IJTE, Vol. 11, No. 3, Winter 2024, pp. 1515-1531
Research Paper

A Joint Mode Change and Mode Choice Decision under Transportation Demand Management Policies (Case of a Copula Approach)

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Received: 2023/05/13 *Accepted: 2023/12/16*

Abstract

As policymakers suggest using Transportation Demand Management (TDM) strategies, understanding the roots of the differences between the predicted and actual results of these policies' implementation is an area of interest for research. Among diverse reasons studies identify for this gap, this study focuses on model capabilities, using copula-based joint models for modal shift and mode choice. The study offered a hypothetical bundle of TDM strategies to 577 commuters who regularly drove to their workplaces during peak hours. Their stated mode choices were gathered. Thereupon, two successive steps were captured from their decision-making process: first, the decision to give up driving or not, and second, the substitute chosen mode if leaving driving was adopted. The joint effect of changing/not changing the travel mode from a private car and picking an alternative while facing a package of TDM strategies was tested with the copula approach. A binary logit is used to model the mode change decision, and the mode choice is modelled using a multinomial logit. Finally, among several copula functions, Frank Copula with the highest maximum likelihood estimation, and the positive value of dependency parameter, with an adjusted ρ2 of 0.158 was chosen as the best model. The findings of this study highlight the importance of considering people's previous mode decisions while trying to increase transit and decrease private use with TDM policies, which was not addressed in the literature using a dependent joint structure.

Keywords: copula-based models, transportation demand management, mode choice, modal shift

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1. Introduction

Transportation is one of the high-rate non-renewable energy consumer sectors. It also pollutes the environment. So, policymakers tried to participate in the transition to sustainable transportation in recent years. Transportation demand management (TDM) as a low-cost solution compared to heavy investments for new transportation facilities has its supporters. As TDM policies mostly try to use the existing infrastructures efficiently and to make the road network less congested as well, the bad impacts of the sector will be lessened.

Many of the TDM strategies aim to change the trip mode from private cars. Therefore, regular commute drivers are the main target of TDM policies. Many studies focus on modeling the mode choice after facing one or a bundle of TDM strategies based on revealed and stated preference data. For instance, Washbrook used a set of stated preference data to test the effects of different levels of road pricing and parking charges, besides the diverse rank of travel time for distinct alternative modes on the demand for single-occupant vehicles [Washbrook, 2006]. Anwar and Yang considering the poor access to public transportation as a major cause of private vehicle tendency, introduced two public transport policies: (i) once-an-hour direct bus services from home to university, and (ii) park-and-ride facilities [Anwar and Yang; 2017]. In a more recent study, Anwar and his colleagues investigated the modal shift to the metro from cars in Saudi Arabia [Anwar et al., 2023]. These articles try to recognize the decision-making processes and the main factors affecting the mode choice decision and to help the policymakers estimate the results of implementing these policies in advance. However, there is still a gap between the expected effects of these practices and the real results. The difference could originate in diverse bases such as researchers' inaccurate understanding of individuals' decision-making processes in dealing with these policies.

Many studies modeling mode choice in response to TDM policies use a discrete choice model as if respondents feel neutral about the choices at first. However, giving up driving and choosing a new mode in response to TDM policies seems to be a two-decision-making process rather than just a mode choice decision. In other words, giving up driving and adopting a new mode to use, looks to be two simultaneous choices. The current study tries to test this idea and examines the joint structure between these two decisions. Finding an approvable joint structure with effective variables suggests that change mode and mode choice should be considered differently. In other words, while planning to use TDM strategies, planners should know which policy will affect current regular users of each trip mode and which will influence new or infrequent users' choices.

Among different approaches to applying joint models, as a first try nested logit was tested according to its excessive and usual use. Results revealed that nested logit is not an acceptable structure for the joint model of change mode and choose a new one. Seemingly the hierarchy of the two choices is different from the one captured in regular nested logit structure. So, a Copula-based structure is chosen for its flexibility in assumptions. A basic assumption in this framework is that the two decisions share common observed and unobserved factors [Train, 1986]. A copula-based joint binary logit-multinomial logit (BL-MNL) modeling framework is developed. Although, several researchers have focused on different copula-based structures in different areas of studies [for example, Bhat and Eluru, 2009; Portoghese, et al., 2011; Pourabdollahi, et al., 2013; Li et al., 2023; Wali et al., 2023], to the authors' knowledge this study is the first use of copula-based joint modeling for the simultaneous decision-making issue of changing current mode and choosing a new one.

The paper continues with a review of related literature, followed by an introduction of the data. Then in the methodology of the copula joint model approach, the choices and descriptive variables are discussed. Afterward, the paper demonstrates the final model and concludes with a discussion of the results and some suggestions for future research.

