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ScienceDirect
Transportation Research Part B 41 (2007) 96–113
TRANSPORTATION RESEARCH PART B
www.elsevier.com/locate/trb

An exploration of the relationship between mode choice and complexity of trip chaining patterns

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Received 9 September 2005; received in revised form 8 February 2006; accepted 29 March 2006

Abstract

This paper investigates the relationship between mode choice and the complexity of trip chaining patterns. An understanding of the causality between these two choice behaviors may aid in the development of tour-based travel demand modeling systems that attempt to incorporate models of trip chaining and mode choice. The relationship between these two aspects of travel behavior is represented in this paper by considering three different causal structures: one structure in which the trip chaining pattern is determined first and influences mode choice, another structure in which mode choice is determined first and influences the complexity of the trip chaining pattern, and a third structure in which neither is predetermined but both are determined simultaneously. The first two structures are estimated within a recursive bivariate probit modeling framework that accommodates error covariance. The simultaneous logit model is estimated for the third structure that allows a bidirectional simultaneous causality. The analysis and model estimation are performed separately for work tour and non-work tour samples drawn from the 2000 Swiss Microcensus travel survey. Model estimation results show that the causal structure in which trip chain complexity precedes mode choice performs best for both work and non-work tour samples. The structure in which mode choice precedes trip chaining pattern choice was found to give significantly inferior goodness-of-fit measures. These findings have important implications for the development of activity-based and tour-based modeling systems and for the design and planning of public transport systems.

Keywords: Tours; Trip chains; Travel behavior; Causal relationships; Mode choice; Simultaneous equations; Econometric modeling

1. Introduction

Over the past few decades, there has been considerable research on people's trip chaining patterns, i.e., the propensity to link a series of activities into a multi-stop tour or journey (Shiftan, 1998; Dissanayake and Morikawa, 2002). The analysis of trip chaining activity may lead to a better understanding of travel behavior and provide a more appropriate framework for examining various transportation policy issues (Strathman

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0191-2615/$ - see front matter
doi:10.1016/j.trb.2006.03.004

and Dueker, 1995). Indeed, the profession has seen tour-based models being developed and increasingly applied in the travel demand forecasting arena in place of the more traditional trip-based models that do not reflect trip chaining behavior and tour formation.

In this paper, the terms trip chain and tour are used synonymously to refer to a sequence of trips that begins at home, involves visits one or more other places, and ends at home. Depending on the number of places visited within the tour or chain, the tour may be classified into two categories: simple and complex. A tour or chain with a single stop or activity outside the home location is defined as a "simple" tour, whereas a tour or chain with more than one stop outside the home location is defined as a "complex" tour. Thus a tour or chain of the form: home → shop → home is considered a simple tour while a tour of the form: home → work → shop → home is considered a complex tour.

As people's activity patterns become increasingly complex and involve interactions with other household and non-household members and as time is a finite resource, it may be conjectured that trip chains are likely to be increasingly complex over time. The ability to chain multiple activities together in a single tour or chain may provide greater efficiency and convenience than a series of single-stop simple tours (Hensher and Reyes, 2000). There are at least two reasons as to why this has significant traffic and policy implications. First, complex tours or chains may lead to an increase in automobile usage. If one needed to pursue complex tours or chains, then the flexibility afforded by the private automobile is desirable. The ability to pursue multiple activities in a single journey is rather limited when constrained by the schedules, routes, and uncertainty associated with public transportation. Thus, complex trip chaining may contribute to an increased auto dependency and consequently, automobile traffic. Second, in the case of workers (commuters), the formation of complex trip chains may entail the linking of non-work activities with the work trip (commute). Then, non-work trips that could have taken place outside the peak periods now occur in the peak periods simply because they are being tied together with the commute. Thus, complex trip chaining patterns may contribute to an increase in peak period travel demand.

The above discussion clearly points to the possible interdependency between trip chaining, auto usage, and trip timing. Strathman and Dueker (1995), in an analysis of the 1990 NPTS, found that complex trip chains may tend to be more auto-oriented. However, the nature of the causal relationship is not unilaterally evident because the availability of an automobile may provide the flexibility and convenience that contributes to the formation of complex trip chains. The flexibility of the automobile may stimulate the desire to undertake additional activities in one tour. For example, the lower travel times typically associated with the auto mode choice may relax time constraints and lead to more stop-making (Bhat, 1997). Moreover, shared rides, which constitute a portion of total auto mode share, are more likely to involve complex tours due to the variety of trip purposes and destinations between the driver and passengers. The central question that is being addressed in this paper is: "Does mode choice influence the complexity of trip chaining patterns or does the complexity of the trip chaining patterns influence mode choice?". The ambiguity in the causal relationship between the complexity of trip chains and mode choice motivates this investigation. This paper is aimed at understanding and quantifying the causal relationships between tour complexity and mode choice using econometric methods.

Previously, Strathman and Dueker (1994) analyzed the probability of an individual engaging in a complex work tour using a binary logit model formulation, where the complexity/simplicity of a tour was modeled as a binary choice. One may also adopt a binary choice formulation to model mode choice at the tour level, i.e., auto vs non-auto mode choice. Thus, the investigation of the mutual influence and causal relationship between tour complexity and mode choice may be reduced to a problem involving two binary discrete choice variables.

The nested logit model is often applied in dealing with problems of this nature. Based on the assumption of a conditional choice mechanism, nested logit models representing two alternative tree structures can be formed. By checking the reasonableness of the estimated inclusive value parameter coefficients and/or comparing measures of goodness-of-fit between models of two different structures, the more plausible structure that is supported by the data may be identified. Hensher and Reyes (2000) used the nested logit model formulation to understand the role of trip chaining in serving as a barrier to the use of public transport modes. This paper is intended to further clarify the relationship between mode choice and tour complexity using rigorous econometric methods that explicitly allow the quantification of the impact of one choice dimension on another. A bivariate simultaneous model formulation is adopted in this paper to accommodate the variety of causal structures that may be considered.

The rest of this paper is organized as follows. Section 2 presents the modeling methodology and formulation for the different causal structures considered in this paper. Section 3 introduces the Swiss Travel Microcensus 2000 and the process by which the tour dataset needed for model estimation was prepared. Model estimation results are discussed in Section 4. Section 5 presents the performance comparison across models representing three different causal structures. Conclusions are drawn and some recommendations for future research are provided in the final section.

2. Methodology

Two different econometric modeling methods are employed in this paper. The first is the recursive simultaneous bivariate probit model, which allows the analysis of one-way causal relationships between two choice behaviors. In this formulation, the random error terms are assumed to follow the bivariate normal distribution. The bivariate normality assumption implies that two endogenous dummy variables may not coexist in mutual functional relations. The existence of an endogenous dummy variable in either function corresponds to two different causal structures (see Section 2.1 for details). Intuitively, this feature of the bivariate probit model provides an appropriate approach to distinguish the causality between tour complexity and mode choice. However, this approach also entails an underlying assumption that an explicit unidirectional causal relationship (or at least the tendency of such a unidirectional causal relationship) exists in the population being studied. A unidirectional causal relationship may exist in a specific tour, but the nature of the causal relationship may vary across individuals and across tours for the same individual. Macroscopically, the presence of a bidirectional causality would possibly appear in the population if neither unidirectional causal relationship dominates the other.

