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What Affects the Number of Non-Work Stops Made During Commute Tours? A Study Based on the 2009 US National Household Travel Survey in Large Metropolitan Areas

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A Study Based on the 2009 US National Household Travel Survey in Large Metropolitan Areas

A thesis submitted in partial satisfaction
of the requirements for the degree Master of Urban and
Regional Planning

by
Haofei Liu

2013

ABSTRACT OF THE THESIS

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by

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Master of Urban and Regional Planning

University of California, Los Angeles, 2013

Professor Rui Wang, Chair

Trip chaining is an important aspect of travel behavior, yet is less well understood than direct trips generated. Using a negative binomial regression model to fit data from the 2009 National Household Travel Survey (NHTS) and the 2010 US Census, this study focuses on the association between the complexity of commute tours (i.e., the number of non-work intervening stops) and the characteristics of commuters, households, and their neighborhoods and regions. The results from the 51 largest metropolitan areas confirm the saliency of household responsibilities, gender, flexibility of work schedule, and household auto ownership, but do not show any strong effect of socio-economic status, the regional and local built environment, or gasoline price. The findings of this study demonstrate the need for travel demand modeling to take into account the effect of trip chaining.

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2013

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1. Introduction

Commutes play a major role in workers' daily travel. Activities under fixed schedules, i.e., mandatory activities, such as work, impose constraints on pursuing other activities, and for those working away from home, commute is an important part in their daily travel-activity patterns (Bhat et al., 2004). To reduce the overall cost of transportation, commuters often complete personal and household errands on the way to and from work during rush hours (Downs, 2004; Chu, 2003). Over time, non-work trips increasingly become a part of the commute, as workers stop for groceries, pick up children, or make other stops on their way to and from work (Downs, 2004). Data from the 2001 National Household Travel Survey (NHTS) show that during the 1990s, there was a 21 percent increase in the number of commuters who linked non-work trips to work trips, as well as a 12 percent increase in commuters who trip-chained in both directions (US DOT, 2001). The increase is primarily fueled by commuters' motivation to save on travel costs and by demographic trends, such a single-adult and dual-earner households, especially those with young children as more women entered the workforce since the 1960s (Gordon et al., 1988; Strathman et al., 1994; Strathman and Dueker, 1995). To understand peak-period travel, it is necessary to investigate the motivations behind non-work trips generated during commuting by considering factors such as mode choice and gas price (Bhat, 1997). Studying trip-chaining behavior also advances our understanding of the linkage between activity and mobility, which is also a challenge to the emerging activity-based travel models (Kitamura, 1988; Strathman et al., 1994).

Trip-chaining behavior is an important perspective when studying both the ends of trips and the trips themselves, since a travel decision is based on activities which an individual participates in (Bowman and Ben-Akiva, 2001). A better understanding of trip-chaining behavior contributes to more convincing travel forecasting or modeling. The traditional modeling method, the four-step trip-based approach, often separates activities and trips and ignores the derived nature of travel demand. In contrast, an activity-based model (ABM) allows transportation planners to not only analyze daily travel patterns, but also to estimate individuals' responses to certain transportation policies (TRB, 2007). For the four-step model, only trip-level models and person or household day-level models are normally applied, depending on the trip generation model structure (either person-based or household-based). The ABM or an activity-based approach (ABA) takes into account multi-destination travel and interactions between household members (McNally and Rindt, 2007, Bhat 2011). However, in the past decades, due to the analytical difficulties incurred by the expansion of choice sets and excessive demand of data, only a few metropolitan planning organizations (e.g. New York, Columbus, Bay Area, Atlanta, and San-Diego) have adopted tour-, or activity-based models (TRB, 2007). Yet recently, more MPOs have been incorporating ABMs into their four-step model routines (e.g. Southern California Association of Governments and PIma Association of Governments).

In this study, I examine the relationship between the number of intervening stops commuters make en route to or from work and the characteristics of the individual and household, work status, built environment and trips. To do this, I develop a negative binomial regression model using data from the tour file of the 2009 NHTS coupled with neighborhood-and CBSA-level data from the 2010 U.S. Census. The analysis focuses on metropolitan areas with populations of one million and above, the densest areas of which are often mandated to comply with quantity regulation in terms of congestion mitigation, air quality management, and sustainable development. The variables of interest also include interactions between the demographics of commuters or trip characteristics and the presence of young children in the household, which improves the model's explanatory power. A more detailed specification of models may increase the accuracy of estimating trips generated when disaggregated trips are aggregated to the level of transportation analysis zones. When a model is sensitive to the travel time of the day, the models centering on commutes in this study may be used to estimate the trips generated in the morning and evening peak periods in weekdays.

Previous researchers have defined trip chaining in various ways. For this study, definitions are based on 2009 NHTS trip chaining documentation (US DOT, 2011) and other previous studies, displayed in Table 1.

Table 1 Definition of Trip Chaining

Terms	Definitions
Anchor	A primary or substantial trip destination, such as workplace and home in this study.
Chained Trips	A series of short trips linked together between anchor destinations, such as a trip that leaves home, stops to drop a passenger, stops for coffee, and continues to work.
Intervening Stop	The stops associated with chained trips. Some researchers also define the stop as a sojourn. (Adler & Ben-Akiva, 1979; Kondo & Kitamura 1987).
Tour (trip chains)	Total travel between two anchor destinations, such as home and work, including both direct trips and chained trips with intervening stops.

Source: US DOT (2011), Adler and Ben-Akiva (1979), and Kondo & Kitamura (1987).

2. Literature Review

Previous research has examined a wide spectrum of factors affecting trip chaining, such as the demographic and socio-economic characteristics of individuals and the households, attributes of trips being made, and land-use patterns. It is well accepted that trip-chaining behavior is closely associated with the interconnection between travel, activities, and time allocation. Adler and Ben-Akiva (1979) use a theoretical model to illustrate that the characteristics of households, the network of the transportation system, and individuals' activity patterns jointly affect each trip made by individuals. They assume that non-work travel decisions are made in the short run and subject to the long-term decisions made by the household, such as location of residence and work place, work mode choices, and automobile ownership. The likelihood of trip chaining is positively related to households' desires to maximize their utility in completing a set of daily activities, given space, time, and travel expenditure constraints. The model also considers travel time and costs, the attributes of chosen destinations, and the socioeconomic characteristics of households as the major factors influencing household travel patterns. From the perspective of marginal benefit of in-home activity time, Kondo and Kitamura (1987) indicate that factors such as longer non-work activity duration, more in-home activities, longer home-work distances, and slower travel speed do not favor a multi-stop trip chain if the marginal benefit of time spent on in-home activities does not decrease. They also find that regardless of the marginal benefit, longer distances between home and activity location are positively associated with the likelihood of trip chaining holding other variables constant.

Numerous studies find that within households, women tend to trip-chain more often than men (Bricka, 2008; Rosenbloom, 2006; Bhat, 1997; Strathman and Dueker, 1995). With an increasing labor participation rate, the average income of women has increased, but so have time costs (Pisarski, 2006). Therefore, women tended to respond to this trend by trip-chaining, and their trip purposes are more likely to be centered on shopping and household errands (Crane, 2007). Previous research also shows that there continues to be gender differences in whether or not commuters incorporate non-work trips within their commute tours, because the gender division of labor does not change much even when women are employed. For example, in two-earner families, McGuckin and Nakamoto (2005) find wives are more likely to transport their children to schools than husbands. The linkage between trip chaining and gender became stronger as women's socioeconomic roles transformed. Hanson and Hanson (1981) show that working married women make slightly more multi-stop trip chains than non-working married women. These findings display the uneven division of labor in terms of non-work activities within households, especially activities related to child-raising. Using the NHTS 2001 trip-chaining dataset collected by telephone survey, Noland and Thomas (2007) find that women tend to make more linked trips than men. Bricka (2008) uses the same dataset and also finds female workers tend to link more trips to tours compared with male workers. However, the authors of both studies don't separate commute tours from other tours.

