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CAR COMMUTERS' MODE CHANGE IN RESPONSE TO TDM MEASURES: EXPERIMENTAL DESIGN APPROACH CONSIDERING TWO-WAY INTERACTIONS*

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Abstract– Many studies have shown that individuals' responses to urban traffic congestion, as usually assumed by policymakers, are significantly different from their respected actual behavior. This paper adopts a behavioral approach to examine this difference, using the design of experiment principles and binary logit models. In this approach, five transportation demand management (TDM) measures including three push and two pull measures were investigated. Then, effects and contributions of the measures in diverting car commuters to seven existing non-car modes were taken into account. This study uses the stated preferences of 288 individuals who regularly use their private cars to access their job locations in the central Tehran area, to calibrate seven non-car mode models. The results show that when considering each mode separately, pull measures are necessary to regulate the market share of each non-car mode. Analysis of the effects of the measures in considering non-car modes shows that although their contributions are about 14% for transit accessed by walking and 7% for taxi, they have never contributed more than 5% to other modes.

Keywords– Transportation demand management measure, stated preference, binary logit model, design of experiments, mode change

1. INTRODUCTION

Congestion is said to be a major problem in most of the world's cities. Daily delays, pollution emissions, nonrenewable energy consumption and degradation of environmental quality are some outcomes of congestion [1-3]. Being discontent about congestion usually compels policymakers to design solutions to reduce congestion. Although such solutions serve social causes, individuals are often looking for a solution to solve their own problems. Many studies have shown that there is a difference between the responses to measures of reducing congestion which are assumed by policymakers and those that are actually adopted by individuals [4-6]. For example, the odd-even scheme which was designed to ban access to the central business district of Athens based on car plate number to reduce automotive emissions, led to an increase in car ownership in the city in the 1980s. In fact, by introducing second cars to households, the problem of congestion emerged in addition to pollution [7]. This issue shows that in order to find an effective measure to improve transportation system performance of a city, more assessment of citizens' behavior, as many researchers have pointed out [8-10] is necessary.

Currently, the solutions called Transportation Demand Management (TDM) measures refer to as many as 80 different strategies that encourage more efficient transportation behavior are widely implemented [11]. A more general classification of TDM measures based on the coerciveness feature and

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called *pull* or *push* measures, has been explored in many studies [12-14]. Pull measures encourage car users into the use of non-car modes by making them attractive. Transit-oriented development, street reclaiming, and bus rapid transit development are examples of pull measures. Inversely, push measures are those that discourage individuals from car use, by making it less attractive. Road pricing, congestion charging and cordon pricing are a few examples of push measures.

While many researchers have studied the effect of a single pull or push measure [8, 9] and some others addressed the importance of simultaneous application of the measures [15-17], few studies have focused on this issue. For example, Vieira et al. explored the concept of multi-instrumentality as a procedure of measure integration and implementation, whereby a systematic search for complementary measures was sought when planning and designing one (or several) core measure(s) aiming to fulfill one particular measure more effectively [18].

Eriksson et al. examined the acceptability of one push measure (increased tax on fuel) and two pull measures (improved public transport and subsidized renewable energy) individually and as packages, combining one push and one pull measure [19]. They proposed a model for predicting the acceptability of TDM measures, and concluded that while the pull measures were perceived to be effective, fair and acceptable, the push measure and the packages were ineffective, unfair and unacceptable. Later, Erikson et al. focused on the improved public transport, increased tax on fuel and the combination of these two measures as a package, and concluded that the integration of the two measures in car usage reduction was more effective than the individual measures [20].

As the number of measures increased, some researchers adopted experimental design approach and stated preference survey for more complicated multi-measure scenarios. The most complete investigation has been reported by O'Fallon et al. in which the potential effects of 11 TDM measures on the respondents' choices to drive to work or school by car during the morning peak period in three cities in New Zealand were studied [21]. However, they ignored all interactions in their study design though they recommended a study with fewer measures to explore the possible impacts of combinations of specific measures.

Based on the above discussion, accounting for the interaction of TDM measures is an important issue within the context of the integration of TDM measures. Unfortunately, this issue is not well addressed in previous studies which are focused on more than two measures. Considering measures' two-way interactions, this study examines the effects of five TDM measures on seven alternatives to car driving to determine the effective measure(s). Thus the following two issues are addressed: first, the effects of the studied TDM measures and their interactions for each of the non-car modes are identified. Second, the contributions of the measures to individuals' mode change are evaluated.

