A Copula-Based Joint Model of Commute Mode Choice and Number of Non-Work Stops during the Commute

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ABSTRACT
In this paper, in the spirit of a tour-based frame of analysis, we examine the commute mode choice and the number of non-work stops during the commute. Understanding the mode and activity stop dimensions of weekday commute travel is important since the highest level of weekday traffic congestion in urban areas occurs during the commute periods. The paper employs a copula-based joint multinomial logit – ordered modeling framework in which commute mode choice is modeled using a multinomial logit formulation and the number of commute stops is modeled using an ordered response formulation. The data used in this study are drawn from the ''Time use'' multipurpose survey conducted between 2002 and 2003 by the Turin Town Council and the Italian National Institute of Statistics (ISTAT) in the Greater Turin metropolitan area of Italy. The results highlight the importance of accommodating the inter-relationship between commute mode choice and commute stops behavior. The results also point to the stronger effect of household responsibilities and demographic characteristics in the Italian context compared to the US context.

Keywords: Tour analysis, copula-based model, work commute, mode choice, stop making behavior

1. INTRODUCTION

The continual increase in urban travel, and in particular of private vehicle trips, is one of the major causes of urban traffic congestion-related problems (such as noise and environmental pollution, energy waste, safety decline, and public spaces given over to parking lots). Recent studies suggest that, notwithstanding the personal comfort and convenience benefits of private car use, the social cost to society in terms of quality of life degradation because of increased private car use can be rather substantial, especially considering that the number of vehicles is likely to double in the next 20 years (*1*).

The problems caused by urban traffic congestion are more severe in areas with rapidly growing populations, where the urban structure is undergoing a transformation toward sprawled forms of spatial expansion. In such a personal vehicle-oriented context, highly complex activity-travel patterns such as trip-activity chaining are more likely to occur. Trip chaining is usually encouraged as a means of reducing vehicle miles travelled (*2*), but, on the other hand, it also represents an impediment to public transport use. Specifically, when chaining of activities becomes a means to reduce overall time spent on travel to perform desired activities within a tight time budget, public transport services appear less appealing to travelers (*3*). This is also documented by Bhat (*4*) in a study of commute-related activity chaining, where he states that "chaining of non-work activities with the commute makes it difficult to wean commuters away from driving alone to work."

In the above context, the effectiveness of demand control policies aimed at modifying individual mode choice toward more sustainable (non-drive alone mode) trips is closely interlinked with individual activity scheduling and patterns. While mode choice has traditionally played a central role in transportation modeling research and applications, the typical trip-based approach used in practice fails to recognize the inter-relationship between stop-making and mode choice. For instance, a trip-based approach may suggest a substantial shift in commute mode from driving alone to a new commuter rail mode that provides very good access/egress accessibility at the home and work ends for a sizeable fraction of commuters, but this may not be realized in practice because of drop-off/pick-up commitments during the commute (especially if these drop off/pick-up locations are not close to the commuter rail mode line).

The inter-relationship between stop-making and mode choice is particularly of importance in the context of the commute. After all, commute-related trips are concentrated in narrow time-windows of the day, and contribute very substantially to urban traffic congestion in the morning and evening peak periods. Besides, the commute serves multiple functionalities today, and is not simply a home-to-work or work-to-home trip for a significant fraction of commuters. This is due to several reasons, but to a substantial extent because of increased time constraints for out-of-home activity participation brought on by such factors as the increasing diversity of household structures [from the traditional one-worker couple/nuclear family households to two-worker couple/nuclear family households, single adult households, and single parent households; see (*3*)]. In fact, there is a trend of increasing chaining of non-work stops with the commute in the US and other countries [see (*5*)]. In a study by Bhat and Sardesai (*6*) based on Austin area commuters, the authors found that 30% of commuters make a non-work stop during the evening commute on any given workday, and about 85% of commuters make one or more non-work stops during the commute in the course of their work week. The association between non-work stop-making and commute mode choice is also clear in their study -- about 70% of commuters making no commute stops drive alone to work as compared to 87% of commuters making a commute stop who drive alone to work.

The importance of explicitly recognizing activity chaining for improved travel forecasting and improved travel demand policy formulation has not been lost on travel behavior researchers.

Indeed, even the practice of travel demand modeling is beginning to embrace an activity-based modeling framework where the unit of analysis is tours (sequences of trips from home-to-home, or from work-to-work for mid-day periods). Several studies in this vein have focused on commute-related stop-making with or without a joint component to examine commute mode choice [see, for example, (*7-11*)].

In this paper, we present a tour-based analysis for the joint choice of the commute mode and the number of non-work stops during the commute (*i.e.* the total number of non-work stops made during the morning home-to-work commute and evening work-to-home commute; in the rest of this paper, we will refer to "non-work commute stops" simply as "commute stops"). Such a model provides the ability to examine the effect of demographic changes and policy actions on the joint decision of commute mode choice and commute stop-making. As in Bhat (*11*), a basic premise of our modeling system is that the joint nature of mode choice to work and number of commute stops arises because the two choices are caused or determined by certain common underlying observed and unobserved factors to the analyst [see Train (*12*), p. 85]. For example, individuals in households with high automobile availability may be more likely to choose the drive-alone commute mode and may also make more commute stops. In this case, an observed factor (high automobile availability) generates the positive association between drive alone mode choice and stop-making. In addition, it is possible that individuals who are "dynamic" and "want to be in control" select the drive alone mode and also have a high commute stop-making propensity. In this case, an unobserved factor ("dynamic" and "wanting to be in control" generates the positive dependence between the drive alone mode choice and stop-making. Alternatively, walking or bicycling may provide more convenience and opportunity to stop at a way-side shop on the commute (especially in the rich land-use mix context in Italian cities). If this convenience and opportunity to stop is not adequately reflected in the observed variables, the result would be a positive dependence in bicycle/walk mode choice and number of commute stops. Thus, the reason for the joint nature of the two choices (commute mode choice and commute stops) is because of common underlying factors, *not because of direct causation* between the choices. A different, but related, interpretation is that individuals choose a particular combination or "package" of commute mode choice and stops. Since both these choices are determined simultaneously, "it is not possible for one choice to cause the other, in a strict sense of causality" [(*12*), p. 85].