With enhanced travel diary survey technology, such as global positioning system (GPS), some recent empirical evidence suggests women take fewer linked trips during morning commute tours. Focusing on morning commute tours in Atlanta, Georgia, Li et al. (2005) use on-road travel data of a 10-day subset of data from GPS-equipped vehicles and find that men tend to stop more frequently, in terms of both the sheer number of stops and the stops ratio, which is defined as the number of commute tours with trip chaining divided by the total number of commute tours. One explanation is that women generally have less access to automobiles, and a higher proportion of their trips are made on transit (Pisarski, 2006). The authors also suggest a larger sampling of instrumented vehicles during a longer period of time might provide more accurate evidence (Li et al., 2005).

Previous research also finds that the household life cycle stage, specifically, the presence of children, has an effect on the total number of non-work stops. Goodwin (1983) notes that "the single most important discovery of activity work to date has been the importance of children – not primarily because of their trips… but because the very fact of children in a household imposes highly complex and binding constraints on the activities and travel patterns of all other members of the households”(p. 472). Strathman et al. (1994) suggest that in Oregon, certain types of households (i.e. single adult, dual-income couples, dual-income families with preschoolers, and multi-worker households) are associated with a higher likelihood of linking peak-period trips than the traditional type of households (i.e. households with two adults, one worker, and with preschoolers, which are set as the benchmark in the research). A study based on the Oregon-Southwest Washington Activity and Travel Survey conducted by Lu and Pas (1999) suggests that having more children in the household corresponds to more multi-destination trip chains, and that employed people make fewer trip chains than people who are not employed and more workers in the household results in fewer chains. As household sizes have decreased and the number of workers per household has increased, the number of trip chains has increased (Oster, 1979). As for the number of stops made for household maintenance purposes[1], Wen and Koppelman (2000) find that it is positively related to household size and the number of children in a household. For commute tours, the presence of children and unemployed persons also plays an important role on workers’ daily travel patterns. On the basis of a household activity survey in the Boston metropolitan region, Bhat (1997) finds that workers from households without unemployed adults but with the presence of kids younger than 11 years old are likely to take more non-work stops on the way to and from work. Wen and Koppelman (2000) find that in households with an unemployed person (or part-time employee), an employed person is less likely to link

[1] Trips for maintenance purpose were defined by the authors as trips serving the need of all members in the household.

maintenance stops. As for trip purpose, evidence from 2001 NHTS show that common types of trips embedded in home-to-work tours are serve-passenger, followed by family or personal business and stops for a meal or coffee. In families with two wage earners, women make 61.3% of the trips involved with dropping off a child (Li et al., 2005).

Previous researchers have examined the connection between trip-chaining behavior and socioeconomic attributes, such as income level or car ownership, but their findings are inconsistent. Applying a recursive model system for trip generation and trip chaining to a Dutch panel travel survey[2], Goulias and Kitamura (1991) report that high-income households tend to consolidate trips into multi-stop chains, but vehicle ownership does not affect the number of chains in trip chain models after trips are generated. Strathman et al. (1994) find that the number of household vehicles has a negative relationship with the tendency of taking complex work tours. However, as Train (1993) noted, a more accurate measurement of the utility of household automobile ownership is the number of vehicles per worker. The research of Lu and Pas (1999) indicates that licensed drivers make more trip chains. Wen and Koppelman (2000) report that the number of household maintenance stops made is positively associated with household income and the number of cars owned. The studies of both Bhat and Misra (2001) and Bricka (2008) find that ethnicity does not have such an effect on chained trips. Using non-work automobile trip data of households from San Diego, Boarnet and Crane (2001) find that the positive effect of housing tenure on the number of non-work trips automobile trips is

[2] As noted by the authors, there are two reasons to use this particular data. First, weekly trip records are available from the survey, which preventing the influences from day-to-day variations. Second, panel data can be used to dynamic modeling of trip-chaining behavior. In the United States, many public use files of travel data only include information of a travel day. They assume trips are generated before the formation of chained trips.

strong but difficult to explain, and that the effect of single family dwelling is not significant. Bricka (2008) also tests the effects of home ownership and dwelling types; however, both effects are insignificant. Table 2 shows the conclusions of several studies on the relationships between socio-economic factors and trip-chaining behavior; the results of the research are not all consistent, despite using US data.

Table 2 Correlations between demographics and trip-chaining behavior

Correlation	No. of trip chains	No. of maintenance stops in commute	No. of non-work stops in commute tours
Female	+ (Lu and Pas, 1999; Mackuki and Nakodo, 2005)		+ (Bhat, 1997; McGuckin et al., 2005; McGuckin and Murakami, 1999)
Being Employed		- (Wen and Koppelman, 2000)	
Driving License	+ (Lu and Pas, 1999)		
Household Size	+ (Lu and Pas, 1999; Wen and Koppelman, 2000)		
Number of Children	+ (Lu and Pas, 1999)		+ (Bhat, 1997; Strathman et al., 1994)
Number of household vehicles		+ (Wen and Koppelman, 2000)	No Significant Relationship (Goulias and Kitamura, 1991; Golob, 1986)
Number of Household	- (Lu and Pas, 1999; Strathman et al.,		

workers	1994)		
Household Income		+ (Wen and Koppelman, 2000;	Goulias and Kitamura, 1991)

Mode choice is also closely related to car ownership and household income. Based on the 1990 National Person Travel Survey, Strathman and Dueker (1995) find that trip chains to or from work with a few non-work activities en route are more likely to be finished by car. Other studies also suggest that tours made by transit are associated with fewer intervening stops and types of activities than tours made by other modes (Frank et al., 2008; Horowitz, 1982; McGuckin et al., 2005; Wallace et al., 2000). However, these arguments are problematic in two aspects. First, oversampling of high-income transit riders leads to skewed estimation. Bernardin et al. (2011) find that a low level of household income and the lack of vehicle ownership correspond with complex multi-stop, multipurpose transit work tours, while more affluent transit commuters, probably over-sampled in many traditional travel surveys, made much simpler tours. An explanation for oversampling could be that in the NHTS, people not reached by telephone survey are absent from the data, and individuals from low-income households are oftentimes associated the lack of telephone services. Second, the issue of endogeneity is tricky to resolve. In other words, the positive relation between mode choice and the number of stops made may also result from other common unobserved factors. For example, a personal preference for a multi-stop commute might encourage some people to own a car, and a secondary role of owning a car for a commuter may be to overcome spatial and temporal constraints and link more activities (Bhat, 1997). Using the work and non-work tour data from

Switzerland and the structural equation model (SEM), Ye et al. (2007) confirm that linking more non-work stops in work commutes increases the propensity of automobile usage. Although it is assumed in some previous research that there is a direct causal relationship between these two variables, Bhat (1997) still suggests that a joint model of mode choice to work and number of non-work stops arising fits work tour data better because the choice of both the mode used and the number of stops chained is determined by common observed and unobserved factors.