2. METHODOLOGY

This study employs a binary logit modeling approach to evaluate commuter car users' mode change behavior under the simultaneous application of five TDM measures for the city of Tehran in Iran. The binary model rather than multinomial logit was selected because it is able to examine each mode independent of the others. Equation (1) shows the probability that decision maker *n* will choose alternative *i* in his/her choice set consisting of alternatives *i* and *j* through binary logit approach.

$$P_n(i) = \frac{1}{1 + e^{\beta(x_{jn} - x_{in})}} \tag{1}$$

where x_{in} is a vector of observed variables of decision maker *n* relating to alternative *i*, and β is a vector of model parameters. Usually, maximum likelihood approach is employed to estimate the model's parameters. To assess how well the model fits the data, Eqs. (2) - (4) show different goodness of fit indices of logit model.

$$\rho^2 = 1 - \frac{L(\beta)}{L(0)} \tag{2}$$

$$\bar{\rho}^2 = 1 - \frac{L(\beta) - k}{L(0)} \tag{3}$$

$$\rho^2{}_{MS} = 1 - \frac{L(C)}{L(0)} \tag{4}$$

where L(0), L(C) and L(β) are the values of logarithms of likelihood functions at zero, constant, and β vector (L(0)≤L(C)≤L(β)), respectively, and k is the number of variables.

The five TDM measures consist of three push and two pull measures. The measures are increasing parking cost, increasing fuel cost, cordon pricing into Tehran central area, transit (bus or subway) time reduction and transit access improvement. The latter two are described by setting policies in favor of the public transit vehicles in streets and intersections, decreasing the time of boarding and alighting at the stations and increasing the number of transit lines and stops in the city.

Parking costs, fuel costs and public transit time measures are designated with three levels, and cordon price and public access time are designed with two levels. Table 1 shows the measures and their levels. All push measures had fixed values for their levels. For pull measures, because there were variations in the transit time and transit access time for individuals, proportional values of the current state were used, which are different for each individual. The term *no change* in Table 1 refers to the current value of a measure that each individual already experiences. The mean values are also presented in Table 1 for a better description of the current state.

Table 1. TDM measures and their respective levels as used in stated choice experiment

Measure	Type	Level 1	Level 2	Level 3	Observed* Mean Value
Increasing parking cost (Rials§/h)	Push	No change	4 000	7 000	71 Rials/h
Cordon pricing (Rials/day)	Push	25 000	50 000	NA	None in place
Increasing fuel cost (Rials/liter)	Push	No change	3 000	5 000	1470 Rials/Liter
Transit time reduction (percent)	Pull	No change	15	30	38.5 min
Transit access improvement (percent)	Pull	No change	25	NA	11 min

* Average of values declared in the stated preferences survey.
§10000 Rials are almost equal to 1 U.S. dollar in the period of the survey.

3. STUDY SAMPLE

The sample of this study is based on the data collected for a more comprehensive study during the summer, 2009. The information used in this study includes individual occupation, home and job locations and distance between these locations, home-workplace round trip time, and the previous day car trips characteristics. The stated preference questions gathered under different scenarios are another part of the information used in this research. In a typical scenario a respondent has been asked “How would you travel to the workplace if all of these changes—*the scenario*—were in place on the day studied?” Based on individuals’ responses, seven options in addition to “continue driving” were distinguished.

These choice options were: transit with walk access (Walk & Ride), transit with car (Drive) access (Drive & Ride), transit with taxi access (Taxi & Ride), ride a motorcycle (Motorcycle), taxi with car access (Drive & Taxi), catch a taxi (Taxi) and take a taxi via telephone (Tel-taxi).

In cases where a respondent changed his/her mode, he/she was asked to present the main reason(s) for the change. In addition, some more travel-related information such as respondents' car dependency (need to serve passenger or carry freight), parking type and average weekly parking costs have also been gathered in the survey. Table 2 summarizes the respondents' travel-related characteristics.