2. Literature Review

Focusing on TDM as a low-cost answer to the congestion problem, several studies have tried to find the effectiveness of different TDM strategies individually or in bundles. Many of these studies use discrete choice models to model the 'mode choice decision' in the presence of demand management policies [Washbrook, 2006; Shahangian et al., 2012; Kavta and Goswami, 2022; Wang et al., 2022]. Some few ones concentrate on individuals who have a regular plan for their trips and while facing a set of TDM policies, they need to consider changing their routine and making a new one. In other words, some believe that it is not a mode choice but first, a mode change decision to make. Satiennam et al. used a set of stated preference data to investigate the potential modal shift of car and motorcycle users to bus rapid transit (BRT). They used two separate binary logit models for regular car users and motorcycle riders. The paper concluded that the presence of the BRT can significantly attract both the private car and the motorcycle users to shift to BRT. However, the shift proportion of motorcycle users was higher than that of car users. Moreover, the final model reveals that some socio-economic factors such as gender, age, having a driving license, and residential location are effective in choosing the BRT [Satiennam et al., 2016]. In another study, Erikson et al. revealed that a combination of two push and pull policies (raised tax on fossil fuel, and improved public transport) led to a larger reduction in the usage of private cars compared to when the measures (i.e., raised tax or improved transit) evaluated individually. They also concluded that the reduction was mainly expected to be made through trip chaining and changing the travel mode. They also tested some psychological factors in two groups: 'intention to reduce car use', and 'personal norm to reduce car use'. These factors appeared to be more effective than gender, age, income, and car access [Erikson et al., 2010]. Kwan et al. examined the binary logistic regression to figure out the relation between the trip characteristics and the intention to shift from private motor vehicles to rail transport. Conclusions illustrated that factors such as trip duration, distance, purpose, vehicle occupancy, and presence of child passengers were considerably associated with the intention to shift [Kwan et al., 2018]. More recently, Chiu explored mass rapid transit effects on motorcycle use. Findings show that both newly introduced metro stations and older existing ones, affect motorcycle share and households' vehicle kilometers traveled [Chiu, 2023]

Li et al., providing a stage-based framework, tried to show the mode shift decision-making process (whether users will shift from private cars to public transit, biking, or walking or continue using cars) under the implementation of some strategies. They used stated preference data to observe the impacts of congestion pricing and some reward strategies on morning commute drives. Results revealed that the former strategy is more important than the latter [Li et al., 2019]. In another study of the combination of both psychological and policy factors, Dirgahayani and Sutanto combined the theory of planned behavior (TPB) and the policy-specific belief to capture determinants affecting motorized drivers' behavioral inclination to a parking management strategy and the use of a new light rail transit (LRT) system in Bandung City, Indonesia. This study revealed that control beliefs, perceived norms, and acceptance considerably affect people's tendency to use LRT [Dirgahayani and Sutanto, 2020].

Recently, Mashrur et al. studied incentives and operational policies to bring transit ridership back after the COVID-19 pandemic. They used a two-stage model to capture pre- and post-pandemic transit usage of people who did not choose transit during the pandemic. Findings revealed that a package of incentives for transit and increased parking costs may encourage travelers to retake transit [Mashrur et al., 2023]. Sklar’s Theorem explained Copula's function (1959) to express a multivariate distribution in terms of its marginal distributions [Sklar 1973]. The first attempt at copula's study was done by Lee who proposed, a fully joint formulation in which the unobserved error terms were allowed to be non-normal [Lee, 1983]. The usage of the copula approach in the specification of binary models started with Smith who used eight different copulas by normal/normal and normal/gamma marginal distributions [Smith, 2003]. Trivedi and Zimmer used Frank’s copula for negative binomial/normal marginal distributions [Trivedi and Zimmer, 2007] (see also [Nelsen, 2006]). These initial approaches led to the application of copulas in finance, medical science, and transport modeling (starting with [Bhat and Eluru, 2009]).

Afterward, several researchers used copula structures in different areas of transportation studies to describe their statistical models. For example, Portoghese et al. used copula in joint modeling the choice of the work trip mode and the non-work stops during the trip. The mode choice model comprised four choices: drive alone, shared ride, active transport, and public transport. The number of stops included 0, 1, 2, and more than 2 stops [Portoghese et al. 2011]. Frank and Gaussian copulas were implemented to estimate the model. Rasaizadi and Kermanshah also confirmed this hypothetical model's structure in another research [Rasaizadi and Kermanshah, 2018)]. Moreover, Sener and Bhat used copulas to illustrate the dependency between the propensity and the frequency of workers' choice to telecommute. The study reveals that full-time employees have a greater tendency to telecommute than part-time ones. Although, among telecommuters, full-time employees telecommute less than part-time workers. The decision-making process is assumed to be a two-stage one. First, to choose to telecommute or not, then to adopt a telecommuting frequency (once a year, a few times a year, once a month or more, once a week or more, and almost every day). The suggested joint model has a binary/ordered logit framework. Frank copula is selected according to its best fit [Sener and Bhat, 2011]. Ermagun et al. modeled the mode choice and the escort decisions of school trips jointly. Comparing a nested logit and a copula-based model the results reveal that the latter fits the data better [Ermagun et al., 2014]. Ermagun and Samimi examined a copula-based joint discrete/ continuous model to explain the interaction between the mode choice and the travel distance for school trips. In comparison with the conventional estimation, joint formulation estimated higher values for the coefficients of both the travel distance and the travel safety perception [Ermagun and Samimi, 2018]. In another study, Seyedabrishami and Rasa Izadi modeled the mode and departure time choices in urban trips using the copula framework. Testing a binary logit-multinomial logit structure, the estimated copula dependence parameter is approved to be highly significant [Seyedabrishami and Rasa Izadi, 2019]. They also used copula to model the interaction among destination and departure time choices in a later article [Rasa Izadi and Seyedabrishami, 2021]. In another recent study, Jafari Shahdani et al used copula and nested logit to model the interaction between activity choice and duration [Jafari Shahdani et al. 2021]. Pourabdollahi et al. modeled the freight mode and the shipment size choices with a copula-based joint multinomial logit/ multinomial logit [Pourabdollahi et al., 2013]. As another example in the logistics area, Keya et al. tested a copula-based joint model in the form of multinomial logit/ordered logit to model the freight transportation mode and the shipment size as well [Keya et al., 2019]. Bilal et al used a copula-based discrete-count joint model to analyze the decision-making between choice and travel itinerary in intra-destination trips to Jeju Island, South Korea. The results revealed that travelers chose their travel mode first [Bilal et al. 2023].

