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Accounting for systematic heterogeneity across car commuters in response to multiple TDM policies: case study of Tehran

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Abstract Modeling commuters' choice behavior in response to transportation demand management (TDM) helps in predicting the consequences of TDM policies. Although research looking at choice behavior has evolved to investigate preference heterogeneity in response to factors influencing mode choice, as far as we know, no study has considered taste variation across commuters in response to multiple TDM policies. This paper investigates the presence of systematic preference heterogeneity across commuters, in response to the TDM policies that can be explained by their socio-economic or commuting-related characteristics. Analysis is based on results of a stated preference survey developed using a Design of Experiments approach. Five policies were assessed in order to study the impact they had on how commuters chose their mode of transportation. These include increasing parking cost, increasing fuel cost, implementing cordon pricing, reducing transit time and improving access to transit facilities. For the sake of assessing both systematic and random preference heterogeneity across car commuters, a form of the Mixed Multinomial Logit (MMNL) model that identifies sources of heterogeneity and consequently makes the choice models less restrictive in considering both systematic and random preference variation across individuals was developed. The sample includes 366 individuals who regularly commute to their workplace in the city center of Tehran, Iran. The likelihood function value of this model shows a significant improvement compared to the base MNL model, using the same variables. The MMNL model shows that taste variation across the studied commuters results in differences in influences estimated for three policies: increasing parking cost, reducing transit time and improving access to

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transit. The analysis examines several distributions for random parameters to test the impacts of restricting distributions to allow for only normality. The results confirm the potential to improve model fit with alternative distributions.

Keywords Transportation demand management · Preference heterogeneity · Random parameter distributions · Stated preferences · Mixed multinomial logit model

Introduction

Car congestion is a common problem in all megalopolises of the world, as it can impose both environmental and social costs such as daily delays, air and noise pollution, depletion of energy as well as road casualties. Among these outcomes, delay is reported to be the most pervasive and costly problem (de Palma and Lindsey 2001). Policymakers and transportation planners have increasingly showed interest in transportation demand management (TDM) restrictive policies, as expanding transportation networks is highly expensive and limited. The TDM is a general term for strategies that result in more efficient use of transportation resources. A comprehensive set of policies is available from the VTPI TDM encyclopedia (Litman 2015), in this respect.

Tehran, the capital city of Iran, is the most populated city of the country with an estimated population of about 8.8 million (World Gazetteer 2012). Globally, it stands 17th by city population (World Gazetteer 2012), 32nd by the size of its GDP (World Bank 2015) and 19th by the population of its metropolitan area (World Gazetteer 2012). It is also the largest city in western Asia with 707 km^2 of urban area (Britannica Online Encyclopedia 2014). Car ownership in Iran was reported to be about 0.025 per capita in 1998, 0.113 in 2008 (Trading economics 2014), and 0.200 in 2012 (Wikipedia 2014), showing a rapid growth trend. This has imposed various problems, especially in Tehran which has been subjected to mass-migration of people from all over the country over the last few decades.

Due to the severity of air pollution and traffic congestion problems in Tehran, two TDM policies have been implemented. The first is a car-free plan[1] in the CBD (about 32 km^2) and the second is an odd–even scheme based on the last digit of car license plates which prevents certain numbers from entering the extended-CBD area on certain days. The latter area is about three times larger (about 96 km^2) and includes the CBD. Although a few people can drive into the CBD area with a yearly exclusive license called *permission,* observations have shown that some problems, such as traffic delays and air pollution remain unresolved in the extended-CBD area.

While TDM policies aim at improving the situation for the entire urban population, individuals are often looking for a solution to optimize their commute. Some studies have shown that there is a gap between the responses to congestion reduction policies that are assumed by policymakers and those actually adopted by the individuals (e.g., (Choo and Mokhtarian 2007; Habibian and Kermanshah 2013a; Raney et al. 2000)). This problem highlights the importance of investigating individuals' behavior to find the most influential policies.

[1] Car-Free Planning refers to developing urban districts (such as a downtown or residential neighborhood) where personal automobiles are unnecessary and automobile traffic is restricted. Such restrictions can be part- or full-time and often include exceptions for delivery vehicles, taxis, and vehicles for people with disabilities (Litman 2015).

This paper focuses on the exploration of the heterogeneity across car commuters in response to simultaneous TDM policies.[2] After describing the research context, the Mixed Multinomial Logit model (MMNL) structure that can control heterogeneity across respondents is explained. Next, the implemented stated choice design and survey are described. Then, the developed mode choice model is presented. Finally, the conclusion summarizes findings and discusses the implications of results.

Previous studies

To choose more appropriate TDM policies, a coerciveness-based classification approach has been recommended in the literature (e.g., (Chen and Lai 2011; Van Malderen et al. 2012)). The policies can be split into pull and push policies (Steg and Vlek 1997). The pull policies encourage the use of non-car modes by giving them incentives for car users. In contrast, push policies are those that discourage car usage by deterrents.