Table 2. Summary of respondents' travel-related characteristics

Characteristics		Frequency	Percent
Trip start time	Before 07:00 a.m.	81	28.1%
	Between 07:00 and 08:00 a.m.	105	36.5%
	Between 08:00 and 09:00 a.m.	69	23.9%
	Between 09:00 and 12:00 a.m.	33	11.5%
Travel time	15 minutes and less	69	24.0%
	Between 15 and 30 minutes	77	26.7%
	Between 30 and 60 minutes	106	36.8%
	60 minutes and more	36	12.5%
Trip numbers by car	2	141	48.9%
	3	50	17.4%
	4	53	18.4%
	5 or more	44	15.3%
Probability of using no subsidized fuel	None	162	56.3%
	Less than 50 percent	112	38.8%
	50 percent and more	14	4.9%
Public access	Private car	29	10.0%
	Taxi	87	30.2%
	Walking	174	59.8%
Reasons for car use	Comfort	167	58.0%
	Car dependence	56	19.4%
	Poor public transit	64	22.2%
	Employer's amenities	1	0.4%

The last part of the questionnaire includes information about socio-economic characteristics of the respondents, among them information about household characteristics, gender, age, household type, employment status and education level are worthy to note. Table 3 presents socio-economic characteristics of the sample.

The final data used for developing binary choice models consists of 1 480 scenario observations from 288 individuals who had access to transit stops and considered non-car modes in at least one scenario, were adopted. As shown in Table 3, the sample included 238 men (i.e., 82.6%) and 50 women (i.e., 17.4%). The figures are close to the employment percentages in the city, according to the Iranian Center of Statistics (ICS). This source indicates that 82.5% of Tehran employees are men, and 17.5% are women [22]. Because this study focuses on car-using commuters, comparisons between the sample and city data, especially regarding educational distribution, were impossible.

Table 3. Summary of respondents' socio-economic characteristics

Characteristics		Frequency	Percent
Gender	Male	238	82.6%
	Female	50	17.4%
Marital status	Single	84	29.2%
	Married	204	70.8%
Age	18-29 years	106	36.9%
	30-39 years	109	37.8%
	40-49 years	43	14.9%
	50-59 years	24	8.3%
	60 years or older	6	2.1%
Education level	High school or lower	79	27.5%
	Associate degree	40	13.8%
	Bachelors degree	106	36.8%
	Master degree or higher	63	21.9%
Job experience	2 years and less	67	23.3%
	Between 2 and 5 years	80	27.7%
	Between 5 and 10 years	63	21.9%
	Between 10 and 20 years	52	18.1%
	More than 20 years	26	9.0%
Having permit to enter to study area	No	267	92.7%
	Yes	21	7.3%
Home place located in study area	No	216	75.0%
	Yes	72	25.0%
Household Size	1	3	1.0%
	2	69	24.0%
	3	101	35.1%
	4	71	24.7%
	5 or more	44	15.2%
Number of children (under 18 years) in household	0	159	55.2%
	1	98	34.0%
	2 or more	31	10.7%
Car ownership	1	185	64.2%
	2	75	26.0%
	3 or more	28	9.7%
Household license	1	56	19.4%
	2	147	51.0%
	3	41	14.2%
	4 or more	44	15.3%

4. RESULTS

a) *Mode change models*

Based on available information, 152 variables were defined, and their effects on each non-car mode were examined during the calibration of different binary logit choice models. Every dependent variable is 1, if the mode is considered and 0 otherwise. After the calibration process the variables that were statistically significant were identified and are presented in Table 4.