Some research shows clear evidence of the effect of land use on trip chaining. For example, Williams (1988) considers the activities of households, trip frequency, and travel time and accessibility indices and finds that residents in less accessible areas are more likely to form trip chains and have higher trip frequencies. Gordon et al. (1988) note that the dispersion of commercial activities has reduced the suburbanite's likelihood of forming a trip chain. Using data from Seattle, Washington, Wallace et al. (2000) show that tours starting in urban centers include fewer intervening stops, while households living outside urban centers are more likely to plan complex tours, i.e. multi-stop trips. Similarly, Noland and Thomas (2007) draw on the 2001 NHTS data, and find that lower residential population density leads to a greater reliance upon both multi-destination tours and tours with more stops en route, holding constant other key attributes of households and individuals. Golob (2000) uses data from the Portland metropolitan region and finds that network- and especially zone-level accessibility measures are positively associated with the participation in out-of-home non-work activities and home-based non-work trip chains. However, not all studies find a land use impact. Krizek (2003) conducted a before-and-after study and observes that households moving from low to medium density neighborhoods make shorter distance tours than before, but there is no difference in terms of the complexity of their tours (e.g. incorporating more destinations between main location of activities, such as residence or work place). However, few of them distinguish commute tours from other types of chained trips. Goulias and Kitamura (1991) test the effect of the number of work trips generated on the number of work trip chains and do not find significant differences between smaller and large cities.

As for other tour attributes, a higher likelihood of congestion during peak periods contributes to commuters' diverting non-work trips to shoulder periods, because those trips are easier to reschedule compared to trips for maintenance activities (Strathman et al., 1994). Longer work-home distance is expected to increase the number of non-work stops linked, because a longer distance may expose commuters to a wider range of locations for activities, which increase commuters' chances to make multi-stop tours (Adler and Ben-Akiva, 1979). This behavior is typical for commuters without access to a car, but with a long distance to traverse.

Although previous researchers have tested a series of relationships between trip-chaining behavior and personal, households, land use, and trip attributes, conflicting findings still exist and the debates continue, such as over the relationship between trip-chaining behavior in commutes and land use. This study focuses on home-to-work (H-W) and work-to-home (W-H) tours and draws on the latest national scale household survey, ultimately providing improved estimation of stops to fill in some gaps in the existing literature.

3. Data

In the NHTS trip-chaining dataset, a direct trip is the individual trip from an origin to a destination reported by the respondent in his/her travel diary. Trip chains or tours are defined by the Federal Highway Administration (FHWA) as the sequence of trips conducted, in which commuters incorporate stops for any purpose. At each stop, activities conducted are finished within 30 minutes. As for commute tours, multiple stops were recorded en route between home and work, or work and home.

I combine data on the characteristics of large metropolitan areas from the 2010 Census with observations from the public use file of the 2009 NHTS dataset, based on two conditions: (1) commuters make only one H-W and one W-H tour; and (2) commuters use the same travel mode for the longest segment of commute for both H-W and W-H directions. In the public use file of the NHTS, only the most populous 51 metropolitan areas with 1 million or more population have a field of 5-digit code assigned by Census Bureau for the Core-based Statistical Areas (CBSA)[3]; in other words, all other CBSAs with a population less than a million are not identified[4], so no characteristics of metropolitan areas from U.S. Census could be joined to those smaller CBSAs. For commuters in households located in large CBSAs, 60,401 travel-day commute tours are made by 31,947 individuals. Among those respondents, 24,262 individuals make one H-W tour and one W-H tour. Among them, the vast majority (23,630) use the same mode for both H-W and W-H tours. This study focuses on the number of stops commuters incorporate into their H-W and W-H tours, which is similar to previous studies conducted by Bhat (1997), Shiftan (1998), Bhat and Singh (2000), Wallace et al. (2000), and Chu (2003). This study examines three groups of explanatory variables; the basic statistics are presented in Table

[3] A more detailed list can be found at the Office of Management and Budget (OMB) Bulletin. http://www.census.gov/population/metro/data/omb.html.

[4] However, as mentioned in NHTS documentation, "NHTS sample is not selected to represent individual areas of one million or more, unless they were in an add-on area…Identifying these major metro areas ensure some comparison on broad travel indicators." Retrieved from http://nhts.ornl.gov/cmsacbsa.shtml.

3. The first group of independent variables includes three subgroups of variables that capture the individual and household attributes that affect the demand for activity and mobility of households. The commuters' demographics are measured by sex (FEMALE), age (AGE), level of education (EDUCA), whether the respondent is able to drive (DRVR), and whether the respondent was born in the US (BORNUS). To rule out potential outliers or measurement errors, I exclude a small number of observations from commuters younger than 16 (24 respondents) and older than 75 (231 respondents). The final sample size is reduced to 18,958 commuters from 15,607 households with complete attribute data. Among this sample, 2,841 commuters in W-H tours and 3,515 commuters in H-W tours made at least one stop.

The second subgroup of independent variables contains several attributes related to employment. It includes whether the respondent has a full-time job (FULLTIME), whether she or he has an option to work at home (WORKHOME), whether the respondent can set or change the start time of their work days (FLEX), whether the respondent is self-employed (SELEMP), and whether a worker can be described as a professional (PROF).

Table 3 Descriptive statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
1. Dependent Variable						
STOPS	Total number of non-work stops during a round-trip commute	18,958	0.427	0.844	0	8
2. Demographics						
2.1 Personal Attributes						
FEMALE	Commuter is female (Yes=1, No=0)	18,958	0.470	0.499	0	1
R_AGE	Commuter's age (years)	18,958	46.859	12.294	18	75
EDUCA	Commuter's level of education	18,958	3.414	1.122	1	5
DRVR	Commuter's ability to drive (Yes=1, No=0)	18,958	0.986	0.116	0	1
BORNUS	Commuter was born in the U.S. (Yes=1, No=0)	18,958	0.833	0.373	0	1
2.2 Employment Attributes						
FULLTIME	Commuter's job is a full-time job (Yes=1, No=0)	18,958	0.860	0.347	0	1
WORKHOME	Commuter has option to work from home (Yes=1, No=0)	18,958	0.142	0.349	0	1
FLEX	Commuter has flexible work hours (Yes=1, No=0)	18,958	0.446	0.497	0	1
SELEMP	Commuter is self-employed (Yes=1, No=0)	18,958	0.080	0.271	0	1
PROF	Commuter is a professional (Yes=1, No=0)	18,958	0.511	0.500	0	1
2.3 Household Attributes						

HHINC	Household income level last year	18,958	14.264	4.586	1	18
HHSIZE	Number of household members	18,958	2.999	1.320	1	13
CHILD	Household has at least one child who is 15-years-old or younger (Yes=1, No=0)	18,958	0.360	0.480	0	1
NUMADLT	Number of adult household members	18,958	2.279	0.809	1	10
SADLT	Household has only one adult (Yes=1, No=0)	18,958	0.097	0.296	0	1
NWALT	Household has non-working adult (Yes=1, No=0)	18,958	0.408	0.492	0	1
WHITE	Household respondent is white (Yes=1, No=0)	18,958	0.807	0.395	0	1
OWN	Household owns residence (Yes=1, No=0)	18,958	0.886	0.318	0	1
SFH	Household lives in single-family home (Yes=1, No=0)	18,958	0.815	0.388	0	1
VWR	Household has more vehicles than workers (Yes=1, No=0)	18,958	0.9	0.230	0	1
3. Land Use and Built Environment						
ln(POPCBSA)	Population of CBSAs in natural log	18,958	15.208	0.800	13.868	16.755
ln(POPCBSADEN)	Population density of MSA (persons/sq. mi.) in natural log	18,958	6.659	0.735	4.768	7.947
MSARAIL	MSA has heavy rail service (Yes=1, No=0)	18,958	0.362	0.481	0	1
LAT	Latitude of MSA center	18,958	34.706	4.657	25.729	47.603
LON	Longitude of MSA center	18,958	-94.467	16.971	-122.679	-71.058
ln(CTPOPD)	Census tract population density level at residence (persons/square miles)	18,958	7.797	1.435	3.912	10.309