Although modeling mode choice behavior is common in transportation studies, the authors could not find any study that specifically models the mode choice of current regular commute drivers after facing a bundle of TDM strategies. In other words, a gap was recognized in distinguishing between the decision to choose a travel mode and the two successive decisions of first, to change the current regular transportation mode, and then to adopt a new travel mode, while facing a bunch of pull and push policies. Addressing this gap and applying a copula-based model are among the important contributions of this research.

3. Data

A data set gathered in 2010 in Tehran, is used in this research. Tehran has a restricted CBD, which at the time of data gathering, cars could enter the area either with a yearly prepaid CBD entrance permission every day or according to their plate numbers just in odd or even days. The respondents were regular commuters who drove most of the days, i.e., days that they had permission to enter the zone, to their workplaces/university, located in CBD, during the morning peak period. They were asked to state what mode (among driving, transit, taxi, rideshare, cycle, or other) they would choose in a hypothetical situation of an experiment based on five TDM policy measures. Besides the stated preference part, information on socio-economic characteristics included age, gender, job status, and education of the individual, plus traits like the household's size; the number of cars and motorcycles; the employment status of the family members; also, some data about the regular commute trip attribute such as distance, trip time, the access time to the nearest transit station proper for the commute trip were gathered. Besides, respondents answered a set of questions to reveal the main reasons they regularly prefer to use their private cars rather than other means of transport [Shahangian et al., 2012].

Table 1 shows the key characteristics of the data. As mentioned before, the SP part was designed based on different levels of five policy measures: three aimed to make driving less attractive and two to encourage the use of transit. The driving discouraging policies included a CBD entrance toll (with three levels of $5/day, $10/day, or $15/day), parking charge (of $1.2/day, $2/day, or $3/day), and fuel price ($0.40/L and $0.80/L). The transit access (of the actual access time, or an access time which was 33% lower than the real time) and the transit travel time (expressed relatively to actual time transit with three levels of no change, a 20% decrease, and a 33% decrease) were the two transit encouraging strategies.

The sample used for model estimation includes the answers of 577 respondents, each to six different hypothetical scenarios, which sums up to 3642 observations. In response to the scenarios, each person had 12 different transport mode choices. Finally, according to the small number of respondents choosing some choices, they were combined into six groups of 'private car', 'transit', 'taxi', 'rideshare', 'cycle', and 'walk and other' based on similarities among choices. More details could be found in Shahangian et al. (2012). In 2627 of the situations (75.9%) the respondents decided to change their mode from private cars. Table 2 shows the frequency and the percentage of the adopted choices in these observations.

4. Methodology

This section presents the methodology used in this study, the model derivation, and the structure of the copula-based binary-multinomial logit framework. To model the mode change choice a binary logit and to model the choice of a new travel mode a multinomial logit model is built. Finally, the interrelationship between the two is determined with a copula function.

4.1. Model Structure

The modal shift from a private car is modeled using a binary choice structure. Let q represent individuals. Also, let t_{qk} be the unobserved propensity to shift from the private car or not [Ben-Akiva and Lerman, 1985].

$$t_{qk} = \beta X_{qk} + \varepsilon_{qk} \tag{1}$$

Table 1. Key Characteristics of the Sample

Characteristic	**Description**	**Absolute Frequency**	**Relative Frequency (percentage)**
Frequencies			
Gender	Female	192	33.3
	Male	385	66.7
Age	Less than 30 years	270	46.8
	Between 31 and 50 years	260	45.1
	More than 51 years	47	8.1
Marital Status	Single	236	40.9
	Married	341	59.1
Education	Associate degree or less	145	25.1
	Bachelor’s or master’s degree	355	61.6
	PhD or MD	75	13.0
	No Response	2	0.03
Employment Status	Freelance worker	74	12.8
	Employee	346	59.9
	Student	157	27.2
CBD	House located in CBD	123	21.3
	Otherwise	454	78.7
FGP	Never	226	39.2
	Rarely (less than 25%)	108	18.7
	Sometimes (26% to 50%)	85	14.7
	Usually (more than 50%)	123	21.3
Descriptive Statistics			
Characteristic	Mean	Variance	Range
No. in household	3.50	1.17	1 - 10
No. of driver's licenses in household	2.50	1.08	1 - 6
No. of cars in household	1.56	0.76	1 - 4
Home to work distance (km)	9.19	8.06	0.46 - 62.78