Table 4. Definition of the significant variables

Variable	Abbreviation
Transportation demand management measures	
Push measures:	
Fuel cost increase, Dummy; 1: if X Rials per liter, 0: otherwise, (X∈ 3 000,5 000)	D fuel cost X
Parking cost increase, Dummy; 1: if X Rials per hour, 0: otherwise, (X∈ 4 000,7 000)	D park cost X
Cordon price, Dummy; 1: if X Rials per day, 0: otherwise, (X∈ 25 000,50 000)	D cordon X
Pull measures:	
Transit time reduction, Dummy; 1:if X percent, 0: otherwise, (X∈ 15,30)	D PT time X
Transit access time reduction, Dummy; 1:if X percent, 0: otherwise, (X∈ 25)	D acc time X
Interaction between push measures:	
Dummy; 1:if parking cost and fuel cost have simultaneous effects, 0: otherwise	DD park & fuel
Dummy; 1:if parking cost and cordon pricing have simultaneous effects, 0: otherwise	DD park & cor
Interaction between push and pull measures:	
Dummy; 1:if access improvement and cordon pricing have simultaneous effects, 0: otherwise	DD acc & cor
Dummy; 1:if PT time reduction and cordon pricing have simultaneous effects, 0: otherwise	DD PT time & cor
Dummy; 1:if PT time reduction and fuel cost have simultaneous effects, 0: otherwise	DD PT time & fuel
Commuting trip characteristics	
Distance between home and workplace	Trip distance
Travel time between home and workplace	Trip time
Likelihood of no subsidiary fuel use (self-reported on a Likert scale)	Exp. Fuel
Number of daily trips	Ntrips
Commuting with no stop (Dummy; 1: yes, 0: otherwise)	Pattern1
Commuting with 1+ stop(s) in go or return (Dummy; 1: yes, 0: otherwise)	Pattern2
Commuting with 2 workplaces (Dummy; 1: yes, 0: otherwise)	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 (Dummy; 1: yes, 0: otherwise)	PTnwacc
Number of passengers in first trip	First Nacco
Any passenger on that day? (Dummy; 1: yes, 0: otherwise)	Passenger
Parking payment in last week	Park_payment
Board/alight a passenger or move freight in the trip (Dummy; 1: yes, 0: otherwise)	Cardependency
I use my car because it is comfortable (Dummy; 1: yes, 0: otherwise)	Comfort
I use my car because transit is not good (Dummy; 1: yes, 0: otherwise)	Poor_PT
HH socio-economic characteristics	
Be the owner of the used vehicle (Dummy; 1: yes, 0: otherwise)	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 (Dummy; 1: yes, 0: otherwise)	D home place
Having permit to enter to study area (Dummy; 1: yes, 0: otherwise)	Permit
Gender (Dummy; 1: female, 0: male)	Female
Age younger than 30 (Dummy; 1: yes, 0: otherwise)	Age <30
Age between 30 and 39 (Dummy; 1: yes, 0: otherwise)	Age 30_39
Age between 40 and 49 (Dummy; 1: yes, 0: otherwise)	Age 40_49
Number of years that individual has been at his/her job	Job_duration
Full-time employee (Dummy; 1: yes, 0: otherwise)	Emp_full
Degree of education is B.Sc. (Dummy; 1: yes, 0: otherwise)	Edu: BS
Degree of education is higher than B.Sc. (Dummy; 1: yes, 0: otherwise)	Edu: BS+
Child younger than 18 in HH (Dummy; 1: yes, 0: otherwise)	D child<=18

Table 5 presents a salient representation of the final models of the seven main non-car modes, including Walk & Ride, Drive & Ride, Taxi & Ride, Motorcycle, Drive & Taxi, Taxi and Tel-taxi. Because the focus of this stage is on the general tendency of the measures' effects on consideration of non-car modes, the salient representation of such effects are presented. A positive sign of a variable in these models indicates that the condition represented by that variable increases the relative probability of considering the associated non-car mode. A negative sign also shows that the condition represented by that variable increases the relative probability of considering other non-car modes of the study. The goodness of fit value of models, ρ^2, varied in a range of 0.19 for Walk & Ride to 0.91 for Drive & Taxi, which seems suitable in individual-based models. This result is confirmed by assessing each model's lack of fit using Hosmer-Lemeshow (H-L) test, which shows that the lack of fit hypothesis is rejected for each of the models at 5% level of significance.

Table 5. Binary logit models

	Walk& Ride	Drive& Ride	Taxi& Ride	Motorcyc le	Drive& Taxi	Taxi	Tel-taxi
Constant	+++	---		--	---	---	---
Transportation demand management measures							
D PT time 15	+++					---	
D PT time 30	+++					---	
D acc. time 25		+++				--	
D park cost 4 000	---				++		
D park cost 7 000	---				++		
D cordon 50 000							+++
DD PT time & cor							-
DD PT time & fuel		++					
DD acc & cor				+++			
DD park & cor			++				++
DD park & fuel				+++			
Commuting trip characteristics							
Trip distance				---		--	
Trip time		+++			++		---
Exp. fuel	+					-	+++
Ntrips					+++		
Pattern1						+++	
Pattern2			+				+++
Pattern3				+++			
First trip time	---		---		+++	+++	+++
Pnocarwk				---			
PTnwacc	---	+++	+++				
First Nacco		-	++	---			
Passenger	---	--				+++	
Park_payment						++	++
Cardependency*car1	++		+++	---			
Cardependency*car2+	---						
Comfort*car1						++	
Comfort*car2+				++			
Poor_PT*car2+						-	+++
HH socio-economic characteristics							
D car own	---	+++					
Car acc.						--	++
Nmotorcycle	---			+++			
D home place		--					
Permit	---			+++			
Female			--		+++		+++
Age <30			++	+++		---	
Age 30_39					+++		
Age40_49		---					
Job_duration	++		-	+++		---	
Emp_full		---		---		+++	
Edu: BS	---			---		+++	
Edu: BS+	---		+++		+++	+++	+++
D child<=18		+++		+++	--		
ρ^2	0.19	0.70	0.85	0.78	0.91	0.24	0.88
$\bar{\rho}^2$	0.18	0.69	0.84	0.77	0.90	0.22	0.86
ρ^2_{MS}	0.05	0.56	0.76	0.61	0.82	0.11	0.81
H-L significance	0.158	0.208	0.063	0.32	0.059	0.079	0.052
Considered scenarios	555	133	58	115	40	459	44