	in natural log					
ln(CTEMPDEN)	Census tract population density at residence (persons/square miles) in natural log	18,958	6.331	1.535	3.219	8.517
4. Trip Attributes						
Travel mode of round-trip						
CAR	Major commute mode = car (Yes=1, No=0)	18,958	95.46%	0.208	0	1
RAIL	Major commute mode = rail (Yes=1, No=0)	18,958	0.88%	0.093	0	1
BUS	Major commute mode = bus (Yes=1, No=0)	18,958	1.52%	0.123	0	1
BIKE	Major commute mode = bicycle (Yes=1, No=0)	18,958	0.60%	0.077	0	1
WALK	Major commute mode = walk (Yes=1, No=0)	18,958	1.07%	0.103	0	1
OTHERS	Other commute mode	18,958	0.47%	0.069	0	1
ln(JOBDIST)	Distance between home and work in natural log	18,958	2.282	1.011	-2.197	4.949
PEAKTOUR	Commute during weekday peak hours (Yes=1, No=0)	18,958	0.223	0.417	0	1
WEEKEND	Commute during weekend (Yes=1, No=0)	18,958	0.070	0.256	0	1
GASPRICE	Average local gas price at time of travel (cents)	18,958	283.227	96.311	149.8	446
SMT	Commute during summer (Yes=1, No=0)	18,958	0.234	0.424	0	1
WTT	Commute during winter (Yes=1, No=0)	18,958	0.291	0.454	0	1
5. Interactions						

CHILD*FEMALE	Presence of young children and being female (Yes=1, No=0)	18,958	15.39%	0.361	0	1
CHILD*PEAKTOUR	Presence of young children and traveling in rush hours (Yes=1, No=0)	18,958	8.43%	0.278	0	1
CHILD*WEEKEND	Presence of young children and traveling at weekend (Yes=1, No=0)	18,958	2.34%	0.151	0	1
CHILD*SMT	Presence of young children and traveling in summer (Yes=1, No=0)	18,958	8.33%	0.276	0	1

Data Source: U.S. Census 2010 SF1[5], NHTS 2009.

[5] Dataset is retrieved from Census Bereau's report, *Patterns of Metropolitan and Micropolitan Population Change: 2000 to 2010*. Retrieved from: http://www.census.gov/population/metro/data/pop_data.html.

The third subgroup of variables describing household attributes includes household income categories (HHINC, measured in categories using total household family income for the last 12 months) and number of household members (HHSIZE). Factors such as life cycle stage and vehicle ownership are also chosen because of their important roles in affecting commuters' daily travel. Most respondents (16,169) in this sample are the household heads or the spouses of household heads. The variables used in this study include whether a household has at least one child who is 16 years old or younger (CHILD), the number of adults in the household (NADLT), whether there is only one adult in the household (SADLT), whether there is any non-working adult in the household (NWADLT), and whether there are more vehicles than workers in the household (VWR). Finally, the study takes into account whether the household respondent's race is white (WHITE), whether the household owns its residence (OWN), and whether the type of residence is single-family housing (SFH).

Additionally, this study investigates the degree to which several built-environment or infrastructure attributes affect commuters' trip-chaining behavior. There are two subgroups of independent variables with regard to the built-environment measures. The first category contains characteristics of metropolitan areas (See Table 6 in the Appendix), including the population of a CBSA (POPCBSA), population density of CBSAs (POPCBSADEN), whether heavy rail service is available in the region (MASRAIL), and the latitude (LAT) and longitude (LONG) of the CBSA's center city (U.S. Census Bureau, 2012). These variables are included for two reasons. First, some of the relevant meta-analyses stratify the cities and metropolitan areas by total population and region (Zhang et al., 2012). Therefore, the total population and latitude and longitude of the central city of each CBSA capture these features. Second, regional land use patterns are more likely to affect commutes by automobile or rail, while non-motorized commutes may be largely influenced by characteristics of the built environment at the neighborhood scale (Zhang et al., 2012; Boarnet and Crane, 2001). The second category consists of measures of density at the home end of commute tours, which has long been used by previous studies (Noland and Thomas, 2007; Krizek, 2003). Population densities at the census tract level are measured by population density (CTPOPD) and density of workers living at each census tract (CTEMPDEN). Natural logarithmic transformation is used for home-work distance (JOBDIST) and population density (POPCBSADEN, CTPOPD, CTEMPDEN).

The models in this study capture a few additional variables depicting the characteristics of tours. These characteristics include travel modes (CAR, RAIL, BUS, BIKE, WALK and OTHER, shown in Table 4), distance between home and work (JOBDIST), whether the commute trips are taken during weekday peak hours or not (PEAK)[6], whether tours are taken during a weekend or not (WEEKEND), the average local price of gasoline at time of travel (GASPRICE), and whether those tours happen from June to August during the summer (SMT) or from December to February in the winter (WTT).

This study also takes into account the interactions between the presence of young children, a key feature affecting trip-chaining behavior as discussed previously, and the other demographic and trip attributes. Figure 1 presents the framework showing relationships among the dependent variable and the three groups of independent variables.

[6] Both the start and end time of each H-W or W-H tour are within 7 to 9 a.m. or 4 to 7 p.m. in weekdays.

All aforementioned variables can also be divided into two groups. Static variables include data items that are independent of the model structure, such as the age and sex of the modeled person. In the model estimation and application, static items are predetermined in the input files of NHTS. Situational variables include data items that describe person and household activities or trips, such as time of commute and mode used. Figure 1 also identifies the classification of independent variables used in this model.

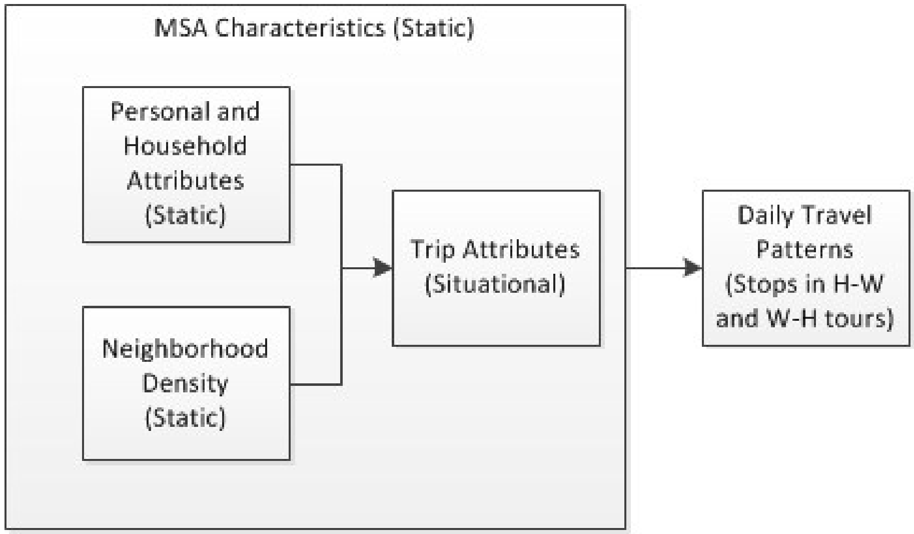

Figure 1 Conceptual framework

4. Methodology

Negative binomial regression is widely used to fit non-negative discontinuous count data. Both Wallace et al. (2000) and Noland and Thomas (2007) have employed this method to estimate the effects of potential determinants on the number of stops respondents make along the way to or from work. In this study, to predict the number of stops made by commuters during their round-trip commutes, the negative binomial model is used because of the highly non-normal distribution of the number of stops (see Figure 2). For the negative binomial models, there are three components: (1) a dependent variable y, the number of intervening non-work stops linked per tour in this study, with a specific error distribution with the mean μ and the variance σ^2; and (2) on the right-hand side of Equation 1, a linear additive regression equation constructing a predictor of the dependent variable y and including an array of independents, among which, let p_i be a vector of predetermined variables measuring personal and household attributes, let b_i denote an array of built environmental and infrastructural variables, and let t_i be a matrix of situational variables depicting the details of commuters' daily travel patterns;

and (3) a natural-log link function combines the dependent variable y and the predicted values for y and the error term, ε (Hox, 2009). A correlation matrix is also computed to detect collinearity between all pairs of the explanatory variables and the results of a variance inflation factors (VIF) test show that the potential collinearity can be minimized.

