Analysis of the interaction among destination and departure time choices

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Abstract

Departure time and destination choices are interrelated decisions that affect urban transportation demand estimation. Most previous studies ignore this interrelation and assume that these decisions are independent. Some other studies use a hierarchy structure, while the literature suggests that destination and departure time are selected simultaneously before the commencing of trips. This paper employs a joint model by using copula functions to explore the interdependency between destination and departure time choices. The destination choice modeling is developed using a multinomial logit model, and a binary logit model is used for modeling departure time choice. To obtain a better-fitted joint model, some copulas are used thereafter; the frank copula is selected for the final model. Results show that there are some common unobserved factors between these decisions by estimating copula dependence parameters with high statistical significance. Furthermore, there are some commonly observed factors, such as socio-demographic and travel characteristics that appear in the utility functions of both models.

Keywords: Joint modeling, Copula, Destination choice, Departure time choice, Multinomial logit
1. Introduction

Generally, traffic congestion in traffic peak hours is caused by high travel demand to some specific destinations (for example, administrative destination) in particular hours. Congestion then leads to many problems such as air pollution, noise pollution, losing energy, and decreasing safety. With the rapid growth in urbanization, expanding the capacity of the transport network is not anymore an efficient and economical option. Managing travel demand is an alternative to tackle congestion in large metropolitan areas with limited infrastructure capacity.

Having in mind the significant impact of destination and departure time choice on traffic load on the network, it is crucial to understand how to model these decisions. Then it is vital to find the suitable modeling structure that can depict the behavior of travellers about the destination choice according to the land use and departure time choice [1].

The literature suggests that destination and departure time choices are interrelated choices. The selected destination has a significant effect on when trips began and selected departure time affects where trips end. For example, if an individual decides to has a shopping trip, choosing the destination with business land use and peak hour is more expected than choosing other destinations and off-peak (early and late) hours. Usually, people choose the departure time and destination simultaneously before they commence trips. The interaction of these two decisions can be captured systematically by including variables relating to them. There might also be some unobserved correlations between the two decisions that can be investigated in an appropriate modeling formulation. This study explores the application of copula functions to capture the correlation between destination choice and departure time choice.

2. Literature review

Many studies ignore the relationship between destination and departure time. For example, Thorhauge et al. [2] employ discrete choice models such as a multinomial logit model to analyze departure time for work trips without considering the reciprocal effect of destination. Sultana [3] also study departure time choice for non-work Trips. Sasic et al. [4] investigate modeling departure time choice by using the heteroskedastic generalized model for home-based commuting trips. Also, some studies focus on destination choice without considering the effect departure time [5, 6]. For example, Clifton et al. [7] use multinomial logit to study the destination choice for pedestrian travel.

Some other studies analyze the interaction of departure time choice or destination choice with other travel decisions [8, 9]. Ding et al. [10] use a cross-nested logit to model trip mode and departure time for urban commuting trips. Bhat [11] employs multinomial logit and nested logit for analysis of mode and departure time of shopping trips. Also, Elmorssy and Onur [12] use generalized nested logit to study the interaction between departure time, destination choice, and travel mode for non-mandatory trips. Some studies consider the interaction between discrete travel decisions using a copula-based joint model [13, 14]. For example, Ermagun et al. [15] investigate on joint modeling of parent escort decision and student mode choice for educational trips and show the benefits of using the Copula-based structure. Rasaizadi and Kermanshah [13] examine the endogenous correlation among number of stops and trip mode using the Copula-based model.
According to the author’s knowledge, there is not any study that models departure time and destination jointly. This paper employs copula-based framework to explore the interdependency among departure time and destination choices. This framework has not any hierarchy between decisions that other models, such as the nested logit model, have a hierarchy structure. The destination modeling is developed using the multinomial logit model, and a binary logit model is used for modeling the departure time choice. Bhat and Sener [1, 16] consider the followings as the benefits of using the copula-based framework:

1- It is a powerful technique to accommodate spatial error correlation
2- It does not impose limiting distribution assumption about the type of dependency
3- It leads to a closed-form without intensive computational
4- It is straightforward to apply using a standard and direct maximum likelihood inference procedure

Employing the copula-based joint modeling structure for modeling departure time and destination, using the travel dataset of Qazvin-Iran as a developing country, and investigating aggregate elasticities are main contributions of the current study.