Note: +++, ++, + = Positive significance at 1%, 5%, 10% level.
Note: ---, --, - = Negative significance at 1%, 5%, 10% level.

For a general review of the model calibration results the effective factors can be grouped under the following three categories: TDM measure characteristics, commuting trip characteristics and household socio-economic characteristics, which are all treated as alternative specific variables. Because the focus of this paper is on the relative role of TDM measures, the commuting trip and socio-economic characteristics are only presented in Table 5, and a detailed inspection was avoided.

Measures are classified according to their levels through a *dummy coding approach* in this study. Such decomposition allows the analysis of each measure in terms of its levels. Thus, the effect of each level of each measure can be determined. As previously noted, a positive sign of a measure in a model indicates that the measure affects the mode consideration. In assessing the Walk & Ride model, a public transit (PT) time reduction of 15 and 30 percent significantly attract the car-drivers to this mode. The parking cost measure also strongly encourages drivers to consider other non-car modes excluding Walk & Ride. Because the interpretation of negative signs is not meaningful in terms of *considering other non-car mode considerations*, this issue is avoided here.

Drive & Ride is a good alternative for car users in the case of transit access improvement, which is expected. By implementing both transit time reduction and fuel cost measures, this mode is also considered. In fact, a reduced time in the transit system or substituting a part of the trip with a trip in transit to avoid high fuel cost, causes drivers to consider this mode.

Taxi & Ride is the mode that may interest drivers who can access transit with a good level of service stations, which may be reason that they transfer their mode in the middle of their commute. By implementing both parking cost and cordon pricing measures drivers consider this mode, which may be reasonable given that cordon pricing and parking cost causes drivers not to enter the study area, and lack of parking in the stations, because of parking place shift to out of study area, causes them not to use their cars to access the stations.

Motorcycles have lower fuel consumption than cars; they also need less space to park, and such spaces are usually free for them. Thus, it is not surprising that the interaction of these two measures (i.e., parking cost and fuel cost) cause drivers to consider this mode. Furthermore, there is no restriction for this mode to enter the cordon. Thus, motorcycles are also an appropriate mode in the case of cordon pricing implementation, which is shown in the table, when this measure is accompanied by access improvement.

Drivers consider Drive & Taxi in the case of parking cost measure implementation. These drivers prefer to park their cars in the study area boundaries and continue on their trips by taxi. Cordon pricing is a good reason to use Tel-taxi for drivers. In fact, the amount that they will pay for the cordon entrance may be somewhat lower than cost of hiring a Tel-taxi. Thus, it is reasonable to consider this mode in such a case. Cordon pricing measures are also significant in considering Tel-taxi in the case of adding the parking cost measure.

Similar findings are also reported in some other studies. For example, transit time reduction only affects the people who are willing to consider Walk & Ride in Auckland, New Zealand [21], and affects the willingness to Drive & Ride in Bristol [15]. In addition, transit access time improvement increases willingness toward the Drive & Ride mode in Wellington [21].

It can be seen that the non-car modes are affected differently by the TDM measures. Thus, it is not possible to detect a measure as a dominant measure in changing the mode of car users to each of the other modes. In other words, different measures have different impacts on considering non-car modes. In the next sub-section, the details are examined further.