Although many studies have investigated the impact of a single TDM policy, such as congestion charging (Borjesson et al. 2012), park and ride (Kono et al. 2014) and road pricing (Furst and Dieplinger 2014), few studies have focused on the impact of multiple policies. As the importance of implementing more than one TDM policy has been addressed (May and Tight 2006), the possibility of simultaneous TDM policies has also been reported due to lack of coordination between public and private organizations when making decisions (Litman 2015). While implementing more TDM policies may cover more individual trips and consequently might be more effective, some studies have pointed out the difficulties in conducting such a research (May and Tight 2006).

Several studies have focused on the effectiveness of TDM policies from the point of view of driver preference (e.g., (Mackett 2001; Stradling et al. 2000)). Thorpe et al. presented individuals' attitudinal responses to four TDM policies. Their results showed evidence of significant interaction effects between levels of public acceptance of TDM policies when considered separately and in combination with other policies (Thorpe et al. 2000). They suggested performing a stated preference experimental design of alternative TDM packages, which allows for examining both main and interaction effects.

Other researchers focused on assessing the effects of simultaneous TDM policies through different ways. By adopting a neural network in an activity-based micro-simulation model system, Pendyala et al. simulated shifting individual travel patterns when implementing six selected combinations of five TDM policies (Pendyala et al. 1997). Through a structural equation model, Eriksson et al. examined the acceptability of three TDM policies individually and their pair-wise combinations as packages (Eriksson et al. 2008). In another study, the same authors focused on improving public transport services, increasing fuel tax and a combination of these two as a package (Eriksson et al. 2010). Vieira et al. explored the concept of multi-instrumentality as a procedure of policy integration and implementation. Using a hierarchical regression analysis, they showed that in general, a combination of policies led to a higher level of expected car usage reduction than in the individual policies result (Vieira et al. 2007). They presented a systematic search for complementary policies when planning and designing one (or several) core policy(s) that aim to fulfill one particular policy more effectively.

[2] This paper is based on a presentation in 92nd Transportation Research Board (TRB) 2013 (Habibian and Rezaei 2013).

In order to focus on individual choice behavior, one needs to look at a few studies that applied discrete choice modeling. Washbrook et al. used a conditional logit model to examine the role of main effects of seven TDM policies on the mode choice behavior (Washbrook et al. 2006). They showed that increasing driving costs will bring greater reductions in Single Occupied Vehicles (SOVs) demand than increasing SOV travel time or improvements in the times and costs of alternatives beyond a base level of service. Focusing on interaction effects in addition to the main effect of TDM policies, Habibian and Kermanshah developed the synergy function of TDM policies through an MNL model for the city of Tehran (Habibian and Kermanshah 2011). They found that the interaction effect of policies in the model can improve the model's goodness of fit up to 15 %. O'Fallon et al. explored the potential main effect of 11 policies on the respondents' decision to drive a car to work or school through a stated preferences survey in three cities of New Zealand (O'Fallon et al. 2004). They developed two Multinomial Logit (MNL) models, one for the city of Wellington and one for the city of Brisbane. They also developed a third Nested Logit (NL) model for the city of Christchurch. While they approved the higher effect of push policies on car usage, they suggested using more advanced choice modeling techniques for further understanding and more accurate information about the impacts of TDM policies on car usage. Therefore, in order to more properly model the commuters' behavior, accounting for commuters' preference heterogeneity in addition to considering TDM policies interaction effects are focused on in this study.

Econometric model structure

The MMNL model (Hensher et al. 2005) is a more general form of the well-known MNL model. Denoting X_{ni} as a $k \times 1$ vector of attributes of travel mode i and the characteristics of commuter n and β as a $k \times 1$ vector of estimated coefficients associated with X_{ni}, the utility for travel mode i may be articulated as Eq. (1).

$$U_{ni} = \beta_n' X_{ni} + \varepsilon_{ni}, \tag{1}$$

where U_{ni} is the utility associated with travel mode i held by individual n, and ε_{ni} captures unobserved influences upon utility. The choice probability of travel mode i is given in Eq. (2), as in the MNL model.

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J} e^{V_{nj}}}, \tag{2}$$

where J is the choice set and,

$$V_{ni} = \beta_n' X_{ni} \tag{3}$$

While in the MNL model, the resulting coefficients in β are fixed and identical across all commuters, the MMNL approach allows β to be a $k \times 1$ vector of random coefficients. Defining the distribution of β by $f(\beta|\theta)$, where θ refers to the parameter of the distribution, the choice probability can be expressed as a weighted average of the MNL models choice probability function, evaluated at different values of β, with the weight given by the noted density function $f(\beta|\theta)$ (Rezaei et al. 2012).