The joint model takes the form of a flexible copula-based joint multinomial logit – ordered logit structure, and captures the observed effects of personal, household, residential location, and commute characteristics together with potential unobserved common effects impacting the two choices. The copula-based methodology facilitates model estimation without imposing restrictive distribution assumptions on the dependency structures between the errors in the discrete unordered and ordered choice components. Specifically, the copula approach allows one to test several different parametric dependency structures for the joint distribution of the error terms in the two equations (as opposed to the usual joint normal distribution used *de facto* in earlier studies). The copula concept has been recognized in the statistics field for several decades now, but it is only recently that it has been explicitly recognized and employed in econometrics. It is simple to implement and does not restrict the analyst from using rich and comprehensive variable specifications, as does a non-parametric dependency formulation. To our knowledge, this is the first application of a copula framework to jointly model an unordered choice variable (commute mode choice) and an ordered choice variable (number of commute stops).

The data used in this study are drawn from the "Time use" multipurpose survey conducted between 2002 and 2003 by the Turin Town Council and the Italian National Institute of Statistics

(ISTAT) in the Greater Turin metropolitan area of Italy. The focus on an Italian context is another important aspect of the current study. Most earlier research on commute activity chaining has been confined to the United States or an Australian or a North European context. To our knowledge, this is the first study to focus on an Italian context.

The rest of this paper is structured as follows. The next section provides a brief literature review of the studies most relevant to the current one. Section 3 describes the methodology employed. Section 4 discusses the data used for model estimation, and Section 5 reports the empirical results. Finally, the paper concludes with a summary of findings and further research avenues.

2. EARLIER APPROACHES AND THE CURRENT STUDY

Several studies have focused on the analysis of commute stops [see, for example, (*7-9*; *13-18*)], while a substantially higher number of studies have focused on commute mode choice in the traditional trip-making frame of analysis. Some of these studies have attempted to make a weak linkage between stop-making and mode choice by using one of the variables as an independent variable in the other [see, for example, (*6, 7, 19, 20*)]. These types of linkages, unfortunately, ignore the interactions between the number of stops and mode choice decisions, as discussed earlier, and therefore may not be adequate to predict the impact of demand control measures aimed at reducing personal vehicle use.

Some other studies have considered a joint commute mode choice – commute tour complexity model, where commute tour complexity is represented as a simple binary variable (simple commute tour with no commute stops, or complex commute tour with one or more commute stops). A recent study (*21*) compared the following three structures for representing the interaction between commute mode choice and commute stop-making: (1) Commute tour complexity affects mode choice, (2) Commute mode choice influences tour complexity, and (3) Commute mode choice and tour complexity are modeled simultaneously. The authors find, in their specific empirical context, that the best fit is obtained when commute tour complexity affects modal choice. Another recent study (*22*) highlights that even if the order of travel mode choice and activity participation may vary, in most cases the decision to makes stops is taken first. This result suggests that mode choice and, in particular, the decision of whether to take the car or public transport, is probably adjusted to the choice to undertake (or forego) chained non-work stops. However, all the studies in this area, like other joint models of modal choice and tour complexity [see (*3, 23, 24*)] represent activity chaining as a binary choice between not making any stops or making one and more stops, without specifying the number of stops in a complex tour.

Bhat (*11*) and Bhat and Singh (*25*) used an econometric structure to jointly model the commute mode choice and the number of commute stops in the Boston Metropolitan Area. The commute mode was modeled using a multinomial logit model, while the number of stops was modeled using an ordered logit model. The joint model explicitly accommodated the jointness between the two decisions generated by common unobserved factors, and found the significant presence of such common unobserved factors.

The model presented in the current research starts from Bhat (*11*) in that it too jointly analyzes commute mode choice and the number of commute stops. However, the methodological advance of the proposed model is that it does not consider an *a priori* bivariate distribution to "tie" the error terms in the two choice processes; rather, the copula model proposed here allows the analyst to test various different radially symmetric and asymmetric copulas based on data fit. The motivation is that one does not know *a priori* what kind of dependency structure holds between the

unobserved factors influencing commute mode choice and number of commute stops. Rather this is an empirical issue to be determined based on which dependency surface fits the data best. Of course, the examination of commute mode and stop-making for an Italian context (Turin city) in the current study also allows us to compare some of the empirical findings with Bhat's (*11*) study for the US context (Boston). In addition, it also provides independent insights into commuting behavior in a large metropolitan area from Italy, using data collected within the past decade (Bhat's Boston study was based on data collected in 1991).