Table 2. Choices' Overview

Alternatives	**Absolute Frequency**	**Relative Frequency (percentage)**
Change mode	2627	75.9
Do not Change mode	835	24.1
Total	3462	100
Transit	1219	46.4
Taxi	1064	40.5
Rideshare	100	3.8
Cycle	71	2.7
Other	173	6.6
Total	2627	100

Where X_{qk} is the column vector of independent variables, β represents a vector of parameters to be estimated and ε_{qk} is the random error term of the utility function. In the usual structure of a binary choice model, the unobserved propensity is reflected in the observed choice [Bhat and Eluru, 2009]. t_{qk}=1 if the qth individual chooses to change mode (choose the choice k) and t_{qk}=0 if the qth individual decides not to change the current private-car mode (choose the choice l). ε_{qk} is assumed to have a Gumbel distribution with a mean of 0 and a variance of 1. The error term captures the effects of unobserved factors in changing mode decisions. So, t_q is also Gumbel-distributed with parameters (βX_q, 1). Person q chooses choice k if its utility is more than the other option.

$$t_{qk} > t_{ql} (l \neq k) \quad (2)$$

If the systematic part of the utility of the choice l is treated to be zero, equation (2) is as:

$$\begin{aligned} &\beta X_{qk} + \varepsilon_{qk} > \varepsilon_{ql} \\ &\varepsilon_{qk} - \varepsilon_{ql} > -\beta X_{qk} \end{aligned} \quad (3)$$

If τ_{qkl} is defined as $\tau_{qkl} = \varepsilon_{qk} - \varepsilon_{ql}$, then:

$$\tau_{qkl} > -\beta X_{qk} \quad (4)$$

So, t_{qk}=1 if and only if $\tau_{qkl} > -\beta X_{qk}$.

As ε_{qk} and ε_{ql} have a Gumble distribution, τ_{qkl} follows a logistic one.

The marginal distribution of τ_{qkl}, i.e., the probability of selecting the choice to change the private car, is shown in equation (5) [Ben-Akiva and Lerman, 1985]:

$$F(-\beta X_{qk}) = \exp(-\beta X_{qk}) / (1 + \exp(-\beta X_{qk})) \quad (5)$$

As mentioned before, the multinomial logit formulation was used for the substitute mode selection. Let an individual and a mode successively be indexed with q and i and S_{qi} be the latent utility of person q for adopting the substitute mode i (3):

$$S_{qi} = \gamma_i Z_{qi} + \eta_{qi} \quad (6)$$

Where, Z_{qi} is the observed attribute vector and γ_i is the coefficient vector to be estimated. Moreover, η_{qi} symbolizes the error term which is hypothetically Gumbel-distributed with parameters (0, 1). According to the utility theory, person q chooses i if and only if the condition (7) holds:

$$S_{qi} > \max_{j \neq i} S_{qi} \quad (7)$$

Let S_{qi} be a dummy variable; S_{qi} =1 if the ith substitute mode is chosen by the qth individual, and S_{qi} =0 otherwise. Defining

$$\upsilon_{qi} = \{\max_{j \neq i} S_{qi}\} - \eta_{qi} \quad (8)$$

Using both equations (6) and (7), reveals:

S_{qi} =1 if and only if $\gamma_i Z_{qi} > \upsilon_{qi}$

Equation (8) and the assumption on the η_{qi} gives the intimated marginal distribution of υ_{qi} [Train; 1986]:

$$G(\gamma_i Z_{qi}) = \exp(\gamma_i Z_{qi}) / \textstyle\sum_j \exp(\gamma_i Z_{qj}), j = 1, \dots, J \quad (9)$$

The joint probability that person q chooses choice k (the giving up driving choice) and a mode i is:

$$\Pr[t_{qk} = 1; s_{qi} = 1] = \Pr[\tau_{qkl} > -\beta X_{qk}; \upsilon_{qi} < \gamma_i Z_{qi}] = \Pr[\upsilon_{qi} < \gamma_i Z_{qi}] - \Pr[\upsilon_{qi} < \gamma_i Z_{qi}; \tau_{qkl} < -\beta X_{qk}] \quad (10)$$

For the calculation of the probability function, a bivariate distribution function between the two error terms is needed. To show the dependency of random variables and make a joint distribution using random variables marginal distribution Copula distribution is useful. [Nelsen, 2006]. We can rewrite equation (10) with copula as:

$$\Pr[t_{qk} = 1; s_{qi} = 1] = G(\gamma_i Z_{qi}) - C_{\theta ki}(G(\gamma_i Z_{qi}); F(-\beta X_{qk})) \quad (11)$$

The marginal distribution functions of change mode and mode choice models are F and G. Moreover, θ_{ik} is the copula dependence parameter and demonstrates the correlation of the utility error terms of the decision to change mode (k) and the new mode (i). Table 3 shows the characteristics of some copulas.

4.2. Estimation Method

Define I[.] as an indicator function equal to 1 if the true condition of the statement in the brackets holds and to 0 if not. And specify:

$$\mathrm{M_{qi}} = \mathrm{I}[\mathrm{t_q} = 1]\mathrm{I}[\mathrm{S_{qi}} = 1] \quad (12)$$

So, the log-likelihood function has the following form (Sener and Bhat 2011):

$$\mathrm{LogL} = \sum_{q=1}^{Q} \mathrm{I}(\mathrm{t_q} = 0) \log[\Pr(\mathrm{t_q} = 0)] + \sum_{q=1}^{Q}\sum_{i=1}^{I} \mathrm{M_{qi}} \mathrm{Log}[\Pr(\mathrm{t_q} = 1, \mathrm{S_{qi}} = 1)] \quad (13)$$

This means that the log-likelihood function consists of two parts, one relates to respondents who chose not to change their current mode, and the other to the group who first chose to give up driving and then selected their alternate mode. In other words, the former stands for the probability of willing to still use a private car, and the latter for the probability of choosing a new mode after accepting to stop driving.

