Revisiting the impact of teleworking on activity-travel behavior using recent data and sequence-based analytical techniques

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16. Abstract

In this project motif and sequence analysis are used in tandem to analyze differences and commonalities between telecommuters and usual commuters. Telecommuters are by far more diverse in their allocation of time to places, activities, and travel. Approximately 20% of telecommuters stay at home all day during a workday, while only 8% of commuters do. Telecommuters that have at least one trip during their workday accrue more vehicle miles travelled and number of trips than their commuter counterparts. However, they drive alone less and tend to have more complex schedules visiting more locations. A substantial proportion of traditional commuters display morning and afternoon peaks of arriving at and departing from work, and telecommuters do not show this pattern. In addition, telecommuters during a day travel to a variety of locations to either visit customers and exploit their spatio-temporal schedule flexibility to perform work tasks from locations other than home or workplaces. Similarly, seniors (60 years and older) enjoy higher activity and travel flexibility due to seniority in jobs or retirement and use telecommuting in a variety of different ways. We find that 15 distinct motifs can capture 82.17% and 86% of the total senior respondents on workdays and non-workdays, respectively. Seniors are more likely to have simple motifs with three or fewer distinct locations on non-workdays, while they present more complex motifs during workdays.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College. The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

Disclosure

Principal Investigator, Co-Principal Investigators, others, conducted this research titled, "Revisiting the impact of teleworking on activity-travel behavior using recent data and sequence-based analytical techniques" at the GeoTrans laboratory of the Department of Geography, Division of Mathematical Life and Physical Sciences, University of California Santa Barbara. The research took place from January 1, 2020 to December 31, 2020 and was funded by a grant from the United States DOT in the amount of $100,000. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

In this project motif and sequence analysis are used in tandem to analyze differences and commonalities between telecommuters and usual commuters. Telecommuters are by far more diverse in their allocation of time to places, activities, and travel. Approximately 20% of telecommuters stay at home all day during a workday, while only 8% of commuters do. Telecommuters that have at least one trip during their workday accrue more vehicle miles travelled and number of trips than their commuter counterparts. However, they drive alone less and tend to have more complex schedules visiting more locations. A substantial proportion of traditional commuters display morning and afternoon peaks of arriving at and departing from work, and telecommuters do not show this pattern. In addition, telecommuters during a day travel to a variety of locations to either visit customers and exploit their spatio-temporal schedule flexibility to perform work tasks from locations other than home or workplaces. Similarly, seniors (60 years and older) enjoy higher activity and travel flexibility due to seniority in jobs or retirement and use telecommuting in a variety of different ways. We find that 15 distinct motifs can capture 82.17% and 86% of the total senior respondents on workdays and non-workdays, respectively. Seniors are more likely to have simple motifs with three or fewer distinct locations on non-workdays, while they present more complex motifs during workdays.

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Executive Summary

This project demonstrates the use of motif and sequence analysis in tandem to analyze differences and commonalities between telecommuters and usual commuters. Motifs are networks of distinct locations visited in a day and the directional movements between them. Sequence analysis lines up the schedule of a person in a day and classifies each minute by the type of activity and travel of the person under examination. In terms of substantive findings, telecommuters are by far more diverse in their allocation of time to places, activities, and travel. Approximately 20% of telecommuters stay at home all day during a workday, while only 8% of commuters do. Telecommuters that have at least one trip during their workday accrue more vehicle miles travelled and number of trips than their commuter counterparts. However, they drive alone less and tend to have more complex schedules visiting more locations. Within both groups, however, we have substantial variation in activity participation and travel. As expected, a substantial proportion of commuters display morning and afternoon peaks of arriving at and departing from work, and telecommuters do not show this pattern. In addition, telecommuters do not only perform work tasks from home, but, during a day they travel to a variety of locations to either visit customers and/or use their spatio-temporal schedule flexibility to perform work tasks from locations other than home. Similarly, seniors who enjoy higher activity and travel flexibility due to leadership of work positions or retirement use telecommuting in a variety of different ways. Using motif analysis a particularly good tool for this type of analysis, we correlate the diverse daily mobility patterns with socio-demographic characteristics as well as built environment factors. We find that 15 distinct motifs can capture 82.17% and 86% of the total senior respondents on workdays and non-workdays, respectively. Seniors are more likely to have simple motifs with three or fewer distinct locations on non-workdays, while they present more complex motifs during workdays. Given 65% of the included seniors are retired, a large number of seniors present diverse and complex daily mobility patterns instead of staying at home all day. Seniors tend to drive alone more on workdays than non-workdays, and accordingly, they tend to have more carpooling trips on non-workdays. In addition, given the similarity between the urban core, urban district, and urban neighborhood in function and spatial proximity, there is significant heterogeneity in the daily mobility patterns among seniors living in these areas. In terms of the effects of built environment variables, we find that seniors living in areas with higher percentages of single-family housing units are most likely to stay at home on workdays. In addition, population density, employment density,

intersection density, and job accessibility have no significant impacts on senior's daily mobility patterns.

The mobility patterns and daily schedules will be most likely dissimilar in different settings due to national, cultural, policy, and infrastructure differences. One could imagine many potential differences in telecommuters' daily schedules between those in more developed environments where telecommuting has been a mature and relatively popular practice and those from less developed places that lack the ICT infrastructure making this option less popular. Transportation infrastructure also has important impacts on telecommuters' daily mobility patterns as well as daily schedules of activities and travel. People living in California mostly rely on automobiles than other transportation modes, which is confirmed in this study for telecommuters and commuters who drive alone the most and telecommuters who made at least one trip. They have 1.37 more VMT as well as 0.53 more trips in a day compared to commuters. Telecommuters living in neighborhoods where grocery stores, restaurants, gyms, and other types of activity opportunities are easy to access are presumably less likely to be selected over driving alone to activity opportunities with longer distances. Telecommuters living in rural areas with low accessibility to places are more likely to visit multiple places to fulfill their daily needs and drive longer distances. As documented in this study when we examine seniors, we find a variety of daily mobility patterns by different groups indicating a strong need to be socially engaged. Meanwhile, seniors in California still rely heavily on automobiles to meet their daily transportation needs. In other words, the findings unveil the deficiency of other transportation mode development and the constraints of automobiles on elderly's daily mobilities in California. In terms of transportation design in the future, some emerging technologies have the potential to address problems regarding mobility constraints of single travel mode (mostly relying on automobiles) and improve overall mobilities. For example, in addition to improving current public transit by optimizing the route, adjusting the frequency, and so forth, municipalities and regional transportation authorities should consider complementing our current transportation system with Mobility as a Service (MaaS). The major components of MaaS schemes include intermodal planning, booking and payment functionalities, and multiple transport modes and mobility packages. MaaS enables the conventional modes of transportation to transform to mobility provided as a service. The main objective of MaaS is to offer mobility solutions based on people's travel needs. In United States, a variety of shared mobility services have recently launched to serve the specific needs of elderly passengers. We also expect a substantial increase in the adoption of telecommuting by companies as a reaction to Covid-19 pandemic and we also anticipate a large number of telecommuters will switch to either staying at home all day and not traveling or use patterns based on a single location (mostly home) with loop trips(same origin and destination). In fact, telecommuters with this pattern most likely work from home but take a walk during the workdays during the COVID-19 pandemic today. In addition, we will see a substantial increase in the telecommuters' patterns visiting multiple locations and moving around the city in less predictable ways. This is where MaaS can serve their patterns in a more sustainable way providing first and last mile services on demand. Action is needed now to avoid a return to the use of the private automobile and maybe a tendency to return to pre-COVID patterns.

Introduction

This final report contains two chapters. The first chapter provides a comparison between telecommuters and traditional commuters by first offering an overview of telecommuting, then a presentation of a new technique combining two state of the art research methods (the motifs and the sequence analysis) that is used to explore data in the National Household Travel Survey California component. The second chapter pays closer attention to people that are older than 60 years. Motivation to do this has been the substantial heterogeneity in the behavior of people in this age group, their potential in becoming more fragile and vulnerable as they grow older, and their substantial increase of their cohort over time. Telecommuting and any type of activity that can substitute physical movement may be a desirable trend to be strengthened by policy. The hope is to maintain or even improve accessibility by either receiving goods at home by a carrier or substituting service at a destination with an electronic version of similar services at home or a facility where a person resides. However, our analysis shows a propensity to travel more and visit a high degree of diverse locations making traditional policy actions particularly inadequate.

Comparison of Traditional Commuters with Telecommuters

Background literature review on telework

Telecommuting and telework is the use of information and telecommunication technology (ICT) to replace the more traditional working at workplaces and traveling to work. In the 1970s telecommuting was envisioned as a policy tool in a Travel Demand Management (TDM) toolkit to help decrease congestion, air pollution, and waste of resources. Legislation and planning at many levels of government support telecommuting as a measure to benefit the public, employers, and employees. Paradoxical findings in the literature of telework is one motivation of the research reported here (Boell et al., 2016; Mokhtarian, 2009; Taskin and Devos, 2005). These paradoxes are also amplified by telework market penetration that is small considering the forces involved. On the one hand, we see a push for more teleworking in public agencies (see United States Office of Personnel Management (2017a), and the Telework Enhancement Act of 2010 (United States Office of Personnel Management, 2017b)), evidence of substantial benefits for agencies and employees with estimates reaching $11,000 per person year for a business, $2,000 to $7,000 savings per year per employee, substantial greenhouse gas emission reduction and energy consumption (Sekar et al., 2018) and $700 Billion a year national savings if eligible workers would work half the time from home (Global Workplace Analytics, 2020; United States Office of Personnel Management, 2017a). On the other hand, before the Covid-19 pandemic only 7% of the US-based firms made telework available, the Bureau of Labor Statistics reported a decline of working at home from the past (United States Bureau of Labor Statistics, 2020), and major corporations as reported by news media were cutting down on telecommuting programs. The most recent American Time Use Survey analysis (year 2019) reports that 24% of the working population in the US did some of their work at home but the striking majority (reported as 82%) did some or most of their work at a workplace. However, due to the recent pandemic telework might become a more popular option with employees.

According to Global Workplace Analytics this can reach 25-30% of the workforce in 2021[1] providing a second important motivation of our research here.

Often paradoxes in the scientific literature are not paradoxes at all. They can be explained by carefully studying the context, data definitions and related analysis (Tal, 2008). The context side of this story needs careful scrutiny because we need to discern differences and commonalities among settings of where telework is adopted (Vilhelmson and Thulin, 2016), demographics (Gimenez-Nadal et al., 2018), technologies used (Messenger and Gschwind, 2016; Pliskin Nava, 1997; Weinbaum et al., 2018), supervisory roles (Lautsch et al., 2009), and perspectives of adopter vs nonadopter and manager vs employee (Illegems and Verbeke, 2004). Similarly, context can also be extracted from databases with documented data collection settings, data collection processes, and wording of questions (the Bureau of Labor Statistics is asking if a person works full time or part time at home and the US Census American Community Survey is asking persons 16 and over if they work from home instead of traveling to work in the week before the Census day). All these are important details that first need to be harmonized in terms of basic definitions of work, telework, and telecommuting and then contextual analysis can reveal the underlying correlations of the propensity to stay at home and work instead of traveling to work. We will return to this point in the conclusions.

Research on telecommuting in California has a long history starting as early as the 1970s (Nilles et al., 1976), tested in different places (Nilles, 1988), and experienced a major push by the State of California Telecommuting Pilot Project and other planning initiatives (Kitamura et al., 1990; Valk and Hellot, 1997). Another push forward was the 1999 National Telecommuting and Air Quality Act's establishment of pilot programs in five large Metropolitan Statistical Areas (MSAs), of which one was Los Angeles. This was an impetus for developing a market-based emission-credit-trading program encouraging telecommuting. However, it did not create a mechanism to track telecommuting impacts over time. Early research studies point out the need for careful telecommuting ontological analysis (Mokhtarian, 1991), the possibility that telecommuting may not be as desirable to a worker as planners think (Salomon and Salomon, 1984), and telecommuting may not have a positive impact on non-work travel (Pendyala et al., 1991). On the more positive side, telecommuting is associated with positive perceived autonomy, job satisfaction, turnover intent, positive impacts on work-family conflict, but may lead to negative impacts on relationships at work (Gajendran and Harrison, 2007). For transportation policy and planning, telecommuting appeared as an important component of Transportation Demand Management (TDM) as a promising option to decrease trip generation, vehicle miles travelled, and peak-period trips, and possibly gains in energy consumption (Mokhtarian et al., 2004, 1995). This is challenged by research that accounts for energy use at work and at home when the telecommuting participation is low in frequency (Kitou Erasmia and Horvath Arpad, 2006). More recent data analyses also challenge the claim that telecommuting leads to travel decrease. In fact, Zhu et al. (2018), in their comparison of the impact of telecommuting among different Metropolitan Statistical Areas (MSA) using data from the National Household Travel Survey of 2001 and 2009 conclude that policies that encourage telecommuting indeed increase

[1] https://globalworkplaceanalytics.com/work-at-home-after-covid-19-our-forecast

travel demand rather than decrease. All these studies offer evidence that the travel behavior impact of telecommuting is evolving and in more recent years we see that telecommuting today is different than the telecommuting we knew in the late 1980s and early 1990s. However, all this analysis about telework and mobility is lacking in fundamental aspects of behavioral measurement.

First, the effects of individual's situational constraints on telecommuting are not accounted for in the literature. Internal personal barriers and motivation to adopt telecommuting are analyzed only tangentially through correlations with person and household characteristics and analyses accounting for endogeneity (Asgari and Jin, 2017). Instead, context needs to also be explored based on commitments people have (e.g., the need to escort children to school). To understand this type of context, we need to statistically examine daily patterns at fine grained time intervals and using a classification of activities that emphasizes the need to escort people to places. Second, studying aggregates such as daily averages may mask a variety of relationships. In fact, we need to be cautious with past analyses because all these studies used average daily summaries such as number of trips to work per day, vehicle miles travelled per day, and so forth. Behind averages we find hidden variability in behavior (heterogeneity) that should have been explored in more detail.

In this research report we demonstrate a new analytical method that captures heterogeneity within and between telecommuters and customary commuters. To do this we use a fine-grained time of day allocation of time to activities and travel and patterns of destinations and trips in between them. Following our previous study (Su et al., 2020), we apply a joint pattern recognition method that combines network-based motif analysis with activity-based sequence analysis on telecommuters' and commuters' activities and travel. The combination of building a taxonomy of daily mobility patterns using the concept of motif with the taxonomy of minute-by-minute daily time allocation patterns derived from sequence analysis, enables the study of interdependency in space and time of multiple facets of behavior that are fundamental in building activity-based models without imposing a priori behavioral assumptions (Su et al., 2020).The notion of human mobility motif introduced by Schneider et al. (2013) refers to a directed network of nodes and links of daily patterns among destinations. Schneider et al. (2013) identify 17 unique motifs that capture approximately 90% of daily mobility patterns of the total population in a travel survey data and a GPS traces data. Recently, another application by Cao et al. (2019) shows that 10 unique location-based motifs and 10 unique activity-based motifs can represent 99.35% and 98.46% of human mobility patterns of total population respectively using a mobile phone positioning data collected in Shenzhen, China. In our previous study using the entire 2017 California-NHTS workday subset, we identified 16 unique network motifs that can capture 83.05% of all the observations (Su et al., 2020) in this database. As pointed out by Su et al. (2020), the advantages of the motif approach in the studies of human mobility pattern analysis are twofold. First, motif approach takes into account the interconnection of visited locations at individual level compared to traditional trip-based models (referred to as "4-step" models, see explanation in McNally (2000)) that only use the individual person trip as the basic unit of analysis. Second, the motif model can be used directly in simplifying modeling and simulation of daily activity scheduling by decreasing the number of possible combinations of the many variables used in activity microsimulation. The analysis is followed by a comparison of telecommuters' and commuters' daily patterns to uncover commonalities and differences across these two groups but also different daily patterns within each group.

Data used in the first part of the analysis

The data used in this project comes from the California component of the 2017 National Household Travel Survey (California-NHTS). NHTS collects social and demographic data about each participating household and every individual in the household. For each person, NHTS also collects a one-day travel diary. The data were collected between April 24th, 2016 and April 24th, 2017 with the one-day travel diary on an assigned day. The assigned day attempts to provide a uniform assignment throughout a complete year, and the diary day for each household can be any weekday, weekend day, or holiday. For this analysis, we use person and household characteristics such as age, sex, education background, job category, household income, full-time or part-time working status, retirement status, and homeworker status. From the one-day diary, we use the trip start time and end time, origin and destination location types, and mode choice. The one-day travel diary contains all reported trips between 4:00 AM on the survey day until 3:59 AM on the following day.

In total, in the NHTS California component we have 24448 part-time or full-time workers (4168 telecommuters plus 20280 commuters). In this study, we only focus on records of workers during non-holiday weekdays (we will use the term "workdays" throughout the report), since human mobility patterns have distinct differences between workdays and non-workdays (Jiang et al., 2012). An immediate next step is to compare the mobility patterns of telecommuters and commuters between workdays and non-workdays. We will get back to this point in the conclusion section. As we aim to explore the difference in mobility patterns between telecommuters and commuters, the records of 15045 respondents (2236 telecommuters plus 12809 commuters) who made at least one trip on a workday are used in this analysis. Telecommuters are the persons in NHTS that answered the question "Do you usually work from home?" The possible responses are "Yes", "No", "Refuse to answer", or "Not applicable". The excluded 9403 workers are people with diary days on non-workdays, or staying at the same location (mostly home) the entire diary day during workdays and have no trips to report (i.e., missing data in the one-day travel diaries). Of the 9403 excluded workers, 1932 are telecommuters and 7471 are commuters. Among the excluded telecommuters, 624 people reporting on a workday did not make any trips. This means that among the 2860 telecommuters interviewed on a workday, 21.82% stay at home all day. In contrast, among the 13918 commuters that were interviewed on a workday, 1109 (7.97%) stayed at home all day and did not make any trips on workdays. Presumably due to personal vacation, sick leave, or to care for another person, etc. However, we do not have the information needed to verify this. Exclusion from the analysis of telecommuters and commuters staying at home the entire diary day is explained later and complemented by a comparison between the excluded and the included samples in a later section.

Table 1 shows the descriptive statistics for the 15045 persons that made at least one trip on the interview workday. Male respondents account for 49.11% of the sample of telecommuters. This is slightly lower than the male percentage of commuters which is 51.36%. When we look at the age groups, it turns out that there is a lower percentage of people under 50 belonging to telecommuters and a higher percentage of people over 50 belonging to telecommuters. Perhaps more senior workers achieve the freedom to choose to work from home and some of them might be part-time home workers. In terms of employment, 56.17% of telecommuters are full-time workers, while 80.12% of commuters are full-time workers. 27.55% of telecommuters work in sales or service industries, which is higher than the 21.21% for commuters. The percentage of clerical or administrative support workers among telecommuters is 5% less than that of commuters. This is not surprising because these occupations usually require face-to-face communication. In terms of household income level, the percentage of telecommuters with household income less than $24,999 is 2% more than the one of commuters. Presumably, as many telecommuters are part-time workers, they earn less money. However, the percentage of telecommuters with household income more than $200,000 is 5% greater than that of commuters, indicating that many telecommuters are high-income individuals. In addition, more than 35% of the telecommuters and commuters are from households with two adults, 17.71% of telecommuters are from households with two retirees, while the corresponding percentage for commuters is only 11.02%, and 33.37% of commuters are living with another adult and people younger than 21 while only 26.12% of telecommuters do. The percentages of people living in urban or rural environment show that apparently, a higher percentage of telecommuters are living in rural areas compared to commuters, which aligns with the generally lower accessibility in rural areas. Presumably, people tend to work from home more to save commuting time. The differences in personal characteristics between telecommuters and commuters are consistent with other past analysis using data from NHTS (Drucker and Khattak, 2000; Jin and Wu, 2011).

According to the 2017 NHTS-California codebook, people's travel mode choices are classified into seven categories including walking, biking, transit, car as passenger, car drive alone, car drive someone else, and one category labeled "other" comprising all other modes. Table 2 summarizes the mean and standard deviation of vehicle miles traveled (VMT), person miles traveled (PMT) as well as the number of trips by different modes. We apply the Mann-Whitney U test to examine whether the average VMT, PMT, and number of trips by different modes of telecommuters are significantly different from commuters. The results indicate that there is no significant difference in PMT for biking and the number of bicycle trips, while the other types of VMT, PMT, and the number of trips of telecommuters are significantly different from commuters at 99.9% confidence level. It is also noteworthy that for telecommuters, VMT total, VMT driving someone else, VMT as passengers, and PMT as walking are significantly higher than the corresponding quantity of commuters, while VMT driving alone, and PMT using transit of telecommuters are significantly lower than commuters. This observation is also consistent with the number of trips by different modes.

Table 1. Descriptive statistics for telecommuters and commuters

Variable	Definition	Subgroup	Telecommuter (n=2236)	Commuter (n=12809)
Individual characteristics				
Sex	Respondent's sex: female or male	Female	50.81%	48.58%
Age group	Respondent's age group	Under 26	2.86%	8.85%
		26-35	11.58%	19.34%
		36-50	25.58%	30.26%
		51-65	40.38%	34.12%
		Above 65	19.54%	7.29%
Education attainment	Respondent's education attainment	Below bachelor's degree	9.79%	15.01%
		Some college or associate's degree	25.00%	29.84%
		Bachelor's degree or above	65.16%	55.11%
Full-time or part-time	Full-time or part-time worker	Full-time	56.17%	80.12%
Job category	Respondent's job category	Sales or service	27.55%	21.21%
		Clerical or administrative support	6.40%	11.61%
		Manufacturing, construction, maintenance, farming	8.59%	10.84%
		Professional, managerial, or technical	57.07%	56.13%
Household-level characteristics				
Household annual income	Respondent's household annual income level	Less than $24,999	9.97%	7.43%
		$25,000 to $99,999	39.89%	44.90%
		$100,000 to $199,999	31.62%	33.90%
		$200,000 or more	16.14%	11.94%
Household structure	Respondent's household structure	One adult	15.16%	14.75%
		2+ adults	35.51%	37.33%
		One adult, retired	2.55%	0.49%
		2+ adults, retired	17.71%	11.02%
		One adult living with people younger than 21	2.95%	3.04%
		2+ adults living with people younger than 21	26.12%	33.37%
Residential setting	Household residential location types: urban or rural	Urban	87.79%	91.01%

Notes: The percentage of the alternative options for some binary variables (i.e. sex, full-time or part-time worker, residential setting) are omitted. The total percentage of some variables is not exactly 100% because very few of the respondents refused to answer the survey questions (mostly below 1%).

Table 2. Statistics for VMT, PMT and number of trips

Variables	Telecommuter (n=2236)		Commuter (n=12809)		Diff.	P-value
	Mean	SD	Mean	SD		
VMT/PMT statistics						
VMT total	37.29	59.30	35.92	47.14	1.37	(<0.001)
VMT drive alone	20.30	40.64	24.06	34.54	-3.76	(<0.001)
VMT drive someone else	10.79	34.96	8.08	28.93	2.71	(<0.001)
VMT as passengers	6.21	33.04	3.79	22.81	2.42	(<0.001)
PMT as biking	0.17	1.29	0.18	1.54	-0.01	(0.116)
PMT as walking	0.42	1.07	0.26	0.86	0.16	(<0.001)
PMT as transit	1.56	17.65	1.71	10.24	-0.15	(<0.001)
Number of trips statistics						
Total number of trips	4.77	2.74	4.23	2.43	0.54	(<0.001)
Drive alone trips	2.40	2.30	2.45	2.03	-0.05	(0.001)
Drive someone else trips	1.15	1.95	0.85	1.61	0.3	(<0.001)
Passenger trips	0.43	1.2	0.32	0.99	0.11	(<0.001)
Bike trips	0.07	0.45	0.06	0.43	0.01	(0.118)
Walk trips	0.65	1.37	0.43	1.08	0.22	(<0.001)
Transit trips	0.06	0.33	0.10	0.46	-0.04	(<0.001)

On the whole, Table 2 tells us that on average, telecommuters make 1.37 more VMT in a day compared to commuters as well as 0.53 more trips in a day. Specifically, telecommuters drive alone 3.76 miles fewer, but drive others 2.71 miles more than commuters, and they carpool 2.42 miles more than commuters on a daily basis. In addition, telecommuters walk 0.16 miles more in a day. These results defy the expectations that telecommuters travel less on workdays. In fact, when we examine people who made at least one trip in a day, telecommuters travel more than commuters on workdays. In contrast, if we include in these statistics the persons that did not make any trips on workdays (624 telecommuters and 1109 commuters), the derived daily total VMT of telecommuters becomes 29.16 miles per day compared to 33.06 miles per day for commuters. It is the inclusion in statistics of people that do not travel at all that show on average less travel by telecommuters than commuters. In subsequent analysis in this report, we first explore further the patterns of telecommuters and commuters who made at least one trip in a day and then turn to the no travel portion of the analysis.

Methodology

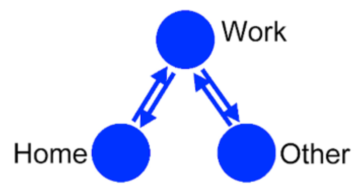
The method used here combines motif analysis that identifies patterns of locations visited in a day with one way or two-way trips in between these distinct locations with sequence analysis of activities and trips applied to minute-by-minute diary records.