The data used in this study are drawn from the "Time use" multipurpose survey conducted between 2002 and 2003 by the Turin Town Council and the Italian National Institute of Statistics (ISTAT) in the Greater Turin metropolitan area. The estimation sample of individuals includes active individuals aged 14 and over who are workers or students, undertook at least one work trip or one study trip on the survey day, and are able to use at least one motorized mode (*i.e.* moped, scooter, motorcycle, car *etc.*). In this regard, it should be noted that the terminology "drive alone" used in the current paper should not be interpreted as drive alone in a car (as is the case with Bhat's earlier research and most earlier research in the US), but as travelling alone on any motorized form of transportation. Further, an important mode choice alternative in the Italian context corresponds to active transport (bicycling and walking). On the other hand, these active forms of transportation comprise a very small percentage of the US commute mode share, and are ignored in several US-based commute mode choice models [including in the paper by Bhat (*11*)]. Also, as will be indicated later on in the paper, the general pattern of inter-relationship between commute modes and number of stops is rather different in the US and in Italy. While a higher level of commute stop-making is generally associated with the use of the drive alone mode in the US, a higher level of commute stop-making is associated with the use of the shared-ride mode in Italy. This corresponds to the case where colleagues or co-workers or individuals working and living in close proximity share a ride together (in a car, or on a moped, or other motorized means) and also make more stops to accommodate the activity needs of each person in the ride-share. On the other hand, there is no overall aggregate-level inter-relationship between drive alone share (or active transport share) and number of stops in the Italian context. However, as in the US context, there is a negative association in the Italian context at the aggregate level between stop-making and the share of the public transit mode.

3. METHODOLOGY
In this section, we discuss the structure of the copula-based joint multinomial logit–ordered response framework to model commute mode choice and the number of commute stops.

3.1 Model Structure
The modeling of commute mode choice is undertaken using a traditional multinomial logit model. Specifically, let q be the index for individuals and let i be the index for mode choice. Also, let h_{qi}^* be the latent (indirect) utility accrued by individual q for choosing travel mode i.

$$h_{qi}^* = \beta' x_{qi} + \varepsilon_{qi}, \tag{1}$$

where x_{qi} is a vector of independent variables, β is a corresponding vector of coefficients to be estimated, and ε_{qi} represents a idiosyncratic error term. Assume that the ε_{qi} terms are identically and independently Gumbel distributed across alternatives i and individuals q with a location

parameter equal to 0 and a scale parameter equal to 1. In the usual random utility set-up, individual q selects alternative i if and only if the following condition holds:

$$h^*_{qi} > \max_{\substack{j=1,2,...I \\ j \neq i}} h^*_{qj} \tag{2}$$

Let r_{qi} be a dichotomous variable; $r_{qi} = 1$ if the ith travel mode is chosen by the qth individual, and $r_{qi} = 0$ otherwise. Defining

$$v_{qi} = \varepsilon_{qi} - \left\{ \max_{j=1,2,...I, \, j\neq i} h^*_{qj} \right\}, \tag{3}$$

and substituting the right side for h^*_{qi} from Equation (1) in Equation (2), we can write:

$$r_{qi} = 1 \text{ if and only if } \beta' x_{qi} + v_{qi} > 0 \tag{4}$$

The implied marginal distribution of v_{qi} can be obtained from Equation (3) and from the distributional assumptions on the ε_{qi} terms as follows:

$$F_i(v) = \text{Prob } (v_{qi} < v) = \frac{\sum_{j \neq i} \exp(\beta' x_{qj})}{\exp(-v) + \sum_{j \neq i} \exp(\beta' x_{qj})} , \quad i = 1, 2, ..., I. \tag{5}$$

Next, let s_{qi} represent the number of commute stops for individual q should s/he choose alternative i, and let s^*_{qi} be a corresponding underlying latent propensity for stop-making. Then, in the usual ordered-response structure, we may write the following:

$$s^*_{qi} = \gamma' z_{qi} + \eta_{qi}, \; s_{qi} = k \text{ if } \delta_{i,k-1} < s^*_{qi} \leq \delta_{i,k} ,$$
$$s_{qi} \text{ observed only if } r_{qi} = 1 \; (i = 1, 2, 3, ..., I). \tag{6}$$

In the above equation system, z_{qi} is a vector of independent variables, γ is a corresponding vector of coefficients to be estimated, and η_{qi} represents an idiosyncratic error term assumed to be standard logistic distributed with a univariate cumulative distribution function given by $G(.)$. The δ_{ik} terms are the threshold bounds that horizontally partition the latent stop-making propensity (s^*_{qi}), and provide the relationship between the latent stop-making propensity and the observed number of stops s^*_{qi}. By convention, $\delta_{i,0} = -\infty$ and $\delta_{i,K} = +\infty$ for each mode i, where k is an index for number of stops (k = 1, 2, 3, ..., K). The probability that an individual q will choose mode i and make k commute stops may be written as follows:

$$\Pr[r_{qi} = 1, s_{qi} = k] = \Pr[v_{qi} > -\beta' x_{qi}, \delta_{i,k-1} - \gamma' z_{qi} < \eta_{qi} < \delta_{i,k} - \gamma' z_{qi}]$$
$$= \Pr[\delta_{i,k-1} - \gamma' z_{qi} < \eta_{qi} < \delta_{i,k} - \gamma' z_{qi}] - \Pr[v_{qi} < -\beta' x_{qi}, \delta_{i,k-1} - \gamma' z_{qi} < \eta_{qi} < \delta_{i,k} - \gamma' z_{qi}]$$
$$= G(\delta_{i,k} - \gamma' z_{qi}) - G(\delta_{i,k-1} - \gamma' z_{qi}) -$$
$$\left(\Pr[v_{qi} < -\beta' x_{qi}, \eta_{qi} < \delta_{i,k} - \gamma' z_{qi}] - \Pr[v_{qi} < -\beta' x_{qi}, \eta_{qi} < \delta_{i,k-1} - \gamma' z_{qi}] \right). \tag{7}$$

The above probability depends upon the dependence structure between the random variables v_{qi} and η_{qi} for each mode i.

