, personal business, or social activities with their Friday commute.

Race and ethnicity also exhibit day-specific associations. Black respondents have a higher propensity than non-Black respondents to make stops in both commute directions. In the W-to-H equation, however, this positive difference is almost entirely offset on Thursday. The main Black coefficient is 0.311, while the Thursday interaction is -0.305, yielding a combined effect close to zero on that day. Hispanic respondents exhibit an additional positive effect on H-to-W stop-making on Saturday. These findings may reflect unobserved differences in work schedules, household obligations, activity timing, or commute circumstances across the week, but the specific mechanisms cannot be identified from the available data.

Household characteristics also play an important role. The presence of one or more children increases stop-making propensity in both commute directions. This finding is consistent with the greater escorting, caregiving, and household-serving responsibilities commonly experienced by households with children and with previous evidence linking the presence of children to greater tour complexity (De Abreu e Silva, 2018). Respondents in two-worker households have a lower propensity to make H-to-W stops than those in households with one worker or three or more workers. This pattern may reflect differences in how household responsibilities are coordinated, although the underlying behavioral mechanism warrants further investigation. Homeowners also exhibit a lower propensity than non-owners to make W-to-H stops.

Telecommuting frequency emerges as one of the most prominent factors in the model. Relative to workers who did not telecommute, those who telecommuted one or two days, three or four days, or five or six days during the reported week exhibit progressively higher stop-making propensities in both commute directions. These results suggest that workers who telecommute more frequently organize the workplace commute trips they retain differently from workers who travel to the workplace every workday. Greater schedule flexibility may enable telecommuters to incorporate additional activities into their commute tours, or workers may consolidate non-work activities into the fewer workplace days on which they travel. Although the model does not identify the specific mechanism, it indicates that telecommuting affects travel not only by eliminating workplace commute days but also by increasing commute-tour complexity on the days workers travel to the workplace. This result is consistent with Zhu and Guo (2022) and Zubair et al. (2026), who report greater trip chaining and tour complexity among telecommuters and hybrid workers.

The association between telecommuting and W-to-H stop-making is, however, not constant across the week. For workers who telecommute one or two days, the positive effect is significantly smaller on Thursday and Friday. The corresponding main coefficient is 0.547, but the combined effects decline to 0.241 on Thursday and 0.284 on Friday after accounting for the negative interaction terms. Similarly, the positive W-to-H effect for workers telecommuting three or four days declines from 1.095 on the reference days to 0.256 on Friday. Yet, these combined effects remain positive. The negative interactions therefore do not indicate that telecommuters become less likely than non-telecommuters to make stops on these days. Rather, they indicate that the

otherwise positive association between telecommuting and stop-making is attenuated toward the end of the conventional workweek. This finding provides direct evidence that hybrid workers do not necessarily organize non-work activities consistently across all workplace commute days.

Commute characteristics further contribute to stop-making propensity. Longer commute distance is positively associated with H-to-W stop-making. Workers with longer commutes may be more inclined to combine other activities with a journey they must already undertake rather than make separate trips. This finding is consistent with Zhu and Guo (2022), although the coefficient is only marginally significant and should be interpreted cautiously. Public-transit commuters have a lower propensity to make stops in both directions than commuters using other modes. This result is consistent with Bautista-Hernández (2020), who report lower trip-chaining propensities among transit users than among private-vehicle users. Fixed routes and schedules, transfer requirements, waiting times, and access and egress constraints may make it more difficult to incorporate intermediate activities into transit commute tours (Rafiq and McNally, 2021). Private vehicle users, in contrast, exhibit an additional positive effect on W-to-H stop-making on Saturday, consistent with the greater spatial and temporal flexibility afforded by automobile travel and greater non-work activity engagement on weekend days (Lockwood et al., 2005; Xianyu, 2013).

Several built-environment and geographic attributes are also associated with stop-making. Respondents living in areas with high auto-network density have a greater propensity to make W-to-H stops, likely because greater roadway connectivity helps to incorporate intermediate stops. This interpretation is especially relevant because 86.6 percent of commute trips in the analysis sample were made by private vehicle. In contrast, high multimodal-network density is associated with a lower propensity to make H-to-W stops. Greater multimodal accessibility may enable residents to complete activities closer to home or through separate local trips or commute by transit, thereby reducing the need or ability to link them to the H-to-W commute.