To estimate the β, the γ, and θ the log-likelihood function should be maximized. R-Studio programming is used for maximizing the log-likelihood as well as to estimate the parameters. Figure 1. Shows the structure of the methodology in a flowchart format.

Table 3. Some Characteristics of Alternative Copula Structures [Smith, 2005]

Copula	C (u_1, u_2)	Dependence parameter range
Frank	$-\theta^{-1}\log\{1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1}\}$	(-∞,∞)
Gumbel	$\exp(-(\tilde{u}_1{}^{\theta}+\tilde{u}_2{}^{\theta}))^{1/\theta}$	[1, ∞)
Product	$u_1 u_2$	-
FGM	$u_1 u_2(1+\theta(1-u_1)(1-u_2))$	[-1,1]
AMH	$u_1 u_2(1-\theta(1-u_1)(1-u_2))^{-1}$	[-1,1]
Gaussian	$\Phi_G(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta)$	(-1,1)
Clayton	$(u_1{}^{-\theta}+u_2{}^{-\theta}-1)^{-1/\theta}$	(0, ∞)

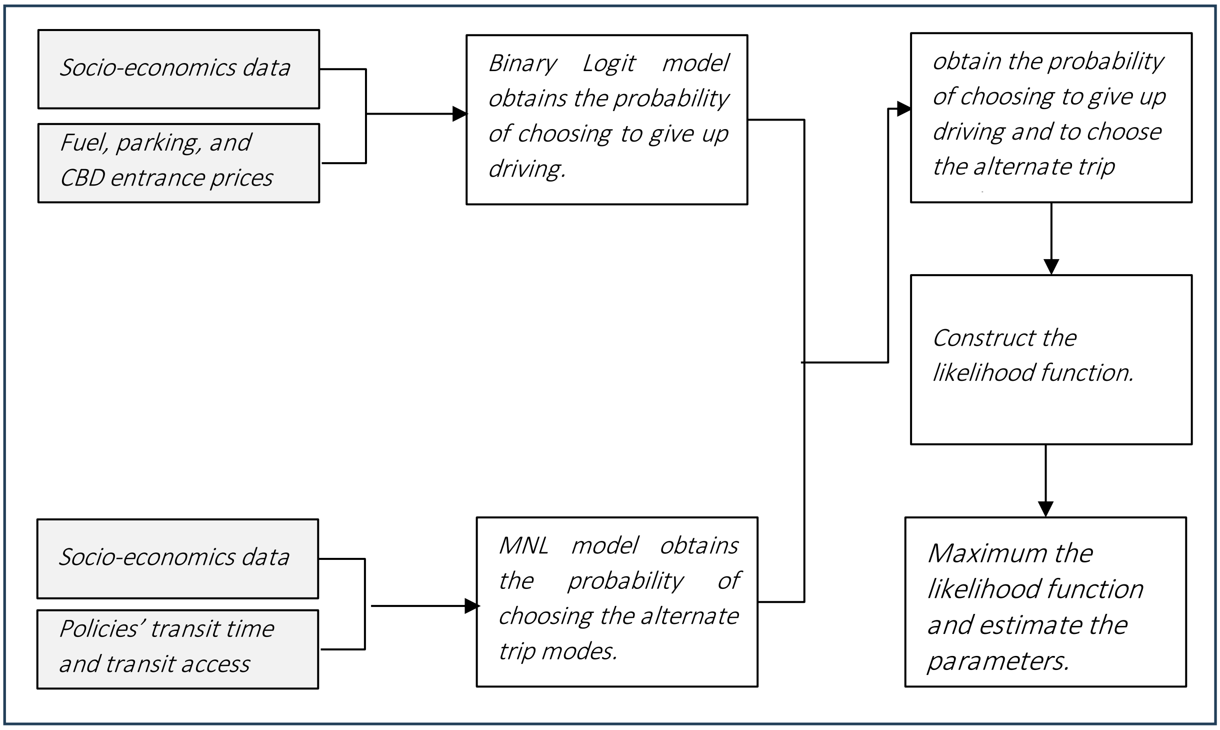

Figure 1. The Structure of the Methodology

5. Results

5.1. General Discussion

As mentioned above, believing the difference between mode choice and change mode decisions copula-based joint model is used to test the idea. First, an independent model of mode change and mode choice decision was estimated to serve as the starting point for the joint model estimation and also to compare with the final joint model. Five different copula structures were applied (FGM, Frank, AMH, Gumbel, and product copula) to consider the correlation between the unobserved factors of the two models. Among them, three ended in acceptable models. General information about these five models is presented in Table 4.