The MMNL model is capable of identifying the systematic sources of heterogeneity, by decomposing the means of the random coefficients by socio demographic and trip-related attributes. It makes the choice models less restrictive than the models that assume either equivalent tastes or truly random taste variation across the sample (Hensher et al. 2005; Hensher and Greene 2003; Hensher 2006). Like the MNL model, in the MMNL model, the utility functions are assumed to have the structure presented in Eq. (1) and the heterogeneity can be introduced into the utility function through β_n, as in Eq. (4):

$$\beta_n = \beta + \Delta Z_n + \eta_n, \tag{4}$$

which can also be expressed as $\beta_{nk} = \beta_k + \delta_k' Z_n + \eta_n$, where β_{nk} is the random coefficient for the kth attribute faced by commuter n. The function considers both systematic and random taste variation for individuals. Systematic heterogeneity in the mean of the distribution of the random coefficients is accommodated by the term ΔZ_n, where Δ is a parameter vector (with its elements δ_k) associated with observed variables Z_n, such as socio-economic characteristics of respondents or commuting-related characteristics. Random heterogeneity is captured by the random vector η_n with K random components in the set of utility functions in addition to the I random elements in ε_{ni}, where K and I stand for number of attributes and number of alternative modes, respectively. Thus, the probability for choice i is computed as

$$P_{ni} = \int \left(\frac{e^{\beta_n' X_{ni}}}{\sum_{i' \in I} e^{\beta_n' X_{ni'}}} \right) f(\beta | \theta, Z_n) d\beta_n, \tag{5}$$

where θ refers to the fixed parameters of the distribution. The integral is approximated through simulation and for given values of parameters θ, values of β_n will be drawn for a defined number of draws (Hensher et al. 2005; Rezaei et al. 2012; Hensher and Greene 2003; Hensher 2006; Rezaei and Puckett 2012).

To test if the additional parameters estimated in the MMNL model improve the predictive capability of the base MNL model, the log likelihood values of the two models can be compared using log likelihood ratio test (Hensher et al. 2005) as follows,

$$-2(LL_{\text{base model}} - LL_{\text{new model}}) \sim \chi^2_{(\text{number of additional parameters estimated in the new model})} \tag{6}$$

It compares the calculated -2LL to a χ^2 (Chi square) statistic with degrees of freedom equal to the number of new parameters estimated, to test if the improvement is significant.

In most applications, the normal distribution has been frequently used for random coefficients (Warburg et al. 2006; Pathomsiri and Haghani 2005; Adler et al. 2005). Adler et al. claim that the normal distribution generally improves log-likelihood values over other distributions (Adler et al. 2005). However, this reflects an a priori assumption that both positive and negative values for the parameter may exist in the population (Hess et al. 2005). In this research, several continuous distributions including Normal, Uniform, Triangular and Weibull distribution were tested for each random parameter. Our findings show that despite some researchers' preference to use normal distributions to accommodate taste variation across respondents, sometimes normal distributions do not appear to best reflect the nature of preference heterogeneity within the sample.

Survey instrument

Design of choice experiments

Five policies were considered for the city of Tehran, three 'push policies' and two 'pull policies'. Push policies include, increasing parking cost, implementing cordon pricing and increasing fuel cost, and the two pull policies were reducing transit (bus or subway) time and improving access to transit facilities. Pull policies are described by setting measures in favor of the public transit vehicles in streets and intersections, decreasing the time of boarding and alighting at stations, and increasing the number of bus lines and stops in the city.

Parking costs, fuel costs and public transit time policies are presented with three levels, but cordon price and public access time are presented with two levels. All push policies had fixed values for their levels, while pull policies are expressed as deviations from the reference level, which is the exact value specified in the corresponding non-stated choice questions, due to existing variations in the transit time and transit access time of the individuals. The policies and their levels are summarized as follows:

1. Increasing parking cost: 0, 4000, 7000 Rials/h
2. Cordon pricing: 25000, 50000 Rials/day
3. Increasing fuel cost: 0, 3000, 5000 Rials/liter
4. Transit time reduction: 0, 15 %, 30 %
5. Transit access improvement: 0, 25 %,

where 10000 Rials was almost equal to 1 U.S. dollar during the time the survey was conducted.

The choice experiment was designed using the *efficient design method*. The design, X, is based on the assumption that "an efficient design for a linear model is a good design for the multinomial logit (MNL) model used in discrete choice studies" (Kuhfeld 2005).[3] Therefore, the design used was independent of priors and resulted in a D-efficiency of 89.5 %[4] (see Kuhfeld 2009) for more details on *efficient design method*). It was performed so that it allows assessing all two-way interactions, as well as the main effects, using only 36 choice tasks. To avoid a time-consuming questionnaire, the choice tasks (scenarios) were randomly ordered and divided into six separate questionnaire types (i.e., code 1 to code 6), each of which had six scenarios.

Descriptive statistics

A stated preference survey was conducted to collect data from morning car commuters to the extended-CBD area. In order to find the real sensitivity of commuters to the policies, they were asked to ignore the two aforementioned restrictive policies (i.e., car-free plan in the CBD and the odd–even scheme in the extended-CBD), when answering the choice tasks. Reasons for selecting the extended-CBD area as the study area can be generalized

[3] This method has also been used in other studies (e.g., Bateman et al. 2007; Huber and Zwerina 1996; Batsell and Louviere 1991).

[4] The D-efficiency index is a function of the geometric mean of the eigenvalues of information matrix (multiplication of the transpose of X time X) which is adopted to measure the variance–covariance size of a candidate design. Efficient design method tries to find a candidate design with the smallest variance-covariance size (highest D-efficiency index).

into two categories: (a) because of odd–even control, respondents were familiar with the fringes, and they can better imagine the entrance pricing area; (b) respondents were familiar with the limitations, and were thus aware of the alternative modes. Based on a random sampling plan which leads to selecting a set of random workplaces in the extended-CBD area, the survey involved face-to-face interviews in the respondents' workplaces midway through the year of 2009.

