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Analysis of the interaction between destination and departure time choices

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Abstract. Departure time and destination choices are interrelated decisions that affect the demand estimation for urban transportation. A majority of the previous studies have ignored this interrelation and regarded these decisions as independent. On the contrary, some other studies have utilized a hierarchy structure; however, the literature suggested that destination and departure time should be simultaneously selected before the commencing of trips. The present study employed a joint model using the copula functions to explore the interdependency between the destination and departure time choices. The destination choice modeling was developed using a multinomial logit model, and a binary logit model was used for modeling the departure time choice. To obtain a better fitted joint model, some copulas were utilized and then, the frank copula was selected for the final model. The obtained results indicated that there were some common unobserved factors between these decisions by estimating the copula dependence parameters with high statistical significance. Furthermore, there were some commonly observed factors such as socio-demographic and travel characteristics that appeared in the utility functions of both models.

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1. Introduction

Generally, traffic congestion at peak hours is caused by significant travel demand for some specific destinations (for example, administrative destination) at particular hours. Congestion will consequently cause a number of problems such as air pollution, noise pollution, loss of energy, and safety reduction. With a rapid growth of urbanization, expanding the capacity of the transport network is no longer an efficient and economical option. Managing travel demand is an alternative to tackle

congestion in large metropolitan areas with a limited infrastructure capacity.

Keeping in mind the significant impact of destination and departure time choices on the traffic load on the network, one can feel the necessity to understand how to efficiently model these decisions. In this respect, it is vital to find a suitable modeling structure that can depict travelers' behavior towards destination choice according to the land use and departure time choice [1].

According to the literature, destination and departure time choices are interrelated choices. The selected destination has a significant effect on when trips began and how the selected departure time could affect where trips end. For example, if an individual decides to take 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 making their

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trips. The interaction between these two decisions can be systematically captured 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 and departure time choices.

2. Literature review

A majority of studies have ignored the relationship between destination and departure times. For example, Thorhauge et al. [2] employed discrete choice models, such as a multinomial logit model, to analyze the departure time for work trips without considering the reciprocal effect of destination. Sultana [3] also studied the departure time choice for non-work trips. Sasic and Habib [4] investigated the modeling departure time choice using the heteroskedastic generalized model for home-based commuting trips. Furthermore, several studies have focused on destination choice without considering the effect departure time [5,6]. For example, Clifton et al. [7] employed the multinomial logit model to study the destination choice for pedestrian travel.

Some other studies analyzed the interaction of departure time or destination choices with other travel decisions [8,9]. Ding et al. [10] employed a cross-nested logit to model the trip mode and departure time for urban commuting trips. Bhat [11] utilized the multinomial and nested logits to analyze the mode and departure time of shopping trips. Moreover, El-morssy and Onur [12] used the generalized nested logit to study the interaction among the departure time, destination choice, and travel mode for non-mandatory trips. Some studies have considered the interaction among discrete travel decisions using a copula-based joint model [13,14]. For example, Ermagun et al. [15] investigated the joint modeling of parent escort decision and student mode choice for educational trips and pointed out the benefits of using the Copula-based structure. Rasaizadi and Kermanshah [13] examined the endogenous correlation among the number of stops and trip mode using the Copula-based model.

To the best of the author's knowledge, no study has been found that could jointly model the departure time and destination. This study employed a copula-based framework to explore the interdependency between departure time and destination choices. This framework is not characterized by any hierarchy among decisions like other models, such as the nested logit model, with a hierarchy structure. While the destination modeling was developed using the multinomial logit model, departure time choice was modeled using the binary logit model. Seyedabrishami and Izadi [1]

and Bhat and Sener [16] pointed to the benefits of using the copula-based framework in the following:

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

The present study employed the copula-based joint modeling structure to model the departure time and destination, utilized the travel dataset of Qazvin, Iran as a developing country, and evaluated the aggregate elasticities.