$$y = \exp(\beta_0 + \beta_{1i}p_i + \beta_{2i}b_i + \beta_{3i}t_i + \varepsilon) \qquad (1).$$

However, as mentioned above, both the number of intervening stops made en route and the array of independents may also be affected by other unobserved factors. Thus, it is tricky to avoid embedded potential biases from endogeneity using a simple regression model. Trip-chaining decisions are subject to choices relevant to both travel (e.g. mode, travel time, and route) and activities (e.g. activity participation, duration and location) (Levinson and Kumar, 1995). Factors affecting travel behavior not only interact with each other, but also influence activity-related factors. Consequently, the explanatory power of an activity-based model seems to be stronger than that of the traditional trip-based approach. However, a model considering both temporal and spatial constraints is not computationally practical due to the expansion of the number of choice sets and subgroups of respondents (Bowman and Ben Akiva, 2001; Kockelman, 1999). Additionally, Table 3 and Table 4 show that only a small proportion of commuters traveling by bus, by bike, or on foot, and as such, the specification of a joint-choice model of travel modes and intervening stops is constrained by the sample size and the distribution of key factors. The first and second columns of Table 5 show the results of single-level regression. Model 2 also considers the interactions of the presence of young children.

Additionally, this study also uses a multi-level regression to increase the accuracy of estimation and avoid the potential underestimation of variance, considering the effects of clusters. The reason for using multi-level regression is to examine the "contextual effect" of characteristics drawn on information from within clusters—CBSAs in this case—to present effects of cluster attributes (Hox and Roberts, 2011). It is very likely that commuters from the same metropolitan areas have more similarities in their daily travel patterns than with commuters from other metropolitan areas in ways not accounted for by their observable characteristics; this violates the assumption of independent errors and random sampling in the negative binomial models. As such, β_0 as the constant term in Equation (1), is random, part of which could be explained by parts of built environment and infrastructural attributes at metropolitan areas level (b_{ij}) derived from the NHTS and the Census, and Equation (2) denotes this relation.

$$\beta_0 = \gamma_{01} + \gamma_{0j} b_{ij} + \mu_{0j} \qquad (2)$$

where γ_{0j} is a matrix of coefficients for characteristic i of metropolitan area j,

μ_{0j} denotes the error term,

and b_{ij} is the characteristic i of metropolitan area j.

The third and fourth columns of Table 5 show the single- and multilevel regressions, taking into account the interactions of the presence of children and other demographic and travel attributes.

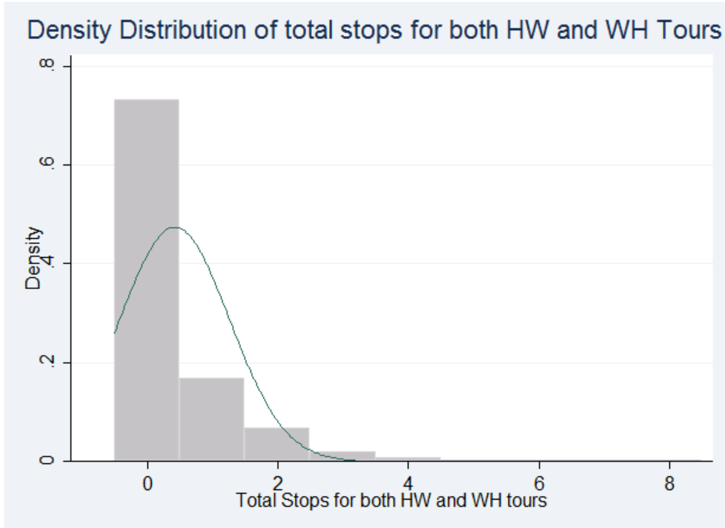

Figure 2 The distribution of intervening stops made in round-trip commute[7]

Table 4 Mode split for the longest segment in the H-W and W-H tours of respondents

	Frequency	**Average number of stops made en route**
Car	18,098	0.43
Rail	166	0.66
Bus	289	0.25
Bike	113	0.12
Walk	202	0.23
Others	90	0.23

Data Source: NHTS, 2009.

Work trips are less endogenous than other travel decisions because the activity participation, duration, and location of work are conditioned on individual and household needs in the long run and/or exogenous factors for most of commuters (Adler and Ben-Akiva,

[7] The blue line shown in Figure 2 demonstrates the normal distribution.

1979, see Figure 1). In addition, for most workers, commute tours take place with high frequency (usually daily) to the same destination during the same periods. This makes commute tours more predictable than tours for other purposes (Ajzen, 1985, 1991). In other words, analyzing commute tours exclusively will not yield significant bias compared with other types of tours.

5. Results

Aforementioned Table 5 displays results from the negative binomial regressions of the numbers of stops made by commuters (STOPS) in the largest metropolitan areas. Incidence-rate ratios (e^{β_i}), reported in Table 5, reflect the marginal effect of one independent variable on the number of stops commuters made, all else equal. Ratios larger than 1 demonstrate a positive relationship between the independent and dependent variables; with ratios smaller than 1, independent variables have a negative effect on the likelihood of incorporating more stops in H-W and W-H tours. A significant α indicates the selected negative binomial model fits data better than a Poisson model. In this section, the effects of the aforementioned five groups of variables will be discussed to construct a picture of the determinants of the number of chained trips.

Table 5. Regression results

STOPS_sum	Model 1		Model 2		Model 3		Model 4	
FEMALE	1.621	***	1.621	***	1.349	***	1.349	***
	(-16.23)		(-14.29)		(-7.74)		(-6.31)	

R_AGE	1.004	**	1.004	***	1.005	***	1.005	***
	(-3.18)		(-4.15)		(-3.44)		(-4.29)	
EDUC	1.075	***	1.075	***	1.072	***	1.072	***
	(-4.59)		(-5.29)		(-4.46)		(-5.23)	
DRVR	1.636	**	1.636	*	1.606	**	1.606	*
	(-2.97)		(-2.48)		(-2.86)		(-2.41)	
BORNUS	1.148	**	1.148	**	1.143	**	1.143	**
	(-3.24)		(-3.00)		(-3.17)		(-2.98)	
FULLTIME	1.094	*	1.094		1.115	*	1.115	*
	(-2.02)		(-1.69)		(-2.47)		(-2.06)	
WORKHOME	1.146	***	1.146	***	1.146	***	1.146	***
	(-3.28)		(-3.91)		(-3.28)		(-3.93)	
FLEX	1.182	***	1.182	***	1.186	***	1.186	***
	(-5.26)		(-6.04)		(-5.38)		(-6.14)	
SELEMP	1.182	**	1.182	***	1.172	**	1.172	***
	(-3.15)		(-3.45)		(-3.01)		(-3.31)	
PROF	0.968		0.968		0.966		0.966	
	(-0.97)		(-1.01)		(-1.02)		(-1.07)	
HHINC	1.001		1.001		1.000		1.000	
	(-0.22)		(-0.21)		(-0.01)		(-0.00)	
HHSIZE	1.028		1.028		1.040		1.040	
	-1.2		-1.02		-1.72		-1.4	