In this study, the joint model of destination and departure time choice is developed for non-work home-based trips. Work trips (education trips are also considered as work trips) are excluded. The passenger has a limited choice on the departure time. Departure time on trips started from home is more flexible.

3. Methodology

This section presents a detailed discussion about the formulation of the joint structure for destination and time of day choice behavior.

3.1. Destination model structure

The multinomial logit structure is employed to model the destination choice. The choice set includes Non-Residential, Residential-Educational, Residential-Administrative, and Residential-Business zones. “q” shows the index of a person, “i” represents destination, and “hqi” stands for utility of destination “i” of person “q”. In such a case, we can define the utility function as [1, 17]:

\[ h_{qi} = \beta x_{qi} + \varepsilon_{qi} \]  \hspace{1cm} (1)

Where \( x_{qi} \) is the vector of exogenous variables, \( \beta \) is the coefficient vector of independent variables that must be estimated, and \( \varepsilon_{qi} \) refers to the error term (random term) of \( h_{qi} \). Assume that \( \varepsilon_{qi} \) follows the independent and identically distribution (iid), which its location and scale parameters are equal to 0 and 1, respectively [1]. Based on the utility theory, “q” selects the option “i” the utility of “i” is more than the maximum utility of the other destinations for “q”. This term can be written as follows [17]:

\[ h_{qi} > max_{j\neq i} h_{qj} \]  \hspace{1cm} (2)
The dependent variable is called \( r_{qi} \) which is a binary variable taking the value of one if the destination “i” is chosen by “q”, and zero otherwise \[18]\). Also, \( v_{qi} \) can be defined as follows \[1, 17\] :

\[
v_{qi} = \left\{ \max_{j \neq i} h_{qj} \right\} - \varepsilon_{qi}
\]  

(3)

By combining equation (1) and inequality (2), we derive the following inequality:

\[
\beta x_{qi} + \varepsilon_{qi} > \max_{j \neq i} h_{qj}
\]  

(4)

Which can be re-written by substituting \( v_{qi} \) from equation (3) into inequality (4) \[1\] :

\[
\beta x_{qi} > v_{qi}
\]  

(5)

So, \( r_{qi} = 1 \) if and only if \( \beta x_{qi} > v_{qi} \).

Based on equation (3), \( v_{qi} \) will result from the differentiation of the utility of the other destination and the error term of chosen destination, as both of them follow the iid extreme value distribution, then, the random variable of \( v_{qi} \) follows the logistic distribution because it obtained from the differentiation of iid distributed variables \[1\]. Then the marginal distribution of \( v_{qi} \) presented in equation (6) is \[17\] :

\[
F_{v_{qi}}(\beta x_{qi}) = \Pr(v_{qi} < \beta x_{qi}) = \frac{\exp(\beta x_{qi})}{\sum_{j} \exp(\beta x_{qj})}
\]  

(6)

3.2. Departure time choice model structure

The binomial logit is employed for the departure time choice modeling. The choice set consist of two options, traffic off-peak hours and traffic peak hours. “q”, “k”, and “\( u_{qk} \)” represent a person, the departure time and the utility of choosing “k” for person “q”, respectively. We have \[1, 17\] :

\[
u_{qk} = \gamma z_{qk} + \mu_{qk}
\]  

(7)

Where \( z_{qk} \) is the vector of exogenous variables, \( \gamma \) is a vector of parameters that must be estimated and \( \mu_{qk} \) is the random error term of the utility function. \( \mu_{qk} \) follows the independent and identically distribution (iid), which its location and scale parameters are equal to 0 and 1\[1, 17\]. “q” chooses “k” if \( u_{qk} \) be more than other utilities.

\[
u_{qk} > u_{ql} (l \neq k)
\]  

(8)

So we have \[1\] :

\[
\gamma z_{qk} + \mu_{qk} > \mu_{ql}
\]  

(9)

\[
\mu_{qk} - \mu_{ql} > -\gamma z_{qk}
\]  

(10)

Also, \( \tau_{qkl} \) will be defined as \( \mu_{qk} - \mu_{ql} = \tau_{qkl} \), then we have \[1, 17\] :
\[ \tau_{qkl} > -\gamma z_{qk} \]  

(11)

So, \( S_{qK} = 1 \) if and only if \( \tau_{qkl} > -\gamma z_{qk} \).