In this study, the joint model of destination and departure time choice was 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 starting 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 was employed to model the destination choice. The choice set comprised non-residential, residential-educational, residential-administrative, and residential-business zones. Here, “ q ” is the index of a person, “ i ” represents the destination, and “ h_{qi} ” denotes the utility of destination “ i ” of person “ q ”. In such a case, we can define the utility function as [1,17]:

$$h_{qi} = \beta x_{qi} + \varepsilon_{qi}, \quad (1)$$

where x_{qi} is the vector of exogenous variables, β the coefficient vector of independent variables that must be estimated, and ε_{qi} the error term (random term) of h_{qi} . Assume that ε_{qi} follows the independent and identically distribution (iid), whose 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 which is more significant than the maximum utility of the other destinations for “ q ”. This term can be written as follows [17]:

$$h_{qi} > \max_{j \neq i} h_{qj}. \quad (2)$$

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 ”; otherwise, it would be zero [18]. Further, v_{qi} can be defined as [1,17]:

$$v_{qi} = \left\{ \max_{j \neq i} h_{qj} \right\} - \varepsilon_{qi}. \tag{3}$$

By combining Eq. (1) and Inequality (2), we derive the following inequality:

$$\beta x_{qi} + \varepsilon_{qi} > \max_{j \neq i} h_{qj}, \tag{4}$$

which can be re-written by substituting v_{qi} from Eq. (3) into Inequality (4) [1]:

$$\beta x_{qi} > v_{qi}. \tag{5}$$

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

Based on Eq. (3), v_{qi} is obtained from the differentiation of the utility of the other destination and error term of the chosen destination. Since both of them follow the iid extreme value distribution, the random variable of v_{qi} follows the logistic distribution obtained from the differentiation of iid distributed variables [1]. The marginal distribution of v_{qi} presented in Eq. (6) is [17]:

$$F_i(\beta x_{qi}) = \Pr(v_{qi} < \beta x_{qi}) = \frac{\exp(\beta x_{qi})}{\sum_j \exp(\beta x_{qj})}. \tag{6}$$

3.2. Departure time choice model structure

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

$$u_{qk} = \gamma z_{qk} + \mu_{qk}, \tag{7}$$

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

$$u_{qk} > u_{ql} (l \neq k). \tag{8}$$

So we have [1]:

$$\gamma z_{qk} + \mu_{qk} > \mu_{ql}, \tag{9}$$

$$\mu_{qk} - \mu_{ql} > -\gamma z_{qk}. \tag{10}$$

Moreover, τ_{qkl} is defined as $\mu_{qk} - \mu_{ql} = \tau_{qkl}$; then, we have [1,17]:

$$\tau_{qkl} > -\gamma z_{qk}. \tag{11}$$

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

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

$$G_k(-\gamma z_{qk}) = \frac{\exp(-\gamma z_{qk})}{1 + \exp(-\gamma z_{qk})}. \tag{12}$$

3.3. Joint model structure

The probability where “ q ” selects destination “ i ” and departure time “ k ” is [1]:

$$\begin{aligned} \Pr[r_{qi} = 1, s_{qk} = 1] &= \Pr[v_{qi} < \beta x_{qi}, \tau_{qkl} > -\gamma z_{qk}] \\ &= \Pr[v_{qi} < \beta x_{qi}] - \Pr[v_{qi} < \beta x_{qi}, \tau_{qkl} < -\gamma z_{qk}]. \end{aligned} \tag{13}$$

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

$$\begin{aligned} \Pr[r_{qi} = 1, s_{qk} = 1] &= u_{qi} - C_{\theta_{ik}}(u_{qi}, u_{qk}) \\ &= F_i(\beta x_{qi}) - C_{\theta_{ik}}(F_i(\beta x_{qi}), G_k(-\gamma z_{qk})), \end{aligned} \tag{14}$$

where $u_{qi} = F_i(\beta x_{qi})$, $u_{qk} = G_k(-\gamma z_{qk})$. F and G are marginal densities of destination and departure time choices. Here, θ_{ik} is the dependence parameter of copula that represents the correlation between random terms of option “ i ” and option “ k ” [1,18,19]. In this study, Frank and AMH (Ali-Mikhail-Haq copula) copulas were used that could estimate the dependence parameter. Moreover, both positive and negative correlations (dependence parameters) were taken into account. These two copula functions were selected because they could explore both positive and negative dependencies among the error terms. Since the copula dependence parameter of other copula functions such as Clayton, Joe, and Gumbel was limited to positive values or excluded zero value, they could not depict negative dependencies or independency; therefore, they were not employed in this study. The product copula shows independent random terms. Table 1 introduces used copulas [1].