In order to address the possibility of a simultaneous bidirectional causality, this paper also uses the simultaneous logit model formulation presented by Schmidt and Strauss (1975) and initially introduced in the transportation context by Ouyang et al. (2002). This model formulation enables the modeling of bidirectional causality that might exist in tour complexity and mode choice. Essentially, the simultaneous logit model may be considered an extension of the more commonly known multinomial logit model, where two endogenous dummy variables can be incorporated into the mutual utility functions simultaneously. The only restriction on these two dummy variables is that their model coefficients must be identical for logical consistency (see Section 2.2 for details). Thus, three different possible causal structures are considered in this paper:

(1) Mode choice → Trip chain complexity (recursive bivariate probit model).
(2) Trip chain complexity → Mode choice (recursive bivariate probit model).
(3) Trip chain complexity ↔ Mode choice (simultaneous logit model).

Through a performance comparison of models across the three causal structures, it is envisaged that the relationship between tour complexity and mode choice may be discussed and clarified.

2.1. Recursive simultaneous bivariate probit model

If the tour's complexity/simplicity and auto/non-auto mode choice are treated as two binary choices, the bivariate probit model can be formulated at the tour level to simultaneously analyze their probabilities with accommodation of random error correlation. The general formulation is as follows:

$$\begin{cases} M_q^* = \gamma' z_q + \alpha T_q + \varepsilon_q \\ T_q^* = \beta' x_q + \eta M_q + \omega_q \end{cases} \tag{1}$$

where

q is an index for observations of tour ($q = 1, 2, \ldots, Q$),
M_q^* is a latent variable representing the mode choice for tour q,
T_q^* is a latent variable representing the complexity of tour q,
$M_q = 1$ if $M_q^* > 0$, $= 0$ otherwise,

i.e., M_q is a dummy variable indicating whether tour q uses the auto mode,
$T_q = 1$, if $T^*_q > 0$, $= 0$ otherwise,
i.e., T_q is a dummy variable indicating whether tour q is complex,
z_q is a vector of explanatory variables for M^*_q,
x_q is a vector of explanatory variables for T^*_q,
γ, β are two vectors of model coefficients associated with the explanatory variables z_q and x_q, respectively,
α is a scalar coefficient for T_q to measure the impact of tour's complexity on mode choice,
η is a scalar coefficient for M_q to measure the impact of mode choice on the choice of tour complexity,
ε_q and ω_q are random error terms, which are standard bivariate normally distributed with zero means, unit variances, and correlation ρ, i.e., ε_q, $\omega_q \sim \phi_2(0,0,1,1,\rho)$.

Based on this normality assumption, one can derive the probability of each possible combination of binary choices for tour q:

$$\text{prob}(M_q = 0, T_q = 0) = \Phi_2[-\gamma' z_q, -\beta' x_q, \rho] \tag{2}$$

$$\text{prob}(M_q = 1, T_q = 0) = \Phi_1[-(\beta' x_q + \eta)] - \Phi_2[-\gamma' z_q, -(\beta' x_q + \eta), \rho] \tag{3}$$

$$\text{prob}(M_q = 0, T_q = 1) = \Phi_1[-(\gamma' z + \alpha)] - \Phi_2[-(\gamma' z + \alpha), -\beta' x, \rho] \tag{4}$$

$$\text{prob}(M_q = 1, T_q = 1) = 1 - \Phi_1[-(\gamma' z_q + \alpha)] - \Phi_1[-(\beta' x_q + \eta)] + \Phi_2[-(\gamma' z_q + \alpha), -(\beta' x_q + \eta), \rho] \tag{5}$$

where

$\Phi_1[\cdot]$ is the cumulative distribution function for standard univariate normal distribution.
$\Phi_2[\cdot]$ is the cumulative distribution function for standard bivariate normal distribution.

The sum of the probabilities for the four combinations of two binary choices should be equal to one, i.e.,

$$\text{prob}(M_q = 0, T_q = 0) + \text{prob}(M_q = 1, T_q = 0) + \text{prob}(M_q = 0, T_q = 1) + \text{prob}(M_q = 1, T_q = 1) = 1 \tag{6}$$

Substituting Eqs. (2) through (5) into Eq. (6), it can be shown that

$$\begin{aligned} &\Phi_2[-\gamma' z_q, -\beta' x_q, \rho] + \Phi_2[-(\gamma' z_q + \alpha), -(\beta' x_q + \eta), \rho] \\ &\quad = \Phi_2[-\gamma' z_q, -(\beta' x_q + \eta), \rho] + \Phi_2[-(\gamma' z_q + \alpha), -\beta' x_q, \rho] \end{aligned} \tag{7}$$

This equation does not hold unless either α or η is equal to zero. This requirement, known as the logical consistency condition (Maddala, 1983), will lead to two different recursive simultaneous modeling structures suggesting two different causal relationships:

(1) $\alpha = 0$, $\eta \neq 0$ (Mode Choice → Tour Complexity)

$$\begin{cases} M^*_q = \gamma' z_q + \varepsilon_q \\ T^*_q = \beta' x_q + \eta M_q + \omega_q \end{cases} \tag{8}$$

In this structure, mode choice is predetermined as per the first functional relationship. Then, the choice of mode is specified as a dummy variable in the second functional relationship for tour complexity to directly measure the impact of mode choice on the complexity of the trip chain or tour.

(2) $\alpha \neq 0$, $\eta = 0$ (Tour Complexity → Mode Choice)

$$\begin{cases} M^*_q = \gamma' z_q + \alpha T_q + \varepsilon_q \\ T^*_q = \beta' x_q + \omega_q \end{cases} \tag{9}$$

Conversely, one may consider the alternative structure in which tour complexity is predetermined as per the second functional relationship. The complexity of the tour is specified as an explanatory variable influencing mode choice as per the first functional relationship.

Thus, the desirable feature of the bivariate probit model in which the coefficients of two endogenous dummy variables do not coexist in both functional relationships provides an appropriate modeling framework to analyze the unidirectional causality between tour complexity and mode choice.

The endogenous nature of one of the dependent variables in the simultaneous equation system can be ignored in formulating the likelihood function. To facilitate formulating likelihood functions, Eqs. (2) through (5) can be rewritten in a format including only the cumulative distribution function of the standard bivariate normal distribution.

$$\text{prob}(M_q = 0, T_q = 0) = \Phi_2[-\gamma' z, -\beta' x, -\rho] \tag{10}$$
$$\text{prob}(M_q = 1, T_q = 0) = \Phi_2[\gamma' z, -(\beta' x + \eta), -\rho] \tag{11}$$
$$\text{prob}(M_q = 0, T_q = 1) = \Phi_2[-(\gamma' z + \alpha), \beta' x, -\rho] \tag{12}$$
$$\text{prob}(M_q = 1, T_q = 1) = \Phi_2[\gamma' z + \alpha, \beta' x + \eta, \rho] \tag{13}$$

Eqs. (10) through (13) and the corresponding likelihood functions can be summarized by the following general formulations for the two different unidirectional causal structures (Greene, 2003):