The random variable of \( \tau_{qkl} \) which is derived from the differentiation of \( \mu_{qk} \) and \( \mu_{ql} \) follows the logistic distribution. Then the marginal distribution of \( \tau_{qkl} \) presented in equation (12) can be written as \([1, 17]\):

\[
G_k(-\gamma z_{qk}) = \frac{\exp(-\gamma z_{qk})}{1+\exp(-\gamma z_{qk})}
\]

(12)

### 3.3. Joint model structure

The probability that “\( q \)” selects destination “\( i \)” and departure time “\( k \)” is \([1]\):

\[
\Pr[r_{qi} = 1, s_{qk} = 1] = \Pr[v_{qi} (\beta x_{qi}, \tau_{qkl}) - \gamma z_{qk}] = \Pr[v_{qi} < \beta x_{qi}] - \Pr[v_{qi} < \beta x_{qi}, \tau_{qkl} < -\gamma z_{qk}]
\]

(13)

The probability function needs to calculate a bivariate distribution among the random terms of models. The copula is a cumulative distribution functions which consist of the marginal densities \([1, 18, 19]\). Equation (13) can be rewritten as follows:

\[
\Pr[r_{qi} = 1, s_{qk} = 1] = u_{qi} - C_{\theta_{ik}} (u_{qi}, u_{qk}) = F_i (\beta x_{qi}) - C_{\theta_{ik}} (F_i (\beta x_{qi}), G_k (-\gamma z_{qk}))
\]

(14)

In which; \( u_{qi} = F_i (\beta x_{qi}) \) and destination of densities are marginal \( G \) and \( F \). \( u_{qk} = G_k (-\gamma z_{qk}) \) departure time choices. \( \theta_{ik} \) is the dependence parameter of copula that represents the correlation among random terms of option “\( i \)” and option “\( k \)” \([1, 18, 19]\). In current study, Frank and AMH (Ali-Mikhail-Haq copula) copulas have been used, because these copulas estimate the dependence parameter. Also, they consider positive and negative correlation (dependence parameters). These two copula functions are selected because they can explore positive and negative dependencies between error terms. As copula dependence parameter of other copula functions such as Clayton, Joe, and Gumbel are limited to positive values or exclude zero value, they could not depict negative dependencies or independency, so they are not employed in this study. The product copula shows independent random terms. Table 1 introduces used copulas \([1]\).

The implication of copulas is not limited to the joint modeling of different choices. For example, Liu et al. \([20]\) propose a correlation and risk measurement model by using Markov-switching mixed-Clayton copula.

### 3.4. Estimation process

Define a binary variable \( M_{qik} \) such that if person “\( q \)” selects destination “\( i \)” and departure time “\( k \)”, then \( M_{qik} \) for that person equals one, and for the other destinations, it is equal to 0.
The likelihood function of this model will be as follows [18]:

\[ \log L = \sum_{q=1}^{Q} \left( \sum_{i=1}^{I} \sum_{k=1}^{K} M_{qik} \log[\text{prob}(r_{qi}, s_{qk})] \right) \]  

Where \( Q \) is the number of individuals, \( I \) is the number of destination alternatives, and \( K \) is the number of departure time choices.

By maximizing this function, the parameters of these models, including \( \beta \), \( \gamma \), and \( \theta \) are estimated. In order to maximize this function, code developed in R-studio is used [1].

4. Database

Used data of current study is related to the travel data of Qazvin-Iran conducted in 2010. The number of non-work trips is 6135 trips.

The departure land-use model choice set includes Non-Residential, Residential-Educational, Residential-Administrative, and Residential-Business. The choice set of departure time consist of peak and off-peak hours. Regarding the frequency of trips during a day, 6 AM-8 AM, 12 PM-13 PM and 17 PM-18 PM have been considered as peak hours. Table 2 shows the frequency of choice sets, and table 3 defines independent variables in the dataset [1].