3.2 General Bivariate Copula Structure

A copula is a device or function that generates a stochastic dependence relationship (*i.e.*, a multivariate distribution) among random variables with pre-specified marginal distributions (*26-28*). The precise definition of a copula is that it is a multivariate distribution function defined over the unit cube linking uniformly distributed marginals. In the bivariate case, let C be a *2*-dimensional copula of uniformly distributed random variables U_1 and U_2 with support contained in [0,1]. Then,

$$C_\theta\,(u_1,\,u_2) = \Pr(U_1 < u_1,\,U_2 < u_2), \tag{8}$$

where θ is a parameter of the copula commonly referred to as the dependence parameter. A copula, once developed, allows the generation of joint bivariate distribution functions with given marginals. In the notation of the earlier section, a bivariate distribution $J_i(v,\eta)$ can be generated for the two random variables v_{qi} (with margin F_i) and η_{qi} (with margin G) using the following expression [see (*29*)]:

$$J_i(v,\eta) = \Pr(v_{qi} < v, \eta_{qi} < \eta) = \Pr[U_1 < F_i(v), U_2 < G(\eta)] = C_\theta[u_1 = F_i(v), u_2 = G(\eta)] \tag{9}$$

A rich set of bivariate copulas $C_\theta(u_1,u_2)$ are available to generate the dependence between the random variables v_{qi} and η_{qi}, including the Gaussian copula, the Farlie-Gumbel-Morgenstern (FGM) copula, and the Archimedean class of copulas (including the Clayton, Gumbel, Frank, and Joe copulas). For given functional forms of the margins, the precise bivariate dependence profile between the variables v_{qi} and η_{qi} is a function of the copula $C_\theta(u_1,u_2)$ used, and the dependence parameter θ. But, regardless of the margins, the overall nature of the dependence between v_{qi} and η_{qi} is determined by the copula. The reader is referred to Bhat and Eluru (*27*) for a detailed discussion of the alternate copulas and the visual plots of their implied dependency. Due to space considerations, we are unable to provide additional details on the structures of the different copula types here. However, note that both the Gaussian and FGM copulas assume that the dependence structure is radially symmetric about the center point in the Gaussian and FGM copulas. That is, for a given dependence parameter, the magnitude of dependence is equal in the upper and lower tails. But it is also possible in empirical contexts that the magnitude of dependence is asymmetric at the upper and lower tails. For instance, environmentally conscious individuals may attribute a very low utility to the drive alone mode and may also uniformly have a very low propensity for stop-making using the drive alone mode. Assuming that environmental consciousness is an unobserved attribute, this would lead to strong clustering of the error term values at the low end of the bi-dimensional drive alone utility and stop-making propensity spectrum. On the other hand, assume that people who are "dynamic and want to be in control" assign a high utility for the drive alone mode. Some of these individuals may have a strong pre-disposition to have a high stop-making propensity (because of being energetic and "gung-ho"), but others may not have that high of a stop-making propensity (because of not wanting distractions). Assuming that "being dynamic and wanting to be in control" is unobserved to the analyst, this situation would lead to a clustering of the error term values at the high end of the bi-dimensional drive alone utility and stop-making propensity spectrum, but not at the same tightness level of clustering at the low end of the spectrum. This then leads to an

asymmetric dependency surface. Such an asymmetric dependence structure cannot be generated by the Gaussian or FGM copulas, but can be generated by the class of Archimedean copulas. Bhat's (*11*) model pre-imposes the Gaussian copula in the joint model of commute mode choice and commute stop-making.

3.3 Estimation Procedure

The parameters to be estimated in the joint unordered-ordered model include the β vector, the $(K-1)$ $\delta_{i,k}$ parameters $(\delta_{i,0} = -\infty$ and $\delta_{i,K} = +\infty)$ for each mode i, the vector γ , and the dependence parameter θ of the best-fitting copula. The probability of an individual choosing a mode i and k commute stops may be obtained from Equation (7) and the appropriate copula expression as:

$$\text{Prob}[r_{qi} = 1, s_{qi} = k] = G(\delta_{i,k} - \gamma'z_{qi}) - G(\delta_{i,k-1} - \gamma'z_{qi}) - \left[C_\theta(u_{qi1}, u_{qi,k,2}) - C_\theta(u_{qi1}, u_{qi,k-1,2})\right], \quad (10)$$

where $u_{qi1} = F_i(-\beta'x_{qi})$ and $u_{qi,k,2} = G(\delta_k - \gamma'z_{qi})$.

Next, let 1[.] be an indicator function taking the value of unity if the expression in parenthesis is true and 0 otherwise. Also, define the following dummy variables for $i = 1, 2, 3, …, I$:

$$M_{qik} = 1[r_{qi} = 1] \times 1[s_{qi} = k]. \quad (11)$$

Then, the log likelihood function for the copula model takes the form

$$\log L = \sum_{q=1}^{Q} \left(\sum_{i=1}^{I} \sum_{k=1}^{K} M_{qki} \log \left[\text{Prob}\left(r_{qi} = 1, s_{qi} = k \right) \right] \right) \quad (12)$$

All the parameters in the model are consistently estimated by maximizing the log-likelihood function, which is accomplished using the GAUSS matrix programming language.

4. DATA DESCRIPTION

The source of data used in the current paper is the 2002/2003 Turin Time Use Survey, which was designed/administered by the Italian National Institute of Statistics (ISTAT) and sponsored by the Turin Town Council and 14 neighboring town councils (Baldissero Torinese, Beinasco, Borgaro Torinese, Collegno, Grugliasco, Moncalieri, Nichelino, Orbassano, Pecetto Torinese, Pino Torinese, Rivoli, San Mauro Torinese, Settimo Torinese, Venaria Reale). The survey collected a daily activity time-use diary from each of 4537 household members aged 3 years and older from 1830 households [see Istat (*30*) for details of the survey design and administration procedures].

The sample used for model estimation includes 862 active individuals (14 years and older) who are workers or students, undertook at least one work trip or one study trip on the survey day, and are able to use at least one motorized mode (*i.e.* moped, scooter, motorcycle, car, *etc.*). After data processing and cleaning, the final sample includes 862 individuals.