Table 4. General Information about Models with Different Copulas

Copula	Acceptable range for (θ)	Dependence parameter	Acceptable model	Log-likelihood
Frank	$(-\infty,\infty)$	3.271[a]	✓	-2718.120
Gumbel	$[1, \infty)$	1.617[c]	✓	-2724.418
Product	-	-	✓	-2736.071
FGM	[-1,1]	2.751	×	-2728.621
AMH	[-1,1]	2.411	×	-2721.994

[a] Significant at 1% level.
[b] Significant at 5% level.
[c] Significant at 10% level.

According to the higher maximum likelihood value of the Frank copula, this structure is presented in the following part.

The final model identifies the factors that have simultaneous effects on the modal shift from a private car and choosing a substitute mode. It also shows the distinct variables for each stage. Concentrating on common factors, policymakers can use more effective policies to increase both the probability of a modal shift from the private car and choosing more sustainable travel modes. Paying attention to distinct variables helps them to predict the effectiveness of each strategy on giving up the driving or choosing a specific choice more accurately.

As shown in Table 6 the dependency parameter (θ) of the model (3.271) is significant at 1%. The log-likelihood of the final model with 55 estimated parameters is -2718.120 and ρ^2_{adj} is 0.158.

Changing the private car is modeled using binomial logit formulation. It is assumed that the error terms of the utility functions have identical and independent Gumbel distributions. Multinomial logit formulation is taken for choosing a substitute mode model. In this research, Frank, Gumbel, FGM, AMH, and Product copula were used to reach a better-fitted model. The general information about models with different copulas can be found in Table 4. As the copula with the greatest log-likelihood and the dependence parameter in the acceptable range is the best copula, Frank copula is chosen to be presented in this paper.

Using the literature as a guide, different kinds of variables were used to model both the decisions to give up driving and to choose a new travel mode. Five policy measures, some work trip characteristics, and several socio-economic aspects were tested. Among them, some seem to be ineffective. Table 5 shows the variables that appeared significant in the final model.

As mentioned earlier, this study aimed to find the common effective variables on choosing to leave driving a private car and to pick a new transport mode as well as to present the best copula model for these two related decisions.

Table 6 demonstrates the common variables of the two models and the model's fit information.

Moreover, Table 7 shows the uncommon variables affecting the two decisions.

5.2. Impact of Variables Common to Both Choices

As shown in Table 6 among those variables common on both giving up the private car and choosing a new travel mode choice, nine have the same signs and two have opposite signs. The negative sign of the variable ACCW2, which is a dummy to show that the respondent needs to use a taxi to access a transit station, in the utility function of giving up driving and choosing transit, suggests that this access way causes disutility for both choices. In other words, relocating the transit stations in a way that fewer people need to use taxis to get to them; either by using the private car to park and ride, or walking to the station, will make both choices of giving up the car and choosing transit more acceptable. The negative common sign of CARA shows that people who are using prepaid CBD entrance permissions are less likely to give up driving in response to a hypothetical bundle of TDM strategies; moreover, if they do so transit has a lower chance of being accepted by them among the five new options. If using transit as a sustainable and more efficient choice is desired, policymakers should take omitting the yearly prepaid CBD entrance permissions into account and make more benefits by changing them to daily passes.

Table 5. Description of Variables

No	Variable	Description	Type or Value
1	ACCT	Transit access time	actual time, a 33% decrease in actual time
2	ACCW2	Access way to transit station: taxi	1 if yes; 0 otherwise
3	ACCW3	Access way to transit station: walk	1 if yes; 0 otherwise
4	AGE1	Age less than 30 years	1 if yes; 0 otherwise
5	AGE2	Age between 31 and 50 years	1 if yes; 0 otherwise
6	CARA	Has prepaid permission to enter CBD	1 if yes; 0 otherwise
7	CBD	House located in CBD	1 if yes; 0 otherwise
8	CBAWK	Need a car before or after work	1 if yes; 0 otherwise
9	CCARR	Need a car to carry things	1 if yes; 0 otherwise
10	CDUWK	Need a car during work hour	1 if yes; 0 otherwise
11	CGIRI	Need a car to give rides to others	1 if yes; 0 otherwise
12	CLSEC	Uses car because of the Low security in transit	1 if yes; 0 otherwise
13	Const.	Constant term	continuous
14	CTVAR	Uses car because of the trip time variation in transit	1 if yes; 0 otherwise
15	DIS	Home to work distance (km)	continuous
16	EDU1	Some colleges or less	1 if yes; 0 otherwise
17	EDU2	Bachelor’s or master’s degree	1 if yes; 0 otherwise
18	EDU3	PhD or MD	1 if yes; 0 otherwise
19	EMP1	The respondent is a freelance worker	1 if yes; 0 otherwise
20	EMP2	The respondent is an employee	1 if yes; 0 otherwise
21	EMP3	The respondent is a student	1 if yes; 0 otherwise
22	ENTF	CBD entrance toll ($ per day)	5, 10, 15
23	FGP	Additional fuel needed beyond coupons	Ordinal variable 0 to 4
24	MALE	Male	1 if yes; 0 otherwise
25	HHDL	No. of driver’s licenses in household	NA
26	HHN	No. in household	NA
27	MAR	Married	1 if yes; 0 otherwise

No	Variable	Description	Type or Value
28	NOC	No. of cars in household	NA
29	PAR1	Mostly parks the car in private parking	1 if yes; 0 otherwise
30	PAR2	Mostly parks the car on-street paid fee	1 if yes; 0 otherwise
31	PAR3	Mostly parks the car on-street for free	1 if yes; 0 otherwise
32	PARKF	Parking fee ($ per day)	1.20, 2, 3
33	TT	Decrease in transit travel time (percent)	0, 20, 33

Note: No. = number; NA = not applicable.