Table 1. Attributes of copulas [1].

Copula	$C(u_1, u_2)$	Range of θ
Product	$u_1 u_2$	—
Frank	$-\theta^{-1} \log \left\{ 1 + \frac{(\varepsilon^{-\theta u_1} - 1)(\varepsilon^{-\theta u_2} - 1)}{\varepsilon^{-\theta} - 1} \right\}$	$(-\infty, \infty)$
AMH	$u_1 u_2 (1 - \theta(1 - u_1)(1 - u_2))^{-1}$	$[-1, 1]$

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

3.4. Estimation process

Define a binary variable M_{qik} such that if person “ q ” selects the destination “ i ” and departure time “ k ”, M_{qik} for that person equals one and for the other destinations, it equals 0.

The likelihood function of this model is as follows [18]:

$$\log L = \sum_{q=1}^Q \left(\sum_{i=1}^I \sum_{k=1}^K M_{qik} \log[\text{prob}(r_{qi}, s_{qk})] \right), \quad (15)$$

where Q is the number of individuals, I the number of destination alternatives, and K the number of departure time choices.

By maximizing this function, the parameters of these models including β , γ , and θ can be estimated. In order to maximize this function, the code developed in R-studio is used [1].

4. Database

The travel data of Qazvin, Iran conducted in 2010 were taken into consideration in this study. 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 consists 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 were 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 whose utility equals zero, and

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

the coefficients of another option (peak hours) are estimated relative to the base option.

Copula functions offer different descriptions about the interaction among random terms of models. The highest log-likelihood is achieved by the frank copula and the detailed results of this model are presented. In addition, the higher log-likelihood of Frank copula compared to the product copula was indicative of the significant role of the interaction [1]. The proposed model is also calibrated with parameterization strategies, and the dependency parameter is allowed to vary across observations [21]. Since the parameterized model does not increase log-likelihood significantly, the unparameterized model is analyzed in the following. Table 4 compares the performances of different calibrated models. Table 5 shows the results achieved through frank copula.

6. Analysis of results

The t statistics estimated for the copula dependence parameters showed the correlation between the error terms of traffic peak hours and destination. While these parameters have a weak significance level for the non-residential and residential-administrative destinations, they have a strong significance level for the residential-educational and residential-business destinations. In other words, decisions about destination and departure time are not much correlated for the non-residential and residential-administrative areas; however, there is a strong interaction between the peak hours and residential-educational and residential-business destinations. 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 destinations indicates that there are some unobserved influential factors that have different effects on choosing residential-business and peak hours. These factors are commonly 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 crowded at traffic peak hours) and peak hour simultaneously. Therefore, 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 than that for 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

Table 3. Independent variables [1].

Information	Variables	Definitions	Shares
Age	AGE 5–18	1: if age is between 6 and 18; 0: otherwise	10.84
	AGE 19-30	1: if age is between 19 and 30; 0: otherwise	22.94
	AGE 31-41	1: if age is between 31 and 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
	Recreational	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

19–30 have greater 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 greater favorability for administrative employment than that

for 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 at peak hours; therefore, there is no more time to do non-mandatory purposes at peak hours [22]. Individuals with low and medium levels of education have more tendency for choosing res-bus than for 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 in

Table 5. Model results using frank copula.