5. Model Estimation, Results, and discussion

For the departure time model, the base is set to the off-peak hour option which its utility equals to zero, then coefficients of another option (peak hours) are estimated relative to the base option.

Copula functions present different description about the interaction among random terms of models. The highest log-likelihood achieved by the frank copula so the detailed results of this model are presented. Also, the higher log-likelihood of Frank copula compared to the product copula shows the significant role of considering the interaction [1]. Model is also calibrated with parameterization strategies, and the dependency parameter is allowed to vary across observations [21]. As the parameterized model does not increase log-likelihood significantly, the unparameterized model is analyzed in the rest of the paper. Table 4 compares the performance of different calibrated models. Table 5 shows the results achieved by frank copula.

6. Analysis of results

The t statistics estimated for the copula dependence parameters show the correlation between error terms of traffic peak hours and destination. These parameters have a weak significance level for the non-residential and residential-administrative destination while having a strong significance level for the residential-educational and residential-business destination. In other words, the decisions on destination and departure time are not as much correlated for the non-residential and residential-administrative area, while there is strong interaction between peak hours and residential-educational and residential-business destination. Regarding the estimated sign for
copula dependence parameters, several correlated unobserved factors have the same effects on selecting the destination and peak hours [9]. For example, the negative estimated copula dependence parameter for residential-business indicated that there are some unobserved influential factors that have different effects on choosing residential-business and peak hours. Commonly these factors are related to the personality of travelers. For example, a person who does not like crowded places and congested traffic does not choose the residential-business destination (usually are crowded in traffic peak hours) and peak hour simultaneously. So the sign of copula dependence parameter for residential-business seems to be logical based on this unobserved factor.

Regarding the estimated coefficient for independent variables, it can be said that res-bus is a more favorable destination for individuals over 31 years old compared to other individuals. Also, the res-adm destination has the least favorability for individuals between 5-30 years old. Usually, this age bracket is not employed and does not need to go to administrative destinations [1]. Individuals between 19-30 have more tendencies to select peak hours, res-bus, and non-res destination. The probability of choosing a non-res destination is high for individuals over 41 years old and low for individuals between 5-18 years old. The non-res destination has more favorability for administrative employment compared to other individuals. The probability of choosing peak hours is low for administrative employees and students. These individuals have their mandatory trips to school and work in peak hours, so there is no more time to do non-mandatory purposes in peak hours [22]. Individuals with low and medium levels of education have more tendency to choose res-bus compared to individuals with a high level of education. Favorability of res-adm is low for individuals with medium and high levels of education. Regarding the tight time budget of individuals with a high level of education, its negative coefficient in peak hour utility function can be expected as the positive coefficient for the low level of education [13]. The increase of travel time has a negative effect on choosing non-res, and res-edu destination and an increase of travel distance have a negative effect on choosing res-adm and res-bus destination. Increasing walking time to the bus station, decrease res-bus favorability, and increase non-res favorability. According to the destination, it can be said that non-res has more favorability for a shopping trip, res-adm has more favorability for visiting and other trips, res-adm has more favorability for other trips, res-bus has more favorability for shopping and other trips and peak hours has more choosing probability for shopping, recreational and visiting trips compared to based trip aims. Individuals have less tendency to use personal vehicles and buses as trip modes to destinations with non-res and res-edu land use, respectively. Also, individuals have more tendency to use active transport as trip modes to destinations with res-adm and res-bus land use, because these areas are more congested and travel distances are fewer compared to other areas [23]. The probability of selecting peak hours is low when individuals use their personal vehicles or active transport [1].

7. Sensitivity analysis

Formally, elasticity may be defined as a unit less measure that can describe the relationship among a percentage change of variables and some percentage change in the quantity demanded [1, 24]. In current study disaggregate elasticities (for persons) are calculated for travel time, walking time, and travel distance which are continuous. Also, the mean of disaggregate elasticities is aggregate elasticities [1]. Table 6 present calculated elasticities.
These elasticities are interpretable; for example, a 1 percent increase of travel time leads to a -2.03 percent decrease in the probability of choosing res-edu destination and traffic off-peak hours departure time. As another example, a 1 percent increase of walking time to bus station concludes a 0.45 percent increase in the probability of choosing non-res destination and traffic peak hours departure time.