The share of working-age residents in the surrounding area exhibits different associations across commute directions. Respondents living in areas with a high working-age population share have a lower propensity to make H-to-W stops, whereas those living in areas with a medium working-age share have a higher propensity to make W-to-H stops. A high concentration of working-age residents may be associated with more intense morning travel demand, potentially discouraging additional stops before work. Areas with a moderate working-age share may offer a more favorable combination of activity opportunities and manageable travel conditions for stops on the return journey. These interpretations merit further investigation because the neighborhood variables do not directly measure traffic conditions or the availability of specific activity destinations at the time of travel. Finally, respondents residing in the Middle Atlantic census division exhibit a higher propensity to make H-to-W stops than respondents other divisions.

Overall, stop-making propensity is higher among workers with children, longer commutes, more frequent telecommuting, and residence in areas with greater auto-network density; several education, race, ethnicity, private-vehicle use, and regional effects also emerge on specific days or commute directions. In contrast, stop-making is lower among women on the return commute, older workers on the journey to work, public transit commuters, homeowners, respondents in two-worker households, and residents of areas with greater multimodal network density or a high share of working-age adults. These underscore that commute stop-making reflects a mix of individual and household responsibilities, commute conditions, work arrangements, and the surrounding built-environment, with several relationships varying by commute direction and day of the week.

5.2 Correlation and Model Goodness-of-Fit

An important finding of the estimation results is the positive and statistically significant correlation between the unobserved propensities underlying H-to-W and W-to-H stop-making. The estimated correlation is 0.318, with a t-statistic of 11.54. Thus, even after accounting for the observed individual, household, commute, telecommuting, day-of-week, geographic, and built-environment characteristics, unobserved factors that increase stop-making in one commute direction also tend to increase stop-making in the other on the same day. These factors may include a general inclination to combine activities, schedule flexibility, or familiarity with convenient stop locations. The correlation does not imply that making a stop in one direction causes stop-making in the other; rather, it reflects shared unobserved influences on the two decisions.

The positive and highly significant correlation provides strong support for the joint modeling approach. Separate binary models would impose independence between the unobserved components of H-to-W and W-to-H stop-making and would therefore overlook this behavioral connection. The bivariate framework appropriately treats the two outcomes as distinct decisions while recognizing that they arise from an inter-related daily activity-travel context.

Also, Table 3 shows that the scales for the time-invariant respondent-specific random effects are statistically highly significant for both commute directions and quite large (relative to the scale of the occasion-specific idiosyncratic random effects). This indicates that, even after accounting for observed sociodemographic, household, commute, telecommuting, geographic, and built-environment characteristics, there are persistent unobserved individual-specific factors that influence stop-making across the multiple commute days reported by the same respondent. In other words, some individuals have a consistently higher or lower propensity to make H-to-W and W-to-H stops. The statistical significance of these effects supports the use of the panel specification.

The goodness-of-fit measures indicate that the final specification provides a meaningful improvement over simpler benchmark models. The log-likelihood improves from -8,012.903 for the constants-only model to -7,699.952 at convergence, yielding a likelihood ratio statistic of 625.902. This result confirms that the explanatory variables and joint correlation structure add significant information beyond the outcome-specific constants. The adjusted likelihood ratio index is 0.035 relative to the constants-only model and 0.496 relative to the equal-probability model. Although the former is modest, such values are not unusual in disaggregate binary behavioral models with considerable individual-level heterogeneity. The latter indicates a substantial improvement over a naïve model that assigns equal probabilities to the two outcomes. The Bayesian information criterion of 15,680.235 provides an additional fit measure that may be used to compare alternative specifications estimated on the same sample.

Overall, the significant cross-equation correlation and model fit statistics support the adopted specification, which captures systematic variation in stop-making while accounting for dependence across commute directions and repeated observations from the same worker.

6. AVERAGE TREATMENT EFFECTS

The coefficient estimates in Table 3 describe how explanatory variables affect the underlying latent propensity to make an intermediate stop, but they do not directly indicate the magnitude of the resulting change in stop-making probability. To provide a more intuitive interpretation of the telecommuting effects on commute stop-making propensity, Table 4 presents average treatment effects (ATEs) and percentage average treatment effects (PATEs) by day of the week and commute direction. The ATEs indicate the percentage-point change in the predicted probability of making at least one intermediate stop when a worker moves from the base condition of no telecommuting

to a low-, medium-, or high-frequency telecommuting arrangement. The PATEs express the same changes relative to the predicted stop-making probability under the no-telecommuting condition.