For this study, 2196 scenario observations from 366 participants were adopted. Almost 90 % of participants declared to have access to public transit stations within a reasonable walking distance. The sample included 308 men (i.e., 84.1 %) and 58 women (i.e., 15.9 %), which is close to the employment percentages in the city, namely 82.5 % men vs. 17.5 % women (Iranian Center of Statistics (ICS) 2009). As this study focuses only on car-commuters, comparisons between the sample and city data were impossible. Table 1 presents demographics of the sample.

The questionnaire was dedicated to gathering the individual socio-economic and all commuting-related characteristics on the previous day or the day before, based on the plate number. It was necessary that the respondents drove their car on the day studied, to complete the trip diary section of the questionnaire. The scenarios formed the remaining portion of the questionnaire. In each scenario, respondents were asked to answer the question "How would you travel to the workplace if all of these changes were implemented on the day studied?" The interviews were enhanced with a special card presented

Table 1 Demographics: Gender, Marital Status, Household (HH) Size, Age, HH Employee (s)

	Number	Percent
Gender		
Male	308	84.1
Female	58	15.9
Marital status		
Single	100	27.3
Married	266	72.7
HH size		
1	4	1.1
2	86	23.5
3	129	35.2
4	90	24.6
5	42	11.5
6+	15	4.1
Age		
18–29	122	33.3
30–39	146	39.9
40–49	58	15.9
50–59	32	8.7
60+	8	2.2
HH employee (s)		
1	156	42.6
2	159	43.5
3	41	11.2
4+	10	2.7

in Fig. 1 to better explain the scenarios. For example, in scenario F, one needs to pay 4000 Rials/h for parking, 50,000 Rials per entrance to the extended-CBD area, no change in transit access time and fuel cost, while facing a 15 % decrease in transit time, simultaneously.

Commuters responses to the choice tasks have been categorized into six groups, including (1) still drive a car (C); (2) walk to a transit station and catch public transit (W&R); (3) drive to a ransit station and catch public transit (D&R); (4) catch a shared taxi (S_T); (5) take an agency taxi (T_T), and (6) ride a motorcycle (MC). D&R is somewhat different from the more familiar "Park and Ride". In fact, there is no specific parking lot dedicated to this purpose on the edges of the extended-CBD area. Commuters had to pay for on-street parking spaces, due to not being allowed to enter this area. It is worth noting that in Iran, typically, taxies are not hired by one person or group of people at a time. Rather, they allow passengers to board or alight along their path, with respect to their capacity. In other words, this mode is functioning similar to the transit mode, but the stops are not predefined. Therefore, this mode is named as shared taxi in this paper. In contrast, the T_T is hiring by one person or group.

	Scenario No. (Code:6)					
	A	B	C	D	E	F
Parking cost per hour	**7000 Rials** 4000 Rials Current cost	**7000 Rials** 4000 Rials Current cost	7000 Rials **4000 Rials** Current cost	7000 Rials 4000 Rials **Current cost**	7000 Rials 4000 Rials **Current cost**	7000 Rials **4000 Rials** Current cost
Fuel cost per liter	5000 Rials 3000 Rials **Current cost**	5000 Rials **3000 Rials** Current cost	**5000 Rials** 3000 Rials Current cost	5000 Rials **3000 Rials** Current cost	**5000 Rials** 3000 Rials Current cost	5000 Rials 3000 Rials **Current cost**
Travel time by public transit	30% decrease 15% decrease **Current time**	**30% decrease** 15% decrease Current time	30% decrease **15% decrease** Current time	**30% decrease** 15% decrease Current time	30% decrease 15% decrease **Current time**	30% decrease **15% decrease** Current time
Access time to the public transit station	**25% decrease** Current time	**25% decrease** Current time	**25% decrease** Current time	25% decrease **Current time**	25% decrease **Current time**	25% decrease **Current time**
Cordon pricing to enter extended CBD area	50000 Rials **25000 Rials**	**50000 Rials** 25000 Rials	**50000 Rials** 25000 Rials	50000 Rials **25000 Rials**	50000 Rials **25000 Rials**	**50000 Rials** 25000 Rials

Fig. 1 The Enhanced Card for interviews

While the respondents were allowed to refuse traveling to work in each scenario, none of them chose this option. Furthermore, none of the respondents stated another workplace as his/her alternative. However, as respondents in less than 1 % of scenarios choose the "use a car as a passenger", this option is aggregated to the T_T option due to its low percent.

MMNL model with decomposition effects

An MMNL model was developed to test if there was any significant preference heterogeneity across commuters in response to TDM policies that can be explained by their observed characteristics (i.e., commuting related and socio-economic characteristics). That is, we were looking for any systematic taste variation across commuters, by trying to decompose the means of random coefficients by observed characteristics. The data set used to estimate models was the same as the data used to estimate the MNL model in previous research (Habibian and Kermanshah 2013b) containing 152 variables.[5]

Explanatory variables

Table 2 presents the variables with statistically significant effects in our final model. For a general review of the model results, the parameters can be grouped under the following three categories: TDM policies, commuting-related characteristics and household socio-economic characteristics, which are all treated as alternative-specific variables.