8. Conclusion

This study examined the destination and departure time choices which have interaction. By reflecting the correlation among unobservable variables this interaction was investigated. The multinomial logit is employed for destination choice, the binomial logit is used for the time of day and the interaction is considered by using three copulas including frank, AMH, and product. Approving the interdependency among these decisions obtained by the highly statically significant dependence parameters is one of the most significant findings of current study. These parameters found to be stronger for the residential-educational and residential business destination. The joint model calibrated with a suitable goodness-of-fit and interpretable coefficients that shows the effectiveness of employing the suggested model for joint modeling of these decisions.

Finally, this paper aims to calibrate the copula-based joint model for departure time and destination choices, using the travel data of a developing country and investigating aggregate elasticities as contributions. These models can be used to predict future travel demands and to describe the relationship between dependent and independent variables. As a suggestion for future works, segmenting data based on trip aim is suggested. It also gives a better view to use land-use characteristics.

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Biographies

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Seyedehsan Seyedabrishami received his Bachelor in Civil Engineering and Master and PhD in Transportation Engineering from Sharif University of Technology (SUT) in 2004, 2006, 2011, respectively. He is now an Assistant Professor in the Civil and Environmental Engineering Department at Tarbiat Modares University (TMU) in Tehran. He has recently received a Georg Forster Fellowship as an experienced researcher from the Alexander von Humboldt Foundation in Germany. Since June 2017, he is a visiting professor at the Research Group on Modeling Spatial Mobility at the Technical University of Munich (TUM).

Tables:

| Copula | $C(u_1, u_2)$ | range of $\theta$ |
|--------|---------------|-------------------|
| Product | $u_1u_2$      | $-$               |

Table 1: Attributes of copulas [1]
Frank
\[
-\theta \log \left\{ \frac{1 + (e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1} \right\} \quad (-\infty, \infty)
\]

AMH
\[
u_u (1 - \theta (1 - u_1)(1 - u_2)^{-1}) \quad [-1,1]
\]

Table 2: Frequency of models choice set

| Choices                        | Frequency | Share |
|-------------------------------|-----------|-------|
| None-Residential              | 1691      | 0.276 |
| Residential-Educational        | 893       | 0.146 |
| Residential-Administrative     | 1273      | 0.207 |
| Residential-Business           | 2278      | 0.371 |
| Peak hours                     | 1700      | 0.277 |
| Off-peak hours                 | 4435      | 0.723 |

Table 3: Independent variables [1]

| Information      | Variables | Definitions                                                                 | Shares |
|------------------|-----------|-----------------------------------------------------------------------------|--------|
| Age              | AGE 5-18  | 1= if age is between 6 to 18, 0= otherwise                                  | 10.84  |
|                  | AGE 19-30 | 1= if age is between 19 to 30, 0= otherwise                                 | 22.94  |
|                  | AGE 31-41 | 1= if age is between 31 to 41, 0= otherwise                                 | 30.99  |
|                  | AGE>41    | 1= if age is more than 41, 0= otherwise                                     | 25.24  |
| Sex              | SEX       | 1= for male, 0= otherwise                                                  | 38.30  |
| Job              | ADM.JOB   | 1= for administrative job, 0= otherwise                                     | 12.42  |
|                  | SERV.JOB  | 1= for service job, 0= otherwise                                           | 13.40  |
|                  | EDU.JOB   | 1= for educational job, 0= otherwise                                       | 14.42  |
|                  | OTHER     | 1= for other jobs, 0= otherwise                                            | 59.76  |
| Education        | LOW.EDU   | 1= for high school education, 0= otherwise                                 | 49.45  |
|                  | MED.EDU   | 1= for Associate’s or Bachelor’s degree, 0= otherwise                       | 37.70  |
|                  | HIGH.EDU  | 1= for Master’s Degree or Doctorate, 0= otherwise                          | 12.87  |
| Driving license  | DL        | 1= for having a driving license, 0= otherwise                              | 48.81  |
| Travel distance  | LGH       | Travel distance (km)                                                       | 2.88   |
| Travel time      | TT        | Travel time (min)                                                          | 6.73   |
| Walking time     | WT        | Walking time to the bus station (min)                                      | 7.5    |
| Trip aim         | SHOPPING  | 1= for shopping aim, 0= otherwise                                          | 36.84  |
|                  | RECREATIONA L | 1= for recreation aim, 0= otherwise                                      | 16.67  |
|                  | VISITING  | 1= for visiting aim, 0= otherwise                                          | 26.39  |
|                  | OTHER     | 1= for other aims aim, 0= otherwise                                        | 20.10  |
| Trip mode        | PRIVATE   | 1= for private vehicle, 0= otherwise                                       | 0.24   |
|                  | TAXI      | 1= for taxi, 0= otherwise                                                  | 0.31   |
|                  | BUS       | 1= for bus, 0= otherwise                                                   | 0.15   |
|                  | ACTIVE    | 1= for active transport, 0= otherwise                                       | 0.30   |
Table 4: Models performance comparison