Construction of motifs

A motif is a directed network, in which nodes represent visited locations and directed edges (links) represent trips between locations (Schneider et al., 2013). The 2017 California-NHTS data keeps a one-day travel diary recording trips for everyone in the day of interview. The one-day travel diary contains an anonymous person id and household id, trip start time and end time, origin and destination unique id, and corresponding location types. To construct motif representations, we use the origin and destination locations as nodes and connect nodes with a directed edge if there is a trip between them. An example is shown in Figure 1. The person in Figure 1 has two commute trips but also visits another destination labeled "Other". Therefore, this person has a motif with three nodes representing home, work, and other location and four directed edges between home and workplace, and workplace and other location (the trips). A human mobility motif was constructed in this way for every respondent in our data.

Household Id	Person Id	Origin	Destination	Origin type	Destination type
H01	1	1000	10	Home	Work
H01	1	10	2001	Work	Other
H01	1	2001	10	Other	Work
H01	1	10	1000	Work	Home

Travel diary



Motif representation

Figure 1. Example of constructing a motif from trip diary

Sequence analysis

A sequence is a series of time points at which a subject can move from one discrete "state" to another. The states are defined by the types of places people visit and stay during their diary day and according to 2017 California-NHTS, they are: Home with unspecified activity (*Home*); Work from home as in telecommuting and home stay combined (*Home&Work*); Work at a workplace or at other places (*Work*); Education at the school location (*School*); Drop off or Pick up someone (*DropPickup*); Change type of transportation (*ChangeTrans*); Purchase goods such as groceries, clothes, appliances, gas (*BuyGoods*); Purchase services such as dry cleaners, banking, service a car, pet care (*BuyService*); Go out for a meal, snack, carry-out (*BuyMeal*); Run other general errands such as post office (*ShopServ*); Engage in recreational activities such as visit parks, movies, bars (*Recreation*); Exercise (*Exercise*); Visit friends and/or relatives (*VisitFrsRls*); and all Other. Travel between these places is also considered a "state" noted as *Trip* (and distinguishable from *DropPickup* and *ChangeTrans*). The daily sequence has a length of 1440 which is the total minutes in an assigned survey day. Every minute of the day contains one of the 15 distinct states for each person. An example of a sequence with length ten minutes can be noted as $x' = \{Home, Home, Home, T\text{rip}, T\text{rip}, T\text{rip}, T\text{rip}, T\text{rip}, Work, Work\}$, that is staying at home for 3 minutes, then travel for 5 minutes and then staying at workplace for 2 minutes.

We use an indicator of *Complexity* to measure the variability of individual daily activity schedule. The Complexity indicator is based on the concept of *Entropy* which is a measurement of “prediction uncertainty” (Gabadinho et al., 2010) and transitions between distinct states within a sequence (x). The explanation follows McBride et al. (2019, 2020) closely. Entropy and Complexity can be calculated as follows.

$$h(x) = h(\pi_1, \ \dots \pi_s) = - \sum_{i=1}^{s} \pi_i \log(\pi_i) \tag{1}$$

$$C(x) = \sqrt{\frac{nt(x)}{(l(x)-1)} \frac{h(x)}{h_{max}}} \tag{2}$$

where $h(x)$ is the entropy function of x which represents the sequence, s is number of potential states and π_i is proportion of occurrences of the ith state in the considered sequence. Since this measure does not account for the number of state changes and contiguity of states, the indicator of Complexity is introduced that includes entropy and the number of transitions $nt(x)$ in a sequence x, normalized by the maximum theoretical entropy h_{max} and the length of the sequence $l(x)$. This indicator takes a value between 0 and 1, with zero corresponding to entropy zero and no transitions (e.g., staying at a single place for the entire day of observation).

Using these sequences, we seek to build a taxonomy of spatiotemporal daily activity and travel. NHTS collects data using a travel diary with information about place and activity at the origin and destination of each trip and the time of day for departure and arrival for each trip. For each one-day travel record, we insert activities before the first trip, after the last trip, and in between trips based on origin-destination place, timing of trips, and information about activity/purpose at the origin and destination of each trip. In this way, for each person, we have a sequence of place-activity-travel as a series of 1440 bins—one for each minute of the survey day starting at 4:00 AM and ending the next day at 3:59 AM. Each bin is assigned to a category by a word (*Home, Home&Work, Work, School, DropPickup, ChangeTrans, BuyGoods, BuyService, BuyMeal, ShopServ, Recreation, Exercise, VisitFrsRls, Other, and Trip*).

To identify similar sequences among the person-sequences of the sample data, we use methods from sequence alignment techniques. In the sequence alignment literature, the measurement of dissimilarity and the number of operations needed to make two sequences exactly the same is called a “distance.” Typically, the distance between two sequences is the minimum combination of substitution and indel (i.e., insertion and deletion) (Kaufman and Rousseeuw, 2009). As Gabadinho et al. (2011) stated, favoring indel reduces the importance of time shifts in the comparison, while favoring substitutions gives more importance to position-wise similarities. The sequential order is of primary concern in daily activity and time allocation patterns recognition because consecutive activities are likely to affect one another (Joh et al., 2001). For this reason, we only consider substitution when computing the dissimilarity between two sequences. Hamming distance is the most appropriate dissimilarity measure, as it measures the minimum cost of substitutions required to change one sequence into another. In this research we call the minimal cost of transforming one sequence to another the “dissimilarity score” between the two sequences. One way of computing a dissimilarity score between two sequences is to use the cost for substitution. Gabadinho et al. (2011) proposed the substitution cost between states S_p and S_q to be:

$$SC(S_p, S_q) = 2 - P(S_p|S_q) - P(S_q|S_p) \tag{3}$$

where $SC(S_p, S_q)$ is the substitution cost between states S_p and S_q with a value between 0 and 2; $P(S_p|S_q)$, the transition rate from state S_q to state S_p, is the probability of observing state S_p at time $t + 1$ given that state S_q has been observed at time t. If the transition rate from state S_q to state S_p has a value close to 1, it means that a person in a given state S_q at time t has a great probability to transition to state S_p at time $t + 1$. Notice that $P(S_p|S_q)$ is not equal to $P(S_q|S_p)$. The idea is to set a high cost when changes between S_p and S_q are not observed often and lower cost when they are frequent.

A substitution-cost matrix can be derived by computing $SC(S_p, S_q)$ for each pair of distinct states. The substitution-cost matrix is a square symmetrical matrix of dimension s by s, where s is the number of distinct states, in our case is 15. Then we can compute Hamming distance between each two sequences based on the substitution-cost matrix. The output of the Hamming distance computation among all the sequences is a matrix of dissimilarity scores. The dissimilarity matrix contains N by N (N is the count of respondents) cells of dissimilarity scores among sequences for each person-day in our sample. The matrix is symmetric with zeros along the diagonal.

$$D\_Matrix = \begin{bmatrix} 0 & d_{x_1,x_2} & \cdots & d_{x_1,x_N} \\ d_{x_2,x_1} & 0 & \cdots & d_{x_2,x_N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{x_N,x_1} & d_{x_N,x_2} & \cdots & 0 \end{bmatrix} (d_{x_i,x_j} = d_{x_j,x_i}\ (i,j \in [1,N])) \tag{4}$$

where d_{x_i,x_j} is the dissimilarity score between two sequences x_i and x_j using Hamming distance as the measurement; D_Matrix is the derived N by N symmetric matrix of dissimilarity scores.

In the next step we derive homogeneous groups of sequences using cluster analysis on the dissimilarity matrix (D-Matrix) among sequences of 1440 minutes in a day, and each minute is classified in one of the 15 categories mentioned above. We use the agglomerative nesting clustering method (AGNES) which is a type of hierarchical clustering (other clustering methods such as Partitioning Around Medoids, PAM, and Divisive Analysis Clustering, DIANA, could also be used to identify distinct groups of sequences with similar patterns, see Gabadinho et al. (2011) and Kaufman and Rousseeuw (2009)). We aim to maximize the variance across groups and minimize the variance within groups to obtain an optimal number of clusters. This optimal number of clusters is determined using as rule the minimization of the within-cluster sum of squares (WSS), maximization of the average silhouette coefficient (Silhouette), and a daily behavior representation conforming to travel behavior literature. Both WSS and Silhouette are used widely for many different types of clustering algorithms (Kaufman and Rousseeuw, 2009). Selecting the number of clusters that minimizes WSS is equivalent to finding the most homogeneous number of clusters possible. Selecting the number of clusters that maximizes Silhouette is equivalent of obtaining the number of clusters that are the most dissimilar.

Figure 2 is an example of the daily time allocation pattern of a group of person-days from Su et al. (2020). The legend presents the 15 distinct states of activity in this study. The x axis shows the time of day in minutes beginning at 4:00 am and ending at 3:59 am in the next day. The y axis represents the relative frequency of people who are doing one of the 15 types of activities in a stacked bar format. The example shows that the majority of people in this cluster start their day from home, leave home to work in the early morning, stay at workplaces during the daytime, gradually return home after 4 pm, and stay at home at night. In addition, people in this cluster also spend a small amount of time in trips, buying goods, buying meal, recreation, drop off and pick up people, and visiting friends or relatives. In general, the pattern we observed in Figure 2 is a typical commuting pattern on workdays in the United States.

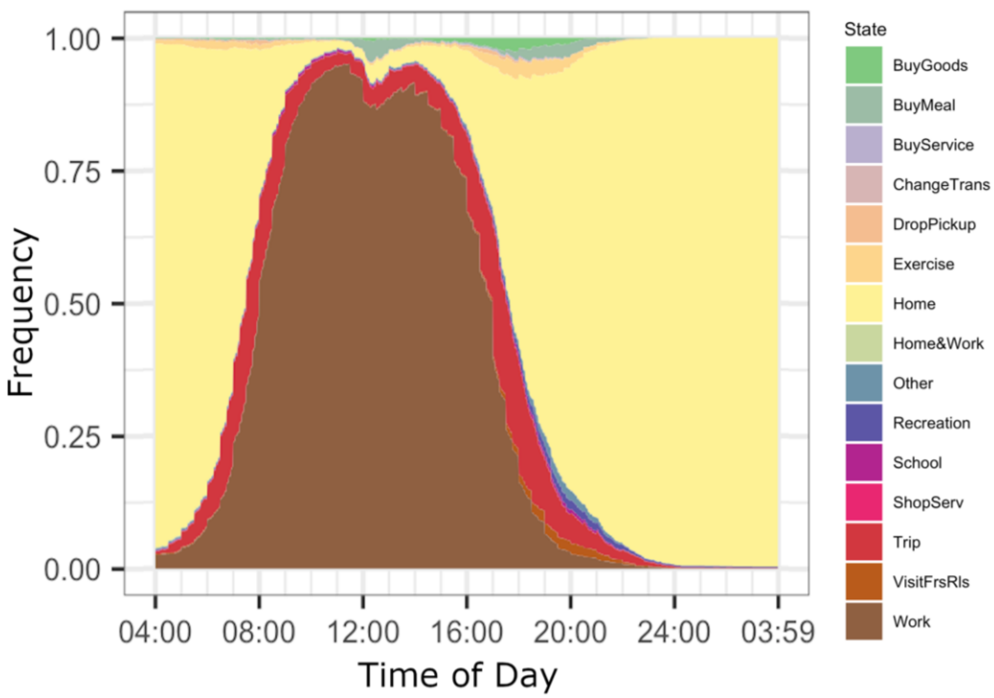


Figure 2. An example of daily pattern of min-by-min activity sequences (from Su et al. (2020))

The Complexity indicator is a measure of the complexity of individual daily activity schedules . The Gini index (or Gini coefficient, Gini ratio) is widely used in econometrics to measure the inequality in a variable of interest (usually income) across a group of people. We apply the Gini index here to measure the heterogeneity in travel mode choice among seniors. The Gini index of mode choice is defined as follows.

$$Gini = 1 - \sum_j (\frac{n_j}{N})^2 \tag{5}$$

where n_j is the number of trips made by mode j for a person, and N is the total number of trips a person made in the survey day. The Gini index of mode choice ranges from 0 and 1 with 0 corresponding to the situation when a person uses a single travel mode throughout the survey day.

Results in composition of motifs

Analysis of the daily motif patterns in California-NHTS workday data shows 218 and 107 distinct types of motifs for telecommuters and commuters respectively. Telecommuters have a smaller sample size, yet more **diverse location visiting** and travel patterns than commuters. This counterintuitive result tells us that telecommuters do not obey uniform travel patterns, and substantial heterogeneity exists among individuals. Figure 3 shows that only 17 unique motifs from telecommuters and 13 motifs from commuters are above 1% of their respective samples. Taken together the 17 motifs of telecommuters capture mobility patterns of approximately 79.96% telecommuters' daily patterns and the 13 motifs of commuters capture 81.93% of commuters' daily patterns. Figure 3 enumerates each of the most popular motifs, the structure of each motif, and its percentage. The motifs are grouped according to the number of nodes separated by dashed lines. One advantage of using motifs is our ability to distinguish multi-tour daily patterns from single tour patterns. In this report, a tour (also known as trip chain) is made up of individual trips and all the stops a person made along the way at distinct locations. Some motifs have multiple tours in a day. For example, compare motifs 16, 17, and 18. Motif 16 is a single tour with a shorter round trip to a location not in the tour, motif 17 contains one tour, and motif 18 contains two tours. It should be noted that each of the remaining motifs of telecommuters and commuters not included in Figure 3 were found in less than 1% of total respondents of telecommuters or commuters, and they are labeled as all other below.

Motif 1 contains respondents whose trips all have the same origin and destination (loop trips). Around 2% of telecommuters and less than 1% of commuters perform motif 1. Motif 2 (with two locations visited and at least a round trip between them in a day) accounts for the highest percentages for both categories. This is consistent with the location-based motif in Schneider et al. (2013) and Cao et al. (2019), given that we only focus on the telecommuters and commuters during workdays in this section instead of the whole sample. 30% of commuters do motif 2, while telecommuters have a lower percentage of motif 2 compared to commuters, presumably because telecommuters are less constrained by a fixed work location. It is also noteworthy that commuters are more concentrated in less complex motifs (with less than five nodes) while telecommuters are more spread out in terms of the percentage of each distinct motif. The substantial heterogeneity in human mobility patterns, especially for telecommuters, points to location-based differences in travel patterns that we analyze in more depth in the next sub-section.

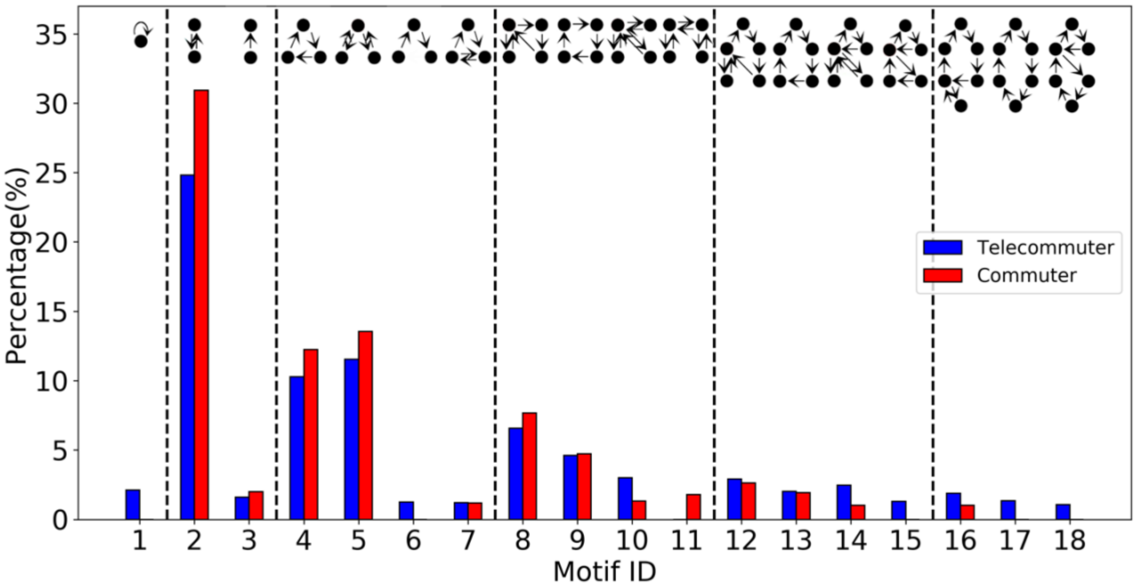


Figure 3. Percentage of human daily mobility motif patterns

For each of these motifs, we compute the average characteristics of the members, including daily travel behavior characteristics. Table 3a provides the list of the telecommuters' 17 motifs, plus one category containing all the other motifs. Table 3b provides the same characteristics for commuters' motifs. For each motif, the tables provide the within-motif average characteristics of time allocation by the survey respondents.

Tables 3a and 3b show that the complexity of daily schedules increases with the number of combinations of nodes and edges in the motifs. This is as expected because people tend to participate in different activities when they visit different places. The same is found for both telecommuters and commuters in spite of their differences in workstyles. In general, given the same structure of motifs, commuters tend to spend more time at work as well as outside home. Specifically, commuters using motif 3 spend the highest amount of time, 734.2 min, at work and 959.1 min outside home on average. When we look at the location type, it shows that 75.09% of the trips made by commuters using motif 3 are making work-related trips (either origin or destination is workplace). Even though similar to commuters using motif 3, telecommuters using the same motif 3 spend a very high amount of time 882.1 min outside home compared to other motifs, the time at work is only 193.3 min for these telecommuters. None of the trips they made are to or depart from workplaces, which indicates that telecommuters using motif 3 go to places labeled "other" to do work for a short time. Except motif 3, commuters using motif 2 representing the popular typical daily commuting pattern spend the highest amount of time at work (463.4min). However, telecommuters using the same motif 2 only spend 236.9 min at work. When we look at the location type, only 0.95% of trips made by telecommuters using motif 2 are work-related while the percentage for commuters is 83.43%. These findings are indicative of the changing nature of workplaces and the flexibility of performing work tasks away from traditional work locations hinted by the literature in the introduction.

Furthermore, in general, time spent traveling also increases from simple motifs to more complex motifs. This is as expected because people need more time traveling when they visit more and different places. However, motifs 3 and 6 of telecommuters are an exception because they contain only unidirectional trips. It is also noteworthy that given the same structure of motif 3 for telecommuters and commuters, telecommuters spend 183.6 min traveling while commuters only use 66.2 min on average. When we look at the location type, it turns out that 97.22% of telecommuters using motif 3 are either leaving home to a place labeled “other” or coming back home from a place labeled “other”. However, for commuters, this percentage only accounts for 17.74%. Given the same motif structure, telecommuters using motif 3 are people who leave home to a place far away from their home or come back home from a distant place while for commuters, the origin and destination types are more diverse and on average they travel relatively shorter time compared to telecommuters. Tables 3a and 3b include another synoptic indicator of daily travel called Travel Time Ratio (Dijst and Vidakovic, 2000), defined as the total travel time in a day divided by the sum of the total time in activities outside the home plus the total travel time in a day. Higher values of TTR indicate a higher proportion of out of home time spent traveling. In general, telecommuters have higher values of TTR on workdays compared to commuters which means telecommuters spend more time traveling and less time in longer out of home activities (e.g., work at a workplace), but in shorter activities such as running errands or picking up and dropping off children at places.

Table 3a. Motifs and time-based behavioral indicators for telecommuters (including size and sample percentage of motif membership)

Motif	Complexity	Time at Work	Time Outside Home	Time Traveling	Travel Time Ratio	Person in Sample	Percent in Sample
1	0.019	81.1	288.7	82.7	0.733	47	2.10%
2	0.026	236.9	400.0	65.9	0.323	555	24.82%
3	0.018	193.3	882.1	183.6	0.262	36	1.61%
4	0.033	228.6	467.0	80.0	0.308	230	10.29%
5	0.043	177.9	416.8	91.6	0.342	258	11.54%
6	0.029	305.9	977.2	224.0	0.238	28	1.25%
7	0.046	157.8	355.1	135.9	0.504	27	1.21%
8	0.050	145.2	447.5	113.0	0.321	147	6.57%
9	0.040	93.9	315.6	96.4	0.372	103	4.61%
10	0.057	137.0	424.1	127.5	0.368	67	3.00%
12	0.056	203.0	513.0	118.2	0.295	65	2.91%
13	0.047	157.7	420.7	116.8	0.325	45	2.01%
14	0.063	94.2	392.5	120.9	0.337	55	2.46%
15	0.057	141.1	412.6	113.9	0.358	29	1.30%
16	0.062	125.3	460.5	153.4	0.353	42	1.88%
17	0.052	157.2	481.7	143.5	0.358	30	1.34%
18	0.061	108.4	432.9	131.8	0.334	24	1.07%
All other	0.067	153.8	573.7	176.8	0.367	448	20.04%

Note: Time is measured in minutes per day. The values of complexity, time at work, time outside home, time traveling, and travel time ratio are the average values of groups of people belonging to each motif. The background color in a gradient is according to the data in each column and the same for the rest of the summary tables in this section. Motif 11 is missing in this table because it is below 1% of the included sample of telecommuters. Same for Tables 4a and 5a.

Table 3b. Motifs and time-based behavioral indicators for commuters

Motif	Complexity	Time at Work	Time Outside Home	Time Traveling	Travel Time Ratio	Person in Sample	Percent in Sample
2	0.028	463.4	574.6	68.1	0.158	3962	30.93%
3	0.017	734.2	959.1	66.2	0.127	255	1.99%
4	0.036	430.8	598.2	83.3	0.171	1568	12.24%
5	0.044	426.6	608.7	94.7	0.18	1734	13.54%
7	0.046	385.8	536.0	81.2	0.203	150	1.17%
8	0.050	404.5	621.5	105.9	0.197	983	7.67%
9	0.043	401.3	612.0	102.0	0.195	604	4.72%
10	0.055	331.2	582.1	114.7	0.234	170	1.33%
11	0.058	443.3	668.6	131.3	0.204	228	1.78%
12	0.057	376.6	642.2	125.1	0.213	336	2.62%
13	0.049	373.1	603.8	112.3	0.215	246	1.92%
14	0.062	299.2	596.2	132.8	0.243	130	1.01%
16	0.062	313.8	613.2	136.0	0.235	129	1.01%
All other	0.062	323.3	675.4	165.2	0.272	2314	18.07%

Note: Motifs 1, 6, 15, 17, and 18 are missing in this table because they are below 1% of the included sample of commuters. Same for Tables 4b and 5b.

Tables 4a and 4b show person's characteristics for each motif. In general, women and men are quite evenly distributed across these distinct motifs except in motif 3 for telecommuters and commuters and motif 13 for commuters. Women are less likely to use motif 3 (the one way trip to elsewhere), presumably because they need to take on household responsibilities (e.g., Kwan (2000, 1999) and McBride et al. (2020)), which makes them less likely to leave home and not return in the survey day. As we showed in Table 1, 43.83% of telecommuters are part-time employees while only 19.88% of commuters are part-time employees. This explains the very high percentage of full-time employees of different motifs among commuters while the percentages of full-time and part-time workers in telecommuters are more balanced. Specifically, a high percent (76.6%) of telecommuters belonging to motif 1 are full-time employees since telecommuters do not need to commute to a workplace and many of them tend to work from home. Motif 18, which includes two tours, for telecommuters has the highest percentage of part-time employees which could be a motif related to some part-time workers who work in multiple jobs. The percentages of full-time employees in the commuters group are quite spread out throughout different motifs except motif 3 and 11. The part-time employee percentages of motif 3 and motif 11 of commuters are substantially below the overall average percentage of 19.88%. Note also that 75.29% of commuters in motif 3 are either leaving home to work or returning home from work. Intuitively, part-time workers are less likely to leave home for work and do not come back after work since they are usually required to work for shorter hours compared to full-time workers. This could explain the very low percentage of part-time workers in motif 3 among commuters. Motif 11 of commuters is a very special mobility pattern accounting for 1.78% (228) of total commuters that are people who need to run errands or give rides as a daily routine before going to work (e.g. escort kids to school) and they also go out for lunch during work. The percentage of full-time (91.23%) and part-time (8.77%) commuters of motif 11 show that full-time commuters tend to be more likely to use motif 11. In terms of retirement status, it is not surprising that we have very few retirees throughout different motifs in commuters since most employed retirees do not commute to work. It is possible for retired people to get a job after retirement and leave their home during a workday. In fact, retirees who telecommute tend to be concentrated in complex motifs such as motifs 13, 17, 18. This shows that many retired persons have quite diverse mobility patterns and do not just stay at home. Note also that retirees can work as part-time workers and many part-time workers tend to telecommute as we discussed before.

Table 4. Motifs and respondents' characteristics (Percent of persons within each motif group)

(a) Telecommuters

Motif	Woman	Full-time Employee	Retired
1	57.45%	76.60%	6.38%
2	47.21%	61.80%	8.11%
3	33.33%	55.56%	11.11%
4	53.04%	53.91%	10.43%
5	51.94%	58.91%	8.91%
6	50.00%	64.29%	7.14%
7	55.56%	55.56%	11.11%
8	51.70%	55.78%	9.52%
9	57.28%	44.66%	13.59%
10	47.76%	55.22%	7.46%
12	46.15%	58.46%	10.77%
13	48.89%	42.22%	33.33%
14	49.09%	47.27%	12.73%
15	48.28%	65.52%	10.34%
16	57.14%	61.90%	9.52%
17	50.00%	50.00%	20.00%
18	45.83%	33.33%	16.67%
All other	53.57%	51.79%	8.04%

(b) Commuters

Motif	Woman	Full-time Employee	Retired
2	44.93%	81.52%	1.56%
3	38.43%	86.67%	1.18%
4	50.26%	80.23%	1.91%
5	46.54%	81.31%	1.61%
7	54.00%	78.67%	0.00%
8	50.46%	80.67%	1.53%
9	54.47%	80.30%	1.66%
10	50.59%	74.71%	1.76%
11	47.37%	91.23%	0.88%
12	52.98%	77.08%	1.49%
13	60.57%	76.42%	2.03%
14	49.23%	76.15%	1.54%
16	51.94%	72.09%	3.10%
All other	51.47%	76.62%	2.81%

Note: The percentages of part-time employees are omitted.