Model estimation results

The simulation-based MMNL estimation was carried out in the Nlogit software, using 200 Halton draws, which are intelligent draws used for calculating multi-dimensional integrals or in quasi-Monte Carlo simulations (Atanassov and Mariya 2003; Rezaei and Puckett 2012). All TDM policy variables were tested to assess if their coefficients include some random parts. For each coefficient, different types of distributions (i.e., Normal, Uniform, Triangular and Weibull) were tested. Furthermore, the existence of any significant source of heterogeneity in response to the TDM policies that can be captured by the variables under the commuting-related or HH socio-economic characteristics groups, presented in Table 2, were tested. This was done by assuming that a part of preference heterogeneity can be explained by the differences in socio-economic and contextual descriptors (Hensher and Greene 2003).

To determine individuals' choice sets, the "ride a motorcycle" option was not removed from the choice sets of individuals who have no motorcycle at home, as this mode can be hired in the CBD of Tehran (as a passenger). Furthermore, transit has been removed from the choice set of people with no access to this system.[6]

The MMNL model presented in Table 3 is the most meaningful model with the largest number of significant random coefficients, and the highest level of significant superiority to the corresponding MNL model[7] (See (Habibian and Kermanshah 2013b) for more details

[5] Regarding the number of observations (i.e., 2196), it is possible to consider this number of variables in order to have coefficients that are significant at a reasonable confidence level (e.g., 99 %).

[6] More focus on such individuals showed that they had not considered the drive and ride option as well as walk and ride in response to the scenarios.

[7] The MNL model variables were significant at least at 0.1 level.

Table 2 Definitions of significant variables in final model

Variable	Abbreviation
Transportation demand management policies	
Parking cost increase, Rials per hour	Parking
Cordon price, Rials per entrance	Cordon
Public Transit access time reduction, percent	Access_time
Parking cost and fuel cost simultaneous effects	Park&Fuel
Cordon pricing and fuel cost simultaneous effects	Cordon&Fuel
Public Transit time reduction and access improvement simultaneous effects	PT_Time&Access
Commuting-related characteristics	
Distance between home and workplace	Trip_distance
Travel time between home and workplace	Trip_time
Likelihood of unsubsidized fuel use[a] (self-reported on a Likert scale)	Exp_Fuel
Number of daily trips	Ntrips
Commuting with 1(+) stop(s) in go or return	Pattern2
Commuting with 2 workplaces	Pattern3
Start time of first trip	First_trip_time
Likelihood of going to work, in absence of that car (self-reported)	Pnocarwk
Non-walk access to transit (yes = 1)	PTnwacc
Number of passengers in first trip	First_Nacco
Any passenger on that day? (yes = 1)	Passenger
Parking payment in last week	Park_payment
Board/alight a passenger or move freight in the trip (yes = 1)	Dependency
I use my car because it is comfortable	Comfort
I use my car because transit is not good	Poor_PT
HH socio-economic characteristics	
Be the owner of the used vehicle (yes = 1)	D_car_own
Car accessibility in household (number of cars to number of HH driving licenses ratio)	Car_acc
Number of motorcycles owned by HH	Nmotorcycle
Home Location is in study area (yes = 1)	D_home_place
Permission to enter to study area (yes = 1)	Permission
Number of full-time employees in HH	Nhempfull
Gender (Female = 1)	Female
Age younger than 30 (yes = 1)	Age < 30
Age between 30 and 39 (yes = 1)	Age30_39
Number of years that individual has been at his/her job	Job_duration
Full-time employee (yes = 1)	Emp_full
Degree of education is B.Sc. (yes = 1)	Edu: BS
Degree of education is higher than B.Sc. (yes = 1)	Edu: BS+
Child younger than 18 in HH (yes = 1)	D child ≤18

[a] According to a government policy, cars manufactured in Iran could use 100 l of subsidized fuel per month

of the MNL model). The model includes 65 explanatory, as well as 7 preference heterogeneity variables, with a goodness of fit of 0.33. The level of significance of each variable is presented by the number of "*" symbols in Table 3.

Table 3 The MMNL model results with decomposition of random coefficients

Mode variable	Car (C)	Walk and ride (W&R)	Taxi (T)	Drive and ride (D&R)	Tel-taxi (T_T)	Motorcycle (MC)
Constant			−1.95346***	11.5085***	−5.29899***	
Transportation demand management policy variables						
Cordon	−.00051***				.00018**	
Parking	−.00231**					
Access_time		−.17192***				
Park&Fuel	−.32155D−05**					
Cordon&Fuel						−.35832D−06**
PT_Time&Access				−.09670***		
Commuting-related characteristics						
Trip_distance						−.04841***
Trip_time			−.00932***		−.02069**	
Exp_fuel	1.81765***		−1.07148***			
Ntrips			−.16449***			
Pattern2						−1.19411***
Pattern3			−.90836***			
First_trip_time		−.00310***		−.01345***		
Pnocarwk	−.02162***					−.02767***
PTnwacc		−.49335***		2.79489***	−1.34986***	
First_Nacco						−1.49326***
Accompany		−1.23886***		−1.02291		
Park_payment	.96391D−04					−.00057**
Comfort*Car1					−1.60873***	
Dependency*Car1						−2.30238***
Dependency*Car1+		−1.15188***		5.80577***	−1.39327**	
Poor_PT*Car1		.42254**				
Poor_PT*Car1+			−.23325			