Four different travel modes have been selected for the MNL estimation: (1) drive alone (DA), (2) shared ride (SR), (3) active transport (AT), and (4) public transport (PT). The mode used for the final leg to work in the morning is used as the commute mode choice (thus, if a person drops off another family member by car during the morning commute and then proceeds alone to work, the person's work mode choice is classified as drive alone). The commute mode split in the sample is as follows: 52.3% drive alone, 17.3% shared ride, 10.7% active transport (walk or bike), and 19.7% public transport.

A stop during the commute has been defined as any episode occurring for at least 10 minutes, at a location other than home or work/study place. No activity purposes have been excluded from this definition (thus, for example, buying a newspaper and getting a coffee are expressly coded as stops, as long as they are of 10 minutes or longer duration). Further, two consecutive activities performed in the same location, with no intermediate trips, are considered as a single stop. In this work only the cumulative number of stops is modeled, and no distinction is made by purpose of stop or commute direction (that is, whether the stop was made during the home-to-work commute or the work-to-home commute, though a very high proportion of the stops are made during the work-to-home commute in the evening). The split of number of stops in the sample is as follows: 63.5% zero stops, 25.0% one stop, 8.0% two stops, and 3.5% with three or more stops. Among those who make no stops, the mode split is 52.1% DA, 15% SR, 10.8% AT, and 22.1% PT, while among those who make one or more stops, the mode split is 52.7% DA, 21% SR, 10.5% AT, and 15.5% PT. These figures reveal the general trend discussed in the paragraph just before Section 3.

A number of exogenous variables were considered for estimation, including (1) Individual socio-demographics (age, gender, marital status, and education level), (2) Household socio-demographics (number of children, number of children by age, vehicle availability, and household income), and (3) Residential location and commute characteristics (location in the Turin area, distance from home to work, and the number of commutes in the day - whether the individual does not return home in the afternoon for lunch, labeled as a "single commute", or whether the individual returns home in the afternoon for lunch, labeled as a "double commute").

Tables 1 and 2 show the distributions by commute mode and by number of stops for individual and household characteristics (Table 1), and for residential location and commute characteristics (Table 2). Note that the percentages sum to 100% for each exogenous variable across the mode columns and across the number of stops columns. The last column shows the average values of the explanatory variables across the entire sample. The discussion below regarding variable effects is only suggestive, since Tables 1 and 2 are based on univariate statistics and do not control for other exogenous variables when examining the effect of an exogenous variable on commute mode choice and number of stops.

4.1 Individual and Household Characteristics

Males account for 57% of the sample, while females account for the remaining 43% of the sample. The results show that men are more likely to drive alone than women (60.7% of men drive alone compared to 41% of women who drive alone; see the column labeled "DA" under "Commute Mode"), and also make fewer commute stops than women (68.8% of men do not make commute stops, while only 56.3% of women do not make commute stops; see the entries in the "0 stops" column under "Number of Stops"). The age category most represented in the sample is individuals who are 41 years or older (42%; see last column of table). Only 6% of the sample is aged 14-17 and the remainder is almost equally divided into the 18-30 years and 31-40 years categories (24% and 28% respectively). Young individuals (aged 14-17 years and 18-30 years) are more likely to be public transport users than their older peers (note that about 59% of those aged 14-17 years use public transport, and about 26.8% of those aged 18-30 years use public transport; these numbers are greater than the public transport shares among the other age groups). Further, those who are 31-40 years of age tend to make more stops than those in other age groups.

The percentage of individuals with low education (middle school or lower) and medium education (high school or undergraduate degree) levels is about the same at about 44%, while the percentage of individuals with a high education (Master's degree or higher) is 13%. The results also

show that individuals with high education levels are less likely to take the public transport and active transport modes, and more likely to take the drive alone mode, relative to those with low education levels. Further, in general, those with high education levels also make more commute stops than those with low education levels. The percentage of married individuals in the sample is 53%; those who are married are more likely users of the drive alone and shared-ride modes, and tend to make more stops (except for the 3+ stops category).

About 29% of the individuals in the sample do not have children in their household. The numbers corresponding to number of children by age indicate, in general, the lower use of drive alone and higher use of public transport among individuals with no children in the household (relative to individuals with children in the household). The results also show the higher disposition to drive alone among individuals in households with younger children, and a higher predisposition to use public transport among individuals in households with older children. Further, individuals in households with very young children (0-5 years of age) are more likely to make commute stops than those in households with no children or older children. This is to be expected, since young children, in particular, will need to be picked up/dropped off by parents from/at child care.

As expected, the results for vehicle ownership (number of motorized vehicles in the household) reveal the higher likelihood of choosing drive alone as the commute mode and making more commute stops as vehicle availability increases. The final variable in Table 1 shows that 89% of the individuals in the sample are from middle income families, while 8% are from low income families and 3% are from high income families.[1] Individuals from middle income families are more likely to use the drive alone mode, and less likely to use active transport, relative to those from low and high income families. In addition, public transport use decreases as family income rises, and shared-ride use increases as family income increases.

4.2 Residential Location and Commute Characteristics
About 45% of the sample resides in the Turin municipality, while the remainder resides in the larger metropolitan area outside Turin. As one would anticipate, those residing in the Turin municipality are more likely to walk/bicycle and take public transport than those residing outside the municipality. Turin residents are more likely to make 1 stop relative to non-Turin residents, while the non-Turin residents are more likely to make two or more stops.

Not surprisingly, those who have very short commute distances (less than 1 km) are most likely to use an active transport mode. Also, those who commute long distances (>5 kms) tend to make more commute stops. The next variable in the table refers to the number of commutes. Clearly, those who double commute shy away from using the public transport mode.