The results reveal a clear and progressive increase in stop-making as telecommuting frequency rises. For low-frequency telecommuters, working remotely increases the probability of H-to-W stop-making by about 8 percentage points across all days. The corresponding W-to-H effect is between 8 and 9 percentage points from Saturday through Wednesday, but it declines to 3.3 percentage points on Thursday and 4.6 percentage points on Friday. Thus, the positive effect remains throughout the week but is weaker toward the end of the conventional workweek.

Table 2: Average Treatment Effects of Telecommuting Frequency by Day of the Week

Base	Treatment	Sunday through Wednesday		Thursday		Friday		Saturday	
		H→W	W→H	H→W	W→H	H→W	W→H	H→W	W→H
ATEs (change in predicted probability)									
None (0 days)	Low (1-2 days)	8.0	8.1	8.0	3.3	8.2	4.6	8.2	9.0
	Medium (3-4 days)	14.3	17.5	14.3	17.3	14.7	4.1	14.7	18.9
	High (5-6 days)	54.4	51.6	54.4	51.5	54.6	51.0	54.5	51.5
Percent ATEs (% change relative to base)									
None (0 days)	Low (1-2 days)	49.0	40.1	49.0	17.0	47.7	17.1	47.7	35.2
	Medium (3-4 days)	88.2	86.5	88.2	88.5	85.5	15.3	85.5	74.2
	High (5-6 days)	334.7	254.3	334.7	263.2	317.8	188.7	318.1	201.6

The effects are larger for medium-frequency telecommuters. Relative to workers who do not telecommute, working remotely three or four days per week increases the predicted probability of making an H-to-W stop by 14.3-14.7 percentage points across the week. Friday is the notable exception: the W-to-H effect falls to only 4.1 percentage points. This result is consistent with the negative Friday interaction in Table 3 and shows that the otherwise strong association between medium-frequency telecommuting and W-to-H stop-making is sharply attenuated on Friday.

The largest effects are observed among high-frequency telecommuters. Telecommuting five or six days per week, rather than not telecommuting, increases the predicted probability of making an H-to-W and W-to-H stop by approximately 54.4-54.6 and 51 percentage points, respectively. These effects are remarkably stable over the week, suggesting that the relatively infrequent workplace commute trips made by high-frequency telecommuters are much more likely to include an intermediate stop than those made by workers who do not telecommute. This result should nevertheless be interpreted cautiously because high-frequency telecommuters constitute only 2.5 percent of the sample and contribute relatively few workplace commute-day observations.

The PATEs reinforce these patterns by expressing the effects relative to the predicted stop-making probability under the no-telecommuting base condition. For low-frequency telecommuters, the probability of making an H-to-W stop is approximately 49 percent higher than for non-telecommuters across all day groups. The relative increase in W-to-H stop-making is 40.1 percent from Sunday through Wednesday and 35.2 percent on Saturday, but only about 17 percent on Thursday and Friday.

For medium-frequency telecommuters, the relative increase in H-to-W stop-making ranges from 85.5 to 88.2 percent. The corresponding W-to-H increase is also large on most days, ranging from 74.2 percent on Saturday to 88.5 percent on Thursday. Once again, Friday stands out: the relative increase in W-to-H stop-making is only 15.3 percent. The absolute and proportional effects therefore convey the same central message that medium-frequency telecommuters are

considerably more likely than non-telecommuters to make commute-linked stops on most days, but this difference is much smaller on the Friday return commute.

Relative effects are especially large for high-frequency telecommuters, with H-to-W stop-making probabilities being 318 to 335 percent higher and W-to-H probabilities being 189 to 263 percent higher than those of non-telecommuters. These large percentages reflect both the strong absolute effects and the relatively low predicted stop-making probabilities under the no-telecommuting base condition. They should therefore be interpreted together cautiously.

Overall, the treatment-effect estimates confirm that telecommuting is associated not only with fewer workplace commute days but also with a greater likelihood of intermediate stops on the workplace days. The progression from low- to high-frequency telecommuting suggests that workers with more intensive remote-work arrangements may have greater schedule flexibility or may consolidate non-work activities into fewer workplace commute trips. At the same time, the smaller W-to-H effects on Thursday and Friday among low- and medium-frequency telecommuters demonstrate that this relationship is not uniform across the week. The findings therefore reinforce the importance of representing telecommuting frequency, commute direction, and day-of-week variation explicitly when modeling commute-related trip chaining.