Table 6. Model Results for Variables Common to Both Choice Models

Var.	Give up the private-car	Transit	Taxi	Rideshare	Walk & other	Cycle
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
			Same Signs			
ACCW2	-4.447[c]	3.273[a]				
CARA	-3.293[a]	-5.262[c]				
CGIRI	0.021[c]	1.290[b]				
DIS	1.030[b]	1.028[a]		0.858[a]		
EDU1	3.723[a]	0.993[a]				
EMP1	7.551[a]				0.141[a]	
EMP3	0.741[c]			0.547[b]		
FGP	-5.145[b]		-2.399[c]			
HHN	5.499[c]			0.763[a]		
NOC	-1.836[a]			-6.393[a]		
			Opposite Signs			
CBD	2.938[a]	-0.893[b]				-0.913[a]
MALE	-2.399[a]		0.147[a]			
Dependency parameter (θ)				3.271[a]		
Log-likelihood at convergence				-2718.120		
Log-likelihood at zero				-3293.003		
Log-likelihood at market share				-3293.003 add please and the ρ2		
ρ^2				0.175		
ρ^{2adj}				0.158		
Number of estimated parameters				55		
Sample size				3642		

Note: Coef.= Coefficient.
[a] Significant at 1% level.
[b] Significant at 5% level.
[c] Significant at 10% level.

People who currently drive their private cars to work because of their need to give rides to others, CGRI, seem to be good cases to give up driving and use transit instead. The positive sign of the DIS variable suggests that while facing the described package of policies, the more the distance between the home and the workplace of the respondents, the more the probability of leaving the driving and choosing to rideshare. The same effect is recognized for having an education level of some college or less (EDU1). Furthermore, final results show that freelance workers are more likely to quit driving and to choose the choice of walking or to change the time of their work trip or their workplace. This conclusion seems rational. Also, students are likely to stop driving, but their substitute choice is to use rideshare. As shown in Table 6, people who currently use more fuel than the monthly coupon, which has a lower price, are less likely to choose the not-driving choice and if they choose this option, using a taxi is barely probable for them.

As the final model reveals, living in households with more members increases the utility of giving up driving while facing the hypothetical scenarios of different levels of TDM policies. On the other hand, as could be expected, the more the household number the more probable a respondent chooses to rideshare. On the contrary, when one lives in a household with more cars, leaving the driving and choosing to rideshare is less expected.

Table 6 also shows that living in the CBD has a positive effect on giving up driving. This could be in response to the availability of and good access to other travel mode choices in this area. However, living in this neighborhood has a negative effect on transit use; maybe because of the good access to other choices, like taxis and the opportunity to access the destination on foot, in this area and the small size of the CBD (compared to the whole city) that both make their trip less attractive with transit. This variable also has a negative sign in the utility function of the cycle. This might have happened because of the higher density of population and buildings in this area and the absence of bike roadways besides the compact roadways and sidewalks. Being a male has a negative impact on the decision to quit driving while it affects the choice of a taxi positively. In other words, men are less likely to choose not to drive and if they do so, they are more likely to choose a taxi, which is a cheaper choice than a car although yet a convenient one.

Table 7. Variables Distinct to the Change Mode Choice and the New Mode Choice

Var.	Give up the private-car	Transit	Taxi	Rideshare	Walk & other	Cycle
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Const.	1.261[a]	-3.436 [c]		-7.051[a]	-1.446[c]	4.907[a]
ACCT		-1.753[b]	0.845[b]			
ACCW3		0.982c			1.068[c]	0.190[c]
AGE1		1.919[c]				
AGE2	1.524[b]					
ENTF	2.851[a]					
HHDL		-0.016[a]		-0.698[a]		
MAR			-2.077[a]		2.026[b]	
PAR1			-2.153[c]			
PAR2			-0.744[c]			
PARKF	0.793[c]					
CBAWK	-3.723[a]					
CDUWK		-1.072[b]	-0.296[a]			
CCARR				-0.022[a]		
CTVAR		0.020[a]				
CLSEC		-0.881[b]		-4.554[a]		
TT		3.627[c]				

Note: Coef.= Coefficient.

[a] Significant at 1% level.

[b] Significant at 5% level.

[c] Significant at 10% level

5.3. Impact of Variables Distinct to the Change Mode Choice and the New Mode Choice

Among the effective variables on the choice of not driving, two policy measures are displayed. As expected, TDM policies to discourage driving appeared with positive signs. It means that the necessity to pay a CBD entrance toll (ENTF) has a direct effect on preferring not to use a private car. A parking charge (PARKF) seems to impact the decision the same way. As could be anticipated, the coefficient of the former is more than the latter due to its higher price. The fuel price did not appear effective in the final model, which suggested that raising the fuel price could not make the use of private cars less. At the time of the data gathering, the actual fuel price was $0.1/L and the model's results indicated that even raising the price to about eight times could not affect the car use. The fuel price raised to $0.7/L soon after the data gathering and was constant for the next four years. The official consumption statistics reveal that the daily gasoline usage in the country increased by almost 13.5% in this period [NIOC, 2014].