(1) $\alpha = 0$, $\eta \neq 0$ (Mode Choice $\rightarrow$ Tour Complexity)

$$\text{prob}_q = \Phi_2[\mu_q \gamma' z_q, \tau_q(\beta' x_q + \eta M_q), \mu_q \tau_q \rho] \tag{14}$$
$$L = \prod_{q=1}^{Q} \left\{ \Phi_2[\mu_q \gamma' z_q, \tau_q(\beta' x_q + \eta M_q), \mu_q \tau_q \rho] \right\} \tag{15}$$

(2) $\alpha \neq 0$, $\eta = 0$ (Tour Complexity $\rightarrow$ Mode Choice)

$$\text{prob}_q = \Phi_2[\mu_q \gamma' z_q + \alpha T_q, \tau_q \beta' x_q, \mu_q \tau_q \rho] \tag{16}$$
$$L = \prod_{q=1}^{Q} \{ \Phi_2[\mu_q(\gamma' z_q + \alpha T_q), \tau_q \beta' x_q, \mu_q \tau_q \rho] \} \tag{17}$$

where $\mu_q = 2M_q - 1$ and $\tau_q = 2T_q - 1$.

As the likelihood functions of the recursive bivariate probit model and the common bivariate probit model are virtually identical, parameter estimation can be accomplished using readily available software such as LIMDEP 8.0 (Greene, 2002):

2.2. Simultaneous logit model (Tour Complexity $\leftrightarrow$ Mode Choice)

One may also consider the possibility where neither of the two unidirectional causal structures is dominant within the population, i.e., both causal structures are prevalent in the population. In addition, one may consider the possibility where the choices regarding tour complexity and mode are made simultaneously. To accommodate such plausible bidirectional causality, the simultaneous logit model is applied in this paper. The simultaneous logit model may be considered an extension of the multinomial logit model commonly used in transportation modeling practice. In the simultaneous logit model, the logarithm of the ratio of probabilities for two alternatives to be selected from one choice set is assumed to equal a linear combination of a set of explanatory variables. One dummy variable indicating the choice of tour complexity may be added into the set of explanatory variables for mode choice; similarly, one dummy variable indicating mode choice may be added into the set of explanatory variables for tour complexity. The formulations may be written as follows (all of the symbols have the same meaning as in Section 2.1):

$$\ln\left[\frac{\text{prob}(M_q = 1|T_q)}{\text{prob}(M_q = 0|T_q)}\right] = \gamma' z_q + \alpha T_q \tag{18}$$
$$\ln\left[\frac{\text{prob}(T_q = 1|M_q)}{\text{prob}(T_q = 0|M_q)}\right] = \beta' x_q + \eta M_q \tag{19}$$

By rewriting Eqs. (18) and (19) across two possible values that T_q and M_q can take, one gets:

$$\ln\left[\frac{\text{prob}(M_q=1,T_q=0)}{\text{prob}(M_q=0,T_q=0)}\right]=\gamma' z_q \tag{20}$$

$$\ln\left[\frac{\text{prob}(M_q=1,T_q=1)}{\text{prob}(M_q=0,T_q=1)}\right]=\gamma' z_q+\alpha \tag{21}$$

$$\ln\left[\frac{\text{prob}(T_q=1,M_q=0)}{\text{prob}(T_q=0,M_q=0)}\right]=\beta' x_q \tag{22}$$

$$\ln\left[\frac{\text{prob}(T_q=1,M_q=1)}{\text{prob}(T_q=0,M_q=1)}\right]=\beta' x_q+\eta \tag{23}$$

The sum of the probabilities for the four combinations of binary choices should be equal to one, i.e.,

$$\text{prob}(M_q=0,T_q=0)+\text{prob}(M_q=1,T_q=0)+\text{prob}(M_q=0,T_q=1)+\text{prob}(M_q=1,T_q=1)=1 \tag{24}$$

By converting simultaneous equations (20) through (23), it can be shown that

$$\begin{aligned}\text{prob}(M_q=1,T_q=1)&=\text{prob}(M_q=0,T_q=0)\exp(\gamma' z_q+\beta' x_q+\alpha)\\&=\text{prob}(M_q=0,T_q=0)\exp(\gamma' z_q+\beta' x_q+\eta)\end{aligned} \tag{25}$$

For logical consistency, α must be equal to η. Endogenous dummy variables T_q and M_q are allowed to coexist in the simultaneous equation system. By replacing η with α and solving the simultaneous equations (20) through (24), the probability for each combination is formulated as follows:

$$P_{00q}=\text{prob}(M_q=0,T_q=0)=1/\Delta_q \tag{26}$$

$$P_{10q}=\text{prob}(M_q=1,T_q=0)=\exp(\gamma' z_q)/\Delta_q \tag{27}$$

$$P_{01q}=\text{prob}(M_q=0,T_q=1)=\exp(\beta' x_q)/\Delta_q \tag{28}$$

$$P_{11q}=\text{prob}(M=1,T=1)_q=\exp(\gamma' z_q+\beta' x_q+\alpha)/\Delta_q \tag{29}$$

where

$$\Delta_q=1+\exp(\gamma' z_q)+\exp(\beta' x_q)+\exp(\gamma' z_q+\beta' x_q+\alpha). \tag{30}$$

Finally, the likelihood function may be formulated as follows:

$$L=\prod_{q=1}^{Q}(P_{00q})^{(1-M_q)(1-T_q)}(P_{10q})^{M_q(1-T_q)}(P_{01q})^{(1-M_q)T_q}(P_{11q})^{M_qT_q} \tag{31}$$

Model estimation is performed using the Gauss programming language (Aptech, 1996).

3. Dataset and sample description

The dataset used for analysis and model estimation is extracted from the Swiss Travel Microcensus 2000. A very detailed description of the survey and the survey sample can be found in Ye and Pendyala (2003). Only a very brief description of the survey sample is provided in this paper in the interest of brevity. The survey respondent sample consists of 27,918 households from 26 cantons in Switzerland. The person sample was formed by randomly selecting one person over 6 years old from each household with less than four household members and two persons over 6 years old from each household with four or more members. As a result of this sampling scheme, the person respondent sample consisted of 29,407 persons. The household and person characteristics of these samples are respectively shown in Tables 1 and 2. As expected, the proportion of households without automobiles in this Swiss sample is substantially higher than in a typical sample from the United States. This may be reflective of the higher level of public transport service in Switzerland that enables mobility and accessibility without the same level of auto dependence. As a result, one might expect the automobile to play a smaller role in the Swiss travel environment than in the US environment.