The day of week of commute does not appear to have much impact on commute mode choice or commute stop-making in this univariate analysis.

5. RESULTS
As cautioned earlier, the descriptive results in the previous section are only suggestive. In particular, the effect of a variable is examined without controlling for the influence of other variables. To obtain a comprehensive picture of the factors affecting commute mode choice and stop-making, there is a need for a rigorous multivariate analysis. In the next section, we present results from such

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[1] The Turin survey did not provide income brackets for individuals to respond in, due to privacy considerations. Rather, individuals had to subjectively assign their household incomes into one of three nominal income levels – low, medium, and high.

an analysis, which involves the estimation and testing of the joint Copula MNL-Ordered Logit using a number of dependency structures (Normal, FGM, Frank, Gumbel, Clayton and Joe) as well as the independent formulation.

The alternative copula models cannot be tested using the traditional likelihood ratio test because these copula models are non-nested. So, the Bayesian Information Criterion (BIC) is employed to select the best copula model from among the competing non-nested copula models [see (*28* page 65, *31*, *32*)]. Using the BIC, the best model fit is obtained with the Gaussian copula that has a log-likelihood value of -1652.39 compared to -1657.72 for the independent model. The second best model turned out to be the Frank copula, which yields a log-likelihood value of -1653.01. Interestingly, both the first best and second best copula forms are radially symmetric and strongly suggest the presence of a symmetric dependency structure. The log-likelihood value for the sample shares model is -1860.20. A nested likelihood ratio test between the Gaussian copula model and the independent model turns up a test statistic value of 10.7, which is higher than the table chi-squared value with one degree of freedom (equal to the restriction that the dependence parameter is zero in the Gaussian copula) at any reasonable level of significance. Also, the test between the Gaussian copula model and the naïve sample share model rejects the absence of variable effects.

In the rest of this section, we only present the model estimation results for the best copula model, to conserve on space. The results are shown in Table 3. The first four rows provide the copula dependency parameters (t-stats in parentheses) for each trip mode. All parameters are significantly different from zero and positive, which indicates the presence of unobserved factors common to both mode choice and number of stops behavior. Specifically, a positive correlation (or dependence) between the error terms v_{qi} and η_{qi} implies that unobserved factors that increase (decrease) the propensity to choose a certain mode to work/study also increase (decrease) the propensity to make stops. As discussed earlier in this paper, this is an expected result that is now confirmed through the rigorous copula-based model. The magnitude of dependence decreases from the drive alone mode to the shared-ride mode to the active transport mode to the transit mode, which may be related to the greater propensity to prefer the drive alone/shared ride modes when there is an intrinsic need to have a flexible arrangement to make stops. The modal constants in the table do not have any substantive interpretations; they simply control for the sample mode shares as well as control for the range of the exogenous variables in the sample.

The effect of other variables on the utility of each mode in the multinomial logit (MNL) model and on the propensity to make stops in the ordered logit (OL) model are discussed by variable category below. Several functional forms for the variables were considered. For example, age was introduced linearly, using a piecewise-linear approach, as well as dummy variables with different cut-off points. The final model specification (including the variables included, the functional form of variables, and interaction effects of variables) was based on intuitive considerations, insights from previous literature, parsimony in specification, and statistical fit/significance considerations.

5.1 Individual and Household Characteristics
Males are less likely than females to use modes other than driving alone and to undertake stops during the commute. The latter result, in particular, has been found in almost all studies of commute stop-making [see (*7, 9, 18, 25*)], and perhaps illustrates the continuing trend of women to be primarily responsible for household maintenance activities and for dropping/picking up children from day-care. Individuals under 18 years of age are more likely to use active transport and public transport than individuals of all other age groups. This could be a reflection of financial constraints, or physical ability to use active transport, or environmental awareness among the young, or

combinations of these. On the other hand, individuals who are 31-40 years old are the least likely to use public transport. However, and interestingly, the results do not show differential stop-making propensities based on age. Education level does not seem to affect mode choice, but individuals with medium and high education levels are more likely to make stops during the commute compared to those who have a low education level. Married individuals are more likely to rideshare than unmarried individuals, which is consistent with the results from the univariate analysis in Table 1.

Moving on to the household variables, individuals in households with several children are less likely to use public transport, while individuals in households with very young children (under 5 years of age) are more likely to make stops during the commute. These results are not surprising since the presence of children, in general, entails a high number of picking up and dropping off activities, and these activities are not conveniently undertaken by public transport. As expected, the higher availability of vehicles (computed as number of vehicles divided by household size) results in lower use of active transport and public transport modes, and higher levels of stop-making propensity. Finally, within the group of household characteristics, the results show the higher stop-making propensity of individuals from high income families relative to individuals from low and medium income families. These last two results are also consistent with those found in earlier studies [see (*3*, *9*, *11*, *20*)], and suggest mobility and expenditure "freedom" to pursue non-work stops during the commute.

5.2 Residential Location and Commute Characteristics
As in the case of the univariate analysis, the multivariate analysis also indicates the higher usage of active transport and public transport (and the lower usage of the drive alone and shared-ride modes) among individuals residing in Turin relative to those residing outside Turin. Commute distances of less than 1 km are more likely to lead to the choice of bicycle and walk modes of travel, but as expected individuals are progressively less likely to bicycle or walk as their commute distance increases. Also, individuals who double commute (go back home for lunch) are unlikely to use public transport because of the need to undertake this midday activity. Finally, individuals are less likely to engage in active transport on Saturdays relative to other regular workdays.

The thresholds listed toward the end of Table 3 do not have any substantial interpretation. They simply serve to translate the underlying stop-making latent propensity to the observed ordinal categories of number of stops.