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Tables 5a and 5b show respondents' travel mode choice for each motif. The percentage of each mode used in the survey day for every respondent can be easily computed. The percentage values of each mode in Tables 5a and 5b are the group average of people belonging to each motif and each row except for the Gini index sums up to one. The Gini index quantifies the daily variation of mode choices and is computed as 1 minus the summation of the squared value of the percentage of each mode choice. The Gini index of mode choices takes values between 0 and 1, with 0 implying that a person only uses one mode to travel throughout the survey day.

From Tables 5a and 5b we can observe that bike, transit and other mode (which contains all unaccounted-for modes including air) are the least favorite modes among all people. As expected, the vehicle-based modes including car as passenger, drive alone, and drive someone else are the most popular modes and they span from 75.95% in motif 10 to 96.57% in motif 13 except motif 1 among telecommuters. Commuters' percentages span from 73.26% in motif 11 to 94.12% in motif 3. Telecommuters who use motif 1 tend to walk most and rarely use other modes, yielding a very low Gini, which complements our previous analysis on this motif of home-based trips that people tend to exercise or take a walk. In terms of the typical commuting pattern motif 2, 71.91% of commuters drive alone, while only 54.08% of telecommuters driving alone. There is also a higher percentage of passenger trips and drive someone else trips among telecommuters compared to commuters. This is consistent with our previous finding in Table 2. We also notice that the loop trip patterns with more than three locations (motifs 9, 13, and 17) all have more than 90% of vehicle-based modes and the lowest Gini index compared to other motifs of the same number of locations. This tells us that when people need to make a loop trip among four or more locations, the vehicle is the most preferable and dominant mode choice. People who are included in motifs 10, 14, 18 of telecommuters and motifs 10, 11, 14 of commuters have a quite large Gini index implying a higher combination of modes used in a day.

Table 5a. Motifs and respondents' travel mode choice for telecommuters

Motif	Walk	Bike	Transit	Passenger	Drive Alone	Drive Someone Else	Other Mode	Gini
1	84.04%	3.19%	0.00%	0.00%	10.64%	2.13%	0.00%	0.011
2	13.35%	2.15%	2.01%	12.13%	54.08%	15.92%	0.36%	0.068
3	8.33%	0.00%	0.00%	27.78%	38.89%	22.22%	2.78%	0.000
4	10.10%	0.29%	1.01%	11.23%	55.76%	21.02%	0.58%	0.111
5	16.70%	2.85%	2.23%	8.32%	48.11%	21.79%	0.00%	0.308
6	1.79%	0.00%	3.57%	23.21%	41.07%	30.36%	0.00%	0.143
7	7.16%	3.70%	0.00%	2.10%	43.09%	43.95%	0.00%	0.254
8	13.61%	2.43%	2.18%	9.63%	51.28%	20.60%	0.27%	0.294
9	6.99%	1.13%	0.97%	12.91%	58.46%	19.53%	0.00%	0.118
10	20.21%	1.85%	1.99%	5.53%	48.96%	21.46%	0.00%	0.413
12	10.52%	0.51%	2.05%	5.46%	58.00%	23.45%	0.00%	0.307
13	3.43%	0.00%	0.00%	8.89%	76.57%	11.11%	0.00%	0.079
14	19.22%	0.18%	1.04%	8.40%	40.75%	30.41%	0.00%	0.383
15	11.68%	3.63%	1.72%	9.20%	42.02%	31.75%	0.00%	0.267
16	12.20%	0.00%	0.68%	8.30%	57.95%	20.52%	0.34%	0.317
17	5.14%	0.00%	1.11%	13.33%	65.42%	15.00%	0.00%	0.073
18	7.25%	0.00%	0.00%	6.61%	51.61%	34.52%	0.00%	0.364
All other	11.37%	1.34%	0.66%	9.71%	48.36%	28.39%	0.19%	0.346

Note: The first seven columns (all except Gini column) are the group average percentages of each mode used on the survey day. The percentage values of the seven modes in each row sum up to 1. Same for Table 5b.

Table 5b. Motifs and respondents' travel mode choice for commuters

Motif	Walk	Bike	Transit	Passenger	Drive Alone	Drive Someone Else	Other Mode	Gini
2	4.68%	1.43%	5.21%	6.08%	71.91%	10.25%	0.43%	0.043
3	1.37%	2.16%	1.96%	10.20%	67.65%	16.27%	0.39%	0.006
4	4.04%	0.75%	3.08%	6.36%	70.52%	15.18%	0.06%	0.122
5	13.59%	2.64%	3.03%	8.32%	54.34%	17.88%	0.20%	0.302
7	7.16%	4.04%	0.80%	5.66%	60.91%	21.32%	0.11%	0.234
8	11.54%	1.10%	2.27%	8.63%	55.93%	20.01%	0.52%	0.318
9	3.61%	1.38%	2.26%	8.09%	65.00%	19.49%	0.17%	0.150
10	19.85%	2.80%	1.48%	7.15%	47.20%	21.33%	0.20%	0.394
11	20.61%	2.05%	3.94%	6.65%	42.78%	23.83%	0.15%	0.441
12	8.89%	0.74%	2.52%	9.12%	55.81%	22.87%	0.05%	0.313
13	4.31%	0.65%	2.03%	7.07%	60.69%	25.25%	0.00%	0.154
14	18.57%	2.77%	1.95%	6.86%	47.78%	22.07%	0.00%	0.392
16	11.23%	0.78%	1.88%	7.52%	54.55%	22.50%	1.55%	0.300
All other	10.71%	1.21%	1.28%	8.98%	51.82%	25.37%	0.63%	0.319

Results in time allocation pattern recognition using sequence analysis

The analysis in the previous section demonstrates a strong relationship between network motifs, daily time allocation, person characteristics, and travel mode choice to activities and travel in a day. In this section, we explore this further using sequence analysis as introduced in previous sections to identify patterns of time allocation to activities and travel as well as to compare the differences in the time allocation patterns between telecommuters and commuters. To begin with, instead of repeating sequence analysis on the 17 motifs plus one category of all other motifs for telecommuters, and 13 motifs plus one category of all other motifs for commuters respectively, and further compare the derived time allocation patterns, we follow the simplification proposed by Su et al. (2020) to merge motifs into five groups based on the number of nodes, which represents the number of distinct locations visited in the survey day. Another reason we cannot directly apply sequence analysis on persons using each of the distinct motif is that the percentages for some motifs are very low (approximately 1%), hence, it is not feasible to implement sequence analysis and clustering on very small samples. Furthermore, as we conclude from Table 3, the complexity of daily schedules increases with the number of combinations of nodes and edges in the motifs. Therefore, it is more intuitive to aggregate motifs by number of nodes than any other strategies. The derived five groups of motifs also reflect five levels of complexity in daily schedules.

To distinguish telecommuters and commuters, we use the name Group T for telecommuters and Group C for commuters to use as labels for each group of patterns. Group T.I and Group C.I are both motif 1 with only one node (recall these are persons that had a trip with the same origin and destination – the loop trip). Group T.II and Group C.II include motifs 2 and 3 with two nodes. Group T.III and Group C.III include motifs with three nodes. Group T.IV and Group C.IV include motifs with four nodes. All the other less frequent motifs with five and more nodes are classified as Group T.V and Group C.V. In the telecommuters' group, there are 47 persons (2.1%) in Group T.I, 591 persons (26.43%) in Group T.II, 557 persons (24.91%) in Group T.III, 405 persons (18.11%) in Group T.IV, and 636 persons (28.44%) in Group T.V. The composition by five groups of motifs for commuters is that 25 persons (0.20%) in Group C.I, 4217 persons (32.92%) in Group C.II, 3654 persons (28.53%) in Group C.III, 2287 persons (17.85%) in Group C.IV, and 2626 persons (20.50%) in Group C.V.

Following the procedure of sequence analysis as introduced in the methods section, we construct daily activity-travel sequence consisting of 15 distinct states with a length of 1440 (total minutes in a survey day) for each respondent in the five motif Groups. The procedure is followed by a computation of dissimilarity matrix among sequences of 1440 minutes in a day and implementing the agglomerative nesting clustering (AGNES) on the dissimilarity matrix to identify distinct clusters of sequences with similar patterns. Our objective is not only to build clusters with as similar sequences as possible, but also to derive clusters in which their most representative "sequence" is as different as possible across clusters. To do this, we use the clustering solution that combines the WSS and Silhouette as introduced in the methods section. The usual procedure is to compute WSS and Silhouette for different numbers of clusters and then plot them as in Figure 4. The well-known elbow method in the clustering literature refers to rapid drop in WSS and then slow reach to an asymptote of the graph in the right-hand side of

Figure 4. Figure 4 shows that selecting 4 clusters, or 5 clusters will lead to similar WSS, so a solution with more than 5 clusters would not be considered. The Silhouette graph of Figure 4 shows the best solution with respect to the separation among clusters is for 4 clusters that has the highest average silhouette coefficient. These two indicators show that 4 clusters would be an optimal solution for motif Group T.II. We apply the same strategy to determine the optimal number of clusters for the other motif groups (see Appendix A).

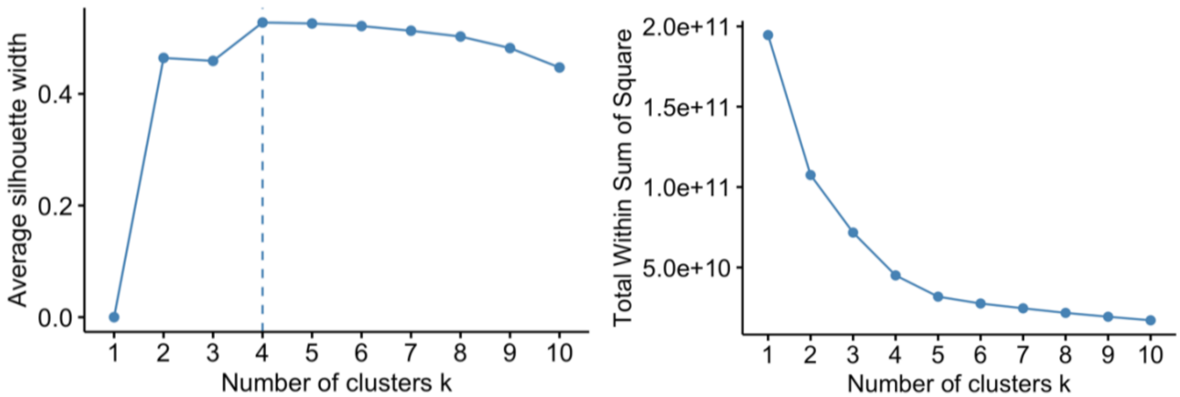


Figure 4. Illustration of the results of Silhouette (left) and WSS elbow (right) for motif Group T.II

Recalling that within each motif group we identify several daily activity-travel cluster sequences that represent different behaviors, we will use a numbering convention that shows motif group and sequence cluster within each group. To distinguish them, we number them by assigning to the motif group a Roman numeral (I, II, III, IV, and V) and the sequence cluster an Arabic numeral (1,2,3,4,5). For example, in Group T.II, we will have more than one distinct type of sequence clusters labelled as II.1, II.2, II.3, and II.4.

Figures 5 and 6 show the distinct daily time of day patterns for each group of motifs for telecommuters and commuters respectively. The daily cluster names are based on the daily behavior each cluster represents. Group T.I and Group C.I both have a very small sample size, and running a cluster analysis on them yields some clusters with only one observation. This implies that a clustering analysis is not applicable to these two small groups. Thus, the clustering results for Group T.I and Group C.I are not reported. On the other hand, all the other four groups of telecommuters have four distinct activity sequence patterns, and Group C. II and Group C.V have four distinct patterns as well while Group C.III and Group C.IV have five distinct patterns. Table 6 shows the statistics for the number of people, average entropy, average complexity, and Gini index of mode choice for each cluster in each group. In general, the average complexity within each group of motifs increases with the number of locations visited in a day. Groups T.I and T.II have the lowest Gini index implying less diverse mode choices compared to other groups of telecommuters. Similarly, Groups C.I and C.II have the lowest Gini index. Also, within each motif group, we find substantial heterogeneity of daily activity-travel patterns with different composition of activities, timing of activities and travel, complexity, and Gini index indicating different transitions and variation of mode choice among activities.

Table 6. Statistics for the number of people, entropy, complexity, Gini index for each cluster in each group

Group	Cluster	Pattern	Number of people	Ave. Entropy	Ave. Complexity	Ave. Gini
Telecommuter						
T.I	/	/	47	0.546	0.0192	0.0106
T.II	T.II.1	Work and Run Errands Day	307	0.635	0.0255	0.0709
	T.II.2	Mostly Out of Home Day	78	0.600	0.0231	0.0599
	T.II.3	Work from Home Day	115	0.906	0.0313	0.0541
	T.II.4	Long Work from Home Day	91	0.404	0.0194	0.0565
T.III	T.III.1	Work and Run Errands Day	247	0.764	0.0364	0.191
	T.III.2	Mostly Out of Home Day	83	0.749	0.0338	0.195
	T.III.3	Work from Home Day	144	1.070	0.0477	0.277
	T.III.4	Long Work from Home Day	83	0.593	0.0314	0.206
T.IV	T.IV.1	Work and Run Errands Day	237	0.901	0.0487	0.319
	T.IV.2	Mostly Out of Home Day	39	1.050	0.0495	0.327
	T.IV.3	Work from Home Day	90	1.200	0.0551	0.250
	T.IV.4	Long Work from Home Day	39	0.741	0.0417	0.166
T.V	T.V.1	Work and Run Errands Day	422	1.060	0.0648	0.296
	T.V.2	Mostly Out of Home Day	50	1.120	0.0623	0.281
	T.V.3	Work from Home Day	128	1.300	0.0697	0.369
	T.V.4	Long Work from Home Day	36	0.890	0.0552	0.178
Commuter						
C.I	/	/	25	0.488	0.0170	0
C.II	C.II.1	Typical Workday	3039	0.810	0.0293	0.0396
	C.II.2	Very Late Workday	243	0.763	0.0273	0.0348
	C.II.3	Leave Home Day	270	0.606	0.0209	0.0203
	C.II.4	Mostly Home Day	665	0.517	0.0221	0.0582
C.III	C.III.1	Typical Workday	2628	0.939	0.0415	0.220
	C.III.2	Very Late Workday	264	0.861	0.0391	0.190
	C.III.3	Leave Home Day	101	1.080	0.0424	0.225
	C.III.4	Mostly Home Day	552	0.668	0.0339	0.188
	C.III.5	Mixed Workday	109	1.000	0.0415	0.229
C.IV	C.IV.1	Typical Workday	1325	1.040	0.0516	0.303
	C.IV.2	Very Late Workday	106	0.987	0.0487	0.222
	C.IV.3	Leave Home Day	95	1.160	0.0513	0.276
	C.IV.4	Mostly Home Day	364	0.732	0.0420	0.253
	C.IV.5	Early Workday	397	1.010	0.0500	0.274
C.V	C.V.1	Typical Workday	1138	1.100	0.0641	0.326
	C.V.2	Late Workday	575	1.210	0.0677	0.363
	C.V.3	Leave Home Day	161	1.250	0.0678	0.321
	C.V.4	Mostly Home Day	752	0.988	0.0609	0.299

All four motifs groups of telecommuters contain four similar major patterns, that is Work and Run Errands Day, Mostly Out of Home Day, Work from Home Day, and Long Work from Home Day. Some telecommuters in Work and Run Errands Day still go to work and they also spend time on recreation activities, buying goods, and other activities. It might be counterintuitive at a first glance that telecommuters still go to workplaces. However, the destination types of these trips show that 15.71% of destinations of the total 1457 trips going to work were at home, a very small percentage (1.65%) were at workplaces, and the majority (82.57%) were at places labeled as other, and only one trip was to a school location. As expected, most telecommuters do not commute to workplaces. Instead, they go to a variety of other locations that include coffee shops, bookstores, customers' locations, or elsewhere to work. This confirms our introductory comments about the increases in work location flexibility and the multiple different locations that function as places where work is performed. In contrast, among the commuters' 15571 work trips, 80.69% are to a workplace, 18.38% are to a place labeled as other, 0.89% are to home, and 0.04% to school. The presence of the substantial number of places labeled as Other is notable because it parallels the telecommuter's tendency of either needing to visit a client's site and/or using some of the flexibility with technology to perform work tasks from anywhere.

The Mostly Out of Home Day pattern includes telecommuters who spend most of their time working, visiting friends and relatives, performing recreation activities, buying goods, and doing other activities, and they rarely return home in the evening. The Work from Home Day, and the Long Work from Home Day are both typical telecommuting daily routines. These two patterns share similar characteristics: telecommuters start to work from home in the very early morning and work most of the day. Beyond that, a few of them still go to a workplace, travel, buy goods, and have fun. The difference is that telecommuters in the Long Work from Home Day pattern work from home until late. In conclusion, telecommuters present very diverse daily activity-travel patterns within each motif group, but we still find four representative daily patterns within each group with similarities across groups.

We turn now to the daily patterns of commuters. All four groups of commuters contain the Typical Workday pattern. This pattern is a typical commuting routine. People leave home to work in the morning and return home after work. Patterns C.V.2 and C.IV.5 are similar to this pattern. However, an obvious difference is that commuters in pattern C.V.2 leave home to work later than the Typical Workday pattern, and commuters in pattern C.IV.5 leave home to work earlier than people in the Typical Workday pattern. Thus, we name pattern C.V.2 Late Workday and pattern C.IV.5 as Early Workday. In addition to these typical commute patterns, patterns C.II.2, C.III.2, and C.IV.2 are very similar and possibly contain people who work night shifts, as they start work in the afternoon and end at midnight. Leave Home Day is also a common pattern among these four groups of commuters. Most commuters in these groups did not return home in the evening. The Leave Home Day patterns C.III.3 and C.IV.3 share similar characteristics: people go to work in the morning and have fun after work. Many people in the Leave Home Day pattern C.II.3 did not return home because of working late. The Leave Home Day pattern C.V.3 has both late-night workers and people having fun after their workday. The common Mostly Home Day patterns within the four groups also share similar characteristics that include long periods at home, going out to buy goods, and a small fraction of time at work and traveling. Pattern C.III.5 is not a typical pattern. People in this group tend to work from home during the daytime and some of them also commute to work. Therefore, we call this pattern Mixed Workday.

Visual comparison of the time of day patterns between telecommuters and commuters for the same number of locations visited reveals that we have substantially different time of day allocation to activities and travel. For example, the peaking of arrival time to and departure time from work that we see in the commuter patterns is mostly absent from the telecommuter groups, although those peaks are present for a small proportion of respondents. Also, an obvious difference as we would expect is the substantial number of telecommuter respondents that work at home for a long amount of time (T.II.3, T.II.4, T.III.3, T.III.4, T.IV.3, T.IV.4, T.V.3, and T.V.4), and only one pattern among the commuters (C.III.5) has some work at home.

Comparing the percentage of people who made dropping off/picking up trips at least once in each pattern, we find that a relatively higher percentage occurs in patterns T.IV.1 (16.54%) and T.V.1 (22.80%) for telecommuters, and in patterns C.III.1 (11.36%) , C.IV.1 (15.09%), and C.V.1 (16.49%) for commuters. This shows a higher percentage of telecommuters in Work and Run Errands Day pattern with 4 or more visited locations, as well as commuters in Typical Workday pattern with 3 or more visited locations, are the designated drivers to escort people (e.g., taking children to school). In addition, telecommuters in patterns T.IV.1 and T.V.1 have a higher percentage of people driving others when compared to commuters in patterns C.III.1, C.IV.1, and C.V.1. Overall, 20.71% of telecommuters made at least one trip for dropping off/picking up people and only 16.52% of commuters did that. All this support our expectation that more persons from the telecommuters group are the designated drivers. However, a substantial number of regular commuters are also performing this task.

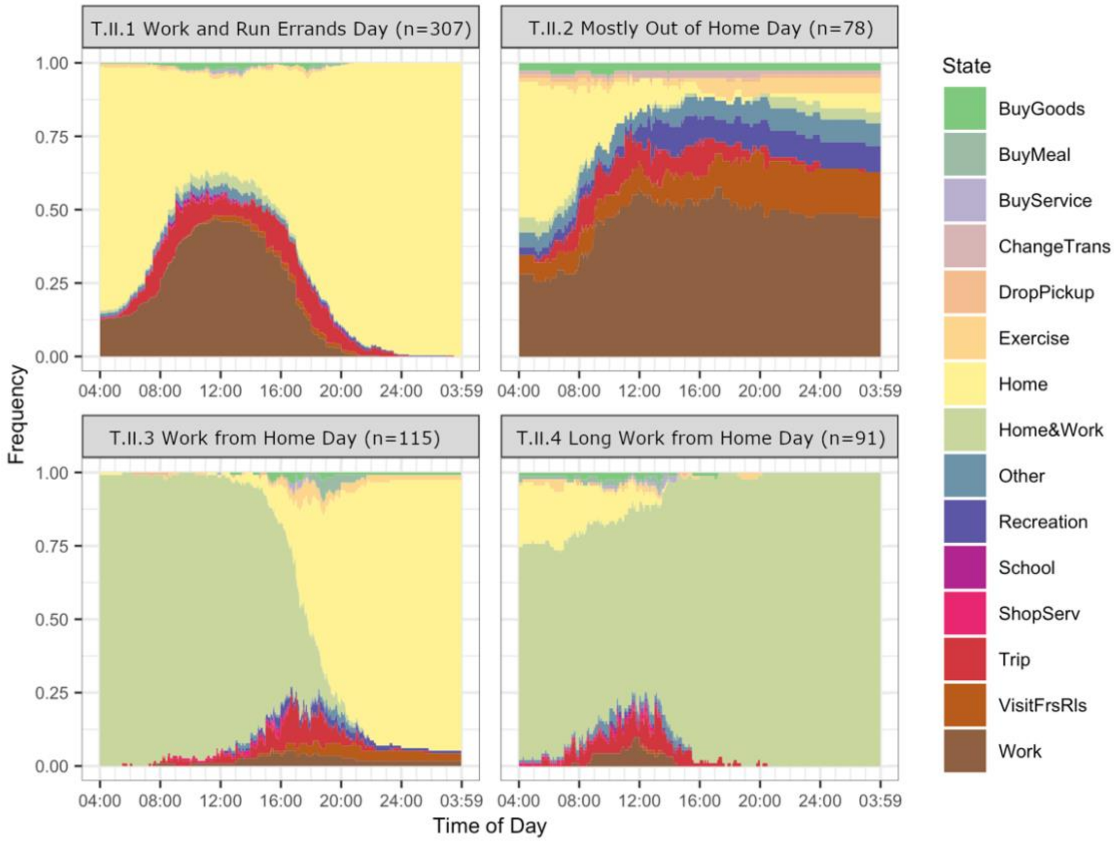


Figure 5 (a). Daily time of day patterns of activity sequences for telecommuters Group T.II

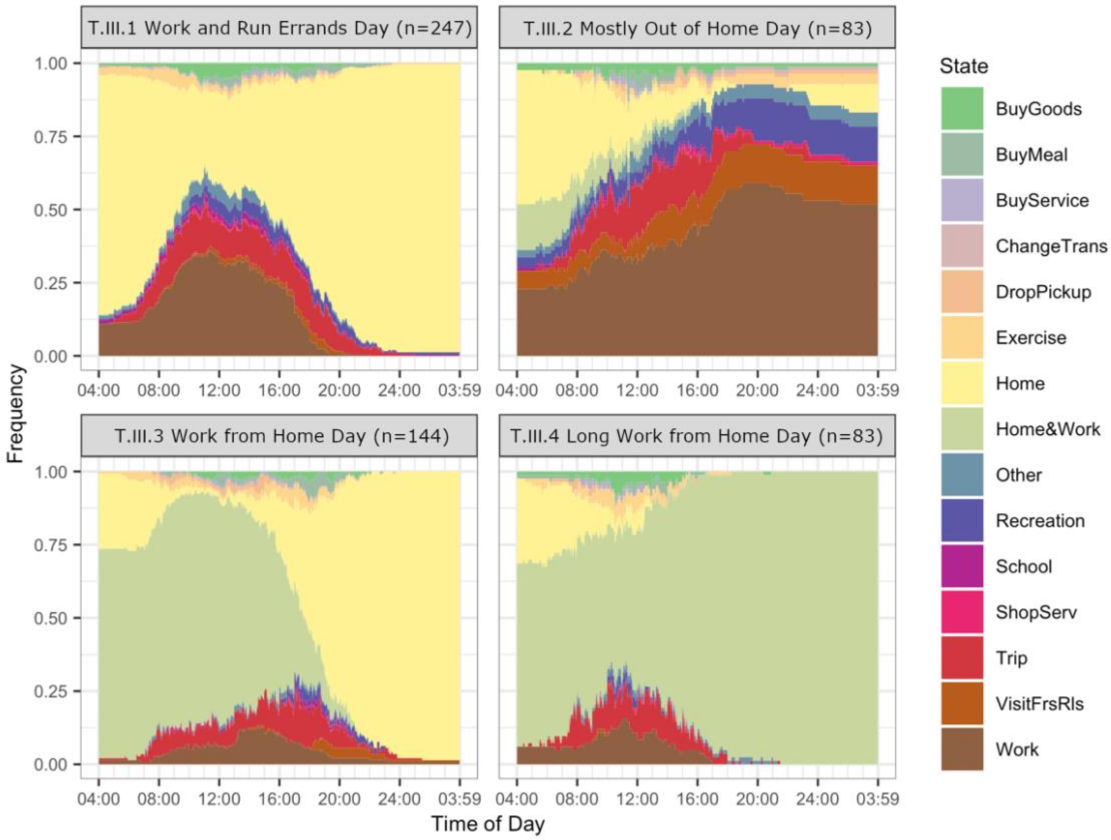


Figure 5(b). Daily time of day patterns of activity sequences for telecommuters Group T.III