Table 1
Household characteristics of Swiss Travel Microcensus 2000 and Zurich subsamples

Characteristic	Swiss sample	Zurich non-work tour makers	Zurich work tour makers
Sample size	27918	2998	1438
Household size	2.43	2.42	2.33
1 person	27.5%	29.9%	31.5%
2 persons	35.1%	33.2%	33.5%
3 persons	14.0%	11.6%	12.0%
⩾4 persons	23.4%	25.4%	22.9%
Monthly income			
Low (<Fr 4K)	20.8%	20.1%	7.6%
Medium (Fr 4K ~ Fr 8K)	35.9%	38.2%	41.7%
High (>Fr 8K)	18.4%	21.5%	35.0%
Missing	24.9%	20.1%	15.7%
Vehicle ownership	1.17	1.07	1.25
0 auto	19.8%	24.2%	16.5%
1 auto	50.5%	49.8%	51.0%
2 autos	24.5%	21.8%	26.1%
⩾3 autos	5.2%	4.2%	6.4%
Family type			
Single	27.2%	29.5%	31.0%
Partner (unmarried and no child)	27.9%	26.4%	26.4%
Married	43.6%	42.0%	40.0%
Other	1.3%	2.1%	2.6%
Presence of children			
Child < 6 years old	10.6%	9.9%	9.0%
Child 6 ~ 17 years old	22.5%	24.7%	19.9%
Household location			
Major city	42.4%	54.4%	54.2%
Surrounding areas of city	30.4%	35.0%	35.7%
Isolated city	1.1%	0.8%	0.8%
Rural	26.1%	9.7%	9.4%

All of the persons in the person sample were asked to report their travel in a one-day trip diary. The resulting trip dataset includes 103,376 trips reported by 29,407 interviewed persons (including the possibility of some respondents making zero trips on the survey day). Table 2 presents summary statistics for the trips reported by the Swiss respondent sample. In this paper, the unit of analysis is the tour or trip chain. A trip chain is defined in this paper as a complete home-to-home journey where the origin of the first trip is home and the destination of the last trip is home. No intermediate home stop is present within the trip chain. Whenever the home location is reached, a chain is formed. A tour-level dataset was formed by aggregating the trip dataset to the tour level. All person and household characteristics were merged into the tour level dataset. In most cases, a single mode was prevalent for the trip chain. In cases where multiple modes were prevalent within the same trip chain or tour, a single mode was assigned based on the whether or not the auto mode was used in the chain. If the auto mode was used for any segment in the trip chain, then the chain was assigned an auto mode and vice versa. One may argue that main mode should be defined as a representation of mode choice at the tour level, however, it is felt that the definition of the mode for a chain is a complex issue. The definition in this study is made in this way because the major concern is not the main mode of the chain, but whether the auto mode was used for any part of the chain thus potentially contributing to the formation of a multi-stop complex chain. Each tour was classified as a simple or complex tour depending on whether it had one intermediate stop or more than one intermediate stops within the chain.

In addition, tours were also classified as work-based tours and non-work-based tours. Any tour that included a work stop (regardless of the presence of other types of stops) was classified as a work-based tour while any tour that included only non-work stops was classified as a non-work-based tour. It was felt that the

Table 2
Person characteristics of Swiss Travel Microcensus 2000 and Zurich subsamples

Characteristic	Swiss sample	Zurich non-work tour makers	Zurich work tour makers
Sample size	29407	3293	1466
Age (in years)	43.9 (Mean)	44.2 (Mean)	41.8 (Mean)
Young (6–29)	26.83%	28.1%	18.3%
Middle (30–59)	47.64%	42.1%	74.6%
Old ($\geqslant$60)	25.48%	29.8%	7.2%
Sex			
Male	46.31%	45.6%	60.8%
Female	53.69%	54.4%	39.2%
Employment status			
Full time	37.34%	29.4%	76.9%
Part time	14.27%	14.5%	20.2%
Not employed	48.39%	56.0%	2.9%
Licensed	67.43%	64.1%	87.9%
#Chains/day	1.33	1.49	1.17
#Trips/day	3.51	4.11	4.46
Work trips	0.46	0.21	1.54
Non-work trips	3.06	3.90	2.92
Work trip mode share			
Auto	55.84%	49.6%	52.0%
Non-auto	44.16%	50.4%	48.0%
Non-work trip mode share			
Auto	48.92%	43.5%	54.1%
Non-auto	51.08%	56.5%	45.9%

causal relationships governing work-based tours may be different from those governing non-work-based tours. This is because the presence of a work stop may impose a certain amount of spatial and temporal rigidity on the activity/travel behavior of the individual in the context of that tour. The constraints associated with the work activity may lead to a different causal structure underlying trip chain formation and mode choice.

Data corresponding to respondents from the Canton of Zurich was extracted to reduce the data to a more manageable size and to control for possible area specific effects. Tables 1 and 2 include summary statistics for the Zurich subsample in addition to those of the overall Swiss sample. There are 3293 persons from 2998 households who report at least one non-work tour in the Zurich sample and 1466 persons from 1438 households who report at least one work tour. It is to be noted that these two samples are not mutually exclusive as some individuals may report both a work tour and a non-work tour. As expected, households in which there are work tour makers report higher income levels than households in which there are non-work tour makers, presumably because the work tour maker households consistently include workers earning wages. The average household size is a little over two persons per household while vehicle ownership is a little over one vehicle per household. As expected, a very small percentage of households in the Zurich subsample report their residence as being in a rural location, presumably due to the urban nature of Zurich and its immediate surrounding areas.

Person characteristics also show similarities between the overall Swiss sample and the Zurich subsamples. As expected, the non-work tour maker sample consists of a greater proportion of elderly (retired) and young persons than the work tour maker sample. On average, work tour makers make about 1.17 trip chains per day where a trip chain is defined as a complete home-to-home tour. Non-work tour makers report, on average, about 1.49 trip chains per day. Work tour makers make 4.46 trips per day while non-work tour makers report fewer trips at 4.11 trips per day. The trip rates are substantially higher than the trip rate for the overall Swiss sample, which is partially caused by the exclusion of zero-trip making persons from the Zurich subsample.

As the model estimation was performed only on the Zurich subsample, all further analysis presented in the paper pertains only to this subsample. The Zurich subsample included 4901 non-work tours and 1711 work tours. Tables 3 and 4 offer simple cross-tabulations of tour complexity against mode choice. Table 3 examines the distribution of tour complexity by mode choice for non-work tours while Table 4 examines the distribution for work tours. An examination of column-based percentages in Table 3 indicates that about 28% of simple non-work tours involve the use of the automobile as the primary mode of transportation. This value is considerably higher at 44% for complex non-work tours. Thus it appears that there is a correlation (at least) between mode choice and tour complexity. Clearly, the auto mode is utilized to a greater degree in the context of complex multi-stop trip chains. Similarly, examining the row-based percentages shows that 80% of non-work non-auto tours are simple in nature (involve only one stop). On the other hand, only 66% of non-work auto tours are simple in nature. Thus it appears that non-auto tours tend to be more simple than auto-based tours.

Table 4 offers similar indications, albeit the tendencies are not as strong as those seen in Table 3. In the case of work tours, it is found that a majority of simple tours are non-auto-based (52%) while a majority of complex tours are auto-based (60%). Similarly, a majority of non-auto-based work tours tend to be simple in nature (55%), while a majority of auto-based tours tend to be complex in nature (57%). Once again, a clear correlation between auto use and trip chain complexity is seen in these cross-tabulations. Given the difference

Table 3
Cross-tabulation of mode choice and tour type for non-work tours

Mode choice	Tour type		Total
	Simple	Complex	
Frequency			
Non-auto	2685	661	3346
Auto	1030	525	1555
Total	3715	1186	4901
Column percent			
Non-auto	72.3%	55.7%	68.3%
Auto	27.7%	44.3%	31.7%
Total	100.0%	100.0%	100.0%
Row percent			
Non-auto	80.2%	19.8%	100.0%
Auto	66.2%	33.8%	100.0%
Total	75.8%	24.2%	100.0%

Table 4
Cross-tabulation of mode choice and tour type for work tours

Mode choice	Tour type		Total
	Simple	Complex	
Frequency			
Non-auto	436	355	791
Auto	397	523	920
Total	833	878	1711
Column percent			
Non-auto	52.3%	40.4%	46.2%
Auto	47.7%	59.6%	53.8%
Total	100.0%	100.0%	100.0%
Row percent			
Non-auto	55.1%	44.9%	100.0%
Auto	43.2%	56.8%	100.0%
Total	48.7%	51.3%	100.0%

in the percent distributions between work and non-work tours, it was considered prudent to examine the causal relationship between tour complexity and mode choice for work and non-work tours separately.