5.3 Comparison with Bhat's (1997) Results
A comparison of the results obtained in the current paper with those reported by Bhat (*11*) highlights differences between the European (Turin Metropolitan Area, Italy) and United States (Boston Metropolitan Area) contexts. The model presented in this research identifies a high positive dependency parameter between the error terms in the shared ride mode utility and the stop-making propensity. By contrast, Bhat (*11*) finds a non-significant value for the corresponding dependency. This may be explained by cultural differences – it is not uncommon in Italy to make stops to accommodate the needs of fellow riders, and the more the fellow riders the more the stops. This may explain the general positive tendency (due to unobserved factors) between shared-ride utility and stop-making. The result may also be due to family members ride-sharing and taking care of household responsibilities. Istat (*30*) suggests that Italians are less "time-hassled" compared to individuals in other Western countries, and this may make Italians more open to ride-sharing and more accommodating of the stop-making needs of fellow riders. On the other hand, both Bhat's model and our current model identify a significant positive dependence between the unobserved

factors influencing drive alone utility and stop-making propensity, As expected, the need for control and independence increases both the preference for the drive alone mode and stop making propensity.

The explanatory variables in Bhat's paper and the current one are somewhat different. But the common variables (such as vehicle availability, income, marital status, and gender) do generally have the same direction of effect on commute mode choice tendencies and stop-making propensities. Bhat included level-of-service variables in his mode choice model, which we could not obtain for the Turin area because of lack of network data from the region. However, the list of demographic variables is longer in our current paper than in Bhat's paper. Another important aspect of the current research is the accommodation of active transport (walk/bicycle) as a commute mode, which Bhat was not able to do in the US context. Our results indicate the significant influences of gender, age, vehicle availability, residential location, and commute distance on the utility of the active transport mode.

Finally, it is interesting that the best copula structure in the current research turned out to be the Gaussian copula, which is the one that Bhat (*11*) imposed *a priori* in his model. It would be interesting to continue to test alternative dependency structures in other empirical contexts, using the flexible copula model structure proposed in this paper, to examine if the Gaussian copula structure is generically appropriate for modeling commute mode choice and stop-making behavior, or whether the convergence to the Gaussian copula in this paper is specific to the Turin context.

6. CONCLUSIONS

In this paper, we have developed a copula-based joint framework of tour mode choice and number of stops during the commute. The methodology developed here, to the authors' knowledge, is the first formulation and application of the copula approach to the estimation of a joint unordered multinomial-ordered discrete choice model. The focus on an Italian context is another important aspect of the current study.

The results indicate the substantial and statistically significant effects of individual and household characteristics on mode choice and stop-making behavior. On the other hand, residential location and commute characteristics seem to affect only commute mode choice and not commute stop-making behavior. Earlier studies have also pointed out the relatively small or zero effect of commute distances and built environment variables on commute stop-making, especially relative to the effects of demographic variables [see, for example, (*7, 11*)].

The model structure presented in this work is capable of capturing self-selection effects in the mode choice decision based on the number of stops during the commute. The presence of self-selection confirms the importance of jointly modeling the mode choice decision and the number of stops, in particular when aggregate percentage changes in each stop category - in response to changes in policy relevant exogenous variables - are intended to be calculated.

There are of course, several avenues to improve and extend the current research. First, the current research does not differentiate between the home-to-work and work-to-home commutes, both in terms of mode choice and stops behavior. But there may be substitution effects or complementary effects in stop-making behavior during the home-to-work and work-to-home commutes. This issue may be particularly relevant in the Italian context as it is not uncommon for Italian workers/students to make two round trip commutes a day (returning home for lunch and going back to work in the afternoon), increasing the opportunity for interaction effects. Second, the current study does not focus on other important dimensions of commute stop-making behavior, including the duration, location, and purpose of stops. Third, the effort does not include level-of-service measures and fine

measures of land-use/urban form due to the unavailability of such data from the Turin region. Further research should focus on expanding the dimensions of commute behavior studied, and including a richer set of demographic, transportation network, land-use, urban form, and individual attitudinal variables.