Table 3 continued

Mode variable	Car (C)	Walk and ride (W&R)	Taxi (T)	Drive and ride (D&R)	Tel-taxi (T_T)	Motorcycle (MC)
HH socio-economic characteristics						
D_car_own				−7.26790***		−1.52467***
Car_acc			−.57647***		.58030	
Nmotorcycle		−5.13596***	−.68402***			1.61692***
D_home_place		.24091*		−2.96455***		
Permission	.81184***					2.36345***
Nhempfull	1.91311***				2.06608***	
Female					1.48103***	
Age <30			−.38085***			2.79087***
Age 30_39					−1.31145***	
Job_duration	.05001***	.05864***				.08477***
Emp_full						−1.09278***
Edu: BS		−.75469***				−2.26306***
Edu: BS+	2.29048***	.88604	1.92566***		2.51198***	
D child <=18						1.03709***
Standard deviation of random parameters						
Parking	.00102** (Weibull)					
Access_time		.07206*** (Normal)				
PT_Time&Access				.02737*** (Normal)		
Heterogeneity in the mean of random parameters						
Parking × PTnwacc	−.00147***					
Access_time × Nmotorcycle		.29364***				
Access_time × First_Nacco		.04768***				
PT_Time&Access × First_trip_time				.94253D−04***		
Number of observations	607	580	592	178	112	127
Log likelihood(β)				−2593.150		

Table 3 continued

Mode variable	Car (C)	Walk and ride (W&R)	Taxi (T)	Drive and ride (D&R)	Tel-taxi (T_T)	Motorcycle (MC)
Number of model coefficients				72		
Log likelihood of base model(β)				−2677.366		
Degrees of Freedom (above MNL)				7		
Chi square				168.432***		

***, **, * Positive significance at 1 %, 5 %, 10 % level

The second column of Table 3 presents the coefficients of the car utility function. This utility function shows that implementing the cordon pricing policy as well as increasing the parking cost discourages respondents from using cars, which is supported by other research in the literature (Hensher and Rose 2007; O'Fallon et al. 2004). Furthermore, the coefficient of interaction between fuel cost and parking cost policies shows a similar effect on car usage. Because fuel cost and parking cost are related to the distance between home and work locations and the work hours, respectively, it can be inferred that the time individuals spend out of home negatively affects the likelihood of choosing the car option. The other coefficients of this utility function also show that individuals with higher incomes are more willing to use their car. This is indicated in the model by the positive signs of the individuals who use fuel at a fixed (unsubsidized) cost and those who pay more parking charges. Furthermore, more years of employment (Job_duration), higher education levels (Edu:BS+), more full-time employees in the household and having permission to enter the CBD area increase the probability of car usage. Finally, the negative sign of the *Pnocarwk* coefficient implies that commuters, who stated that their commute depends on car availability, would be more willing to use their cars.

The third column of Table 3 presents the coefficients of the W&R utility function. It shows that access time to transit stations negatively affects the choice of the W&R option, which is intuitively reasonable and similar to the findings for the city of Sydney (Hensher and Rose 2007). The coefficients with negative signs in the utility function of the W&R option indicate a deterrent to using W&R in the following cases: not being an early commuter, having no walking access to transit stations, serving passengers on daily trips, having a greater number of motorcycles in a household and having been educated at BS level. By considering household car ownership as a proxy for household income to individuals, the negative sign of Dependency*car1+ suggests that those who earn more and have to use their car during, before or after work are less willing to use W&R. In contrast, living in the central part of the city (i.e., study area), belonging to the lower-income commuters group while using a car due to poor public transit service (Poor_PT*Car1) and having more years of employment (Job_duration) in the workplace increase the utility of this mode.

The fourth column of Table 3 is dedicated to the shared taxi (S_T) utility function. Given its functionality in Iran as a non-private and non-public mode of transport, none of the noted policies have a significant effect on shared taxi usage. The coefficients with a negative sign indicate that making longer trips, using unsubsidized fuel, making more trips in a day, being employed in more than one workplace (Pattern3), higher levels of car ownership (reflected through (Poor_PT*Car1+) and having access to more cars in a household (Car_acc), having more household motorcycle ownership, and finally being young, reduce the probability of choosing the shared taxi mode. In contrast, commuters with higher levels of education are more likely to use this mode.