4. Model estimation results

This section presents estimation results for the models developed in this paper. The variables used in the models to explain choice behavior mostly constitute dummy variable indicators that take a value of one if the condition is satisfied and zero otherwise.

4.1. Estimation results for non-work tours

Estimation results for non-work tour models are provided in Table 5. The left block of Table 5 provides estimation results for the causal structure where tour complexity affects mode choice, the middle block of the table provides estimation results for the causal structure where mode choice affects tour complexity, and the right block provides estimation results for the simultaneous logit model that is intended to capture simultaneous causality between the two variables.

Table 5
Non-work tour model estimation results

Variable	Complex Tour → Auto Mode Choice		Auto Mode Choice → Complex Tour		Auto Mode Choice ↔ Complex Tour	
	Parameter	*t*-Test	Parameter	*t*-Test	Parameter	*t*-Test
Auto Mode Choice Model						
Constant	−2.100	−24.98	−1.988	−23.86	−3.966	−19.64
Number of autos in household = 0	−1.185	−12.84	−1.290	−13.32	−2.360	−11.34
Number of autos in household ⩾ 2	0.201	4.36	0.197	3.90	0.367	4.45
Person has auto license	1.933	19.76	2.222	26.86	4.159	20.62
Person subscribes general type of seasonal ticket	−0.178	−4.24	−0.203	−4.39	−0.341	−4.37
Person subscribes other type of seasonal ticket	−0.391	−6.95	−0.423	−6.94	−0.679	−6.68
Person lives in rural area	0.121	1.86	0.125	1.75	0.196	1.62
Tour is complex (multi-stop)	1.409	11.42	–	–	–	–
Complex Tour Choice Model						
Constant	−0.282	−5.31	−0.384	−6.12	−0.665	−6.67
Number of household members	−0.130	−7.92	−0.121	−6.74	−0.238	−7.60
Person < 18 years old	−0.210	−3.46	−0.137	−1.82	−0.088	−0.73
Person > 60 years old	−0.150	−3.17	−0.108	−2.12	−0.187	−2.21
Primary purpose of the tour is service	0.676	8.49	0.495	5.95	0.914	6.77
Primary purpose of the tour is school	−0.206	−4.73	−0.267	−5.73	−0.433	−5.34
Tour starts in AM peak period (7:00–8:59)	0.258	5.10	0.285	5.21	0.497	5.48
Tour starts in PM peak period (16:00–17:59)	−0.258	−3.58	−0.325	−4.36	−0.550	−4.13
Auto mode choice for tour	–	–	0.227	2.60	–	–
ρ (error correlation)	−0.622	−7.65	0.111	1.81	–	–
α (joint dependence)	–	–	–	–	0.658	8.81
Log-likelihood function and likelihood ratio						
At convergence	−4573.906		−4589.533		−4578.426	
At market share	−5719.416		−5719.416		−5719.416	
At zero	−6794.229		−6794.229		−6794.229	
$\rho_0^2, \bar{\rho}_0^2$	0.3268, 0.3243		0.3245, 0.3220		0.3261, 0.3238	
$\rho_c^2, \bar{\rho}_c^2$	0.2003, 0.1973		0.1976, 0.1946		0.1995, 0.1967	
Sample size	4901		4901		4901	
Number of parameters	17		17		16	

Note: Primary purpose of a tour is defined as the trip purpose other than "return home" that accounts for the longest cumulative distance within the tour. If two different trip purposes account for equal distances within the tour, then the primary purpose is defined based on the following priority sequence: school > service > shopping > recreation > other.

In the causal structure where tour complexity affects mode choice, the coefficient for tour complexity is statistically significant and positive in the mode choice model. This lends credence to the hypothesis that the need to make a complex tour is likely to increase dependency on the auto mode. In addition, it was found that demographic and socio-economic characteristics, the tour's primary purpose, and time-of-day significantly influence mode choice and tour complexity. In the auto mode choice model, it is found that tour makers with zero autos are less likely to use auto mode as evidenced by the negative coefficient while those with more than one auto are more likely to use the auto mode as shown by the positive coefficient. As expected, those with a driver license are more prone to using the auto mode while those with seasonal transit ticket subscriptions are less likely to use the auto mode. Transit pass subscribers are likely to be more transit-oriented and have greater access to transit services. Tours made by persons living in rural areas are likely to be more auto-oriented, presumably due to the more limited transit accessibility in those areas.

In the tour complexity model, it is found that individuals in larger households tend to make less complex tours as opposed to individuals in smaller households. One may conjecture that the possibility of task allocation present in a multi-person household may reduce the need to perform multi-stop trip chains (Strathman and Dueker, 1994). The young and the elderly are less likely to pursue complex non-work tours, possibly because they have fewer household obligations than those in the middle age groups. It is rather interesting that tours undertaken in the AM peak show a greater propensity to involve multiple stops than those undertaken in the PM peak period. However, in the context of non-work tours, this may be a plausible result in that people combine a series of errands and school activities in the morning and complete their activities by mid-day. Another possible explanation is that time constraints towards the end of the day (PM period) limit the number of activities that an individual can pursue at that time. Another interesting finding is that gender does not significantly influence tour complexity in the case of non-work tours. Other studies have suggested that females tend to make more complex trip chains than males (McGuckin and Murakami, 1999). The analysis in this paper does not support that finding in the Swiss travel context. The tour's primary purpose appears to affect tour complexity. While service (serve passenger) tours tend to be complex in nature, shopping tours do not tend to be complex in nature. Thus it appears that the shopping activity may be more prone to being a stand-alone activity within a tour. The error correlation is found to be statistically significant and this is indicative of the validity of the assumption that non-work tour complexity and mode choice should be modeled in a simultaneous equations framework. The negative sign associated with the error correlation indicates that the unobserved factors influencing these two variables are negatively correlated. It is not straightforward to interpret the negative sign of the error correlation, since the unobserved variables associated with complex tour choice and auto mode choice would be expected to be positively correlated. For example, the unobserved personal preference to be more efficient may stimulate more auto mode selection as well as more multi-stop tours. Indeed, error correlations were found to be positive in the preliminary analysis in which bivariate probit models were estimated without endogenous dummy variables. The inclusion of the endogenous dummy variable, which is likely to be positively correlated with unobserved variables, may be contributing to the negative error correlation. The negative error correlation may also be due to the exclusion of unobserved factors from the model and this happens often when data are analyzed at a higher aggregation level. For example, no distinction is made between "drive alone" and "drive/ride with others", both of which entail the use of the auto mode. As a result, person and household correlations are absorbed in the unobserved part of the models that, in turn, leads to negative correlations among the error terms used in the model formulations. Further analysis is warranted to fully understand the source and interpretation of the negative error correlations.