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LIST OF TABLES

TABLE 1 Sample Characteristics – Individual and Household Characteristics

	COMMUTE MODE				NUMBER OF STOPS				Avg
	DA	SR	AT	PT	0	1	2	3+	
Individual characteristics									
Gender									
Male	60.7%	16.0%	9.3%	14.0%	68.8%	21.9%	6.7%	2.6%	57%
Female	41.0%	19.0%	12.5%	27.5%	56.3%	29.3%	9.8%	4.6%	42%
Age									
Age 14 – 17	5.9%	15.7%	19.6%	58.8%	80.4%	13.7%	3.9%	2.0%	6%
Age 18 – 30	49.8%	16.2%	7.2%	26.8%	65.6%	23.4%	7.2%	3.8%	27%
Age 31 – 40	64.6%	18.5%	8.6%	8.3%	56.0%	30.0%	9.5%	4.5%	28%
Age 41 and more	52.1%	17.3%	12.8%	17.8%	64.9%	24.2%	8.1%	2.8%	42%
Level of Education									
Low Education (middle school and lower)	44.5%	19.1%	14.3%	22.1%	70.9%	20.5%	5.9%	2.7%	43%
Medium Education (high school or undergraduate degree)	56.2%	15.8%	7.9%	20.1%	61.7%	25.6%	8.4%	4.3%	44%
High Education (Master's degree or higher)	65.2%	16.1%	8.0%	10.7%	44.6%	38.4%	13.4%	3.6%	13%
Marital Status									
Unmarried	48.5%	12.7%	10.5%	28.3%	64.7%	24.5%	7.1%	3.7%	47%
Married	55.7%	21.4%	10.8%	12.1%	62.3%	25.6%	8.8%	3.3%	53%
Household characteristics									
Num of children by age									
No kids	50.7%	18.0%	13.7%	17.6%	58.5%	27.8%	8.8%	4.9%	29%
Kids 0 – 5	68.5%	15.3%	9.9%	6.3%	51.4%	33.3%	10.8%	4.5%	16%
Kids 6 – 13	60.2%	20.5%	9.9%	9.4%	65.8%	22.4%	8.1%	3.7%	22%
Kids 14 – 17	58.4%	15.6%	13.0%	13.0%	62.3%	23.4%	11.7%	2.6%	11%
Kids 18+	49.7%	20.6%	11.6%	18.1%	65.8%	25.2%	7.1%	1.9%	22%
Vehicle Ownership (number of motorized vehicles owned)									
0 vehicles	21.6%	13.5%	18.9%	45.9%	51.4%	37.8%	5.4%	5.4%	4%
1 vehicle	44.7%	16.4%	13.8%	25.1%	62.7%	26.7%	7.7%	2.9%	36%
2 vehicles	55.8%	17.7%	9.3%	17.2%	66.8%	22.0%	7.3%	3.9%	41%
3 vehicles and more	66.7%	18.9%	5.7%	8.7%	60.4%	25.8%	10.7%	3.1%	19%
Household Income (as defined by the household head)									
Low Income	45.7%	11.4%	14.3%	28.6%	72.9%	21.3%	2.9%	2.9%	8%
Medium Income	53.1%	17.4%	10.2%	19.3%	63.4%	25.6%	7.7%	3.3%	89%
High Income	48.2%	29.6%	14.8%	7.4%	40.7%	18.5%	29.6%	11.2%	3%

TABLE 2 Sample Characteristics – Residential Location and Commute Characteristics

	COMMUTE MODE				NUMBER OF STOPS				Avg
	DA	SR	AT	PT	0	1	2	3+	
Residential Location									
Turin Municipality	49.0%	15.1%	13.8%	22.1%	60.8%	28.7%	7.2%	3.3%	45%
Outside Turin Municipality	55.1%	19.1%	8.1%	17.7%	65.7%	22.0%	8.7%	3.6%	54%
Commute Distance									
Distance ≤ 1 km	31.9%	15.4%	49.5%	3.2%	63.7%	23.1%	11.0%	2.2%	13%
Distance 1–5 km	61.6%	17.7%	9.6%	11.1%	64.6%	23.2%	8.6%	3.6%	29%
Distance 5–10 km	55.6%	19.6%	2.1%	22.7%	57.1%	28.6%	9.5%	4.8%	28%
Distance > 10 km	63.2%	17.2%	2.0%	17.6%	62.3%	27.5%	6.4%	3.8%	30%
Number of commutes									
Single Commute	52.3%	16.9%	8.6%	22.2%	64.1%	24.2%	7.9%	3.8%	85%
Double Commute	52.3%	19.2%	22.3%	6.2%	60.0%	30.0%	8.5%	1.5%	15%
Day of the week									
Workday	52.5%	17.5%	10.7%	19.3%	62.3%	25.6%	8.3%	3.8%	73%
Saturday	51.7%	16.7%	10.7%	20.9%	66.7%	23.5%	7.3%	2.5%	27%

TABLE 3 Model Estimates

Variables	MNL				Ordered Logit (N°Stop)
	Drive Alone	Shared Ride	Active Transport	Public Transit	
Copula Dependency Parameter (θ)					
Drive Alone	-	-	-	-	0.469 (2.56)
Shared Ride	-	-	-	-	0.375 (3.79)
Active Transport	-	-	-	-	0.238 (2.03)
Public Transit	-	-	-	-	0.194 (1.82)
Mode Constants	-	-0.966 (-5.01)	-0.626 (-1.72)	1.125 (4.41)	-
Individual Characteristics					
Male	-	-0.626 (-3.63)	-0.626 (-3.63)	-1.133 (-5.46)	-0.286 (-3.40)
Age (age ≥ 41 yrs and age 18-30 yrs are the base)					
Age 14 – 17	-	-	1.511 (4.01)	1.511 (4.01)	-
Age 31 – 40	-	-		-0.980 (-3.49)	-
Level of Education (Low education is the base)					
Medium Education (High school or undergraduate degree)	-	-	-	-	0.190 (2.14)
High Education (Master's degree or higher)	-	-	-	-	0.411 (2.99)
Married	-	0.394 (2.05)	-	-	-
Household Characteristics					
Number of Kids					
Number of total kids	-	-	-	-0.431 (-3.14)	-
Number of kids ≤ 5 years	-	-	-	-	0.282 (2.43)
Vehicle Availability (# of motorized vehicles/household size)	-	-	-1.485 (-3.47)	-1.798 (-7.68)	0.249 (2.82)
Household Income (low and medium income are the base)					
High Income (as defined by the household head)	-	-	-	-	0.493 (2.55)
Residential Location and Commute Characteristics					
Turin Municipality	-	-	0.788 (2.96)	0.342 (1.68)	-
Commute Distance (1-5 km is the base)					
Distance ≤ 1 km	-	-	2.458 (7.91)	-	-
Distance 5 – 10 km	-	-	-1.568 (-2.97)	-	-
Distance > 10 km	-	-	-1.669 (-2.81)	-	-
Double commute (goes back home for lunch)	-	-	-	-1.232	-

				(-2.92)	
Saturday	-	-	-0.481 (-1.64)	-	-
Threshold 0 – 1 stops	-	-	-	-	0.886 (6.27)
Threshold 1 – 2 stop	-	-	-	-	1.752 (13.56)
Threshold 2 – 3 and more stops	-	-	-	-	2.368 (17.50)