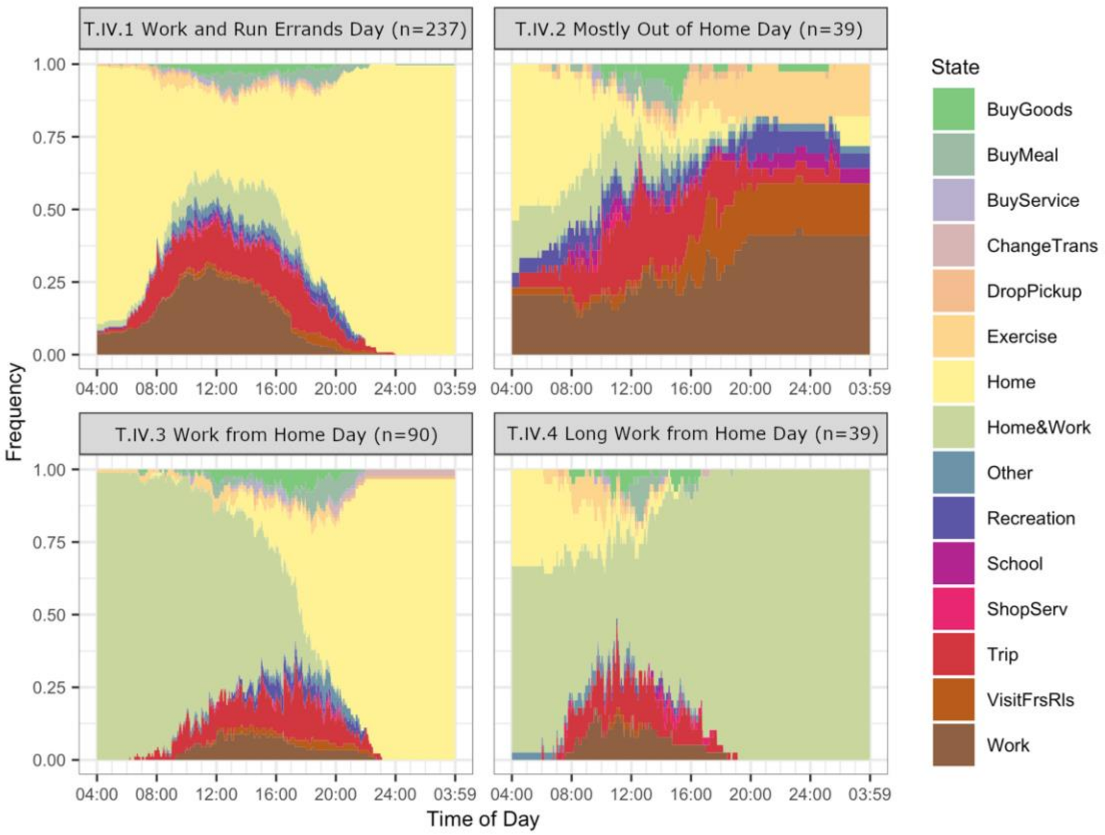


Figure 5 (c) Daily time of day patterns of activity sequences for telecommuters Group T.IV

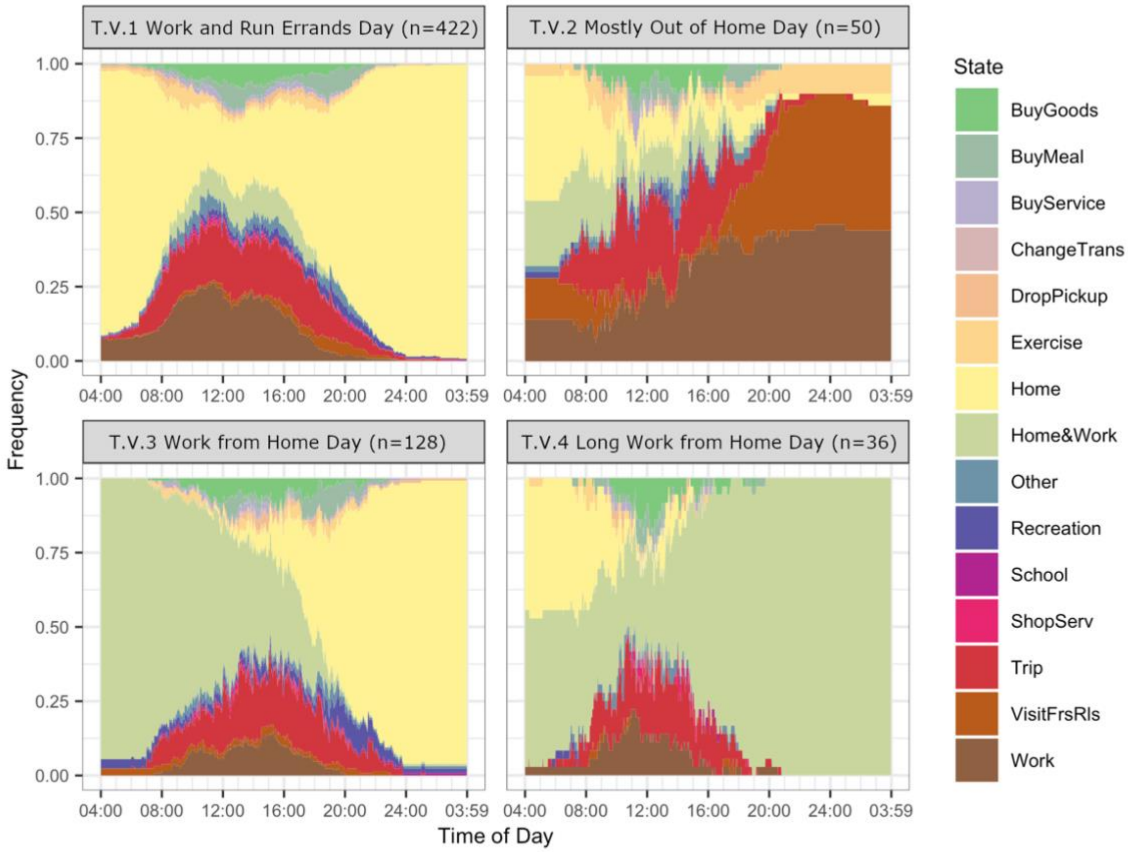


Figure 5(d). Daily time of day patterns of activity sequences for telecommuters Group T.V

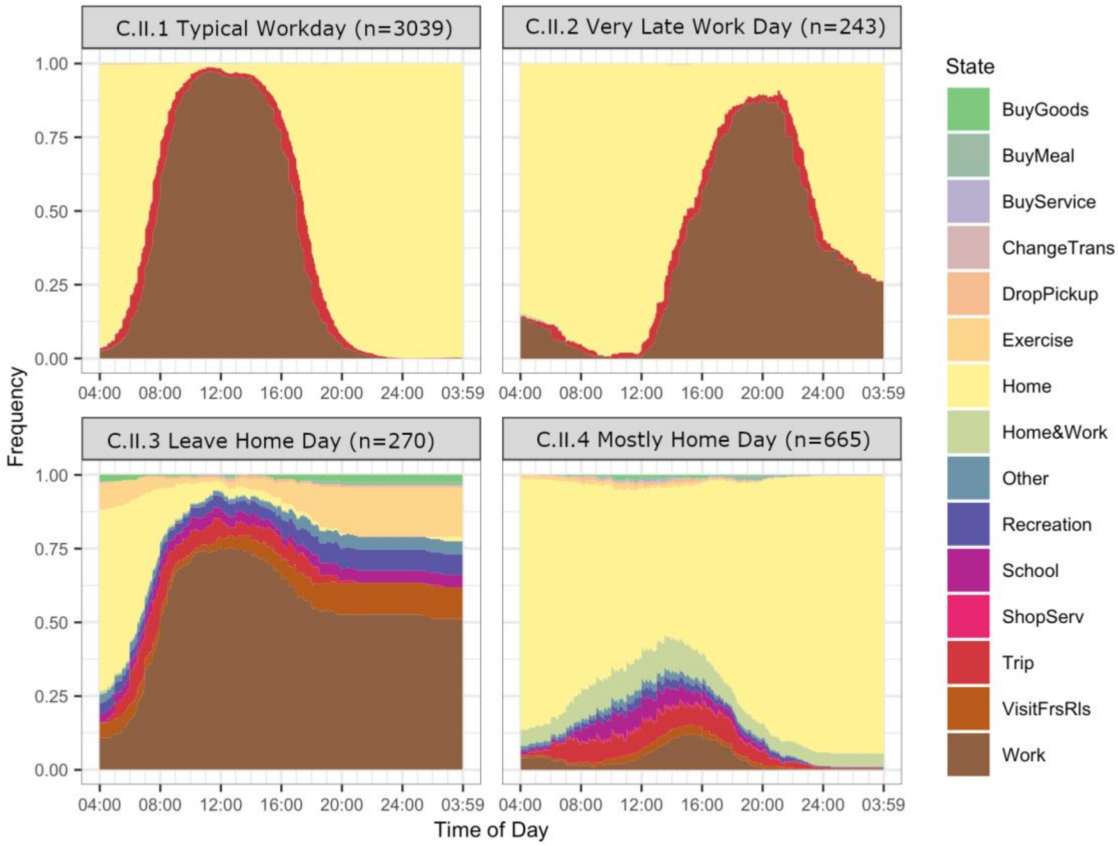


Figure 6(a). Daily time of day patterns of activity sequences for commuters Group C.II

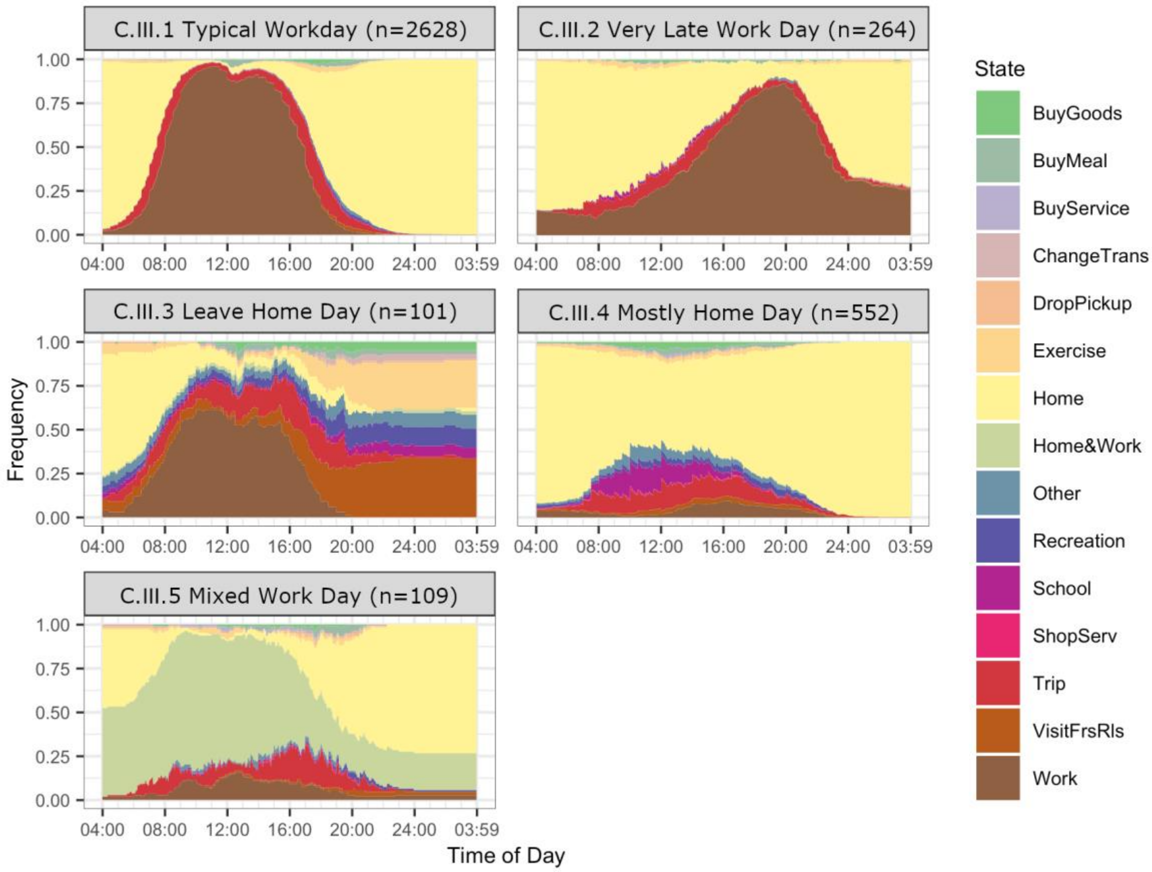


Figure 6(b). Daily time of day patterns of activity sequences for commuters Group C.III

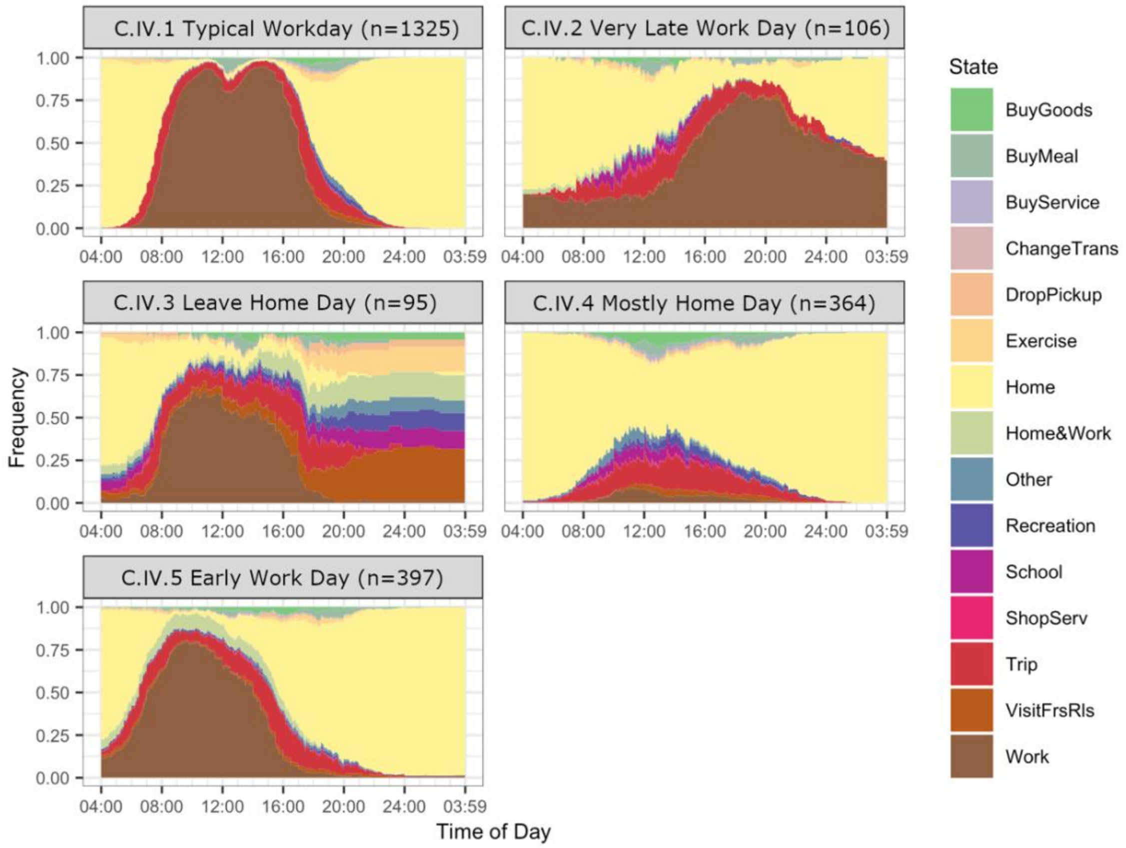


Figure 6(c). Daily time of day patterns of activity sequences for commuters Group C.IV

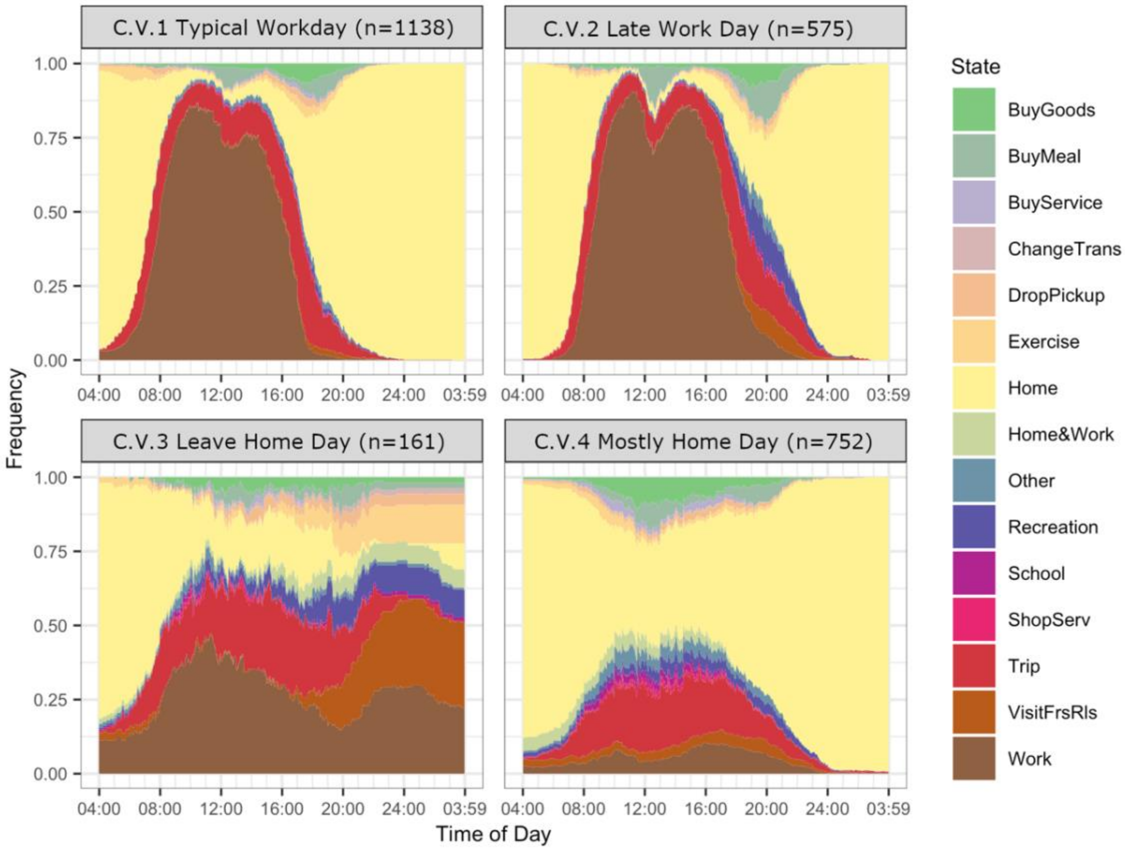


Figure 6(d). Daily time of day patterns of activity sequences for commuters Group C.V

Results of intrahousehold interactions

Paleti and Vukovic (2017) studied the intrahousehold interactions of dual-earning household members and found a very strong association of telecommuting frequency and time allocation. With our techniques we explored these associations without imposing the strong assumptions required in regression-like statistical models. As a follow-up exploratory analysis, we use 8385 workers in 4328 dual-earner households and 1618 workers in 566 three-earner households (including workers making no trips) to investigate the combination of daily time of day patterns of activities and travel for the dual-earner and three-earner households.

The frequency of different combinations of telecommuters and commuters for the dual-earner and three-earner households are listed in Table 7. It shows that 2 commuters is the most popular combination (67.24%) in dual-earner households; likewise, 3 commuters is the dominant combination for three-earner households. The second most popular combinations for dual-earner and three-earner households are combinations that have 1 telecommuter plus 1 commuter for dual earner households (21.05% of the sample of dual-earner households) and 1 telecommuter plus 2 commuters (22.30% of the sample of three-earner households). All the other less frequent combinations are below 6%. We further look into the female percentage in the 1 telecommuter plus 1 commuter households as well as 1 telecommuter plus 2 commuters households. The statistics show that 54.67% of telecommuters are women while 44.68% of commuters are women in dual-earner households, which demonstrates that a higher percentage of women are more likely to be telecommuters in dual-earner households. However, in the three-earner households, only 49.19% of telecommuters are women and 50.81% of commuters are women which implies that men and women are almost equally likely to work as commuters or telecommuters in three-earner households.

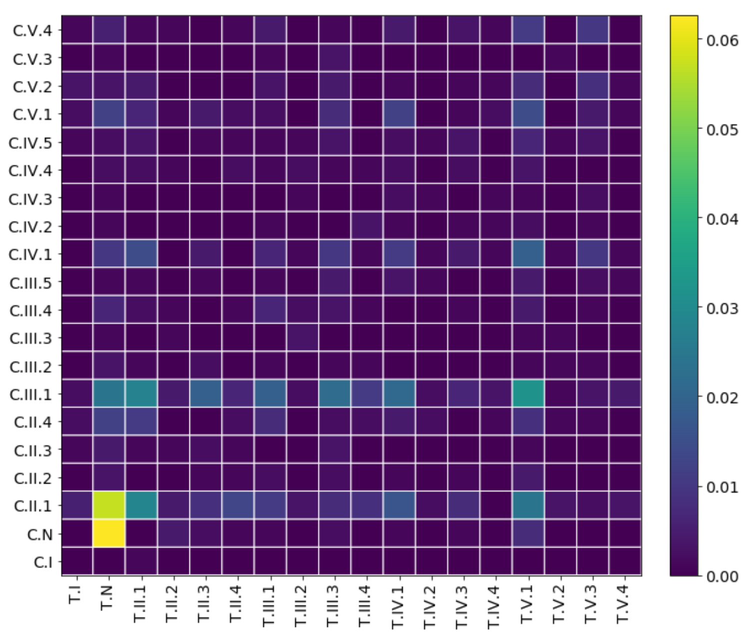
Table 7. Combinations of telecommuters and commuters for the dual-earner and three-earner households

Category	Number of households (Percentage)
Dual-earner household (n=4328)	
2 commuters	2910(67.24%)
1 telecommuter + 1 commuter	911(21.05%)
2 telecommuters	236(5.45%)
1 commuter	229(5.29%)
1 telecommuter	42(0.97%)
Three-earner household (n=566)	
3 commuters	351(63.13%)
1 telecommuter + 2 commuters	124(22.30%)
2 commuters	33(5.94%)
2 telecommuters + 1 commuter	30(5.40%)
1 telecommuter + 1 commuter	6(1.08%)
3 telecommuters	5(0.90%)
1 commuter	4(0.72%)
2 telecommuters	3(0.54%)

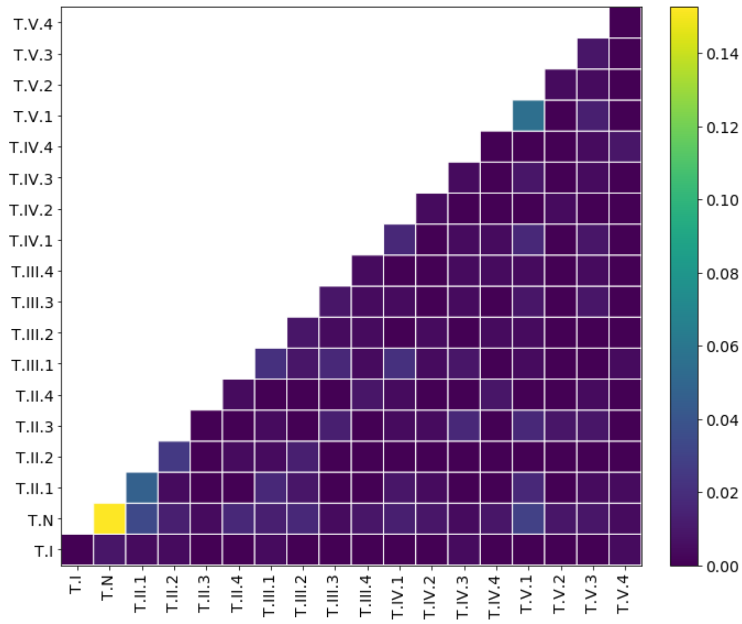
Note: If a category contains only one worker in a dual-earner household, another worker was not included in NHTS because the worker might be outside California. Likewise, for three-earner households.