As mentioned earlier in this section, measures are decomposed into their levels by a dummy coding approach. In other words, different scenario levels are assumed to have different slopes in utility functions of the models. The more simple assumption is that the models are linear in their parameters, and to serve that purpose, a Wald-test can be introduced [23]. By using this test and chi-square distribution tables, the statistical difference of different coefficients of a measure in the utility function can be inspected. Table 6 shows the results of the Wald-test for the models with at least one measure variable with two significant levels. Walk & Ride and Taxi are the models that show this feature.

Table 6. Wald-test results for the models

Mode	H_0	Chi-square	Sig.	Result
Walk & Ride	$\beta_{park\ cost4000}$-$\beta_{park\ cost7000}\neq 0$	0.05	0.827	Accepted
	$\beta_{PT\ time15}$-$\beta_{PT\ time\ 30}\neq 0$	1.13	0.288	Accepted
Taxi	$\beta_{PT\ time15}$-$\beta_{PT\ time\ 30}\neq 0$	0.30	0.581	Accepted

The Wald-test results show that the nonlinearity assumption is accepted in these models. Therefore, developing models with dummy variables to reflect the TDM measures produce more precise results.

b) Marginal effects

To explore the effects each measure has on mode choice, the marginal effects approach can be adopted. Although the coefficients of the models' utility functions are important, and their interpretations show the drivers' behavior when facing one or more measures, the marginal effects of each measure may show the results of its implementation. A marginal effect may be defined as the average change in the probability of choosing Drive, resulting when a measure (such as 50 000 Rials cordon charge) is applied, compared to the status quo, where none of the measures is applied. Table 7 presents the marginal effects of the studied measures on mode choice. The results are shown in the form of trip percents transferred away from the car to the studied modes. It is worth noting that this table is fully compatible with Table 5, but the marginal effects more than 5% level of significance have been removed.

Table 7. Marginal effects of measures (percent)

Variables	Walk& Ride	Drive& Ride	Taxi& Ride	Motorcycle	Drive& Taxi	Taxi	Tel-taxi
D PT time 15	15.11§						
D PT time 30	21.40§						
D acc. time 25		5.00§					
D cordon 50 000							0.5*¤
DD park & fuel				0.96*¤			

Note: §, * = Significant at 1%, 5% level.
Note: ¤ = Effect is lower than 1%.

Interactions were all insignificant except when both parking cost and fuel cost measures were implemented simultaneously, which motivated less than 1% of people to choose motorcycles. According to Table 7, a decrease in transit time and improvement in the transit access have the greatest effects on the mode change of car users. In fact, pull measures that encourage people to consider transit mode usage show higher and more significant effects. As in binary modeling, which assists in distinguishing the effective variables in each mode consideration separately, push measures were not expected to be significant. In fact, these measures are only responsible for transferring individuals away from the Car mode and not for the attraction to specific mode. In contrast, pull measures are the ones that attract drivers to other modes, which appear more effective in this study.

About 15.1% of car users change to Walk & Ride, if the transit time is decreased by 15%. If this time were decreased two-fold (i.e., 30%), 21.4% of car users would change. Transit access improvement would encourage 5% of car users to choose Drive & Ride.

Therefore, to answer the first issue of this paper, pull measures have a significant role in attracting car users (who previously decided not to use cars due to push measures) to non-car modes.

c) The measures' contributions to mode change

The contribution of the measure variables to mode change is an issue assessed in this section. It is worth noting that the high values of goodness of fit indices in some of the models may depend on the imbalance in considerations (i.e., few or many) of the studied modes [24]. In this paper, the method based on the information-theoretic interpretation of ρ^2 is adopted to assess the contributions of the measure variables [25]. To find the range of such variables contributions, forward inclusion and backward exclusion methods are adopted. As a priori, one may expect the backward approach to provide the lower bound (since the variables remaining after the exclusion of the measure variables could be somewhat correlated with the excluded variables and hence assume some of the explanatory power of those variables) and the forward stepwise approach to provide the upper bound (since having only the measure variables in the model should allow them to carry some of the explanatory power of the excluded variables with which they are correlated) [6]. However, that was true in only four of the seven cases. Table 8 shows the results of this method. The first and second rows present the goodness of fit of the final (ρ^2_p) and market-share (ρ^2_{MS}) models. The third row shows the goodness of fit of the model with only measure variables in addition to constants by the forward inclusion approach. The fourth row shows the goodness of fit of the model without measure variables by the backward exclusion approach. The fifth and sixth rows present the goodness of fit improvements resulting from measure variables by forward and backward approaches, respectively.