The middle block of Table 5 provides estimation results for the causal structure where mode choice affects tour complexity for non-work tours. Interestingly, it is found that mode choice significantly affects tour complexity and that the choice of auto is positively associated with the formation of complex tours. Thus it appears from this model that the choice of the automobile mode for a tour contributes positively to the formation of multi-stop trip chains. In addition, the error correlation is positive for this model structure, consistent with expectation. All of the other indications provided by the model system are similar to those seen in the left block.

The models in both unidirectional causalities appear to support the notion that there is a bidirectional causality between mode choice and tour complexity. In both models (representing two different causal structures), the coefficient associated with the endogenous variable on the right-hand side is statistically significant and consistent with expectations and trends in the dataset. In addition, both models offer significant error correlation supporting the simultaneous equations formulation for representing the relationship between mode choice and tour complexity. For non-work tours in which mode choice and tour complexity influence each other simultaneously, bidirectional causality is accommodated through the use of the simultaneous logit model. Estimation results for this model are shown in the right block of Table 5. The significantly positive joint dependence parameter, α, shows the presence of significant positive correlation between auto mode choice and tour complexity. The other explanatory variables provide similar indications as those in two unidirectional causalities.

The models presented in Table 5 can be used to estimate marginal effects of one choice variable on another. From the first model representing a causal structure in which tour complexity affects mode choice, it is found that, on average, an individual is 45.6% more likely to choose the auto mode given that a complex tour pattern needs to be undertaken. Conversely, the second model representing a causal structure in which mode choice affects tour complexity suggests that an individual is 7.1% more likely to adopt a complex tour pattern, given that the auto mode is chosen. Finally, the simultaneous logit model indicates that, on average, an individual is 8.4% more likely to choose the auto mode given the choice of a complex tour pattern and is 12.3% more likely to choose a complex tour pattern given the choice of the auto mode. These marginal effects represent estimates of the effects of one choice variable on another that may have important implications from a transport policy and planning perspective. This is discussed further in the concluding section of the paper.

As all of the estimation results in Table 5 offer plausible and similar interpretations, a more rigorous performance comparison must be conducted among the models to potentially identify the causal structure underlying the dataset. This performance comparison is presented in Section 5 following the discussion of the estimation results for the work tour models.

4.2. Estimation results for work tour models

Estimation results for work tour models are provided in Table 6. Similar to Table 5, three blocks in Table 6 also represent three different causal structures. In the causal structure where tour complexity affects mode choice, it is found that tour complexity has a positive impact on auto mode choice. This is consistent with expectations, trends in the data, and the models of non-work tours. The coefficient associated with tour complexity variable in the mode choice model is positive and statistically significant. Thus the model supports the notion that a complex tour or trip chaining pattern contributes to the choice of auto as the mode for the tour. In addition, the error correlation is statistically significant, once again supporting the simultaneous equations formulation of the relationship between tour complexity and mode choice. Similar to the non-work tour model estimation results, auto ownership and the possession of a driver license contribute positively to auto mode selection, whereas seasonal transit ticket subscription contributes negatively to auto mode choice. With respect to work-related variables, it is found that the availability of free parking at the work place and longer commutes are both positively associated with the choice of auto for work tours. All of these findings are consistent with expectations. In the tour complexity model, it is found that persons of higher income are prone to make complex work tours. In addition, individuals owning their business enterprise are more likely to engage in multi-stop trip chains. It is possible that these individuals have occupational characteristics that lead to the formation of complex trip chains. Individuals of Swiss Nationality are more likely to engage in complex work tours, possibly because they have a denser network of social contacts and a larger set of activity options. Another interesting finding is that time-of-day indicators play an important role in influencing tour complexity. Tours ending within the lunch hour are less prone to be complex possibly due to time constraints and the presence of a single lunch stop/destination. However, those beginning in the morning period of 6–9 AM are more prone to being multi-stop trip chains, possibly due to the linking of a non-work activity with the work activity in the overall tour. A more detailed time-of-day based analysis of trip chain formation is warranted to fully understand the relationship between trip chain complexity and time of day choice behavior. Within the context of this study, time of day choice is assumed exogenous to the model system. However, one may argue that time of day choice is endogenous to trip chain complexity and mode choice. The study of the simultaneous causal relationships among trip chain formation, mode choice, and time of day choice (three endogenous entities) remains a future research effort.

Table 6
Work tour model estimation results

Variable	Complex Tour → Auto Mode Choice		Auto Mode Choice → Complex Tour		Auto Mode Choice ↔ Complex Tour	
	Parameter	*t*-Test	Parameter	*t*-Test	Parameter	*t*-Test
Auto Mode Choice Model						
Constant	−2.149	−8.32	−1.768	−7.06	−3.525	−6.43
Number of autos in household = 0	−1.247	−6.77	−1.259	−7.06	−2.204	−6.60
Number of autos in household ⩾ 2	0.430	4.89	0.467	5.58	0.807	5.36
Person has auto license	1.996	7.83	2.040	8.24	3.691	6.83
Reserved parking lot at the work place is free	0.797	9.00	0.790	9.32	1.438	9.22
Person subscribes half-price seasonal ticket	−0.421	−5.30	−0.397	−5.05	−0.695	−5.08
Person subscribes other type of seasonal ticket	−1.440	−12.41	−1.413	−13.24	−2.441	−12.15
Distance between residence and work place (km)	0.015	5.00	0.017	6.06	0.032	5.11
Tour is complex (multi-stop)	0.915	3.42	–	–	–	–
Complex Tour Choice Model						
Constant	−0.414	−4.24	−0.439	−4.06	−0.927	−5.56
Monthly household income > Fr10000	0.295	3.80	0.277	3.54	0.430	3.39
Person owns enterprise/business	0.304	3.30	0.244	2.64	0.433	2.90
Person is of Swiss Nationality	0.299	3.38	0.321	3.62	0.506	3.52
Tour starts in time period from 6:00 to 8:59	0.327	4.39	0.310	4.11	0.531	4.29
Tour starts in time period from13:00 to 14:59	−0.389	−3.39	−0.422	−3.59	−0.686	−3.60
Tour ends in time period from 12:00 to 12:59	−0.760	−7.64	−0.725	−7.24	−1.248	−7.46
Auto mode choice for tour	–	–	0.053	0.60	–	–
ρ (error correlation)	−0.293	−1.63	0.246	3.49	–	–
α (joint dependence)	–	–	–	–	0.490	4.90
Log-likelihood function and likelihood ratio						
At convergence	−1779.440		−1783.900		−1786.044	
At market share	−2354.272		−2354.272		−2354.272	
At zero	−2371.950		−2371.950		−2371.950	
$\rho_0^2, \bar{\rho}_0^2$	0.2498, 0.2426		0.2479, 0.2408		0.2470, 0.2403	
$\rho_c^2, \bar{\rho}_c^2$	0.2442, 0.2369		0.2423, 0.2351		0.2414, 0.2346	
Sample size	1711		1711		1711	
Number of parameters	17		17		16	

The middle block of Table 6 gives estimation results for the model where the choice of mode affects work tour complexity. The coefficient associated with the auto mode choice variable in the tour complexity equation is not statistically significant, but the error correlation is positive and statistically significant. This result does not support the hypothesis that auto mode choice positively affects the formation of a complex work tour, although the model does support the notion that these choices should be modeled in a simultaneous equations framework.