We further investigate the combination of daily time of day patterns of activities and travel for the dual-earner and three-earner households. We select three categories in Table 7 including 1 telecommuter plus 1 commuter, 2 telecommuters, and 1 telecommuter plus 2 commuters households as case studies. We aim to use these three groups containing telecommuters to explore the situation when there are commuters in a household how the other telecommuter's daily schedule looks like and when both of the household members are telecommuters how their daily time allocation patterns look like on workdays. The results show that there are 205 distinct combinations for 1 telecommuter plus 1 commuter households, 92 distinct combinations for 2 telecommuters households, and 102 distinct combinations for 1 telecommuter plus 2 commuters households. Figures 7(a)-(b) show the percentages of all possible combinations of daily time of day patterns of activities and travel for the 1 telecommuter plus 1 commuter, and 2 telecommuters households respectively. Note that C.N and T.N indicate commuters making no trips and telecommuters making no trips respectively. It is noticeable that in the 1 telecommuter plus 1 commuter households, a combination of a commuter making no trip associated with a telecommuter making no trip accounts for the highest percentage (6.26%). Likewise, in the 2 telecommuters households, the percentage of T.N together with T.N is also the highest percentage (15.25%). A possible explanation could be that people from these two combinations coordinate their schedule to be together at home for family events or other situations that require every household member to be involved at home. In addition, C.II.1 and C.III.1 associated with other telecommuter patterns also have a relatively high percentage, which implies that given a household member works as a commuter, the other household member working as telecommuters has much more diversity in daily time of day patterns and takes on more household responsibilities such as escorting kids to school, grocery shopping, and so forth. This is even more obvious by some frequent telecommuter patterns including T.II.1, T.IV.1, and T.V.1 indicating that telecommuters tend to perform a Work and Run Errands Day pattern. While in the 2 telecommuters households, the highest percentages occur in the diagonal pattern combinations including T.II.1+T.II.1 (11 households, 4.66%) and T.V.1+T.V.1 (13 households, 5.51%). The travel diaries of the household members following these two diagonal combinations show that 5 out of the 11 households doing T.II.1+T.II.1 are having the same daily schedule. The same happens in 5 out of the 13 households doing the combination T.V.1+T.V.1. This proves that many people in 2 telecommuters households doing the pattern combination of T.II.1+T.II.1 and T.V.1+T.V.1 tend to do activities jointly through the day.

We next turn to the 1 telecommuter plus 2 commuters households. Given that there are 102 pattern combinations from the 124 households with 1 telecommuter plus 2 commuters, when we look at the pattern distribution of the telecommuters, it shows many telecommuters are concentrated in patterns T.N (23.39%), T.II.1 (16.13%), T.V.1 (15.32%), T.IV.1 (8.06%), only 0.81% of telecommuters do T.I, and the rest are all below 5%. This tells us that given that many telecommuters from 1 telecommuter plus 2 commuters households do not make any trips on workday (23.39% of T.N), a substantial number of telecommuters still visit 2, 4 and 5 locations to perform a Work and Run Errands Day. This is consistent with the dual-earner households that when the other household members are commuting, the telecommuter take on household responsibility activities.



(a) 1 telecommuter plus 1 commuter households



(b) 2 telecommuters households

Figure 7. Percentages of different combinations of daily time of day patterns for the 1 telecommuter plus 1 commuter (a) and 2 telecommuters (b) households. Figure (b) is symmetric, so we only visualize half of the matrix of percentages.

Results of stay-at-home persons

As mentioned in previous sections, of the total 24448 workers (4168 telecommuters and 20280 commuters) in 2017 California-NHTS, we only keep the workday subset comprising 2236 telecommuters and 12809 commuters for the motif and sequence analysis. The 9403 excluded workers are people who were interviewed on non-workdays or stayed at the same location (mostly home) all day during workdays with no trips to report. To understand the differences between people who stayed at home all day and people who made at least one trip, two binary logistic regression models are estimated for telecommuters and commuters respectively. We use individual-level and household-level characteristics as explanatory variables and test their significance on telecommuters' and commuters' decision on making trips. The final specification of the model was obtained by a systematic process of eliminating insignificant variables.

Table 8 summarizes the results of the two estimated binary logistic regression models. Among the set of individual socio-demographic variables, we find that commuters aged 66 and over are most likely to leave home and make trips compared to the rest age groups. Surprisingly, commuters younger than 26 are the age group that are least likely to leave home and make trips. Presumably, many of them are college students working as part-time commuters and their job duties are flexible which allows them to ask for leave and stay at home the entire survey day. However, none of the coefficients of the four age groups are significant for telecommuters, which indicates that different age groups do not have significant impacts on telecommuters' decision on making trips. In addition, both telecommuters and commuters who attained a bachelor's degree or above are more likely to leave home and make trips compared to people who have less than a bachelor's degree. Telecommuters who work as part-time workers are more likely to leave home and make trips compared to their non-part-time worker counterparts. Nevertheless, the situation is opposite for commuters. In terms of travel day (survey day), commuters are found more likely to leave home and make trips during weekdays as opposed to weekends. Meanwhile, commuters are most likely to stay at home during Sundays. When it comes to telecommuters, we do not observe the same trend and most of the coefficients are not significant indicating that telecommuters' decision on making trips largely do not affect by the day of the week. This is reasonable as we discussed before that telecommuters do not need to commute to work resulting a flexible daily schedule.

We turn now to the effects of household characteristics on telecommuters' and commuters' decision on making trips. In general, higher-income commuters are more likely to make trips compared to lower-income commuters. Telecommuters with annual household income more than $200k are most likely to make trips compared to the other telecommuters with lower household income. As expected, both telecommuters or commuters that live in urban areas are more likely to leave home and make trips compared to people living in rural areas (presumably due to higher accessibility to opportunities but we turn to this in the conclusions). The effect of household structure indicates that compared to two-retiree households, telecommuters or commuters from a household with one adult and people under 21 are most likely to make trips, which is reasonable because they need to run errands for the younger members of their households. We also find that regardless of being telecommuters or commuters, single non-retired persons, and people from a household with two or more adults with people under 21 are more likely to leave home and make trips compared to two-retiree households. The differences between telecommuters and commuters are that telecommuters from a household with two adults are as likely as telecommuters from two-retiree households to make trips; however, commuters from a household with two adults are more likely to make trips compared to two-retiree households. Similarly, single retirees working as telecommuters are more likely to make trips compared to two-retiree households; while there is no significant difference between commuters from single-retiree households and commuters from two-retiree households in terms of the propensity of making trips. The findings here point to the need for more in-depth household structure and task allocation information to tease out the motivation underlying the behavior described above.

Table 8. Estimated parameters of binary logistic regression models for telecommuters and commuters

Variables	Model 1: Telecommuter		Model 2: Commuter	
	Estimate	**z-value**	**Estimate**	**z-value**
Individual characteristics				
Age (base: Under 26)				
26-35	0.262	1.039	0.268	2.716***
36-50	0.197	0.834	0.334	3.564***
51-65	0.369	1.585	0.297	3.271***
Above 65	0.222	0.901	0.397	3.064***
Education attainment (base: Below bachelor's degree)				
Some college or associate's degrees	0.118	0.860	0.077	1.024
Bachelor's degree or above	0.505	3.829***	0.350	4.602***
Part-time or full-time employee (base: Non-part-time employee)				
Part-time employee	0.237	2.635***	-0.115	-1.726*
Travel day (base: Sunday)				
Monday	-0.054	-0.36	0.972	10.847***
Tuesday	0.305	1.926*	1.363	13.525***
Wednesday	0.023	0.154	1.291	13.118***
Thursday	0.372	2.430**	1.281	13.115***
Friday	0.012	0.084	1.184	12.484***
Saturday	0.151	1.001	0.165	2.234**
Household characteristics				
Household annual income (base: Less than $24,999)				
$25,000 to $99,999	0.187	1.443	0.200	2.337**
$100,000 to $199,999	0.128	0.925	0.284	3.046***
$200,000 or more	0.518	3.085***	0.283	2.449**
Household structure (base: 2+ adults, retired)				
1 adult	0.734	4.591***	0.481	4.590***
2+ adults	0.052	0.458	0.273	3.252***
1 adult, retired	0.717	2.113**	0.108	0.317
1 adult with people under 21	0.901	2.839***	0.584	3.301***
2+ adults with people under 21	0.484	3.484***	0.376	4.186***
Residential setting (base: Rural)				
Urban	0.471	4.278***	0.293	3.642***
Constant	-0.163	-0.534	0.398	2.498**
Model statistics				
Number of observations	4168		20280	
Log-likelihood Restricted	-1976.5		-5790.6	
Log-likelihood Unrestricted	-1911.3		-5476.6	
Log-likelihood Ratio	130.4***(df=22)		627.96***(df=22)	
McFadden's Pseudo R^2	0.033		0.054	

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Conclusions in the first part of analysis

In this research project we show that using motif and sequence analysis in combination provides more insights on differences and commonalities between telecommuters and usual commuters. This research proposes to add these new methods in the toolbox of travel behavior analysis. In terms of substantive findings, we see here that telecommuters are by far more diverse in their time of day allocation of time to places, activities, and travel. First approximately 20% of the telecommuters stay at home all day during a workday, while only 8% of the commuters do the same. Telecommuters that have at least a trip during their workday travel more (in VMT and trips) than their counterpart commuters but travel less driving alone. In addition, telecommuters have by far greater variety in their motifs with more complex tour formation and a distinct time of day allocation to activities and travel from the commuters. Within telecommuters and commuters, however, we have substantial variation in activity participation and travel. Commuters show a substantial proportion in a routine morning and afternoon peaks of arriving at and departing from work. In addition, telecommuters do not perform work tasks only from home. Instead, during a day they visit a variety of locations to visit customers and/or using their spatio-temporal flexibility to perform work tasks anywhere they want. In addition, a higher proportion of telecommuters function as the designated driver escorting other people to their activity locations.

In the comparison between people that stay at the same place (mostly home) all day and people that make at least a trip, we find that telecommuters and commuters who have higher educational attainment (bachelor's degree or above), higher household income, living in urban areas, or living with people younger than 21 are less likely to be homebound. Commuters under 26 years old are least likely to leave home and make trips compared to the other age groups, while age group membership does not significantly impact telecommuters' decision of leaving home on the interview day. The bottom line is that commuters are more likely to make trips on weekdays and stay at home on weekends, while telecommuters do not have such constraints and are more flexible.

Understanding Senior Residents Daily Patterns

In the previous chapter we showed that older individuals in senior working positions tend to have higher flexibility in their work arrangements and in telecommuting. In this second p[art of the analysis of this project we explore in more detail senior (60 years and older) daily patterns using motif analysis. Our motivation to select this group stems from the size of this segment (also named the baby boomers) with global population aged 60 or over of about 962 million in 2017 and will most likely double by 2050 reaching nearly 2.1 billion (United Nations, 2017). According to the 2017 National Population Projections from the U.S. Census Bureau (U.S. Census Bureau, 2017), the number of Americans ages 65 and older is projected to nearly double from 49 million in 2016 to 95 million by 2060, and the share of the total population will rise from about 15 percent to nearly one-quarter of the total population. In California, seniors older than 60 years in 2010 were approximately 16% of the population, this is currently estimated to be approximately 21.5% (8.6 million persons) and expected to increase to more than 30% in the next 40 years[2]. In addition, seniors in the U.S. have a great dependency on the automobile (Rosenbloom, 2001) and a substantial proportion of them do not cease driving until reaching 80 years of age (Alsnih and Hensher, 2003).

Population ageing and the corresponding increasing number of older drivers pose new challenges to transportation design and transport policy development. Older people have significantly different travel behavior characteristics compared to their younger counterparts, and the seniors of today are significantly different in their behavior than they were in the past (Goulias et al., 2007). For example, existing studies show that in general, the majority of seniors no longer need to commute to work and their daily trips are mostly for leisure and running errands (Choo et al., 2016; Hjorthol et al., 2010; Pettersson and Schmöcker, 2010; Schwanen et al., 2001). In addition to trip purposes, numerous studies have been focused on investigating travel distance, travel frequency, as well as the mode choice among the seniors. Previous studies have confirmed that seniors travel relatively short distances and with lower frequency compared to younger people (Choo et al., 2016; Collia et al., 2003; Szeto et al., 2017). However, the results are dissimilar in different settings due to cultural, policy, and infrastructure differences. For example, van den Berg et al. (2011) found no significant age effects on travel distance and time in the Netherlands. Elderly people have been found to rely less on public transport and more on the private car in many western countries (Alsnih and Hensher, 2003; Donaghy et al., 2004; Pettersson and Schmöcker, 2010; Rosenbloom, 2001; Tacken, 1998). The increasing dependency on the private car in North America led to researcher's attention to its impacts on road safety, road congestion, and environmental sustainability (Rosenbloom, 2001; Scott et al., 2009; Stamatiadis and Deacon, 1995). Previous studies found that older people tend to have higher accident rates (Burkhardt, 1999; Burkhardt and Mcgavock, 1999; Hildebrand, 2003) and produce more wasted VMT due to wayfinding errors and trip-scouting behaviors, hence creating more air pollution (Rosenbloom, 2001). However, many transit-oriented Asian countries present the opposite trend in terms of private car usage. For example, walking and public transit are the most popular travel modes for seniors in China, and the use

[2] http://www.dof.ca.gov/Forecasting/Demographics/Projections/

of private cars is less popular (Hu et al., 2013; Szeto et al., 2017; Zhang et al., 2019). Similarly, in Seoul, South Korea, compared to younger people, seniors tend to walk more and use public transit as the major travel mode and their car use decreases drastically as they reach 75 years of age (Choo et al., 2016).

Existing studies have primarily used two categories of variables including socio-demographic characteristics and built environment factors to explain the heterogeneity in senior's travel behaviors in terms of activity patterns, travel frequency, travel distance, and transport mode choices. Some widely used socio-demographic characteristics include age, sex, educational attainment, employment status, income level, household size and structure, and occupation category. An important issue in senior mobility studies is that there is substantial heterogeneity among different age groups of seniors. For example, Alsnih and Hensher (2003) found that the distinction between younger (65-75) and older (75+) elderly is useful because 75 is the threshold in which limitations due to health problems become more prominent. Moreover, age was found to be negatively associated with public transit usage in well-developed western countries (Pettersson and Schmöcker, 2010). In addition to the substantial difference among different age groups of seniors, previous literature also confirmed that female or unemployed elderly people make fewer and shorter trips than their male or employed counterparts (Newbold et al., 2005; Paez et al., 2007). Other findings include having a driver's license and access to a car being associated with higher trip frequencies for seniors (Paez et al., 2007), elderly with higher incomes are more likely to drive or carpool (Kim and Ulfarsson, 2004; Paez et al., 2007), and less educated seniors make more trips than more educated ones (Böcker et al., 2017). In terms of the household structure, it is reported that elderly from single-person households are more likely to use public transport (Hess, 2009). Seniors who live with others in small households tend to use less public transport and special transport services and make more trips (Golob and Hensher, 2007; Hess, 2009; Pettersson and Schmöcker, 2010).

An important aspect in the literature and our research report is understanding the effects of built environment factors on senior's travel behaviors. Some widely used variables for this understanding include population density, employment density, land use types, and accessibility to public transit surrounding the place of residence. It was found that seniors living in high population density areas tend to travel more frequently in Manila (Pettersson and Schmöcker, 2010). A study in London suggests that neighborhoods with a medium high population density are more likely to link trips and destinations together leading to more trip chaining (Schmöcker et al., 2010). Presumably because there is a good mix of land use types serving multiple functions in these areas compared to other areas. Another study conducted in Canada suggests that although a high commercial and residential land-use mix reduces trip distances, there is no significant effect of population density on trip distance (Mercado and Paez, 2009). In addition, elderly living in highly walkable neighborhoods are more likely to use active transportation modes including walking and cycling (Winters et al., 2015). In addition, bus stop density is more important than bus service frequency on the usage of public transportation for seniors (Su and Bell, 2009).

Existing studies have examined the effects of socio-demographic characteristics and built environment factors on senior's activity patterns, travel frequency, travel distance, and transport mode choices. To the best of our knowledge, there are no studies focusing on the relationships among daily visited locations as seniors execute their schedules, daily travel patterns, socio-demographic characteristics, and built environment factors. To capture the interconnection among daily visited locations as well as the heterogeneity in individual based daily travel patterns, recent studies have successfully applied the network-based approach of human mobility motif to investigate possibly recurring and distinct patterns in daily travel (Cao et al., 2019; Schneider et al., 2013; Su et al., 2020). Our previous study discovered that 16 unique motifs can capture 83.05% of the total population in the 2017 California component of the National Household Travel Survey (California-NHTS) workday sample (Su et al., 2020). In the study presented here, we adopt the same approach of human mobility motif to construct individual based daily mobility patterns for every senior respondent in the entire 2017 California-NHTS data. We then correlate these motifs with senior's individual-level and household-level characteristics, travel-related attributes as well as several built environment factors. Separating the analysis into workdays and non-workdays, we find significant differences in terms of the effects of explanatory variables on the propensity of using various motif patterns by seniors.

This chapter continues by first providing an introduction of the 2017 California-NHTS data used in this chapter. Then the composition of motifs and the correlation of motifs with senior's attributes and built environment variables are discussed in the next section. Finally, the chapter ends with conclusions and an outline of future work.

Data used in the second part of analysis

In this chapter, similarly to the previous chapter, we use the data of the California component of the 2017 National Household Travel Survey. In this study, we are interested in seniors aged 60 or above. They are 20,707 (37.1%) of the total 55,819 respondents in 2017 California-NHTS. To investigate the daily mobility patterns for seniors in California, we use the records of 10,833 seniors (from 8,034 households) on workdays and 4,577 seniors (from 3,399 households) on non-workdays. We separate workday and non-workday travel diaries because human mobility patterns have substantial differences between workdays and non-workdays (Jiang et al., 2012). The excluded 5,297 persons are seniors who stay at home during the assigned diary day and have no trips to report. Among them, 3,350 were recorded on workdays and 1,947 were on non-workdays, which indicates that a higher proportion of seniors do not make any trips on non-workdays (29.84%) as compared to workdays (23.62%). Exclusion from the motif analysis of seniors staying at home the entire diary day is explained later and complemented by a comparison between the excluded and the included seniors in a later section of this chapter.

Table 9 shows the descriptive statistics for the included sample of senior respondents in 2017 California NHTS. It is noticeable that there is no substantial difference between workdays and non-workdays in terms of the percentage of the composition for each attribute. Female seniors account for 52% of the total sample and 54% are between 60 to 69. It is worth mentioning that age was categorized into five finer groups in this study because of three major concerns. Firstly, different age groups have significant impact on senior's travel behaviors (e.g. Alsnih and Hensher, 2003; Hjorthol et al., 2010; Rosenbloom, 2001; Szeto et al., 2017; Zhang et al., 2019). Secondly, the age group of 75 years and above is characterized by lower income, lower car ownership rates and greater physical limitations than younger cohorts in the U.S. (Coughlin, 2001; Evans, 2001; Georggi and Pendyala, 2000; McKnight, 2000). Thirdly, a substantial proportion of people ceased driving once they reach 80 years of age because of declining physical and mental health (Burns, 1999; Foley et al., 2002; Skinner and Stearns, 1999). Almost 50% have bachelor's or more advanced degrees. In terms of employment status, about 30% are either full-time workers or part-time workers, 7% are homeworkers, and around 65% to 66% are retired. It is noteworthy that the sum of full-time, part-time and retired is lower than 100%, because some non-retired seniors do not have full-time or part-time jobs (e.g. persons in home duties). The percentage distribution of different household annual income levels shows that more than 50% of the seniors come from a household with $25,000 to $99,999 annual income. In addition, more than 50% of the seniors are from households with two or more retirees, 18% are from single retiree households, 8% are from single-person households, 15% are from households with two or more adults, and less than 5% are living with people younger than 21. In terms of the residential place type, approximately 75% live in suburban neighborhoods, 20% live in rural areas, and only 5% live in urban environments. The residential settings are retrieved by spatial joining each household's home location as well as their attributes with the built environment variables which are presented next.

To incorporate the interactions between senior daily mobility patterns and different built environment settings, we use a built environment dataset containing both community design and regional accessibility measures of 23,190 U.S. census blocks in California (CalTrans, 2020). The two categories of built environment measures reflect location efficiency and the fit between the physical environment and transportation system (CalTrans, 2020; Smart Mobility, 2010). As shown in Table 10, the community design measures include frequently studied elements of population density, employment density, diversity and design. The indicators of job accessibility via fixed rail transit and automobile are used to depict a neighborhood's regional accessibility. The spatial distributions of these built environment variables are shown in Figure 8. The definition of the five residential settings in Table 9 is based on the community design measures as well as the regional accessibility measures (see details in (CalTrans, 2020)). Figure 9 illustrates the spatial distribution of the five residential settings. The inset map of the Los Angeles (LA) area properly reflects the polycentric nature of LA.

Table 9. Descriptive statistics for senior respondents in 2017 California-NHTS

Variables	Subgroup	Workday (n=10833)	Non-workday (n=4577)
Individual characteristics			
Sex	Female	52.16%	52.13%
Age group	60-64	27.86%	28.23%
	65-69	27.07%	25.78%
	70-74	19.68%	19.64%
	75-79	12.15%	12.56%
	≥ 80	13.09%	13.59%
Education attainment	Below bachelor's degree	16.95%	17.0%
	Some college or associate's degree	33.12%	32.62%
	Bachelor's degree or above	49.76%	50.34%
Full-time or part-time	Full-time	18.47%	16.52%
	Part-time	11.84%	11.71%
Homeworker	Yes	7.66%	7.36%
	No	22.7%	20.89%
Job category	Sales or service	6.85%	6.6%
	Clerical or administrative support	3.62%	3.02%
	Manufacturing, construction, maintenance, farming	3.32%	3.54%
	Professional, managerial, or technical	16.45%	15.05%
Retired	Yes	65.39%	66.35%
Household-level characteristics			
Household income	Less than $24,999	14.04%	13.92%
	$25,000 to $99,999	53.09%	51.72%
	$100,000 to $199,999	22.4%	23.36%
	$200,000 or more	6.58%	6.53%
Household structure	One adult	8.23%	8.13%
	2+ adults	15.32%	14.59%
	One adult, retired	18.67%	18.77%
	2+ adults, retired	53.45%	54.27%
	One adult with people younger than 21	0.35%	0.22%
	2+ adults with people younger than 21	3.97%	4.02%
Categorical built environment variable			
Residential setting	Rural area	19.47%	20.26%
	Suburban neighborhood	75.47%	74.22%
	Urban neighborhood	3.58%	3.76%
	Urban district	1.11%	1.07%
	Urban core	0.36%	0.68%

Note: The percentage of the alternative option for some binary variables (i.e. sex, retired) are omitted. The total percentage of some variables is not 100% because the corresponding survey question does not apply to the senior respondent (e.g. the variable of homeworker is designed for seniors who still have work so it does not apply to the retired seniors) or very few of them refused to answer (usually below 1%).

Table 10. Descriptive statistics for continuous built environment variables

Variable	Definition	Workday				Non-workday			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Community design measures									
Population density	Number of persons per acre	7.30	9.17	0	178.67	7.44	9.71	0	178.67
Employment density	Number of jobs per acre	2.29	14.41	0	899.68	2.29	8.27	0	211
Single-family housing	Percent of single-family housing units in a census block	0.76	0.25	0	1	0.75	0.25	0	1
Intersection density	Street intersections per square mile	64.69	57.82	0	990.40	65.15	60.33	0	679.45
Regional accessibility measures									
Transit access to jobs	Proportion of jobs within 0.5 mile of fixed rail transit to the total number of jobs in a census block	0.04	0.16	0	1	0.04	0.17	0	1
Auto access to jobs	Number of jobs within 45 minutes via auto travel time (unit:1k)	106.99	137.20	0.01	874.50	109.37	140.94	0	859.44

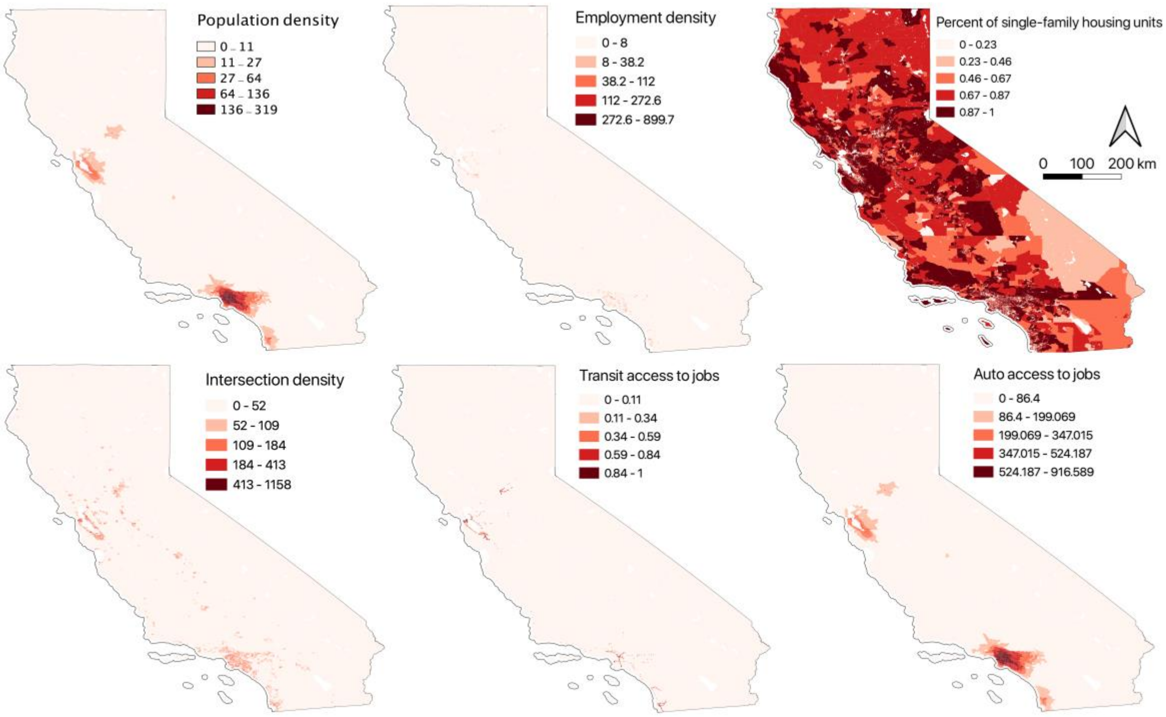


Figure 8. Spatial distribution of the built environment variables in California (see Table 10 the unit and definition of each variable)

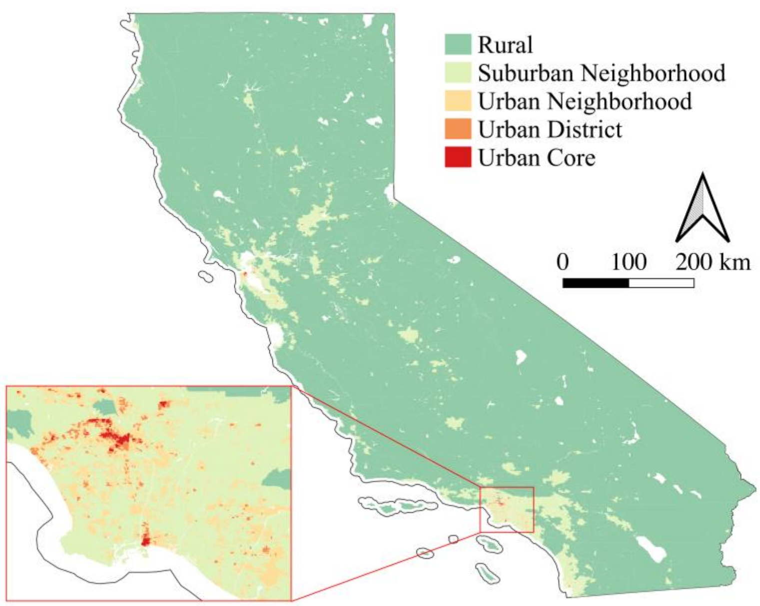


Figure 9. Spatial distribution of five categories of residential settings in California

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Methodology in the second part of analysis

In this section, we use the same method of developing motifs as in the previous chapter and define sequences and their complexity as in the previous chapter. We have however a few added indicators that will be used in the statistical modeling analysis later, including five time-based behavioral indicators and a measurement of heterogeneity in transport mode choices. We will also estimate two multinomial logit models (MNL) for workday and non-workday data respectively to understand the correlation of various motif patterns with seniors' socio-demographic characteristics, travel-related attributes as well as built environment factors and to make a comparison between workdays and non-workdays.