Table 8. Contributions of TDM measure variables to the models' performances

Row	Index	Walk& Ride	Drive & Ride	Taxi & Ride	Motor cycle	Drive & Taxi	Taxi	Tel-Taxi
(1)	ρ^2	0.1920	0.7028	0.8490	0.7808	0.9082	0.2378	0.8754
(2)	ρ^2_{MS}	0.0456	0.5640	0.7614	0.6060	0.8207	0.1067	0.8070
(3)	ρ^2_{FW}	0.0726	0.5791	0.7666	0.6140	0.8278	0.1210	0.8141
(4)	ρ^2_{BW}	0.1662	0.6939	0.8452	0.7426	0.9033	0.2185	0.8593
(5)	$\Delta\rho^2_{FW}=\rho^2_{FW}-\rho^2_{MS}$	0.0271	0.0151	0.0052	0.0081	0.0071	0.0143	0.0071
(6)	$\Delta\rho^2_{BW}=\rho^2-\rho^2_{BW}$	0.0258	0.0089	0.0038	0.0382	0.0049	0.0192	0.0161
(7)	Lower bound (percent) *	13.57	1.27	0.45	4.90	0.54	8.01	1.83
(8)	Upper bound (percent) §	14.25	2.16	0.61	1.03	0.78	5.95	0.81

*: $100*(\Delta\rho^2_{BW})/(\rho^2)$, §: $100*(\Delta\rho^2_{FW})/(\rho^2)$

Contributions of the measure variables to the improvement of goodness of fit of models are derived by dividing such improvements by the goodness of fit of the final models. The seventh and eighth rows present the lower and upper bounds of these ranges for the models.

Table 8 shows that the contributions of the measure variables affects the choice of Walk & Ride by 14% and the Taxi between 6 and 8%, but no more than 5% for other modes. This result shows that the contributions of TDM measures to mode change are finite and different, in comparison to the large contributions of socio-economic and commute-related variables. In line with other studies, this indicates that there is a difference between policymakers' expectations and individuals' behavior [4, 6].

5. CONCLUSION

This study explores which measures are effective in prompting 288 individuals who regularly use their private cars to access their job location in the Tehran central area, to consider non-car modes. Five measures including increasing parking cost, increasing fuel cost, cordon pricing in the central part of the city, transit time reduction and transit access improvement are investigated, of which the former three were push and the latter two were pull measures. The design of experiments approach was used to design the questionnaire to capture the stated preferences of car commuters. The data for this study was collected from a seven-page survey which is a face to face interview in the respondents' work places.

Seven binary logit models are developed to access the mode choice of such individuals in response to the mentioned TDM measures. This study focuses on three transit modes accessed respectively by walk, drive and taxi, in addition to taxi accessed by either walk or drive, and taxi taken via telephone as alternatives of car commuting.

- The results show that for respondents who decide to change their mode, pull measures are significant in the models, whereas push measures are not. In fact, because these drivers have decided to change their modes, they have already been affected by push measures. It is worth noting that cordon pricing, which is conventionally defined as a push measure, has a different role in prompting commuters to consider the Tel-taxi mode. In fact, this measure acts as a pull measure only for this mode. Thus, it is not surprising that the results shows that pull measures are effective only in the related modes.
- The effective pull measures are significant when considering the modes that are related to those measures. For example, transit time reduction is significant in the Walk & Ride mode. This could indicate that push measures generate non-car mode trips, and pull measures distribute these trips toward the available alternative modes. One could say that push measures are *generic* in mode change and pull measures are *alternative-specific*.
- In this study, the dummy coding approach is used to capture the effect of each measure level, and this is verified by the Wald-test. The study shows that transit time reduction by 15% leads to a 15.1% mode change to transit. Furthermore, if the reduction reaches 30%, then 21.4% of drivers change their modes to Walk & Ride.
- This study shows that, except for Taxi and Walk & Ride, the contributions of TDM measures are negligible to changing car use to other modes. This confirms the above-mentioned gap between the policymakers' aims and the individuals’ behavior.
- Future studies should explore the reasons for mode change, especially for the investigated modes. Additionally, it is reasonable to assess these models in a multinomial form to study the interactions of the modes in addition to the interactions of the measures. Such an approach is a method of determining the effects of push measures to generate non-car trips.

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