As shown in Table 7, being in the age group between 31 and 50 years (AGE2) has a positive effect on choosing to give up driving to work. The final model also reveals that, as expected, needing a car to accomplish some tasks before or after the work-time (CBAWK) has a significant negative effect on choosing not to drive. In other words, people who need their car not only for the commute trip but also to do some other things are less likely to give up driving.

Paying attention to the alternate mode choice model it is recognized that final transit utility variables disclose that both the improved access time (ACCT) and the decrease in transit travel time (TT) strategies have significant effects on the choice of the transit. So, the results suggest that implementing these two policies may increase the probability of choosing transit. It should be taken into account that the access time that is used in the modeling process is the improved access time, and according to the obvious negative effect of access time on transit, the negative sign of this coefficient is expected. On the other hand, the transit time used in the models shows the percentage of the decrease in the travel time with transit, which is expected to be positively significant. The positive sign of ACCT in the taxi utility function reveals that as anticipated the more the access to transit station takes the more the taxi choice becomes attractive.

The positive sign of ACCW3 in transit utility function implies that people who reported walking as their access way to the transit station seem to choose transit more. According to this result, not only the transit access time but also the transit access way, significantly affects the utility to choose transit. The final utility function of the transit also shows that being less than 30 years old (AGE1) has a positive effect on transit use. The negative sign of CDUWK reveals that the need for a private car during work hours makes transit less acceptable.

The final results imply that the number of household driver license holders (HHDL) has a negative sign in both transit and rideshare utility functions. In other words, in families with more drivers using transit or sharing a car with others is less attractive, as expected. The negative sign of the MAR variable in choosing a taxi suggests that married people are less likely to choose this mode. On the other hand, being married has a positive sign in the utility function of the 'walk and other' choice. Both signs suggest that married people might be more sensitive about expenses.

The negative signs of both PAR1 and PAR2 in the taxi utility function indicate that for people who currently park their cars for free, either in private parking or on-street, a taxi is not a preferred choice when they face a bundle of TDM policies.

Needing the car during work hours (CDUWK) makes both transit and taxi less attractive. Also, the need to carry things (CCARR) has a negative sign in the rideshare utility function. People who currently use private cars because of the variation in transit travel time (CTVAR) prefer transit more while facing an improved one. But for commuters who choose to drive because of the lack of security in transit (CLSEC) the improvement of the transit in travel time and access time is not enough motivation to choose transit. The security issue has a negative impact on the rideshare utility function as well. It seems that the security problem is interconnected with the absence of privacy in the vehicles.

5.4. Correlation Parameter

According to Table 6, the estimated copula correlation parameter is positive and significant; which indicates that there is a positive correlation between the unobserved factors of both choosing to give up driving and adopting a new travel mode (i.e. the error terms ε_q and υ_q). In other words, while trying to choose between continuing to use their regular travel mode (i.e., a private car) and giving up driving, respondents also have a glance at other modes' characteristics. On the other hand, choosing between modes rather than the private car won't take place without choosing to give up driving in response to TDM policies. This positive correlation means that some similar unobserved variables increase the utility of both giving up the private car and choosing a substitute mode. For instance, environmental concerns and lack of individual interest in driving might be among these variables.

6. Conclusion

In this study, a joint structure for the driver's change mode shift decision-making was tested. The commuter’s first decision is to change his/her current travel mode or not, and the second is to choose a different mode (among those presented if he/she chose 'the not to drive choice' in the previous step). The experiment took place under a series of hypothetical situations in which different levels of five TDM policy measures were implemented in a survey conducted in May 2010 in Tehran. Different socio-economic and work trip traits were examined as well. Testing different copulas for the joint structure, Frank copula seems to give the best fit. The final model specifies the significant observed variables, while the correlation parameter gives the coefficient for the unobserved factors of both models. The common variables on both decisions conduct actions that are effective in pulling commute drivers from their cars and pushing them to other more sustainable travel modes.

According to model results, two pull policies (CBD entrance toll and parking fee) seem to be effective in motivating driver commuters to shift away from driving. On the other hand, raising the fuel price does not show a significant impact. Besides, the study reveals that decreasing transit travel time and transit access time have significant effects on mode choice by making transit more acceptable. Based on the actual impact of these four policy measures among the five used in this study, which ended in almost 76% of respondents choosing a new mode rather than their regular private car, using both pull and push TDM strategies is suggested. Moreover, using these four tested policies is recommended as the first candidates.

Moreover, as model results suggest, people who use a taxi to access a transit station, are more apt not to shift away from driving. It also makes the transit choice less attractive for people who choose not to drive. In fact, transportation planners might come to a new allocation of transit stations in which as many as possible people could reach the stations either on foot to near stations or in their private cars to stations with good parking facilities nearby.

A comparative study of two sets of a stated preference and a revealed preference data might display more details about the decision-making process. Also, a gender-based joint model could help to understand the effective parameters of each gender's mode choice better. The more specified the impressive factors are known, the better the policymakers choose effectual strategies. Using psychological and environmental variables could be an illustrative way. Further studies might target 'habit' as an obstacle to changing mode and suggest how to overcome this issue to make TDM policies more effective.

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