In this chapter, we use five time-based behavioral indicators including Time at Work, Time Outside Home, Time Traveling, Travel Time Ratio, and Complexity to depict the characteristics of time allocation patterns in activities and travel. To begin with, Time at work is the amount of time spent on work-related activities. Time outside home includes all of the time spent outside home (including both traveling and activities). Time traveling is the amount of time spent traveling. Travel Time Ratio (TTR) was defined by Dijst and Vidakovic (2000) as the ratio of the total travel time and the sum of the total time in activities outside the home plus the total travel time. A higher TTR indicates a higher proportion of time outside of the home spent traveling.

Differences in the composition of motifs between workdays and non-workdays for seniors

Analysis of the senior respondents in 2017 California-NHTS shows 413 distinct motifs on workdays and 178 distinct motifs on non-workdays. On average, seniors visited 3.69 locations on workdays (std=1.75) and 3.40 locations on non-workdays (std=1.58). Among these motifs, only 14 motifs on workdays are above 1%, as well as for non-workdays. However, the 14 motifs are not completely identical between workdays and non-workdays. To enable the comparison between workdays and non-workdays patterns, we retain the union of the two sets of motifs of workdays and non-workdays. Figure 10 enumerates the union sets of motifs of workdays and non-workdays, which comprises 15 unique motifs and their respective percentage. It is noteworthy that motif 1 represents a single location-based daily mobility pattern with loop trips. The location types of the single node in motif 1 are mostly home (98.4% and 93% are home for workdays and non-workdays respectively) implying that seniors using motif 1 are staying at home and making home-based loop trips such as walking the dog and jogging. The 15 motifs are separated by vertical dashed lines based on the number of nodes and ordered by their sample frequency. The 15 motifs can capture 82.17% and 86% of the total senior respondents on workdays and non-workdays, respectively. Notice that each of the rest of the motifs not shown in Fig.3 were found in less than 1% of the total observations on workdays as well as on non-workdays, and they are analyzed as a group in this section. When comparing the percentage distribution of 15 most frequent motifs between workdays and non-workdays, we observe that non-workday has slightly higher percentages in motifs 1, 2, 3, 4, 5, 6 and slightly lower percentages in the rest of the motifs in Figure 10. This indicates that seniors are more concentrated in simple motifs with three or fewer nodes on non-workdays while they complete more complex motifs during workdays. Overall, we find that given 65% of the included seniors are retired, a large number of them present diverse and complex daily mobility patterns instead of staying at home all day.

Compared with our previous study using the entire 2017 California-NHTS observations (Su et al., 2020), a noticeable difference is that we find 30% of the total population use motif 2 while only 25% of the seniors use it on workdays. Presumably because 65% of the included seniors from the workday sample are retirees and many of them are less constrained by a fixed workplace. We verify this statement by computing the percentage of work-related trips over the total number of trips made by persons using motif 2. The results show that only 23.22% of trips made by seniors belonging to motif 2 are work-related while the percentage is 36.72% for the whole California-NHTS workday sample. The rest of the motifs in Figure 10 have very similar percentages to the ones in our previous analysis using all the observations in the 2017 California-NHTS (Su et al., 2020), which again confirms a substantial heterogeneity in daily mobility patterns among Californian seniors.

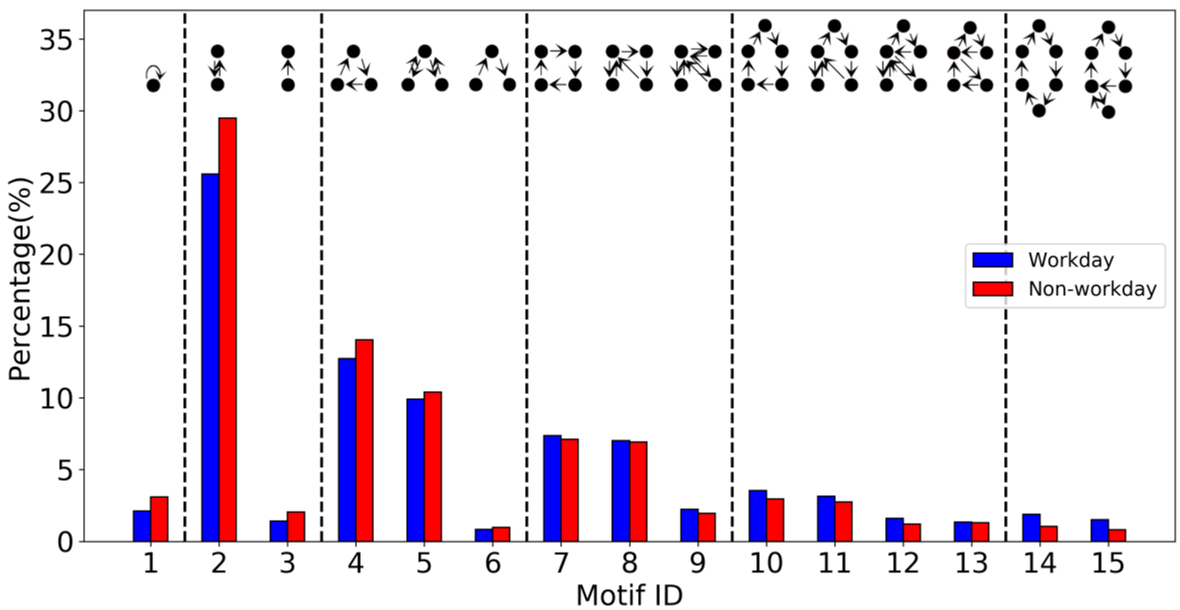

Figure 10. Percentage of seniors' mobility motif patterns on workdays vs. non-workdays

In the rest of this section, we create several tabulations for the 15 motifs as well as one category including all other motifs on workdays and non-workdays to explore heterogeneity in time-based behavioral indicators, senior's characteristics, and travel mode choices across different motifs. Table 11 shows the average of each of the five time-based behavioral indicators introduced in the previous as well as the population size and the percentage over the total population of each motif. A few major trends can be observed in Table 11. In general, as the motif structure becomes more complex from motif 1 to motif 15 and later to all other motifs, the complexity indicator increases gradually. This is as expected because people tend to participate in different activities when they visit different places. In addition, seniors spend longer time at work on workdays compared to non-workdays for most of the motifs. Seniors using motif 3 and motif 6 have the longest time outside home and traveling. These two motifs are special as they contain only unidirectional edges. In other words, these two motifs identify people who left home and did not come back at the end of the survey day (e.g., for long distance travel with overnight stays outside home). Furthermore, motif 1 has the highest travel time ratio not only on workdays but on non-workdays too. Overall, except for the indicator of time at work, the indicators are very similar across different motifs between workdays and non-workdays.

Table 11. Motifs and time-based behavioral indicators on workdays vs. non-workdays (including size and sample percentage of motif membership)

Motif	Complexity		Time at Work		Time outside Home		Time Traveling		Travel Time Ratio		Person in Sample		Percent in Sample	
	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday
1	0.011	0.012	0.4	8	165.7	212.5	71.6	84.5	0.886	0.87	229	142	2.1%	3.1%
2	0.022	0.021	146.5	40.4	320.8	259	56.8	49.6	0.307	0.324	2773	1350	25.6%	29.5%
3	0.017	0.019	198.9	53.5	837.5	816.9	155.2	156	0.296	0.276	152	93	1.4%	2.0%
4	0.029	0.029	99.6	36.3	333.1	291.2	74.1	71.1	0.323	0.314	1380	642	12.7%	14.0%
5	0.037	0.037	118.9	41.6	376.3	352.2	85.5	87.8	0.311	0.314	1073	476	9.9%	10.4%
6	0.029	0.03	104.9	34.9	860.6	862.4	231.4	212.2	0.307	0.297	89	44	0.8%	1.0%
7	0.036	0.036	79.0	13.4	347.5	315.4	89.8	93.8	0.338	0.345	798	325	7.4%	7.1%
8	0.044	0.043	95.9	16.1	391.1	378.7	101.7	104.1	0.320	0.32	759	317	7.0%	6.9%
9	0.049	0.049	61.1	9.3	397.5	341.6	99.6	102.1	0.314	0.338	242	89	2.2%	1.9%
10	0.043	0.044	56.7	29.3	350.1	355.9	110.0	103.6	0.352	0.315	383	135	3.5%	2.9%
11	0.050	0.049	84.3	7.5	406.6	371.4	113.9	110.1	0.333	0.328	340	125	3.1%	2.7%
12	0.055	0.054	49.5	13.6	401.8	353.7	116.5	110.1	0.331	0.344	172	55	1.6%	1.2%
13	0.051	0.052	78.4	18.1	424.2	408.2	115.3	131.9	0.323	0.332	146	59	1.3%	1.3%
14	0.048	0.052	39.1	24.8	373.2	415.1	116.4	138.2	0.345	0.354	204	47	1.9%	1.0%
15	0.056	0.055	59.5	24.6	412.2	409.8	116.3	124.5	0.313	0.349	162	37	1.5%	0.8%
All other	0.060	0.058	87.8	33.3	524.3	549.5	169.3	181	0.364	0.365	1931	641	17.8%	14.0%

Note: Time is measured in minutes per day. The values of complexity, time at work, time outside home, time traveling, and travel time ratio are the average values of groups of people belonging to each motif. The background color in a gradient is according to the data in each two columns of workday and non-workday of each behavioral indicator. The background color of person in sample and percent in sample in a gradient is according to the data in each column.

Table 12 shows senior respondents' characteristics on average for each motif on workdays and non-workdays. We see a few major trends by comparing the percentage of each variable across different motifs and day types. First of all, it is reported in our previous research using the entire 2017 California-NHTS that women tend to have more complex motifs than men (Su et al., 2020); however, this trend is not observed in senior respondents. Presumably, many female seniors do not have the same household responsibilities as their younger counterparts. We will verify this point in a later section with a statistical modelling approach. In addition, a substantially higher percentage of female seniors tend to use motifs 3, 6, and 15 on non-workdays compared to workdays. Homeworkers (aka telecommuters) only account for a small percentage of the total population in each motif. Among them, motifs 6 and 12 have relatively higher percentages of homeworkers on workdays as well as on non-workdays, and so does motif 14 on non-workdays. Full-time employees are concentrated in motifs 2, 3, and 5 on workdays and motifs 3, 9, 13, 14 on non-workdays. The percentage of part-time workers of each motif is quite evenly distributed on workdays but fluctuates on non-workdays. It is noteworthy that travelling on non-workdays usually has nothing to do with people's occupation, especially among seniors as they are less constrained by work. Presumably, this could explain the different percentage distributions of part-time and full-time employees. The retired respondents show that simple motifs (motifs 1, 2, 3, and 5) on workdays have lower percentages of retirees compared to non-workdays; while in general, more complex motifs on workdays have higher percentages of retirees compared to non-workdays. This tells us that in general, retirees tend to use complex motifs (i.e. diverse mobility patterns) on workdays and simple motifs on non-workdays.

Table **12.** Motifs and senior respondents' characteristics on workdays vs. non-workdays

Motif	Woman		Homeworker		Full-time Employee		Part-time Employee		Retired	
	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday
1	57.21%	47.89%	8.73%	6.34%	6.55%	6.34%	4.80%	7.75%	79.48%	80.28%
2	50.31%	52.45%	6.82%	6.61%	23.64%	15.16%	11.26%	10.92%	59.76%	68.35%
3	41.45%	56.99%	7.89%	7.53%	25.66%	24.73%	12.50%	6.45%	54.61%	63.44%
4	53.33%	52.65%	7.03%	7.17%	15.58%	15.11%	12.03%	11.84%	67.61%	66.98%
5	47.16%	49.68%	7.92%	6.32%	21.53%	13.47%	11.93%	12.63%	64.31%	68.84%
6	43.82%	63.64%	11.24%	11.36%	16.85%	18.18%	11.24%	27.27%	66.29%	50.00%
7	60.03%	56.00%	6.39%	7.69%	14.41%	14.46%	10.53%	16.00%	68.05%	65.85%
8	53.44%	48.90%	8.47%	7.57%	17.86%	18.61%	13.10%	10.41%	66.53%	64.67%
9	44.63%	47.19%	8.26%	6.74%	13.64%	24.72%	9.50%	7.87%	73.55%	62.92%
10	60.31%	52.99%	5.22%	6.72%	8.88%	16.42%	10.18%	14.18%	77.02%	66.42%
11	55.88%	52.00%	6.47%	9.60%	15.59%	18.40%	12.65%	9.60%	67.94%	69.60%
12	48.84%	45.45%	11.05%	12.73%	13.95%	20.00%	13.37%	16.36%	71.51%	60.00%
13	57.53%	52.54%	4.79%	5.08%	16.44%	27.12%	13.01%	5.08%	65.75%	54.24%
14	58.33%	52.38%	8.33%	11.90%	10.29%	21.43%	13.24%	9.52%	73.04%	61.90%
15	48.15%	59.46%	8.64%	8.11%	13.58%	16.22%	15.43%	18.92%	70.99%	56.76%
All other	51.92%	52.57%	9.49%	8.62%	19.19%	20.90%	13.23%	12.27%	64.37%	61.53%

Note: The background color in a gradient is according to the data in each two columns of workday and non-workday of each variable.

Table 13 presents the percentage distribution of different age groups of seniors in each motif on workdays and non-workdays. We divide the senior respondents into five age groups (see introduction to this chapter for explanation). In general, the percentages of different age groups are quite spread-out across the 15 motifs and the one category with all the other motifs. Surprisingly, seniors aged 75 and over do not just stay at home all day but follow diverse daily mobility patterns on both workdays and on non-workdays. In addition, motif 1 has a relatively low percentage of seniors in the 60 to 64 age group and has the highest percentage of 80 plus age group compared to other motifs. This is reasonable because many people aged between 60 to 64 are still in the labor force, so they are less likely to stay at home all day. Second, as seniors age, especially for the 80 plus age group, the accessibility of different travel modes becomes lower (e.g. due to difficulty walking), often resulting in decreased opportunities to socially connect with others (Alsnih and Hensher, 2003; Rosenbloom, 2001; Tacken, 1998; van den Berg et al., 2011). We also observe some trends by comparing workdays with non-workdays. For example, the unpopular motifs for the 60 to 64 age group on workdays, that is motifs 10, 12, and 14, are much more popular ones on non-workdays, as we can observe a substantial increase in their percentages. Similarly, as for 65 to 69 age group, motifs 9, 10, 13, 14, and 15 are less popular on workdays compared to on non-workdays. Seniors in 70 to 74 age group are more concentrated in simple motifs 1, 3, 4, and 6 on non-workdays and in complex motifs 12, 13, and 14 on workdays. Seniors between 75 to 79 years old are more concentrated in motifs 3, 6, 7, 10, 13, and 14 on workdays and in complex motifs 11 and 15 on non-workdays. It is noteworthy that the same motif structure on workdays and non-workdays, contain embedded destination choices that can be strikingly different. For example, 23.22% of the trips in motif 2 are related to work on a workday while only 6.79% are work-related on a non-workday. We will dive into the heterogeneity in the embedded destination choices in motifs in the next section.

Table 13. Percentages of different age groups of seniors in each motif on workdays vs. non-workdays

Motif	60 to 64		65 to 69		70 to 74		75 to 79		80+	
	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday
1	17.90%	17.61%	25.33%	21.83%	19.21%	24.65%	13.10%	14.79%	24.45%	21.13%
2	29.63%	26.45%	26.56%	23.77%	18.01%	19.32%	10.90%	13.67%	14.76%	16.57%
3	30.26%	33.33%	19.74%	20.43%	19.74%	24.73%	18.42%	13.98%	10.53%	7.53%
4	25.94%	26.32%	26.01%	24.92%	17.39%	24.14%	13.62%	9.81%	16.81%	14.49%
5	29.17%	29.05%	28.15%	26.32%	19.85%	17.05%	10.16%	13.05%	12.58%	14.11%
6	29.21%	25.00%	28.09%	29.55%	19.10%	29.55%	14.61%	9.09%	8.99%	6.82%
7	26.19%	30.46%	23.43%	24.62%	21.30%	17.54%	15.16%	10.15%	13.91%	16.92%
8	30.29%	31.23%	26.59%	26.50%	21.03%	20.19%	12.57%	11.99%	9.26%	10.09%
9	26.03%	22.47%	26.86%	32.58%	20.66%	22.47%	13.22%	13.48%	13.22%	8.99%
10	17.75%	24.63%	26.89%	32.09%	22.98%	20.90%	17.23%	12.69%	15.14%	9.70%
11	26.76%	24.00%	26.47%	23.20%	20.59%	20.80%	11.76%	19.20%	14.12%	12.80%
12	25.58%	40.00%	31.40%	23.64%	21.51%	12.73%	12.79%	14.55%	8.72%	9.09%
13	28.77%	32.20%	24.66%	33.90%	21.23%	15.25%	13.70%	8.47%	10.96%	10.17%
14	22.06%	32.14%	27.94%	34.52%	25.00%	14.29%	14.71%	8.33%	10.29%	10.71%
15	30.86%	21.62%	20.99%	32.43%	22.22%	24.32%	11.73%	16.22%	14.20%	5.41%
All other	29.56%	33.67%	30.76%	28.52%	20.44%	16.42%	10.43%	12.44%	8.71%	8.79%

Note: The background color in a gradient is according to the data in each two columns of workday and non-workday of each variable.

Table 14 shows the percentage distribution of seven travel modes across 15 distinct motifs plus one category with all other motifs on workdays and non-workdays. Following the NHTS codebook, the travel mode choice consists of seven modes including walk, bike, transit, car as passenger, drive alone, drive someone else, and one category noted as "other mode" that contains all other modes. The percentage of each mode is the group average ratio of the number of trips by that mode and the total number of trips a person made in a day. Accordingly, the percentage values of the seven modes for each motif sum up to 1. We see a few trends in Table 14. Walking is the most popular mode for seniors using motif 1 on workdays (94.54%) as well as on non-workdays (89.91%). In addition, seniors using complex motifs have a very low percentage of walk trips in a day. Biking and taking transit both account for an extremely small portion of trips among California seniors no matter what motifs they used (both below 3.5%). In general, driving alone is the most preferred mode among seniors on both workdays and non-workdays. We can also observe that seniors tend to drive alone more on workdays than non-workdays, and accordingly, they tend to have more carpooling trips on non-workdays compared to workdays. In terms of the Gini index of mode choice, we observe that motifs comprising only one tour (i.e., motifs 1, 2, 3, 4, 6, 7, 10, 14) have very low Gini which indicates single mode choice. On the other hand, motifs with two or more tours (i.e. motifs 5, 8, 9, 11, 12, 13, 15) present higher Gini indicating mixed mode choice. This is consistent with people's travel behavior when daily trips are connected by multiple tours (e.g. adding a walk tour during lunch time in a daily pattern that includes a major work tour served by driving alone).

Table 14. Motifs and senior respondents' travel mode choice and Gini index on workdays vs. non-workdays

Motif	Walk		Bike		Transit		Passenger		Drive Alone		Drive Someone Else		Other Mode		Gini	
	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday	Workday	Non-workday
1	94.54%	89.91%	1.53%	3.40%	0.00%	0.00%	0.66%	2.82%	1.75%	0.70%	1.53%	3.17%	0.00%	0.00%	0.007	0.010
2	10.21%	11.53%	0.81%	0.39%	3.15%	1.55%	16.71%	24.47%	55.62%	42.21%	13.06%	19.34%	0.46%	0.52%	0.056	0.039
3	9.21%	6.09%	0.66%	0.00%	0.66%	1.08%	26.64%	36.38%	40.46%	34.41%	22.37%	20.97%	0.00%	1.08%	0.007	0.026
4	6.77%	6.22%	0.63%	0.26%	2.53%	1.25%	17.93%	26.23%	55.47%	41.09%	16.48%	24.94%	0.19%	0.00%	0.080	0.066
5	13.60%	14.95%	0.99%	1.26%	1.84%	0.79%	13.51%	20.04%	51.78%	36.55%	18.14%	26.42%	0.14%	0.00%	0.267	0.293
6	2.43%	2.27%	0.00%	0.00%	3.37%	2.27%	29.96%	27.27%	32.77%	39.77%	31.46%	28.41%	0.00%	0.00%	0.038	0.057
7	5.36%	5.05%	1.17%	0.54%	1.19%	0.75%	18.59%	29.92%	54.76%	34.93%	18.94%	28.81%	0.00%	0.00%	0.083	0.081
8	10.95%	11.73%	1.14%	1.89%	1.49%	1.89%	13.47%	18.38%	51.93%	38.16%	20.62%	27.94%	0.39%	0.00%	0.268	0.268
9	14.50%	21.45%	0.92%	1.12%	0.49%	1.12%	9.67%	17.48%	55.85%	37.40%	18.42%	21.05%	0.14%	0.37%	0.350	0.360
10	5.82%	3.67%	0.30%	0.12%	1.41%	2.54%	18.47%	18.26%	51.25%	42.75%	22.59%	32.51%	0.16%	0.15%	0.107	0.081
11	9.91%	13.81%	1.32%	0.80%	1.36%	1.16%	12.01%	22.53%	53.29%	34.06%	21.80%	26.97%	0.33%	0.67%	0.264	0.281
12	16.58%	10.80%	1.56%	2.34%	1.16%	0.52%	11.92%	17.92%	48.53%	43.42%	20.24%	25.00%	0.00%	0.00%	0.353	0.351
13	8.40%	6.73%	1.03%	2.57%	0.57%	0.00%	13.29%	20.42%	49.92%	31.61%	26.34%	38.67%	0.46%	0.00%	0.270	0.269
14	4.87%	8.62%	0.22%	1.70%	1.14%	1.33%	12.52%	20.15%	62.34%	41.45%	18.90%	26.76%	0.00%	0.00%	0.104	0.185
15	11.10%	16.81%	0.88%	0.77%	1.15%	1.54%	14.66%	20.94%	50.47%	36.13%	21.65%	23.42%	0.09%	0.39%	0.282	0.302
All other	9.46%	8.11%	1.10%	0.26%	0.70%	0.69%	14.26%	23.23%	49.37%	35.50%	24.72%	32.05%	0.38%	0.18%	0.293	0.255

Note: The first 14 columns (all except the two Gini columns) are the group average percentages of each mode used on the survey day. The percentage values of the seven modes in each row for workday as well as non-workday add up to 1.

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Correlation of motifs with senior attributes including work at home and the built environment

The analysis above reveals aspects of homogeneity as well as heterogeneity among seniors in terms of time-based behavioral indicators, socio-demographic characteristics, and travel mode choices across different motifs between workdays and non-workdays. We further estimate two MNL models for workday and non-workday samples respectively to explore the differences in the correlation of motifs with senior's attributes and built environment factors between workdays and non-workdays. Table 15, Parts A-D summarizes the results of the estimated MNL models. We separate the explanatory variables into four groups comprising individual characteristics, household characteristics, travel-related variables, and built environment variables. Following Su et al. (2020), motifs are merged into five groups based on the number of nodes (i.e. number of distinct locations visited in the survey day) as some motifs only include an extremely small percentage of the total population. Thereafter, we have Group I motifs consisting of motif 1, which represents the single location based loop-trip pattern, Group II motifs comprising motifs 2 and 3 with two visited locations, Group III motifs including motifs 4, 5, 6 and other less frequent but legitimate motifs with three nodes, Group IV motifs including motifs 7, 8, 9 and other less frequent but legitimate motifs with four nodes, and Group V motifs consisting of all the other motifs not included in previous four groups. The five motifs groups are then used as the categorical dependent variable in the MNL model with the motif Group I used as the reference category. The final specification of the MNL models was obtained by a systematic process of eliminating insignificant variables and the selection of the explanatory variables was guided by previous related literature, data availability, parsimony and intuitive considerations.