CHILD	1.777	***	1.777	***	1.349	***	1.349	***
	(-11.43)		(-9.71)		(-4.71)		(-4.28)	
NUMADLT	0.926	*	0.926		0.916	**	0.916	
	(-2.39)		(-1.74)		(-2.72)		(-1.92)	
SADLT	1.214	***	1.214	**	1.221	***	1.221	***
	(-3.44)		(-3.19)		(-3.55)		(-3.23)	
NWALTHH	0.878	***	0.878	***	0.890	***	0.890	***
	(-3.91)		(-3.98)		(-3.54)		(-3.62)	
WHITE	0.884	**	0.884	**	0.892	**	0.892	**
	(-3.16)		(-3.05)		(-2.95)		(-2.87)	
OWN	0.962		0.961		0.961		0.961	
	(-0.73)		(-0.71)		(-0.75)		(-0.72)	
SFH	0.932		0.932		0.929		0.929	
	(-1.66)		(-1.81)		(-1.73)		(-1.86)	
VWR	0.818	**	0.818	*	0.816	**	0.816	*
	(-2.89)		(-2.55)		(-2.93)		(-2.54)	
lgPOPCBSA	0.982		0.982		0.987		0.987	
	(-0.59)		(-0.54)		(-0.42)		(-0.37)	
lgPOPCBSADEN	0.994		0.994		0.994		0.994	
	(-0.18)		(-0.30)		(-0.18)		(-0.29)	
MSARAIL	1.016		1.016		1.011		1.011	
	(-0.38)		(-0.46)		(-0.26)		(-0.31)	

LAT	1.002		1.002		1.002		1.002	
	(-0.66)		(-0.9)		(-0.69)		(-0.92)	
LON	1.001		1.001		1.001		1.001	
	(-1.06)		(-1.77)		(-1.04)		(-1.66)	
lgCTPOPD	1.010		1.010		1.010		1.010	
	(-0.6)		(-0.69)		(-0.63)		(-0.7)	
lgCTEMPDEN	0.975		0.975	*	0.975		0.975	*
	(-1.72)		(-2.23)		(-1.73)		(-2.17)	
Reference group: Private Vehicle								
Rail	1.351	*	1.351		1.351	*	1.351	
	(-2.2)		(-1.93)		(-2.21)		(-1.87)	
Bus	0.582	*	0.582	*	0.587	***	0.587	
	(-3.84)		(-2.01)		(-3.79)		(-1.95)	
Bike	0.340	***	0.340	**	0.340	***	0.340	**
	(-3.58)		(-3.10)		(-3.53)		(-2.97)	
Walk	0.725		0.725		0.715		0.715	
	(-1.79)		(-1.55)		(-1.88)		(-1.67)	
Others	0.598	*	0.598	*	0.610		0.610	*
	(-2.01)		(-1.97)		(-1.96)		(-1.97)	
JOBDIST	1.111	***	1.111	***	1.112	***	1.112	***
	(-6.48)		(-8.47)		(-6.59)		(-8.5)	

PEAKTOUR	0.913	**	0.913	***	0.754	***	0.754	***
	(-2.63)		(-3.31)		(-5.80)		(-6.26)	
WEEKEND	0.631	***	0.631	***	0.725	***	0.725	***
	(-6.79)		(-7.03)		(-3.88)		(-4.04)	
GASPRICE	1.001	*	1.001	*	1.001	*	1.001	*
	(-2.53)		(-2.38)		(-2.57)		(-2.35)	
SMT	0.857	***	0.857	***	0.927		0.927	
	(-3.35)		(-4.88)		(-1.41)		(-1.84)	
WTT	1.050		1.050		1.054		1.054	
	(-1.13)		(-1.51)		(-1.22)		(-1.64)	
Interactions								
CHILDFEMALE					1.527	***	1.527	***
					(-7.39)		(-9.1)	
CHILDPEAKTOUR					1.477	***	1.477	***
					(-5.7)		(-6.04)	
CHILDWEKND					0.674	***	0.674	***
					(-2.83)		(-3.32)	
CHILDSMT					0.847	*	0.847	*
					(-2.42)		(-2.34)	
Constant	0.128	***	0.128	***	0.130	***	0.130	***
	(-4.41)		(-4.90)		(-4.40)		(-4.82)	
Natural log of	0.209	***	0.209	***	0.173	***	0.173	***

alpha								
	(-5.05)		(-3.32)		(-4.11)		(-2.66)	
N	18958		18958		18958		18958	
Log likelihood (Constant only)	- 16413.3		- 16413.3		- 16413.3		- 16413.3	
Log likelihood (Full model)	- 15853.5		- 15853.5		- 15797.4		- 15797.4	
McFadden's R Square	0.034		0.034		0.038		0.038	
t statistics in parentheses								
* p<0.05, ** p<0.01, *** p<0.1								

5.1 Demographics

The results of the models confirm the demographic findings made by previous research. The differences in terms of sex and life cycle stage continue based on the results from the latest household travel survey. Female commuters make 1.6 times as many intervening non-work stops as do males, all else equal. For female commuters from households without young children, the gender difference in the number of stops is down to roughly 35 percent. Meanwhile, including the effect of the children-related interactions in Model 3 also indicate an increase of 50 percent in intervening stops for female commuters with young children in their households, which is consistent to the expectation that women engage in more children-related activities. Results show a small, positive, and statistically significant effect of the respondents' age on the number of non-work stops en route. In Model 1, being able to drive increases commuters' predicted number of intervening stops by about 64 percent, because a higher level of mobility helps commuters overcome spatial and temporal constraints. Commuters' potential for trip-chaining increases because they are more likely to meet their multiple travel needs when they can access a larger area of destinations. Being born in the US is positively related to more stops in chaining trips, partially because new immigrants undergo the process of spatial assimilation; as the time in U.S. increases, their residential location converges with native commuters, and their limited knowledge of the environment outside where they live and work constrains their choices. Native commuters also predominately use cars as the travel mode compared to those new immigrants, all else equal. The probability of making more trips increases with level of education, even though the magnitude of such an effect is small, at about 7%).

5.2 Employment Characteristics

As expected, a more flexible employment schedule can increase the number of stops. Commuters having the option to work from home made about 15 percent more stops during their commutes. Similarly, workers who can change when they start working tend to increase STOPS by roughly 18 percent. Also, commuters who are self-employed make 17 percent more stops in both Model 1 and Model 3. For full-time workers, there is a one-tenth increase in the number of stops in chaining work trips. As for being a professional, no significant effect is found on the number of stops during a commute in any of the models.

5.3 Household Characteristics

Table 5 also shows findings relevant to household characteristics. Commuters tend to make more stops when they have young children in their households, and this result is in line with the existing literature; the presence of young children is associated with an 80 percent increase in the number of stops made. As shown by the interactions in Models 3, around 60 percent of the effects can be attributed to the stops made by peak-hour commuters and by female commuters. The increase of the number of adults in a household (NADLT) is associated with a drop of the number of stops by 12 percent, due to the sharing of domestic responsibilities among the adults within a household. Additionally, if a commuter is the only adult in a household (SADLT=1), she or he may make about 20 percent more stops than other commuters. Since all sampled respondents are workers, this finding echoes conclusions made by previous research, that single adult workers tend to link more non-work trips (e.g. Strathman et al. ,1994; Lee et al. ,2007). The variable NWADLTHH (whether there is at least one non-working adult in a household) tests whether the presence of non-working adults may reduce the probability of trip-chaining behavior. With one or more non-working adults in the household, a commuter makes about 10 percent fewer stops.