The right block of Table 6 furnishes estimation results of the simultaneous logit model for work tours. The joint dependence parameter, α, is found to be statistically significant and positive. This model supports the notion that there is a significant and positive bidirectional causal relationship between tour complexity and auto mode choice. All of the other explanatory variables are found to offer indications very similar to those seen in the first two blocks.

As was done in the case of the non-work tour models, marginal effects were computed to determine the impact of one choice variable on the other. Results of the first model structure in which tour complexity is assumed to affect mode choice suggests that a person is 35.6% more likely to choose the auto mode, given that a complex tour pattern is chosen. The second model structure which assumes that mode choice affects tour complexity suggests that a person is only 2.1% more likely to adopt a complex tour pattern, given that the auto mode is chosen. This small value is presumably because the endogenous dummy variable is statistically insignificant in the model that is based on the causal structure where mode choice affects tour complexity. Finally, the simultaneous logit model indicates that, on average, an individual is 12.0% more likely to choose the auto mode given the choice of a complex work tour pattern and is 12.2% more likely to choose a complex work tour pattern given the choice of the auto mode.

5. Model performance comparisons

The model estimation results presented in Section 4 generally offer plausible statistical indications for alternative causal paradigms. The only model that may be rejected on qualitative grounds is that in the middle block of Table 6 where the mode choice decision precedes the tour complexity decision. The statistically insignificant coefficient associated with the endogenous auto mode choice variable in the tour complexity model implies that the choice of the auto mode does not significantly influence the complexity of work tours. Although this is possible, it is not consistent with the trends noted in the descriptive cross-tabulations and with any of the other models where the endogenous dummy variables have been consistently statistically significant. Given the preponderance of evidence to the contrary, it is difficult to explain and defend this statistically insignificant coefficient. For all other models, however, the statistical indications are plausible. This section presents a rigorous comparison across models to see if it is possible to identify the most likely causal structure governing the relationship between mode choice and trip chaining.

A goodness-of-fit comparison among the models of different causal structures is conducted first. The adjusted likelihood ratio index as a goodness-of-fit measure can be used for testing and comparing non-nested relationships in discrete choice models. The indices are given as follows:

$$\bar{\rho}_0^2 = 1 - \frac{L(\beta) - K_0}{L(0)} \tag{32}$$

$$\bar{\rho}_c^2 = 1 - \frac{L(\beta) - K_c}{L(c)} \tag{33}$$

$\bar{\rho}_0^2$ = adjusted likelihood ratio index at zero,
$\bar{\rho}_c^2$ = adjusted likelihood ratio index at market share $L(\beta)$: Log-likelihood value at convergence,
$L(0)$ = log-likelihood value at zero,
$L(c)$ = log-likelihood value at market share (model including only the constant term),
K_0 and K_c = the number of parameters in the corresponding model.

The adjusted likelihood ratio indices for all of the models are presented at the bottom of Tables 5 and 6. To choose between two models (say, 1 and 2), Ben-Akiva and Lerman (1985) provide a test where under the null hypothesis that model 1 is the true specification, the following holds asymptotically:

$$\Pr\left(\bar{\rho}_2^2 - \bar{\rho}_1^2 > z\right) \leqslant \Phi\{-[-2zL(0) + (K_2 - K_1)]^{1/2}\}, z > 0 \tag{34}$$

where

$\bar{\rho}_i^2$ = the adjusted likelihood ratio index at zero for model $i = 1, 2$,
K_i = the number of parameters in model i,
Φ = the standard normal cumulative distribution function,
$L(0)$ = log-likelihood value at zero if all N observations in the sample have all J alternatives, $L(0) = N\ln(1/J)$.

The probability that the adjusted likelihood ratio index of model 2 is greater by some $z > 0$ than that of model 1, given that the latter is the true model, is asymptotically bounded by the right-hand side of Eq. (34) above. If the model with the greater $\bar{\rho}^2$ is selected, then this bounds the probability of erroneously choosing the incorrect model over the true specification. Using this procedure, models of alternative causal structures can be compared against one another.

For non-work tour models, the differences in adjusted likelihood ratios are 0.0023 and 0.0005 between the model in the left block (tour complexity → auto mode choice) of Table 5 and the models in the right two blocks. According to Eq. (34), the calculated bounding probability on the right-hand side of the expression for the comparison between the two unidirectional causal structures is almost zero. The bounding probability for the comparison between the causal structure depicting tour complexity → auto mode choice and the structure depicting tour complexity ↔ auto mode choice is 0.0026. Thus, it may be concluded that the model in the left block is more closely capturing the causal structure underlying the relationship between mode choice and tour complexity. The significantly better goodness-of-fit of the model in the left block suggests that the causal structure where the complexity of the tour affects mode choice (tour complexity → auto mode choice) is statistically, and possibly behaviorally, dominant in the population for non-work tours.

For work tour models, the situation is very similar. In comparing the models, the seemingly better model in the left block (tour complexity → auto mode choice) of Table 6 has an adjusted likelihood ratio index that is 0.0018 and 0.0023 greater than those of the models in the other two causal structures. The bounding probabilities, as per the right-hand side of Eq. (34), are calculated as 0.0017 and 0.0003, respectively. The non-nested test rejects the models in the middle block and right block of Table 6, i.e., the causal structures where auto mode choice drives the complexity of the work tour (auto mode choice → tour complexity) and where a bidirectional causality is assumed. Also, as mentioned earlier, the statistically insignificant coefficient associated with the endogenous dummy variable appears to suggest that the causal structure where auto mode choice drives complex work tour formation is not capturing the trends in the dataset. Once again, it may be concluded that the causal structure where the complexity of the tour affects mode choice (tour complexity → auto mode choice) is statistically, and possibly behaviorally, dominant in the population for work tours.

From the viewpoint of activity-based travel behavior theory where travel choices are considered to be derived from activity patterns (and activity needs that are distributed in time and space), one may consider the findings of this paper to be quite consistent with expectations. For both non-work tours and work tours, the statistical model estimation results show that tour complexity (which is reflective of the activity pattern) drives mode choice. This finding is also consistent with and confirms previous results regarding the nature of the relationship between trip chaining and mode choice reported by Hensher and Reyes (2000).

6. Discussion and conclusions

Mode choice behavior is a fundamental element of travel behavior that has significant implications for transportation planning. Estimates of public transit ridership and the use of alternative modes of transportation are largely based on studies of mode choice behavior and modal split models. Public transport agencies face increasing competition from the automobile as automobiles become increasingly affordable and the road infrastructure becomes increasingly ubiquitous. Undoubtedly, the automobile is considered to provide greater flexibility and convenience when compared with public transport modes that are generally constrained with respect to schedules and routes/destinations.