The fifth column of Table 3 shows that D&R is affected slightly by the simultaneous effects of transit time and transit access (PT_Time&Access), which is reflected by the fact that individuals are more willing to use this mode if the transit system improves. The coefficients with a positive sign indicate that having no walking access to transit stations is encouraging commuters to use D&R. In addition, commuters who earn more and also depend on their car during, before, or after work (Dependency*car1+) are more likely to use D&R. The negative coefficients indicate that commuting in the late morning, serving passengers, using individuals own car, and residing in non-central parts of the city, deter car commuters from using D&R.

The coefficients of the Tel-Taxi (T_T) utility function are shown in the sixth column of Table 3. The positive sign of *Cordon* coefficient indicates that implementing the cordon pricing policy increases the probability of using T_T. In fact, by increasing the price of entering the restricted area, individuals are more willing to use T_T. It seems reasonable as T_T is a mode with a similar level of service to cars, while excluding driving stress and the time spent searching for parking. It is worth noting that due to the possibility of considering other non-car modes, the effect of cordon pricing in pushing car commuters into non-car modes (0.00045) is greater than its effect when considering the T–T (0.00019) option. Positive signs of the *Nhempfull, Caracc, Female* and *Edu:BS+* imply that those with more full-time employees in the household, individuals who have greater access to cars in the household, females and the higher educated respondents are more willing to use the T_T mode. In contrast, using more unsubsidized fuel, having no (reasonable) walking access to transit stations and belonging to the younger group reduce the probability of using the T_T mode. Furthermore, individuals who earn more and also depend on their car during, before, or after work time (Dependency*Car1+) and those with lower levels of income who use their cars for the sake of comfort (Comfort*car1) are less willing to use the T_T mode.

The last column of Table 3 is dedicated to the coefficients of the Motorcycle (MC) utility function. Motorcycle usage is affected by a majority of variables compared to the other modes. This may be due to the fact that MC is not a common mode for Tehran residents. In addition to individuals who are more sensitive to safety concerns who do not use this mode, women are just allowed to ride on it as a passenger. The MC utility function implies that increasing fuel cost and implementing cordon pricing policy simultaneously discourage the consideration of the MC mode. Table 3 shows that commuting and socio-economic variables have appeared in the MC alternative with intuitively reasonable signs. Quite notably is the very different number of relevant variables across the studied modes. While about only seven explanatory variables describe the car alternative, the number is doubled for the motorcycle. For other choice alternatives, these numbers vary in between. Such findings may be attributed to a rather uniform nature of car users in the sample (in fact, all sampled individuals go to work by car) with fewer car choice variations and therefore, fewer explanatory variables are needed.

Preference heterogeneity

The findings suggest that there are significant taste variations across commuters, in response to increasing parking cost (Parking), improving access to transit (Access_time), and also the simultaneous effect of reducing public transit time and improving access to this mode (PT_Time&Access) that the MNL model cannot accommodate. The Weibull distribution appears to be the best for accommodating random taste variation of commuters in response to *Parking*, whilst the normal distribution appears to be the best distribution for explaining preference heterogeneity regarding *Access_time* and *PT_Time&Access*. Most importantly, the model reveals systematic sources of preference heterogeneity for these variables through decomposition effects. All explanatory variables under the commuting-related or HH socio-economic characteristics groups, presented in Table 2, were examined to see if they can explain the means of the random parameters. Significant relations were found between responses to parking cost (Parking) and a threshold specification for non-walk access to transit (PTnwacc); *Access_time* and both the number of motorcycles owned by HH (Nmotorcycle) and the number of passengers in the first trip (First_Nacco); and lastly, *PT_Time&Access* and the start time of the first trip (First_Trip_time). Table 3 compares the MMNL model with the basic MNL model, using a Log Likelihood (LL) ratio test ($\chi^2 = 168.432$), indicating that the MMNL model offers a significantly improved fit at a level of significance of 0.1.

In general the findings imply that differences in the marginal utilities held for *Parking*, *Access_time* and *PT_Time&Access* may be explained in part by: having walking access to transit, number of motorcycles owned by HH and the number of passengers in the first trip and the start time of the first trip, respectively. Therefore, the full marginal (dis)utility effects of *Parking*, *Access_time* and *PT_Time&Access* drawn from the noted distributions, as presented in Table 3, can be presented through Eqs. (7) to (9).

$$Parking = -.00231 - .00147 \times PTnwacc + .00102 \times w \tag{7}$$

$$Access\_time = -.17192 + .29364 \times Nmotorcycle + .04768 \times First\_Nacco + .07206 \times n \tag{8}$$

$$PT\_Time\&Access = -.09670 + .94253D - 04 \times First\_trip\_time + .02737 \times n \tag{9}$$

where, w and n stand for random variables from Weibull and Normal distributions, respectively.

As presented in Eq. (7), the negative sign of *Parking* by *PTnwacc* coefficient (−.00147) suggests that the sensitivity to parking cost decreases across respondents if they do not have walking access to transit. That is, the individuals who do not have walk-access to transit stations were more sensitive to the offered parking cost. However, the positive sign of the public transit access time reduction policy (Access_time) by *Nmotorcycle* and *First_Nacco* coefficients (.29364 and .04768) in Eq. (8), suggests that those who own more motorcycles in their household or have more passengers in their first trip are less sensitive to improving access time to public transit. Likewise, the positive coefficient for *PT_Time&Access* by *First_trip_time* (.94253D-04), in Eq. (9), implies that those who start their first trip earlier in the morning are more sensitive to the simultaneous effects of reducing public transit time and improving access to transit policies.