7. CONCLUSION

Accurately representing commute stop-making is increasingly important for travel demand forecasting amid widespread remote and hybrid work. Traditional assumptions of regular weekday commuting and stable commute-tour structures are becoming less tenable as workers vary where they work across the week and reorganize non-work activities around fewer workplace commuting days. This study uses Wave 2 of the 2026 Transportation Heartbeat of America Survey to examine intermediate stop-making on H-to-W and W-to-H commute trips. The analysis included 2,409 full-time workers and 11,074 workplace commute-day observations. A panel bivariate binary probit model jointly estimates both outcomes while accounting for repeated observations, telecommuting frequency, day-of-week variation, and correlated unobserved factors across commute directions.

Several findings stand out. Intermediate stops are more common on W-to-H trips than on H-to-W trips, reflecting the greater flexibility workers generally have after leaving the workplace. More importantly, stop-making rises strongly and progressively with telecommuting frequency. Relative to workers who did not telecommute, low-, medium-, and high-frequency telecommuters were increasingly more likely to make intermediate stops on the days they traveled to the workplace. The treatment-effect estimates indicate that these differences are substantial, particularly among medium- and high-frequency telecommuters.

The relationship between telecommuting and stop-making is also not uniform across the week. The positive association between telecommuting and W-to-H stop-making is attenuated on Thursday and Friday for low-frequency telecommuters and on Friday for medium-frequency telecommuters. This finding suggests that hybrid workers do not follow a single, stable pattern of commute trip chaining across all commuting days. Shopping, errands, household responsibilities, and discretionary activities may be distributed across remote and workplace days according to weekly schedules and activity needs. The results therefore reinforce the importance of treating day of week as a behavioral dimension rather than assuming that all weekdays are equivalent.

Other findings provide additional context. Workers with children are more likely to make stops in both directions, consistent with escorting and household-serving responsibilities. Older workers are less likely to make H-to-W stops, while public-transit commuters are less likely to make stops in either direction. Built environment and commute characteristics also influence stop-

making. Overall, commute trip chaining reflects the combined influence of household obligations, travel conditions, work arrangements, and the surrounding transportation environment.

The planning implications are significant. Telecommuting should not be represented simply as the removal of commute trips on remote days. Fewer workplace commute days may be accompanied by more complex tours, additional trip segments, and changes in departure time, route, and destination on commute days. These changes may influence peak-period demand even when total commute frequency declines. The findings do not establish that additional stop-making offsets the travel reductions associated with remote work. They do show, however, that a simple commute-trip substitution framework provides an incomplete account of telecommuting impacts.

Activity-based travel demand models should therefore distinguish among telecommuting frequencies, represent H-to-W and W-to-H stop-making separately, and account for day-of-week variation. Treating all telecommuters as a homogeneous group or applying the same tour structure to every weekday may misrepresent trip generation, tour complexity, and network demand. The significant dependence between the two commute-direction outcomes supports a joint modeling approach, while the significant respondent-specific effects show that some workers have a persistent tendency to make more or fewer stops across their commute days, reinforcing the importance of accounting for repeated observations from the same individual.

The study has several limitations. The survey identifies only whether at least one intermediate stop occurred and does not capture the number, purpose, timing, location, duration, or travel distance associated with those stops. It is therefore not possible to determine whether stops generated additional travel, replaced separate trips, or represented minor deviations along the commute route. High-frequency telecommuters also constitute a relatively small share of the sample, and hence their large estimated effects should be interpreted cautiously.

Future research should use richer weekly activity-travel data to examine stop sequences, purposes, locations, timing, and the sequencing of remote and workplace days. Larger samples of high-frequency telecommuters would allow more precise estimates of their workplace-day travel patterns. Additional research analyzing commute travel mode choice jointly with commute stop-making and teleworking choice would better recognize potential package decision-making among these dimensions. Overall, the study shows that hybrid work reorganizes the weekly activity and travel rather than merely eliminating commute days. Capturing this reorganization is essential for travel demand models seeking to represent the post-COVID mobility landscape accurately.

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