Variable	MNL			BL		
	Non-residential	Residential-educational	Residential-administrative	Residential-business	Off-peak hours	Peak hours
Copula dependence parameter	0.484 (0.869)	-1.095 (-2.001)	-0.297 (-0.578)	-0.768 (-1.394)	—	—
Constants	—	0.862 (4.656)	0.959 (4.916)	0.840 (4.563)	—	0.653 (3.227)
Personal info.						
AGE						
AGE 5–18	-0.467 (-2.542)	—	-0.320 (-2.748)	—	—	—
AGE 19–30	—	-0.781 (-6.712)	-0.407 (-4.037)	—	—	0.510 (6.153)
AGE 31–41	—	—	—	0.350 (4.241)	—	—
AGE > 41	0.306 (3.674)	—	—	0.488 (5.323)	—	—
JOB						
ADM.JOB	—	—	—	—	—	-0.247 (-2.340)
SERV.JOB	-0.258 (-1.873)	-0.223 (-1.869)	—	—	—	—
EDU.JOB	-0.513 (-2.997)	—	—	—	—	-0.319 (-3.801)
Other	-0.278 (-2.426)	—	—	—	—	—
Education						
LOW.EDU	0.436 (4.383)	—	—	0.252 (2.146)	—	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)	-0.269 (-6.377)	—	0.183 (5.434)	—	—
LGH	—	0.278 (3.418)	-0.233 (-3.178)	-0.610 (-9.411)	—	—
WT	0.069 (7.882)	—	—	-0.024 (-2.967)	—	—
AIM						
Shopping	0.678 (6.110)	—	—	0.173 (1.859)	—	0.887 (10.951)
Recreational	—	-0.238 (-1.746)	—	-0.341 (-3.060)	—	0.501 (5.146)
Visiting	-0.322 (-2.640)	0.191 (1.630)	—	—	—	0.756 (8.816)
Other	—	0.884 (5.390)	0.563 (3.995)	0.694 (4.649)	—	—
Mode						
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.

Variable	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
TT	-0.41	-2.03	-0.14	1.18	-0.44	-1.91	-0.14	1.04
WT	0.42	-0.12	-0.12	-0.31	0.45	-0.11	-0.11	-0.28
LGH	0.63	1.51	-0.05	-1.20	0.68	1.42	-0.05	-1.06

travel time has a negative effect on choosing non-res and res-edu destinations, and the increase in travel distance has a negative effect on choosing res-adm and res-bus destinations. Increasing walking time to the bus station decreases res-bus favorability and increases non-res favorability. According to the destination, it can be said that non-res enjoys 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 than 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 shorter than 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 unitless measure that can describe the relationship between a percentage change of variables and some percentage change in the demanded quantity [1,24]. In the present study, disaggregate elasticities (for persons) were calculated for travel time, walking time, and travel distance which were continuous. Furthermore, the mean of disaggregate elasticities is aggregate elasticity [1]. Table 6 presents calculated elasticities.

These elasticities are interpretable. For example, a 1% increase in the travel time leads to an 2.03% decrease in the probability of choosing res-edu destination and departure time at traffic off-peak hours. Moreover, a 1% increase in walking time to the bus station leads to a 0.45% increase in the probability of choosing non-res destination and departure time at traffic peak hours.

8. Conclusion

The present study managed to examine the destination and departure time choices with interaction which was investigated by reflecting the correlation among unob-

servable variables. While the multinomial logit was employed for destination choice, the binomial logit was used at day time. The related interaction was taken into account using three copulas including frank, Ali-Mikhail-Haq copula (AMH), and products. The confirmation of the interdependency among these decisions obtained by the highly statically significant dependence parameters was one of the most significant findings of this study. These parameters were 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 which demonstrated the effectiveness of the proposed model for joint modeling of these decisions. The main objective of this study was to calibrate the copula-based joint model for departure time and destination choices using the travel data of a developing country and to investigate aggregate elasticities as contributions. These models were employed to predict the future travel demands and describe the relationship among the dependent and independent variables. As a suggestion for future studies, segmenting data based on trip purposes is suggested. It also gives a better insight into utilizing land-use characteristics.

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