Although household vehicle ownership is near ubiquitous in the US, there is significant variation in vehicles owned per worker (Train, 1993). Commuters from households with at least one vehicle per worker (VWR = 1) make about 15 percent fewer stops compared with households with fewer vehicles than workers in their households. This finding confirms the high correlations among vehicle ownership, mobility, and travel demand presented by many researchers (Train, 1993; Gliebe and Koppelman, 2002).

However, the effects of social and economic factors are mixed. On the one hand, this study differs from others in that many social economic explanatory variables, such as home ownership (OWN), and residence type (SFH), do not show strong relationships with the number of intervening stops. Household income level (HHINC) has no significant effect on commute trip chaining. Nevertheless, results of other socio-economic characteristics of households such as race (WHITE) of the household head, suggest that being white is associated with fewer stops in commute tours.

5.4 Regional and Local Environmental and Geographic Characteristics

Compared with attributes of individuals and households, regional and local environmental and geographic characteristics have little explanatory power. The increase in population size of a metropolitan area predicts a slight fall in the number of stops made by commuters, though the significance of this effect is marginal. Similarly, a small negative effect is found for urban area population density, which is marginally significant. Slightly fewer stops (about 3%) by commuters correspond to households living in tracts with a higher worker density. There is no statistically significant relationship between the number of stops and an urban area's geographical location (latitude and longitude), or land use densities at the local level (i.e., census tract level population density at the home end).

5.5 Other Commute Trip Characteristics

Compared to those who commute by private vehicle (the default mode), workers riding a bus or bicycle make significantly fewer stops during H-W and W-H tours. As Table 5 shows, workers commuting by bus or bicycle make half, or even one-third, as many stops as those who commute by car. Such results indicate that private vehicles provide commuters with more flexibility, and therefore more activities could be incorporated into work-related tours. However, rail riders seem to make about 35 percent more stops than car commuters, all else being equal, although the statistical significance of the coefficient is marginal (with a p-value around 0.027) in all four models. Besides the unobservable differences in land use, rail transit may better facilitate trip chaining than the bus for reasons such as punctuality. Another possibility is that the existence or success of rail service is a reflection of fairly dense urban development (Cervero and Guerra, 2011), which might also encourage a commuter to consider a multi-stop tour because of destinations located close to each other. Additionally, a more accurate classification of mode choice should also capture the influence of "park and ride" on commuters' trip-chaining behavior. In this case, it is hard to separate the effects of the rail on the number of stops from the car if the longest distance of segments commuters traverse is made by rail.

As for the time of travel, H-W and W-H tours during weekday peak periods (PEAKTOUR=1) decrease the predictive number of stops per tour. A decline in the number of non-work stops by 9 percent is associated with a tour taking place in peak periods, all else being equal, for models without interactions. The magnitude of this negative effect, however, increases to 35 percent when the interaction between peak-hour commutes and the presence of at least one young child is included in the regression. This suggests that independent from the presence of young children, the bulk of peak and off-peak difference remains.

Both models without children-related interactions show that non-work stops in tours are down by 37 percent on weekends. The magnitude of the effect of weekend commutes reduces when the interactions between weekend commutes and the presence of at least one young child is included in the regression (by 28% percent in Model 3 and Model 4). Nonetheless, the magnitude of the weekday-weekend difference in trip-chaining behavior remains independent from the presence of young children. Similarly, the reduction in the potential of incorporating non-work stops in tours made in the summer also indicates that transporting pre-driving-age children is an important activity for stops made by commuters. Commuters' distance to work has a fairly small effect on the number of stops during a commute. An increase of the distance to work by one in natural log increases non-work stops a commuter makes by roughly 10 percent.

5.6 Multi-level Regression Results

The second and fourth columns (Model 2 and Model 4) in Table 5 show results using the multilevel negative binomial regressions. After controlling for the randomness embedded in the constant term in Equation (1) as written in Equation (2), the values of the t statistic are larger for variables related to characteristics of their jobs. The only land use and built environment factor at the metropolitan level showing an association of strength is the residential density of workers in each census tract. Living in a dense census tract slightly decreases the number of non-work stops made, and workers in those denser tracts may replace the number of non-work stops by taking separate trips (i.e. shopping or retaining other errands after arriving at home or before going to work from home) because destinations are located close to each other. No other metropolitan-level attribute becomes more significant after conducting multilevel regressions. However, because a round-trip commute (H-W and W-H tours) is more predictable compared to other more randomly generated non-work trips, and the differences across those largest metropolitan areas are not very significant, a better control over the randomness is not evident in terms of R square, the increase of which may indicate a better estimation.

The statistical significance of other independent variables in single-level models is also different from that of multilevel models. The values of the t-statistic increase for some of the factors, such as being self-employed or traveling during peak periods. These findings suggest the importance of a commuter's time of travel or work schedules after the multilevel modeling technique is applied. On the contrary, a reduction of significance is found in variables such as the mode used and automobile ownership. This indicates that after controlling for the variation among MSAs, the effects decrease for mode choice and social-economic status on stops made. That is, part of the behavioral differences in different groups of commuters by travel mode or automobile ownership might be attributed to the variation of different metropolitan areas.

6. Conclusion

Results of this study are consistent with some of the findings made by previous researchers on trip-chaining behavior. First, in accordance to Bhat (1997), McGuckin and Nakamoto (2005), McGuckin and Murakami (1999), Goodwin (1984), Noland and Thomas (2007), there is a significant gender difference in the number of stops made in commute trip chains. However, this difference can only partially be explained by the fact that women shoulder more children-related errands. Second, household types and intra-household labor division also affect trip chaining behavior, which is reflected by variables depicting a traveler's life cycle stage: 1) the presence of young children in a household predicts significantly more stops, especially during peak hours and by female commuters; and 2) the increase of total number of adults in household decreases the number of intervening stops made by commuters, as does the presence of non-working adults in a household. These findings confirm conclusions made by Golob (1986), Lu and Pas (1999), Noland and Thomas (2007), Strathman et al. (1994), Wen and Koppelman (2000).

A higher level of mobility often leads to trip-chaining behavior. Incident-rate ratios of two sets of independent variables support this finding. First, modes such as transit, bicycling, and walking are associated with tours with fewer stops than private vehicles and urban rail. These observations are consistent with the findings of Bhat (1997), McGuckin et al. (2005), and McGuckin et al. (1999). Second, similar to findings of Lu and Pas (1999), being able to drive is positively related to the number of stops made independent from mode choice. Finally, even though longer commute distances are associated with increased commute trip chaining, the magnitude of this effect is quite small. This finding is similar to that reached by Strathman et al. (1994) in Portland, Oregon.

However, some of the results differ from many previous studies. First, this study suggests limited explanatory power of the regional and local built environmental characteristics on the number of stops commuters make; this is in line with Krizek's (2003) study, but different from others (Golob, 2000; Noland and Thomas, 2007), even though all of them measure land use patterns (population density or accessibility) at the home end of tours. Second, a higher level of socio-economic status also has little effect on the number of non-work trips chained in commutes. For instance, although a higher level of education slightly increases the number of one's stops in commute tours, household income and being a professional do not affect the non-work stops linked to commute tours. Other socio-economic characteristics at the household level, such as being a homeowner and residing in a single-family house, reduce the number of non-work trips incorporated. These findings do not support the conclusions of Goulias and Kitamura (1991), Noland and Thomas (2007), or Wen and Koppelman (2000), that household income is positively related to trip chaining. Such a difference may result from the fact that these three previous researchers do not treat commute tours and other trip chains differently. As for automobile ownership, commuters from households with fewer vehicles than workers tend to make more stops.