Effects of individual characteristics

As shown in Table 15 Part A, among the set of individual socio-demographic variables, we exclude the variables of sex and education attainment because their coefficients are not significantly different from zero. This indicates that female seniors are equally as likely as male seniors to use the five motif Groups on either workdays or non-workdays. In addition, different levels of education attainment do not significantly impact senior daily mobility patterns. In terms of the age group, we use seniors aged 80 and over as the base case. The results indicate that compared to seniors older than 80, there is no significant difference in the propensity of using the five groups of motifs on workdays for seniors in 60 to 64, and they are most likely to use motif Group V on non-workdays. The 65 to 69 age group tends to use motif Group II and is least likely to use motif Group I on workdays. There is no significant difference between the 65 to 69 age group and the above 80 age group during non-workdays in terms of the propensity for using the five groups of motifs. The 70 to 74 age group tends to use motif Groups II and III on non-workdays compared to seniors aged 80 and above. However, there is no significant difference between the 70 to 74 age group and above 80 age group during workdays. Similarly, seniors between 75 to 79 are equally likely to use the five motif Groups on both workdays and non-workdays compared to seniors aged 80 and above. The above findings indicate that older seniors are not necessarily less mobile than their younger seniors' counterparts. Instead, older seniors travel actively and present complex daily mobility patterns.

In terms of seniors' work status, compared to non-part-time employees, part-time employees are most likely to use the complex motif Group V followed by Groups III, II, IV, and I on workdays, and they were found equally likely to use the five motif Groups on non-workdays. Elderly homeworkers are less likely to leave home and visit other places on workdays than their non-homeworker counterparts and equally likely to have Group I motif as well as have other four motif Groups on non-workdays. Retirees are least likely to use motif Group II on workdays, which is reasonable because they do not need to commute to work. During non-workdays, they are found to be most likely to use the most complex motif Group V, followed by Groups IV, III, II, and I. Among the set of occupancy categories, the results indicate that compared to seniors who work in sales or service and all other industries, seniors whose job category is professional, managerial, or technical are most likely to use Group II motifs, and they are less likely to use more complex motif Groups IV and V on workdays. On the contrary, they tend to have motif Groups IV and V on non-workdays. Seniors doing clerical or administrative support work as well as manufacturing, construction, maintenance, and farming work are equally likely to have motif Groups I and II and less likely to use other more complex motifs on workdays. During non-workdays, the former group of seniors tend to leave home and have various mobility patterns as opposed to Group I motif. Seniors doing manufacturing, construction, maintenance, and farming work are more likely to use Groups II and IV on non-workdays.

Table 15 Part A. Estimated parameters of multinomial logit models for workday and non-workday

Variables	Model 1: Workday				Model 2: Non-workday			
	Group II	Group III	Group IV	Group V	Group II	Group III	Group IV	Group V
Individual characteristics								
Age group (base: above 80)								
60-64	0.31	0.211	0.324	0.059	0.665	0.718	0.558	0.887
	t = 1.457	t = 1.010	t = 1.513	t = 0.265	t = 1.421	t = 1.489	t = 1.115	t = 1.707*
65-69	0.459	0.367	0.388	0.384	0.384	0.284	0.085	0.322
	t = 2.332**	t = 1.891*	t = 1.931*	t = 1.840*	t = 0.864	t = 0.621	t = 0.180	t = 0.653
70-74	0.316	0.148	0.262	0.154	0.761	0.8	0.53	0.598
	t = 1.460	t = 0.687	t = 1.184	t = 0.674	t = 1.654*	t = 1.680*	t = 1.071	t = 1.162
75-79	0.102	0.115	0.371	0.318	0.623	0.245	0.084	0.417
	t = 0.420	t = 0.475	t = 1.492	t = 1.235	t = 1.219	t = 0.462	t = 0.152	t = 0.731
Part-time or full-time worker (base: non-part-time employee)								
Part-time employee	0.562	0.614	0.493	0.676	-0.901	-0.61	-0.805	-0.854
	t = 3.077***	t = 3.559***	t = 2.783***	t = 3.672***	t = -1.490	t = -0.992	t = -1.280	t = -1.336
Homeworker status (base: non-homeworker)								
Homeworker	-0.913	-0.631	-0.86	-1.137	0.25	0.216	0.218	0.287
	t = -4.652***	t = -3.434***	t = -4.491***	t = -5.658***	t = 0.385	t = 0.324	t = 0.318	t = 0.412
Retirement status (base: not retired)								
Retired	-0.548	-0.235	-0.076	-0.004	1.163	1.284	1.387	1.492
	t = -2.938***	t = -1.296	t = -0.406	t = -0.020	t = 3.102***	t = 3.379***	t = 3.505***	t = 3.624***
Occupancy (base: sales or service and all other)								
Professional, manage -rial, or technical	0.368	0.046	-0.279	-0.579	0.438	0.776	1.066	1.09
	t = 2.159**	t = 0.293	t = -1.737*	t = -3.389***	t = 0.868	t = 1.527	t = 2.052**	t = 2.064**
Clerical or administra -tive support	0.003	-0.475	-0.712	-1.046	1.934	1.594	1.994	1.97
	t = 0.019	t = -4.062***	t = -5.709***	t = -6.718***	t = 7.694***	t = 8.570***	t = 9.971***	t = 7.948***
Manufacturing, constr -uction, maintenance,	0.039	-0.723	-1.037	-0.924	0.852	0.44	0.884	0.302
Farming	t = 0.238	t = -5.440***	t = -7.220***	t = -5.544***	t = 1.848*	t = 0.944	t = 1.824*	t = 0.589

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Effects of household characteristics

Household annual income level and household structure are considered in our model specification. Table 15 Part B shows that compared to households earning $200k or more per year, seniors with household annual income less than $24,999 are more likely to use the most complex Group V than they are to use all other Groups on workdays. Seniors with household annual income between $25,000 and $99,999 are more likely to use motif Groups I, IV and V as opposed to Groups II and III on workdays. Seniors with household annual income between $100,000 to $199,999 are least likely to use Group II motifs as opposed to the other four motif groups on workdays. However, household income does not significantly impact seniors' daily mobility patterns on non-workdays.

The effect of household structure indicates that compared to two-retiree households, single non-retired seniors are most likely to use the Group I motif on workdays and travel actively and use the other four groups of motifs on non-workdays. In addition, there is no significant difference between single retired seniors and two-retiree households in terms of the propensity of using the five motif Groups. Compared to two-retiree households, seniors from households with two non-retired adults are least likely to use the most complex motif Group V on workdays and most likely to use Group II motifs on non-workdays. Single seniors who live with people younger than 21 are more likely to have motif Groups III, IV, or V than they are to stay at home or use motif Group II on workdays. However, they are equally likely to use the five groups of motifs on non-workdays. Seniors who live with other adults and people younger than 21 are the most mobile groups, and they tend to use all four groups of motifs more than Group I on workdays. During non-workdays, they are equally likely to use the five groups of motifs.

Table 15 Part B. Estimated parameters of multinomial logit models for workday and non-workday

Variables	Model 1: Workday				Model 2: Non-workday			
	Group II	Group III	Group IV	Group V	Group II	Group III	Group IV	Group V
Household characteristics								
Household annual income (base: $200,000 or more)								
Less than $24,999	-0.226	0.125	0.246	0.705	0.059	-0.301	0.198	0.055
	t = -1.128	t = 0.640	t = 1.211	t = 3.269***	t = 0.121	t = -0.602	t = 0.383	t = 0.102
$25,000 to $99,999	-0.602	-0.269	-0.244	-0.052	0.318	0.395	0.562	0.339
	t = -3.685***	t = -1.720*	t = -1.516	t = -0.308	t = 0.796	t = 0.963	t = 1.318	t = 0.776
$100,000 to $199,999	-0.375	-0.218	-0.143	-0.017	-0.089	-0.092	0.072	-0.211
	t = -1.932*	t = -1.167	t = -0.751	t = -0.084	t = -0.181	t = -0.182	t = 0.138	t = -0.396
Household structure (base: 2+ adults, retired)								
1 adult	-1.075	-0.939	-0.665	-0.54	1.586	1.547	1.622	1.378
	t = -5.572***	t = -5.349***	t = -3.705***	t = -2.815***	t = 2.939***	t = 2.887***	t = 2.986***	t = 2.475**
2+ adults	-0.081	-0.284	-0.289	-0.465	0.973	0.851	0.798	0.648
	t = -0.367	t = -1.325	t = -1.315	t = -2.027**	t = 1.799*	t = 1.570	t = 1.444	t = 1.149
1 adult, retired	0.004	0.136	0.265	0.217	0.09	0.258	-0.006	-0.034
	t = 0.017	t = 0.575	t = 1.088	t = 0.867	t = 0.211	t = 0.580	t = -0.014	t = -0.071
1 adult with people younger than 21	-0.439	0.769	1.657	0.996	-0.762	-0.56	0.703	1.188
	t = -0.798	t = 2.207**	t = 5.175***	t = 2.354**	t = -0.868	t = -0.869	t = 1.177	t = 1.633
2+ adults with people younger than 21	0.69	0.61	0.784	0.68	0.949	0.58	0.069	-0.123
	t = 4.941***	t = 5.601***	t = 6.902***	t = 4.831***	t = 1.417	t = 0.837	t = 0.095	t = -0.165

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Effects of travel related variables

As shown in Table 15 Part C, the next set of variables related to travel includes complexity of daily schedule, time at work, travel time ratio, composition of six travel modes in percentage, and Gini index of travel mode choice. The complexity indicator is transformed into four dummy variables according to the four quartiles of the population distribution of the value itself (noted as Complexity Q1, Complexity Q2, Complexity Q3, Complexity Q4). Consistent with our previous finding (Su et al., 2020), the coefficients of complexity present an increasing trend as the motifs become more complex, indicating a more complex daily schedule is more likely to be associated with a multi-stop motif for both workdays and non-workdays. The coefficient of minutes at work is only significant and negative for Groups IV and V on workdays, indicating that seniors spending more time at work are less likely to use Groups IV and V motifs. However, higher minutes at work increase the same likelihood of being in the other three motif groups on workdays. The coefficient of minutes at work on non-workdays are all significant and negative and present a decreasing trend of the coefficient as the motifs become more complex, implying that higher minutes at work is associated with simpler motifs on non-workdays. The coefficients of travel time ratio on workdays are all significant and negative and have an increasing trend indicating that seniors having higher travel time ratios are more likely to use complex motifs or motif Group I, which is consistent with the finding in Table 11 that Group I has the highest travel time ratio. This is reasonable because multi-stop motifs require more trips to connect the stops. During non-workdays, seniors having higher travel time ratios are less likely to use Groups II and III and equally likely to have the other three groups of motifs.

In terms of the travel mode choice, we can observe from Table 15 Part C that in general, walking and biking are less preferred for seniors using complex motifs on workdays as well as on non-workdays. Transit is more preferred for seniors who use motif Groups II and III on workdays, and for seniors who use motif Groups II, III and IV on non-workdays. Seniors who are passengers in cars more frequently on workdays are more likely to have Group III's motifs, followed by motif Groups V, IV, II, and I. However, during non-workdays, higher passenger trip ratio is associated with motif Groups III and IV. Seniors who use drive alone mode more frequently are more likely to follow more complex motifs Groups III, IV and V on workdays and Groups III and IV on non-workdays. The coefficient of drive someone else ratio presents similar trends as drive alone ratio. The only difference is that higher drive someone else ratio is more likely associated with motif Group I as opposed to Groups II and V on non-workdays. Presumably, seniors prefer not to carpool with others when they are going to a place and returning home or when they need to travel to five or more places. The coefficient of the Gini index shows that seniors using more diverse mode choice are most likely to follow motif Groups III either on workdays or non-workdays. These could be seniors who drive to a place, make a subtour to another place by walking, then drive home.

Table 15 Part C. Estimated parameters of multinomial logit models for workday and non-workday

Variables	Model 1: Workday				Model 2: Non-workday			
	Group II	Group III	Group IV	Group V	Group II	Group III	Group IV	Group V
Travel-related variables								
Complexity (base: Complexity Q1)								
Complexity Q2	0.104	2.063	3.797	5.606	1.173	3.061	5.36	6.998
	t = 0.350	t = 6.956***	t = 11.976***	t = 32.521***	t = 2.543**	t = 6.528***	t = 9.147***	t = 15.968***
Complexity Q3	-2.916	1.535	4.501	7.393	-0.196	4.119	7.539	10.504
	t = -21.269***	t = 14.340***	t = 34.489***	t = 44.480***	t = -0.256	t = 5.403***	t = 9.006***	t = 21.034***
Complexity Q4	-5.961	-0.698	4.293	9.193	0.192	4.263	9.578	14.33
	t = -22.410***	t = -4.735***	t = 26.937***	t = 53.593***	t = 0.696	t = 21.952***	t = 32.151***	t = 46.037***
Minutes at work	0.001	-0.001	-0.002	-0.004	-0.002	-0.004	-0.007	-0.007
	t = 1.310	t = -1.399	t = -2.831***	t = -4.092***	t = -1.678*	t = -2.748***	t = -4.435***	t = -4.551***
Travel time ratio	-4.633	-3.7	-2.176	-0.601	-4.201	-2.661	-0.626	0.738
	t = -23.759***	t = -19.148***	t = -10.393***	t = -2.570**	t = -8.724***	t = -5.172***	t = -1.122	t = 1.242
Walk ratio	-3.294	-2.699	-4.198	-4.365	-5.015	-1.574	-3.891	-7.993
	t = -16.702***	t = -12.766***	t = -17.429***	t = -16.465***	t = -15.181***	t = -4.187***	t = -9.245***	t = -17.295***
Bike ratio	-1.88	-0.8	-0.91	-1.168	-4.883	-0.564	-2.127	-6.154
	t = -6.829***	t = -3.373***	t = -4.196***	t = -4.106***	t = -8.512***	t = -0.985	t = -3.552***	t = -8.799***
Transit ratio	1.685	1.759	-0.928	-1.242	1.451	4.951	2.841	-1.25
	t = 8.197***	t = 10.277***	t = -4.235***	t = -4.497***	t = 3.796***	t = 15.579***	t = 8.408***	t = -2.815***
Passenger ratio	0.799	2.247	1.501	1.73	-1.217	3.339	1.479	-1.855
	t = 6.428***	t = 19.734***	t = 12.766***	t = 12.718***	t = -2.417**	t = 6.488***	t = 2.790***	t = -3.416***
Drive alone ratio	0.272	1.826	1.106	1.553	0.811	5.554	4.004	1.042
	t = 1.191	t = 8.034***	t = 4.740***	t = 6.483***	t = 1.606	t = 11.391***	t = 8.253***	t = 2.143**
Drive someone else ratio	0.416	1.982	1.17	1.424	-1.732	2.982	1.179	-2.027
	t = 2.331**	t = 11.644***	t = 6.791***	t = 7.738***	t = -3.581***	t = 6.013***	t = 2.305**	t = -3.860***
Gini index	2.757	3.999	3.452	3.07	1.002	2.746	2.078	1.871
	t = 18.109***	t = 39.586***	t = 32.280***	t = 24.159***	t = 3.771***	t = 13.951***	t = 10.058***	t = 8.052***

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Effects of the built environment variables

Except for the two variables of residential setting and single-family housing as shown in Table 15 Part D, the other five built environment variables are excluded in our final specifications because the coefficients are not significant. This indicates that population density, employment density, intersection density, transit access to jobs, and auto access to jobs have no significant impacts on senior's daily mobility patterns.

To begin with, in terms of residential setting, we find that in general, compared to seniors living in rural areas which is used as the base category, seniors living in suburban neighborhoods have no significant difference in terms of the propensity of using the five groups of motifs on workdays as well as on non-workdays. Surprisingly, the three urban residential settings do not present the same trends in terms of the preference of motif patterns. The coefficients of urban core, urban district, and urban neighborhoods in the two models are all positive and significantly different from zero. This indicates seniors living in these three types of residential areas are more likely to use all motif Groups except Group I on workdays as well as on non-workdays. Specifically, seniors living in an urban core are most likely to use complex motifs Groups IV and V on workdays compared to the other motif groups. Seniors living in urban districts are most likely to use motif Group III with three visited locations on workdays and Group V consisting of five or more locations on non-workdays. Seniors living in urban neighborhoods are most likely to use motif Group II with two visited locations on workdays and Group IV with four visited locations on non-workdays. These findings tell us that given the similarity between the urban core, urban district, and urban neighborhood in the function and spatial proximity, there is a significant heterogeneity in the daily mobility patterns among seniors living in these areas. The substantial variation in daily mobility patterns among seniors in the three urban settings is a reflection of the different urban forms, land use opportunities and functions offered in each urban type and worthwhile exploring this further when more detailed data become available. These new findings also imply that one should be cautious when aggregating attributes spatially by a simple urban category. Instead, it is worth not only testing whether or not to treat separately the urban core, urban district, and urban neighborhood as we did here, but also expanding the analysis using finer grained classification to suburbs and rural environments as we attempt later in this research.

The coefficients of the percent of single-family housing units are all significant and negative and show a decreasing trend on workdays indicating that seniors living in areas with a higher percentage of single-family housing units are less likely to use complex motif groups and most likely to stay at home on workdays. However, the coefficients are not significant on non-workdays, implying that the percentage of single-family housing units has no significant impacts on senior's daily mobility patterns.

Model performance

Overall, the two models represent the data very well as shown by the model statistics in Table 15 Part D lower half. The likelihood ratio test for testing the presence of exogenous variable effects is 12654 and 5550.4 for workdays and non-workdays respectively, which is substantially larger than the critical chi-square value with 140 degrees of freedom. The McFadden's Pseudo R^2 of 0.403 and 0.417 for workdays and non-workdays also indicates a good fit of the two models.

Table 15 Part D. Estimated parameters of multinomial logit models for workday and non-workday

Variables	Model 1: Workday				Model 2: Non-workday			
	Group II	Group III	Group IV	Group V	Group II	Group III	Group IV	Group V
Built environment variables								
Residential setting (base: rural area)								
Suburban Neighborhood	0.205	0.201	0.057	-0.036	-0.354	-0.223	-0.043	-0.318
	t = 0.943	t = 0.910	t = 0.252	t = -0.153	t = -1.035	t = -0.631	t = -0.118	t = -0.844
Urban core	2.139	2.522	2.925	2.978	2.821	3.052	2.92	2.939
	t = 4.405***	t = 7.660***	t = 9.019***	t = 7.630***	t = 5.044***	t = 7.549***	t = 6.628***	t = 5.890***
Urban district	2.14	2.729	2.174	1.759	4.771	4.924	4.971	5.222
	t = 7.771***	t = 14.146***	t = 10.111***	t = 6.620***	t = 12.426***	t = 16.779***	t = 15.169***	t = 13.668***
Urban neighborhood	1.454	1.097	1.301	1.159	3.85	4.177	4.508	4.023
	t = 8.935***	t = 8.303***	t = 9.799***	t = 7.039***	t = 15.873***	t = 23.233***	t = 23.693***	t = 16.478***
Single-family housing	-0.294	-0.325	-0.65	-0.822	0.739	0.679	0.339	0.028
	t = -1.970**	t = -2.553**	t = -4.917***	t = -5.519***	t = 1.331	t = 1.191	t = 0.573	t = 0.046
Constant	6.978	3.555	1.532	-2.33	5.478	-1.727	-4.068	-4.571
	t = 36.641***	t = 22.819***	t = 8.327***	t = -12.708***	t = 15.356***	t = -5.330***	t = -9.869***	t = -12.148***
Model statistics								
Number of observations	10833				4577			
Log-likelihood	-9365.6				-3885			
Log-likelihood Ratio (Chi-square)	12654	df=140	p < 2.2e-16 ***		5550.4	df=140	p < 2.2e-16 ***	
McFadden's Pseudo R^2	0.403				0.417			

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Comparison of stay-at-home seniors with those that do not stay at home

As mentioned in the data section, of the total 20707 senior respondents in 2017 California-NHTS, we only keep 10833 and 4577 seniors respectively for the motif analysis for workdays and non-workdays. The rest of the excluded 5297 seniors are people who stay at home during the assigned diary day and have no trips to report. Even though we can construct motif for these stay at home all day seniors as it will become a motif with a single node without any link, all of the travel-related attributes in Table 11 will be zero. One solution is to merge them with motif 1 (i.e. home-based loop trip pattern); however, as we found in earlier sections, there is substantial variety for motif 1 in terms of time-based behavioral indicators, senior's characteristics, and travel mode choices. Including the large sample of stay at home all day seniors would eliminate the heterogeneity findings for motif 1. However, we still need to understand the differences between people that do not leave a location all day and people that make at least a trip. For this reason, we estimate a binary logistic regression model for seniors making no trip vs making at least one trip during the assigned survey day. To explore the effects of seniors' attributes and built environment factors on seniors' decisions to make trips, we use these characteristics as explanatory variables and test their significance. The final specification of the binary logistic regression model was obtained by a systematic process of eliminating insignificant variables.

Table 16 summarizes the results of the estimated binary logistic regression model. Except for the set of travel-related variables, the other three sets of variables used as explanatory variables are individual characteristics, household characteristics, and built environment variables. Among the set of individual socio-demographic variables, female seniors are found less likely to leave home compared with their male seniors' counterpart. Seniors aged 60 to 79 are all found more likely to leave home compared to seniors aged 80 or over. In general, there is a decreasing trend in the coefficient as ages go up, which indicates that as seniors progress in ageing, they are less likely to leave home and make trips. The coefficients of education attainment show that compared to seniors with bachelor's degree or above, seniors who have less than a bachelor's degree or have some college or associate's degrees are less likely to leave home. In terms of senior's work status, compared to non-part-time employees, part-time employees are more likely to leave home. Elderly homeworkers are less likely to leave home compared to elderly non-homeworkers. Among the set of occupancy categories, the results indicate that compared to seniors who work in sales or service and all other industries, seniors whose job category belongs to the other three are more likely to leave home. The coefficients of the set of travel day variables show that seniors are more likely to leave home on weekdays compared to weekend days.

In terms of household characteristics, compared to households earning $200k or more per year, seniors with household annual income less than $24,999 are more likely to stay at home all day and seniors with household annual income between $25,000 to $99,999 or between $100,000 to $199,999 are found more likely to leave home and make trips. The effect of household structure indicates that compared to two-retiree households, seniors from a household with only one adult regardless of the retirement status are more likely to leave home and make trips. A single senior living with people younger than 21 is most likely to leave home and make trips compared to the other household structures. In terms of residential setting, we find that in general, compared to seniors living in rural areas, which is used as the base category, seniors living in suburban neighborhoods are more likely to leave home and make trips. There is no significant difference between seniors living in rural areas, urban core, and urban neighborhoods in terms of the propensity of making trips. Only two built environment variables are found significant in our final model specification. The results show that seniors living in higher employment density areas and higher intersection density areas are more likely to make trips.

Table 16. Estimated parameters of binary logistic regression model

Variables	Estimates	z-statistic	p-value
Individual characteristics			
Sex (base: not woman)			
Woman	-0.212	-6.224	4.85e-10 ***
Age (base: above 80)			
60 to 64	0.580	10.607	< 2e-16 ***
65 to 69	0.483	9.387	< 2e-16 ***
70 to 74	0.486	9.029	< 2e-16 ***
75 to 79	0.341	5.867	4.43e-09 ***
Education background (base: bachelor's degree or above)			
Below bachelor's degree	-0.555	-12.311	< 2e-16 ***
Some college or associate's degrees	-0.229	-5.822	5.80e-09 ***
Part-time or full-time worker (base: non-part-time employee)			
Part-time employee	0.366	4.897	9.72e-07 ***
Homeworker status (base: non-homeworker)			
Homeworker	-0.588	-7.490	6.89e-14 ***
Occupancy (base: sales or service and all other)			
Professional, managerial, or technical	0.607	8.829	< 2e-16 ***
Clerical or administrative support	0.896	6.762	1.37e-11 ***
Manufacturing, construction, maintenance, farming	0.876	6.884	5.83e-12 ***
Travel day (base: Sunday)			
Monday	0.195	3.266	0.001 ***
Tuesday	0.440	7.183	6.80e-13 ***
Wednesday	0.280	4.683	2.82e-06 ***
Thursday	0.429	7.031	2.05e-12 ***
Friday	0.261	4.370	1.24e-05 ***
Saturday	0.058	0.989	0.322
Household characteristics			
Household annual income (base: $200,000 or more)			
Less than $24,999	-0.212	-3.129	0.002 ***
$25,000 to $99,999	0.135	2.394	0.017 **
$100,000 to $199,999	0.174	2.751	0.006 ***
Household structure (base: 2+ adults, retired)			
1 adult	0.498	6.216	5.09e-10 ***
2+ adults	-0.005	-0.085	0.932
1 adult, retired	0.447	9.397	< 2e-16 ***
1 adult living with people younger than 21	1.230	2.576	0.010 ***
2+ adults living with people younger than 21	-0.200	-2.519	0.012 **
Built environment variables			
Residential setting (base: rural area)			
Suburban neighborhood	0.167	3.54	0.0004 ***
Urban core	-0.051	-0.165	0.869
Urban district	0.514	2.218	0.027 **
Urban neighborhood	0.043	0.391	0.696
Employment density	0.008	2.317	0.020 **
Intersection density	0.001	3.19	0.001 ***
Constant	0.255	3.072	0.002 ***
Model statistics			
Number of observations	20707		
Log-likelihood Unrestricted	-11162		
Log-likelihood Ratio	1203.2	df=32	p< 2.2e-16 ***
McFadden's Pseudo $R^2 = 0.051$	Note: *p < 0.1; **p < 0.05; ***p < 0.01		

Contributions and Policy Implications

Our contributions in this project are fourfold. First, our study advances people's understanding of telecommuter's travel behavior nowadays. For example, contrary to conventional belief, telecommuters in California that have at least a trip during their workdays travel 1.37 more VMT and 0.53 more trips than their counterpart commuters. In addition, telecommuters tend to use carpooling more than drive alone. Second, this study reveals the substantial heterogeneity in daily mobility patterns and time allocation patterns for telecommuters and commuters. Third, armed with this new method combining motif and sequence analysis, the self-selection bias discussed in the literature (Asgari and Jin, 2017; Pouri and Bhat, 2003; Tal, 2008) can be handled using the patterns described here in a way that account for behavioral heterogeneity in a more insightful and behaviorally informative way. Fourth, we challenge the crisp distinction between commuters and telecommuters that should be replaced by different ways of work from many different places accounting for the work task flexibility enabled by information and communication technology. This complements the Asgari et al. (2014) and Asgari and Jin (2015) different ways of telecommuting, but now it can be done using observed patterns that are classifying respondents in statistically derived groups based on time allocated to work, home, household responsibilities, shopping and serving activities, and travel.