| Model        | Log-likelihood |
|--------------|----------------|
| Frank copula | -10937.9       |
| AMH copula   | -10941         |
| Product copula | -10967.5     |

Table 5: Model results by using frank copula

| Variable         | MNL | BL |
|------------------|-----|----|
| Copula Dependence Parameter | 0.484 (0.869) | -0.467 (-2.542) |
| Constants        | 0.862 (4.656) | 0.840 (4.563) |
| Personal info.   |     |    |
| AGE              |     |    |
| AGE 5-18         | -0.467 (-2.542) | 0.306 (3.674) |
| AGE 19-30        | -1.095 (-2.001) | 0.959 (4.916) |
| AGE 31-41        | -0.297 (-0.578) | 0.840 (4.563) |
| AGE>41           | -0.768 (-1.394) | -0.653 (3.227) |
| JOB              |     |    |
| ADM.JOB          | -0.258 (-1.873) | 0.247 (2.340) |
| SERV.JOB         | -0.871 (-6.712) | 0.258 (1.873) |
| EDU.JOB          | 0.407 (-4.037) | 0.223 (1.869) |
| OTHER            | 0.350 (4.241) | -0.319 (-3.801) |
| EDUCATION        |     |    |
| LOW.EDU          | 0.436 (4.383) | 0.380 (5.580) |
| MED.EDU          | -0.183 (-1.873) | 0.249 (2.419) |
| HIGH.EDU         | -0.389 (-2.874) | -0.172 (-1.646) |
| Travel info.     |     |    |
| TT               | -0.040 (-1.288) | 0.183 (5.434) |
| LGH              | -0.269 (-6.377) | 0.183 (5.434) |
| WT               | 0.069 (7.882) | -0.024 (-2.967) |
| AIM              |     |    |
| SHOPPING         | 0.678 (6.110) | 0.173 (1.859) |
| RECREATIONAL     | -0.238 (-1.746) | -0.341 (10.951) |
| VISITING         | -0.322 (-2.640) | -0.610 (-3.060) |
| OTHER            | 0.884 (5.390) | 0.694 (4.649) |
| Mode                              | Non-res and off-peak | Res-edu and off-peak | Res-adm and off-peak | Res-bus and off-peak | Non-res and peak | Res-edu and peak | Res-adm and peak | Res-bus and peak |
|----------------------------------|----------------------|----------------------|----------------------|----------------------|------------------|------------------|------------------|------------------|
| Personal Vehicle                | -0.444 (-5.079)      | -                    | -                    | -                    | -                | -                | -                | -0.353 (-4.422)  |
| Taxi                             | -                    | -                    | -                    | -                    | -                | -                | -                | -                |
| Bus                              | -                    | -0.302 (-2.415)      | -                    | -0.219 (-2.468)     | -                | -                | -                | -                |
| Active Transport                 | -                    | -                    | 0.299 (3.298)        | 0.197 (2.415)        | -                | -                | -0.674           | (-9.193)         |

Table 6: Elasticity for final model