This study examines the inter-relationship between the complexity of people's activity-travel patterns and their mode choice. In order to conduct the analysis, this paper examines mode choice behavior in the context of multi-stop (complex) vs single-stop (simple) trip chains. Through a series of econometric model formulations, this paper presents a rigorous analysis of the most likely causal relationship between these two phenomena at the level of the individual trip chain or tour. It should be emphasized that the analysis in this paper does not attempt to replicate causality at the level of the individual traveler, but rather at the macroscopic level to identify the causal tendency that appears to be dominant in the population.

Using data derived from the 2000 Swiss Travel Microcensus, the paper estimates bivariate probit models and simultaneous logit models that provide a rigorous analytical framework for analyzing and testing alternative causal structures. For both non-work tours (i.e., tours that do not involve any work stops) and work tours (i.e., tours that involves at least one work stop), the analysis suggests that the causal structure where the complexity of the trip chaining pattern drives mode choice is the dominating behavioral trend in the population.

These findings have important implications for public transport service providers who are interested in attracting choice riders. If mode choice decisions precede activity pattern/agenda decisions, then it may be possible for public transport service providers to simply attract choice riders by improving amenities, schedule, route coverage, safety and security, and comfort. On the other hand, if the formation of the activity agenda precedes or drives mode choice decisions, then the public transport industry has a greater challenge before it. Trip chaining and tour complexity serve as impediments to public transport usage as it is generally more burdensome to undertake multi-stop tours using public transportation where travelers are constrained by routes, schedules, and access/egress issues. The analysis in this paper suggests that the dominant relationship in the dataset is one in which tour complexity drives mode choice, both for work and non-work tours. Then, not only do public transport service providers have to improve service amenities, but they also have to cater to a multi-stop oriented complex activity agenda. This is extremely difficult to do with a fixed route, fixed schedule system. As activity-travel patterns and tours become increasingly complex, it is likely that public transport agencies will have to develop new types of services to try and retain existing riders in addition to attracting new riders. Fixed route bus and rail services may continue to be useful in serving longer line-haul portions of multi-stop tours. However, serving shorter multi-stop trips calls for the provision of more flexible circulator and paratransit-type services that may involve the use of smaller buses and vans than conventional vehicles. Also, attention needs to be paid to land use developments around transit stops/stations. Concerted efforts need to be made to promote mixed use land developments and multi-purpose activity centers so that travelers are able to fulfil a variety of activity needs at a single location (without the need for undertaking additional trips).

The analysis and findings of this paper are also useful and important in the specification and development of activity-based and tour-based models. Most activity-based and tour-based travel demand model systems consist of hierarchical structures involving, at a minimum, activity agenda or tour formation, mode choice, destination choice, and time of day choice. Although many of the model systems utilize simultaneous equations systems to represent joint choice processes and recognize endogeneity, there is invariably a causal hierarchy that is implied in the specification of the model system. Knowledge about the nature of the relationships among key choice dimensions can aid in the specification of activity-based model structures that reflect the dominant behavioral trends in the population (Pendyala and Bhat, 2004). For example, consider the findings of this paper in which it is found that the activity agenda or tour formation drives mode choice for both non-work and work tours. Clearly, this finding suggests that activity-based models should be formulated such that individual activity agendas and tours are formed first and then mode choice is determined based on the nature of the activity agenda or tour complexity. Such a model would more accurately reflect behavioral changes that might result from a system change, say, the improvement of transit service in a corridor or region. If, for example, one developed an activity-based model system assuming a different causal structure, i.e., one in which mode choice precedes and drives tour formation, then the model is prone to erroneously over-estimate the potential benefits or impacts of the transit service improvement and may alter the nature of the individual tour patterns in response to the mode shift. According to the results obtained in this paper, the dominant relationship is one in which people make decisions regarding their activity agendas or tour complexity first and this decision drives the mode choice decision. Many individuals with complex tour patterns will not be able to shift modes in response to improvements in transit service and thus, in reality, the impacts of the improved transit service may be substantially lower (than that which might be obtained had the reverse causal structure where mode choice drives tour complexity been assumed).

Future research efforts should focus on analyzing whether these findings regarding causal relationships between tour complexity and mode choice hold in other datasets as well. In addition, the modeling framework can be extended to consider multinomial choice situations as opposed to pure binary choice variables considered in this paper. Mode choice can be expanded to consider multiple modes including SOV, shared ride, public transit, and non-motorized modes. Similarly, tour complexity can be expanded to consider different levels of tour complexity or different tour types such as that presented in Strathman and Dueker (1995). Another consideration that merits further investigation is the extent to which findings such as those presented in this paper are sensitive to model specification. It is possible that statistical indicators of model performance will change depending on the model specification chosen. One of the limitations of this paper is that detailed level of service and price variables were not available for all trips as many trips had either an origin or a destination outside the Zurich region. While level of service variables are available for trips with known origins and destinations within the Zurich region, they are not available when one of the trip ends is outside the region. This problem is exacerbated when one is conducting analyses and modeling efforts at the tour level. Limiting the analysis to the subset of trips with known origins and destinations within the Zurich region would have resulted in a very restrictive sample of tours. It is unclear whether the inclusion of such variables would significantly alter the findings reported in this paper and therefore the sensitivity of findings to model specification merits further investigation.

A few additional issues are worthy of attention in the context of this study. First, it must be noted that causal relationships are being extracted and examined in this paper from statistical relationships estimated on revealed outcome data. While such data provides insights into what people have done, it does not provide true insights into the decision mechanisms and behavioral processes underlying the revealed outcomes. One must exercise care when drawing inferences regarding behavioral causality from statistical indicators. In order to truly understand and identify causal relationships, data regarding underlying behavioral processes and decision mechanisms are needed. Future research into the development of microsimulation models of activity and travel behavior should include attempts to collect and analyze such data.

Second, it is necessary for the profession to clarify and define the differences and similarities between various pairs of terms including "causality" and "conditionality", "recursive" and "sequential", and "joint" and "simultaneous". It is not clear whether these pairs of terms are synonymous and interchangeable in all model estimation situations. The structural equations modeling literature routinely uses the "causality" interpretation consistent with the sociometric literature from which those methods are derived (Golob, 2000, 2003). In view of the fact that it is possible to draw a "path diagram" corresponding to the bivariate model structures presented in this paper, the "causality" interpretation has been adopted and used in this paper as well. However, in reality, one could question whether the model structures truly represent "causality" or simply represent a "conditionality" that is not necessarily reflective of a true cause-and-effect relationship. Also, the bivariate probit model systems presented in this paper are considered to be recursive simultaneous equations model systems that are estimated using full-information maximum likelihood methods. In that sense, it may be appropriate to interpret the "causality" implied in this paper as representative of a joint, but sequential, choice process where decisions regarding the tour complexity and mode choice are made together (jointly), but in a certain order (representing a sequential process). The simultaneous logit model specification, on the other hand, represents a joint decision-making process with no order, thus representing a simultaneous choice mechanism.

Acknowledgements

The authors are grateful to three anonymous reviewers for their constructive suggestions that helped improve the paper. The authors are responsible for all errors and omissions. The authors also thank the Federal Ministry of Transport in Switzerland for providing the data used in this study.

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