Telecommuting is an official policy in California and appears in many regional plans and sustainability strategies as defined by California legislation[3]. Unlike the conventional definition of telecommuting in late 1970s, telecommuting nowadays as verified in this study is no longer a home-based work arrangement, but is multiple-place-based. With the advancement of Information and Communication Technologies (ICT), the emergence of ubiquitous workplaces allows telecommuters to work not only at home but at many places with available internet connection such as a coffee shop, a bookstore, a restaurant, and so forth. As confirmed in this research using 2017 California-NHTS as a case study, telecommuting has already a positive impact on transportation with a lower number of trips and number of miles driving alone, less travel during peak hours, and enables escorting people to places of activity. We also find substantial heterogeneity in daily mobility patterns and time allocation to activities and travel among telecommuters. We can view the higher variety of scheduling arrangements and visiting places among telecommuters as a positive impact because internet is ubiquitous and enables visiting more diverse places. But we can also view this as a not so positive impact when the added freedom of telecommuters may motivate them to circulate for longer time in the network and possibly contributing to emissions. It is unknown, however, if they do this because the type of vehicle used plays a major role in estimating emissions. Moreover, also unknown for the telecommuters that did not leave home at all during the day of the interview if this was done voluntarily or by necessity.

The mobility patterns and daily schedules will be most likely dissimilar in different settings due to national, cultural, policy, and infrastructure differences. For example, as Jackson and Van der Wielen (1998) discussed in the late 90s, this is due to evolving telework needs supportive social norms and/or legal protection of the workers. One could imagine many potential differences in

[3] https://www.calhr.ca.gov/employees/Pages/telework-policy.aspx

telecommuters' daily schedules between those from well-developed Western countries where telecommuting has been a mature and relatively popular practice and those from developing countries where telecommuting is still new and less popular. Transportation infrastructure also has important impacts on telecommuters' daily mobility patterns as well as daily schedules of activities and travel. People living in California mostly rely on automobiles than other transportation modes, which is confirmed in Table 2 with both telecommuters and commuters use driving alone the most and telecommuters who made at least one trip travel 1.37 more VMT as well as 0.53 more trips in a day compared to commuters. However, we anticipate the results will be different in other cities where public transit is more developed, such as Washington D.C., Boston, and Chicago. In addition, it is also of importance to take into account land-use types, community design, and infrastructure accessibility in investigations of daily mobility of telecommuters. Telecommuters living in neighborhoods where grocery stores, restaurants, gyms, and other types of activity opportunities are easy to access are presumably less likely to be selected over driving alone to activity opportunities with longer distances. Telecommuters living in rural areas with low accessibility to places are more likely to visit multiple places to fulfill their daily needs and drive longer distances. All in all, when one studies telecommuters' daily mobility patterns and daily schedules should always take into account the local cultural, policy, and infrastructure characteristics in the study area to better explain the observed behavior and data analysis findings. A promising future work for this study is to correlate the various mobility patterns and time allocation patterns with built environment characteristics.

The unexpected global event of COVID-19 pandemic forced people to stay at home and reduce traveling in order to contain the spread of the virus. People adjusted to the new norm of daily life with COVID-19 (see Maryland Transportation Institute (2020)). In fact, we expect a substantial increase in the adoption of telecommuting by companies as it is happening at the time of writing this article and we also anticipate a large number of telecommuters will switch to motif Group I pattern, which is a single location-based (mostly home) loop trips pattern. Telecommuters using motif Group I will most likely work from home but take a walk during the workdays during the COVID-19 pandemic. In addition, we will see a substantial decrease in the telecommuters' patterns comprising a large time period being present at workplaces, such as telecommuters' Work and Run Errands Day, and Mostly out of Home Day. Meanwhile, telecommuters will be less likely to use complex motif groups such as motif Groups IV and V as they work from home most of the time and have less time left for other activities and also out of the concerns of reducing the risk of infection by traveling less. We also anticipate that different socio-demographic groups will react in different ways and occupation that already plays a major role in defining daily commuting schedules will continue driving COVID-19 induced telecommuting. However, longitudinal data analysis as in MOBIS-COVID19[4] show that we may experience a return to the use of the private automobile and maybe a tendency to return to pre-COVID patterns.

[4] https://ivtmobis.ethz.ch/mobis/covid19/reports/mobis_covid19_report_en_2020-11-02.html

The senior residents analysis motivated by the large population ageing happening worldwide demonstrates the need to understand its implications for infrastructure and service provision. One of the challenges is how to improve and change transportation design and transport policy development to adapt to dramatic changes in the composition of population. In this report, we apply a network-based approach of human mobility motifs to investigate the distinct patterns in daily travel for seniors in California. A thorough comparison between motif and other tour formation models was made by Su et al. (2020) and is used here to explore the daily life of seniors. One of the advantages of motif analysis compared to traditional trip-based models (often referred to as “4-step” models, see McNally (2000)) using the individual person trip as the basic unit of analysis is that the network-based motif approach is able to capture the interconnection among daily visited locations at individual level. A case study using 2017 California-NHTS provides more insight into the heterogeneity in daily mobility patterns among seniors and the correlation between the diverse daily mobility patterns with socio-demographic characteristics as well as built environment factors.

In terms of substantive findings, we find that 15 distinct motifs can capture 82.17% and 86% of the total senior respondents’ spatial behavior on workdays and non-workdays, respectively. Seniors are more concentrated in simple motifs with three or fewer nodes on non-workdays while they present much complex motifs on workdays. Given that 65% of the included seniors are retired, a large number of seniors, contrary to conventional wisdom, have diverse and complex daily mobility patterns on workdays or on non-workdays. Unlike younger female adults who tend to use more complex motifs on workdays to take care of household responsibilities, female seniors do not present similar trends. Seniors tend to drive alone more on workdays than non-workdays, and tend to have more carpooling trips on non-workdays. The estimated MNL models for workdays and non-workdays reveal greater variety in daily mobility motifs with more complex tour formation across different age groups, work status, occupation categories, and household income levels of seniors. In terms of household structure, single non-retired seniors are most likely to use the Group I motif on workdays and travel actively and use the four groups of motifs other than Group I on non-workdays. Seniors who live with other adults and people younger than 21 are the most mobile groups, and they tend to leave home and have more diverse mobility patterns on workdays. As for the effect of various residential settings, seniors living in suburban neighborhoods and rural areas present similar propensity of using the five groups of motifs. In addition, given the similarity in function and spatial proximity of the urban core, urban district, and urban neighborhood, there is a significant heterogeneity in the daily mobility patterns among seniors living in these areas. This new finding implies that one should be cautious when aggregating attributes spatially by a simple urban category, and the addition of more detailed land use indicators becomes of paramount importance. For example, seniors living in areas with higher percentages of single-family housing units are less likely to use complex motifs on workdays and most likely to stay at home on workdays. However, we find population density, employment density, intersection density, transit access to jobs, and auto access to jobs have no significant impacts on senior’s daily mobility patterns. In the comparison between seniors that stay at the same place (mostly home) all day and seniors that make at least a trip, as expected we find younger seniors, living in suburbs, of higher household income, part-time employed, and living with people younger than 21 are less likely to be homebound.

As documented in this study, the variety of daily mobility patterns presented by different groups of seniors indicates a strong need to be socially engaged. Meanwhile, seniors in California still rely heavily on automobiles to meet their daily transportation needs. In other words, the findings unveil the deficiency of other transportation mode development and the constraints of automobiles on elderly's daily mobilities in California. In terms of transportation design in the future, some emerging technologies have the potential to address problems regarding elderly mobility constraints of single travel mode (mostly relying on automobiles) and improve overall elderly' mobilities. For example, in addition to improving current public transit by optimizing the route, adjusting the frequency, and so forth, municipalities and regional transportation authorities should consider complementing our current transportation system with Mobility as a Service (MaaS). The major components of MaaS schemes include intermodal planning, booking and payment functionalities, and multiple transport modes and mobility packages (Kamargianni et al., 2016). MaaS enables the conventional personally-owned modes of transportation to transform to mobility provided as a service. The main objective of MaaS is to offer mobility solutions based on people's travel needs. In United States, a variety of shared mobility services have recently launched to serve the specific needs of elderly passengers. For example, a pilot program, Freedom in Motion, was launched by Uber in Gainesville, Florida in 2015 to subsidize rides for residents ages 60 and older. Participants only need to pay up to $5 per ride and can request to receive smartphone[5]. Microtransit provider Via uses dynamically routed shuttles to provide shared rides for a flat fee in more than 18 cities in United States and also operate worldwide in more than 20 countries. It was reported that nearly 30 percent of Via's New York City customer base is over age 55[6]. Seniors appreciate Via's relatively reasonable fares and enjoy the social aspect of sharing a ride[6]. Even though many smart transportation solutions have been implemented across the state, many of them focus on urban areas and yet to expand to suburban and rural areas. The analysis of 2017 California-NHTS in this research shows that more than 95% of seniors live in rural or suburban neighborhoods and they mostly rely on automobiles for daily travel. Policy makers and transportation officials in California should realize that universal MaaS, while initially a concept for urban areas, could result in expanded mobility in small towns and rural areas as well, although the shift to this new paradigm will happen at a slower pace than in cities (Lynott, 2018). Transportation policy should support the best mix of transportation options that facilitate broad mobility not only for seniors living in urban areas but also those in suburban and rural areas.

There are several limitations that need further investigation. First, unlike a weekly based travel diary, the data used in this study, 2017 California-NHTS, contains only one-day travel diary for a respondent. Some of the respondents might not follow their regular workday schedule due to unexpected reasons such as sickness, business travel, personal vocation, emergency, etc. Granted that there is little to do about this bias, a promising future study can apply a longitudinal survey to study the recurrent mobility patterns and to further detect anomaly

[5] https://www.wuft.org/news/2018/02/12/uber-offers-lower-prices-for-senior-gainesville-residents/

[6] https://nymag.com/intelligencer/2015/12/via-ride-sharing-app-seniors.html

travel patterns at individual level. Second, an immediate next step is to apply the motif and sequence analysis to the excluded non-workday samples to further compare the differences in daily mobility patterns of telecommuters and commuters between workdays and non-workdays (to some extent this was accomplished for the seniors analysis). Third, to extend the intrahousehold analysis in more depth, we plan to leverage the more detailed information in the survey regarding the intrahousehold interactions of daily activity to understand how a household member's daily mobility pattern can influence other household members' mobility in the same day. In one section we tested this and provided a small example of the research potential along this path of analysis. In the seniors analysis we found substantial heterogeneity and activity travel patterns that complement and contribute to the existing literature. In a future study will be interesting to perform a more detailed comparison between the included seniors with people in the child rearing age (25 to 60) and their much younger counterparts. Similarly, one can also compare diverse household structures and then explore intrahousehold interactions. For example, how can a household member's daily mobility pattern influence other household members' mobility in the same day? This question is more important for seniors and for children who live with others. Is the mobility of other household members constrained by the need to take care of the seniors in the household? Or do we see parallel lives without mutual influence between a senior and a non-senior in the same social unit? Can we infer roles played by different members of the same household? We leave these questions for future work.

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Data Management Plan

Basic Information

Principal Investigator: Konstadinos G. Goulias
Other Participants in Research Activities: Rongxiang Su (PhD student), Elizabeth McBride (PhD candidate)
Aim of Data Management Plan: To share high quality metadata with the scientific community.

Products of Research
No new data were collected during this research. We used the National Household Travel Survey data California Component publicly available at NREL and from CALTRANS.

Data Format and Content
Details of the data are available at

1. https://nhts.dot.ca.gov
2. https://www.nrel.gov/transportation/secure-transportation-data/tsdc-nhts-california.html
3. https://nhts.ornl.gov

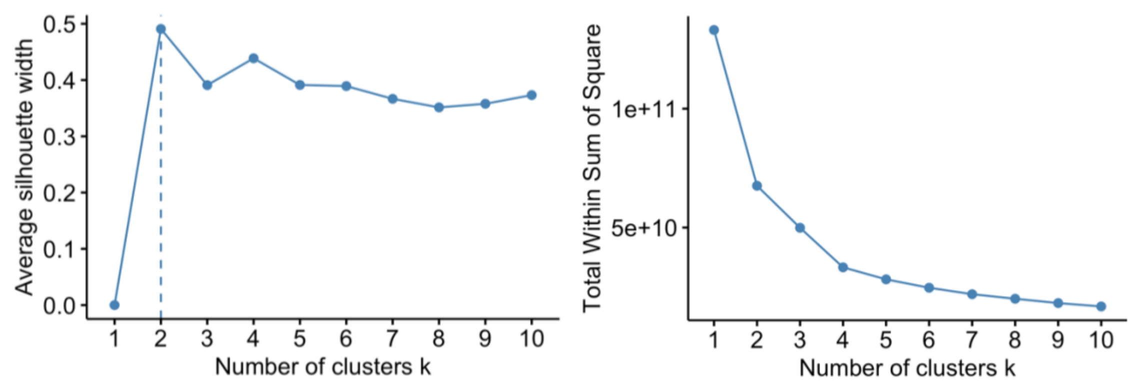
Data Access and Sharing
The general public can access the data from the agencies listed above. **Charts, figures, and tables** resulting from our analysis of raw data will be generated for presentation and publication. Data that are not used towards publication include raw data that can be valuable for other research teams and classroom teaching and will be kept in a safe UCSB server for post project use. We will be happy to share charts and tables as well as the secondary databases after publication of submitted journal papers. We would expect that upon completing their independent data analysis, researchers would cite our published work and/or provide co-authorship as necessary. The usage of data not used towards publication will become a database to be used by other graduate students in GeoTrans. We are working to develop a public database in which raw data may be deposited, we do not yet have infrastructure or funding to provide such a service but we can use the Open Source infrastructure. Consequently, requests for data will be treated on a case-by-case basis and then posted on places such as Github. The most likely outcome is that we will provide unpublished data upon request, in exchange for authorship and/or establishment of a formal collaboration.

Archiving and Preservation
Generated data are not substantial and are archived on dedicated external hard drives (BOX used by UCSB). We did not collect any new data. Instead, we integrated different databases publicly available.

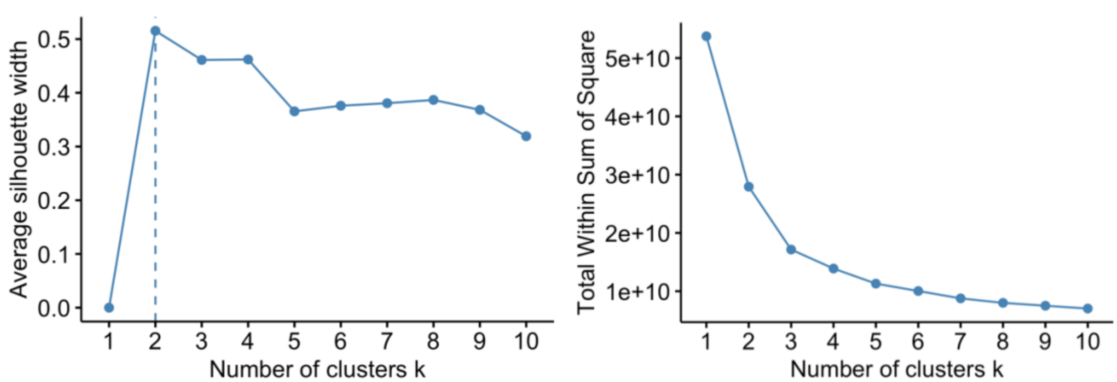
Appendix A

The silhouette graphs suggest the best solution with respect to dissimilarity among clusters is the 2-cluster solution that has the highest average silhouette coefficient for all the three motif groups. However, selecting 4 clusters yields very small WSS and may not be worth selecting a solution with more than 4 clusters. These two indicators show that 2 or 4 clusters would be an optimal solution. Selection then between 2 and 4 clusters is left to the researcher using behavioral interpretation of the patterns produced by the 2-cluster and 4-cluster solutions. By comparing the time allocation patterns produced by the 2-cluster and 4-cluster solutions, we finally choose 4 clusters as the optimal solution because it could identify more distinct activity sequence patterns, for example, the Mostly Out of Home Day and Long Work from Home Day patterns, while the 2-cluster solution cannot.

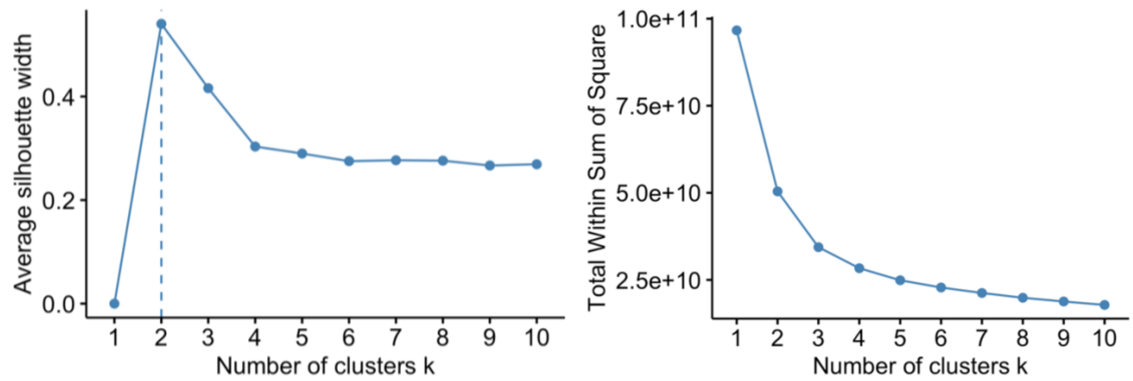
The two indicators show that 2, 4, or 5 clusters would be an optimal solution. By comparing the time allocation patterns produced by the 2-cluster, 4-cluster, and 5-cluster solutions, we finally adopt 4-cluster solution for Groups C.II and C.V, and 5-cluster solution for Groups C.III and C.IV.



(a) Group T.III

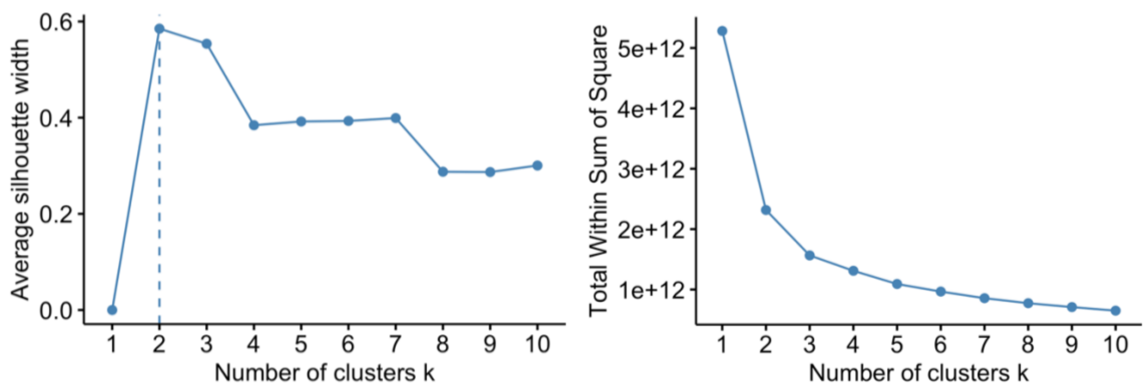


(b) Group T.IV

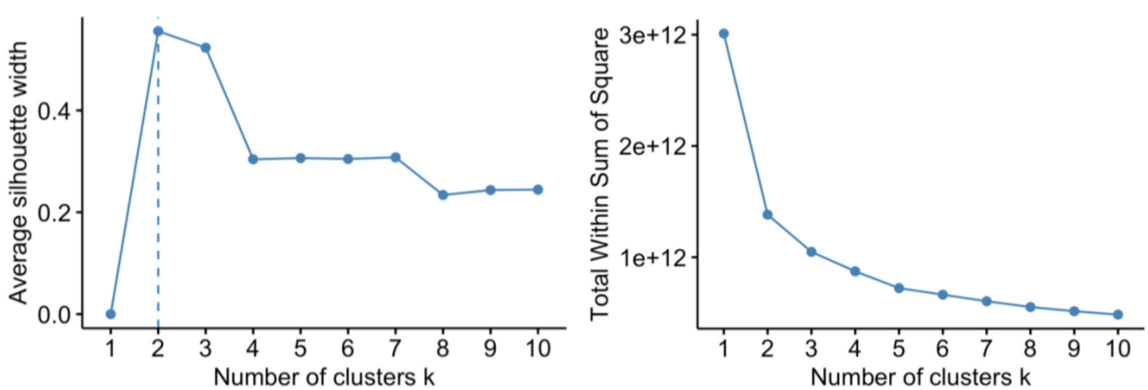


(c) Group T.V

Figure A.1. Silhouette and WSS elbow methods for motifs Groups T.III, T.IV, and T.V.

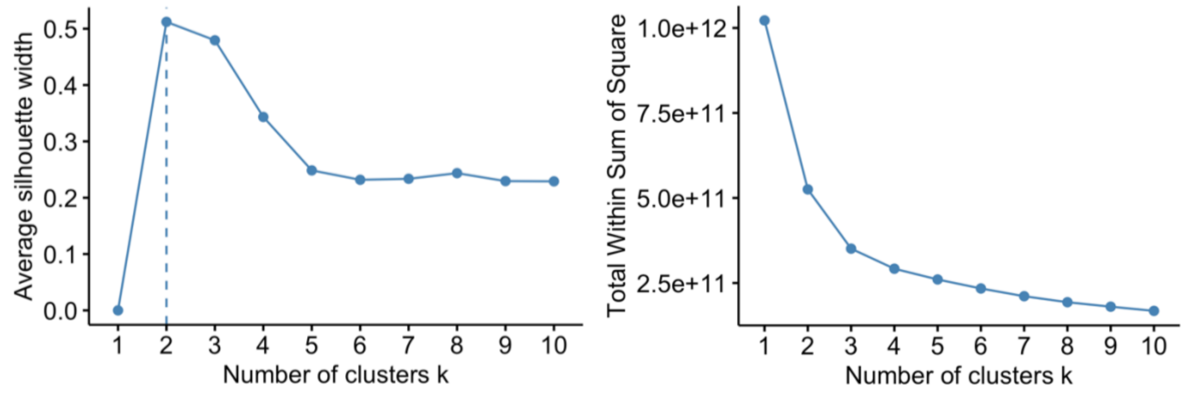


(a) Group C.II

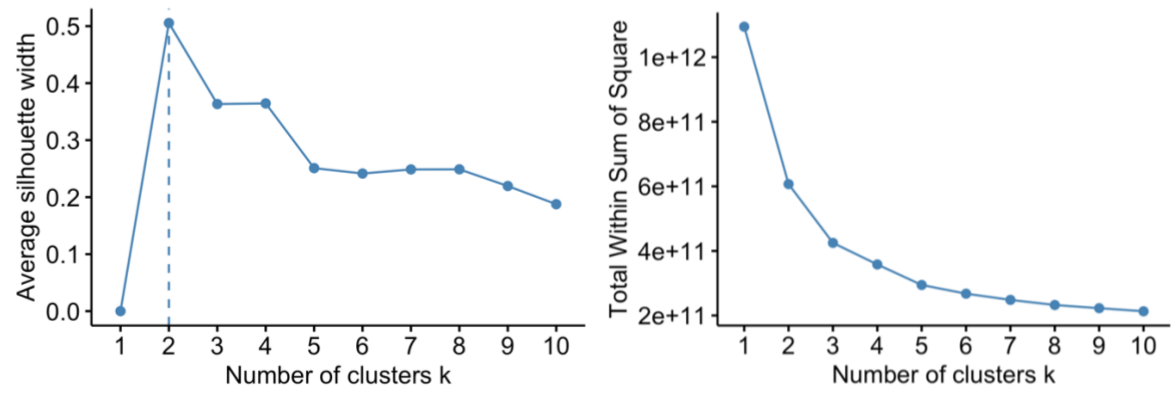


(b) Group C.III

Figure A.2. Silhouette and WSS elbow methods for motifs Groups C.II, C.III



(c) Group C.IV



(d) Group C.V

Figure A.3. Silhouette and WSS elbow methods for motifs Groups C.IV, and C.V.