Summary and conclusion

This study examined the role of TDM policies in car commuters' mode choice behavior for work trips in the city of Tehran through the MMNL model. The MMNL structure used in this study considers both systematic and random heterogeneity across respondents. Five policies were examined: increasing parking cost, increasing fuel cost, implementing cordon pricing in the extended-CBD of the city, reducing transit time and improving access time to transit facilities. A stated preference survey with six alternative modes to get to work was conducted to collect data. We identified some sources of taste variation in response to TDM policies using the extended MMNL model. In general, this approach makes the choice models less restrictive by considering both systematic and random preference heterogeneity across individuals. We compared several distributions of random parameters to test the impacts of restricting distributions to allow for only normality. It confirms the potential to improve model fit with alternative distributions.

The estimated model incorporates different descriptive variables, including TDM policy main effects as well as their interaction effects. This study shows the contribution of policy interactions to describe the commuters' mode choice decisions. Almost all mode choices reflect the environment in which individuals make choices influenced either by policy variables and/or policy interaction terms. The only exception, however, is taxis which are not directly affected by the studied policies. This might be attributed to their especial function in the city of Tehran, as mainly regarded as a non-public and non-private mode of travel.

Consistent with the literature, this study finds that push policies play an important role in car utility function. While the main effects of cordon pricing and parking pricing policies significantly affect car usage, the increasing in fuel cost policy is just effective in the form of simultaneous implementation with either of the two former push policies. Therefore, it can be concluded that solely increasing fuel cost in the studied range would not be effective in reducing car usage. Furthermore, simultaneous implementation of the increasing fuel cost policy with increasing parking cost would result in car usage reduction, while simultaneous implementation of increasing fuel cost policy with cordon pricing would result in not considering the MC.

The studied pull policies also affect the consideration of transit-related modes. While improvement in the access time of transit modes increases the utility of these modes, decreasing the transit time is just effective in simultaneous implementation with the access time improvement and encourages the D&R usage.

The random parameters show that there are some relations between responses to some of the studied policies and the individuals' commuting-related or socio-economic characteristics. In fact, the model shows the existence of preference heterogeneity around the mean of random coefficients of TDM policies in the utility functions. Accounting for such a heterogeneity across commuters results in a better understanding of their choice behavior. Our findings suggest that differences in the marginal utilities across respondents' preferences can be explained primarily by differences in having walking access to transit stations, the number of motorcycles owned by HH, the number of passengers on the first trip and the start time of the first trip.

Overall, the analysis of this paper extends the insight of Habibian and Kermanshah (Habibian and Kermanshah 2013b) by identifying behaviorally meaningful determinants of the preference heterogeneity across respondents. The findings are relevant to decision-makers for developing policies to decrease car usage in the CBD area of Tehran. Interpretation of the taste variation across commuters is a complex issue which could be performed on professional knowledge of the transportation conditions of the studied society. The investigation of this issue in the case under consideration reveals that commuters who do not have walking access to transit stations (PTnwacc), are more sensitive to increasing parking costs. This may be due to the narrower choice set of such people considering the parking cost they should pay in case of using public transit.

Commuters who have a motorcycle may potentially use it in the case of restrictions for cars. Since, motorcycle usage is not influenced by the odd–even scheme (and even parking policy); it could be a competitive alternative for the transit modes in case of restrictions for car usage. Therefore, more motorcycle ownership (Nmotorcycles) may result in higher probability of motorcycle usage by the sampled commuters. Therefore, commuters who have more motorcycles seem to be less sensitive to the pull policies. This hypothesis is verified by the positive coefficient of *Nmotorcycle* in Eq. (8).

Furthermore, commuters who have more commitment to their household members' transportation, due to a greater number of passengers on the first trip, are less willing to change their mode and thus less sensitive to pull policies. It can be concluded that access time improvement program (e.g., improving network coverage) should start from the regions with more single occupied vehicles.

Equation (9) shows that early morning commuters are more sensitive to the improvements of transit systems. Therefore, one may conclude that to encourage people to use D&R, transit system improvement policy would be more effective if implemented on transit lines in earlier peak periods.

Finally, this study is based on a sample of 366 respondents, which seems to be a small sample size. Therefore, in order to achieve more robust results for policy making in a megalopolis, a larger sample should be employed. Furthermore, one may raise the issue that while using indicators (e.g., Pnocarwk, Comfort, Poor_PT), directly as explanatory variables results in a better goodness of fit, they may introduce a bias to the model coefficients due to measurement errors. Although the authors are aware of such a problem, these variables were retained in order to be able to compare the MMNL model with the MNL model presented in previous publications (Habibian and Kermanshah 2013b).

Further research can focus on examining the effects of other TDM policies on commuter behavior. Furthermore, more advanced choice models like Latent Class (LC) models can be employed to achieve better insight toward the behavior of different segments of commuters. In addition, more advanced choice design can be developed for future studies based on the values estimated for the policy coefficients as priors.

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