Apart from trip attributes, several other variables also have a significant effect on intervening stops made in a commute. First, more flexible schedules enable commuters to engage in activities en route to work or home. In other words, if commuters have the option to work at home, if they can change when to start work during a day, or if they are self-employed, their chances of linking more stops in commutes increases. Second, being born in the US has a positive effect on the number of stops made in a commute. For individuals born in the US, a better understanding of local society and geography, coupled with a greater reliance on cars, contributes to more stops in commute tours (Myers, 1996; Rosenbloom and Fielding, 1998; Tal and Handy, 2010) .Third, because there is no need to drop off or pick up their children to or from schools, workers commuting on weekends are likely to go straight to work and tours made are related to fewer stops. Lastly, the increase in the cost of gasoline may not effectively motivate drivers to link multiple trips, since more expensive fuel may also result in a reduction in the total number of trips, including but not limited to commute.

In this study, multilevel regressions do not provide a significantly better estimation of the number of stops than other models. There are two main reasons that explain the limited differences between the two sets of models. First, all respondents selected are from the 51 largest metropolitan areas, which implies a limited variation across metropolitan areas in terms of population size and density. Second, since the H-W and W-H tours are relatively more predictable than other types of tours, commuters across the nation likely have similar daily work travel patterns.

Finally, this paper suggests a variety of topics suitable for further research. As shown in Table 5, the values of pseudo-R square of the models ranging from 0.34 to 0.38 show the limited predictive power. There could be several reasons to explain this. Although commuting is more predictable compared to other types of trips, many unobserved factors still affect the independent variable. For instance, the public use file of NHTS data lack variables relevant to job-end land use and urban design. Second, even though commute trips are less endogenous, future studies may tackle the endogeneity issue, such as the interactions between the number of non-work stops linked in commute tours and travel modes (or even automobile ownership). Further research may also consider the trip purpose of the stops, such as whether the intervening stops are for maintenance or recreation as some studies (e.g., Wen and Koppelman, 2000). Finally, as Gordon et al. (1988) indicate, previous transportation policy analysis largely overemphasizes the journey to work. Studies should also pay attention to the relation between commute tours and non-work tours.

Appendix

Table 6 Characteristics of Metropolitan Areas from 2010 U.S. Census

CBSA FIPS code for HH address	CBSAs	Freq. of obs. in the subset of NHTS 2009	ln(POPCBSADEN)	ln(POPCBSA)	Latitude of Central City	Longitude of Central City
12060	Atlanta-Sandy Springs-Marietta, GA	379	6.449	15.477	33.749	-84.390
12420	Austin-Round Rock, TX	475	6.008	14.356	30.265	-97.747
12580	Baltimore-Towson, MD	48	6.949	14.813	39.291	-76.611
13820	Birmingham-Hoover, AL	35	5.364	13.936	33.520	-86.810
14460	Boston-Cambridge-Quincy, MA-NH	112	7.174	15.331	42.359	-71.058
15380	Buffalo-Niagara Falls, NY	223	6.587	13.943	42.887	-78.879
16740	Charlotte-Gastonia-Concord, NC-SC	167	6.345	14.380	35.222	-80.838
16980	Chicago-Naperville-Joliet, IL-IN-WI	272	7.181	16.063	41.883	-87.632
17140	Cincinnati-Middletown, OH-KY-IN	69	6.184	14.572	39.104	-84.519
17460	Cleveland-Elyria-Mentor, OH	48	6.947	14.547	41.505	-81.694
18140	Columbus, OH	37	6.138	14.423	39.963	-83.003

19100	Dallas-Fort Worth-Arlington, TX	1,920	6.570	15.667	32.777	-96.796
19740	Denver-Aurora-Broomfield, CO	48	5.719	14.749	39.739	-104.991
19820	Detroit-Warren-Livonia, MI	72	7.008	15.273	42.329	-83.044
25540	Hartford-West Hartford-East Hartford, CT	31	6.685	14.008	41.763	-72.674
26420	Houston-Sugar Land-Baytown, TX	1,294	6.513	15.598	29.760	-95.370
26900	Indianapolis-Carmel, IN	280	6.122	14.379	39.768	-86.154
27260	Jacksonville, FL	321	6.041	14.112	30.330	-81.659
28140	Kansas City, MO-KS	56	5.561	14.526	39.100	-94.578
29820	Las Vegas-Paradise, NV	40	5.510	14.484	36.173	-115.139
31100	Los Angeles-Long Beach-Santa Ana, CA	1,482	7.881	16.367	34.054	-118.243
31140	Louisville-Jefferson County, KY-IN	56	5.744	14.065	38.254	-85.759
32820	Memphis, TN-MS-AR	101	5.661	14.090	35.149	-90.052
33100	Miami-Fort Lauderdale-Pompano Beach, FL	1,031	6.999	15.532	25.729	-80.234
33340	Milwaukee-Waukesha-West Allis, WI	132	6.975	14.258	43.042	-87.910
33460	Minneapolis-St. Paul-Bloomington, MN-WI	99	6.299	15.003	44.977	-93.266
34980	Nashville-Davidson--Murfreesboro--Franklin, TN	197	5.633	14.279	36.168	-86.784

35380	New Orleans-Metairie-Kenner, LA	26	5.978	13.971	29.952	-90.076
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	1,439	7.947	16.755	40.713	-74.005
36420	Oklahoma City, OK	29	5.426	14.041	35.469	-97.521
36740	Orlando-Kissimmee, FL	334	6.419	14.574	28.538	-81.379
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	125	7.167	15.601	39.952	-75.163
38060	Phoenix-Mesa-Scottsdale, AZ	49	5.662	15.249	33.449	-112.077
38300	Pittsburgh, PA	59	6.101	14.673	40.438	-79.997
38900	Portland-Vancouver-Beaverton, OR-WA	55	5.808	14.616	45.515	-122.679
39300	Providence-New Bedford-Fall River, RI-MA	76	6.917	14.286	41.824	-71.413
39580	Raleigh-Cary, NC	105	6.280	13.938	35.778	-78.642
40060	Richmond, VA	740	5.400	14.045	37.540	-77.433
40140	Riverside-San Bernardino-Ontario, CA	450	5.043	15.256	33.980	-117.376
40380	Rochester, NY	214	5.886	13.868	43.157	-77.615
40900	Sacramento--Arden-Arcade--Roseville, CA	380	6.045	14.581	38.582	-121.494
41180	St. Louis, MO-IL	58	5.788	14.850	38.627	-90.199

41620	Salt Lake City, UT	42	4.768	13.933	40.760	-111.888
41700	San Antonio, TX	654	5.680	14.577	29.425	-98.495
41740	San Diego-Carlsbad-San Marcos, CA	1,769	6.601	14.945	32.717	-117.163
41860	San Francisco-Oakland-Fremont, CA	676	7.470	15.282	37.779	-122.418
41940	San Jose-Sunnyvale-Santa Clara, CA	276	6.530	14.424	37.336	-121.890
42660	Seattle-Tacoma-Bellevue, WA	67	6.373	15.051	47.603	-122.330
45300	Tampa-St. Petersburg-Clearwater, FL	479	7.010	14.839	27.947	-82.457
47260	Virginia Beach-Norfolk-Newport News, VA-NC	1,038	6.455	14.329	36.751	-76.057
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	793	6.905	15.535	38.895	-77.031

Data Source: U.S. Census 2010 SF1, NHTS 2009

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