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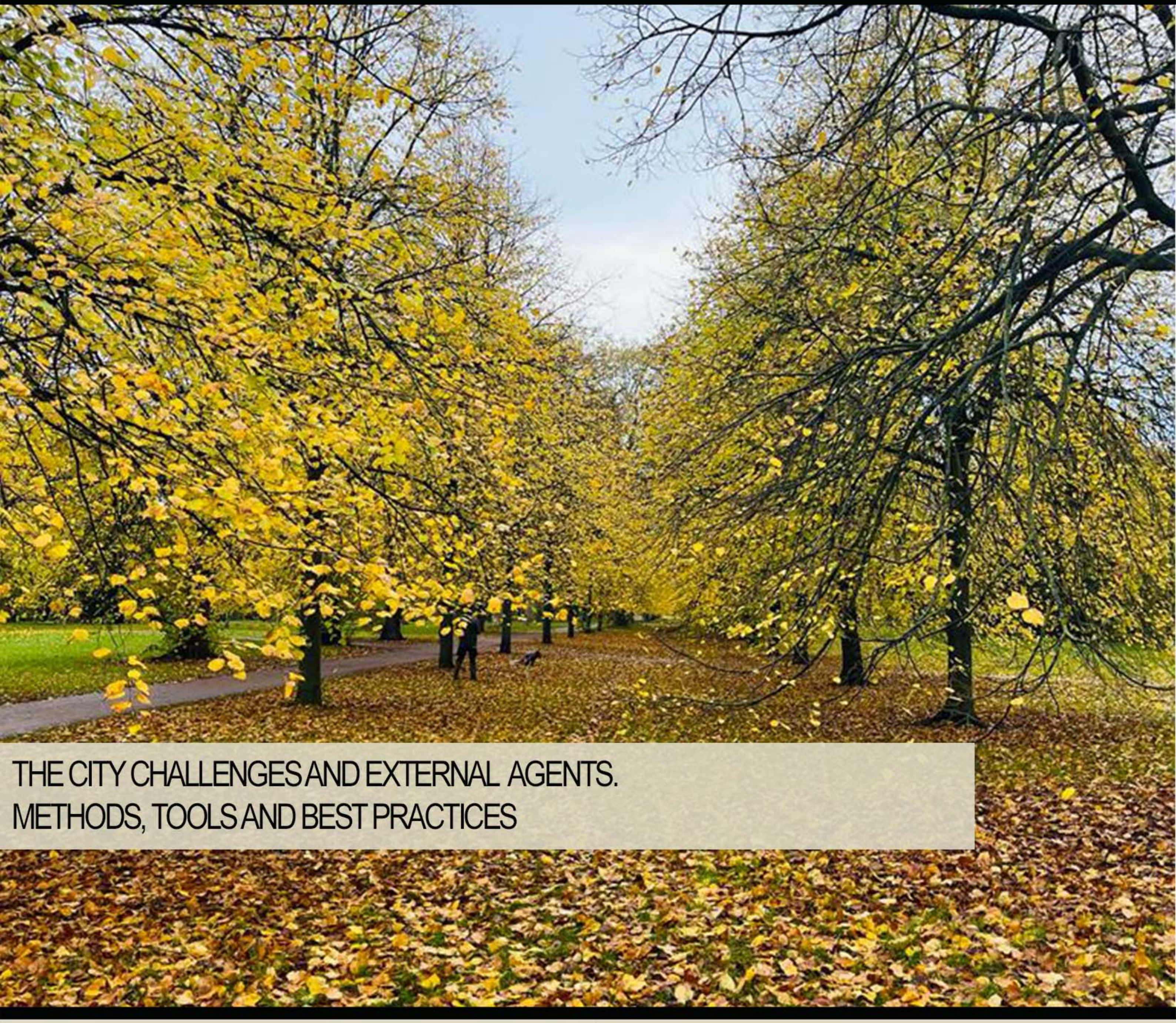

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METHODS, TOOLS AND BEST PRACTICES

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The cover image shows a view of Hyde Park in London (United Kingdom) during the autumn season.
The photo was taken by Enrica Papa in November 2023.

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Duration-based or time-based congestion toll pricing?

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Abstract

Pricing and traffic rationing have emerged as effective and economically feasible strategies for mitigating traffic congestion in the central business districts of large cities. In Tehran, Iran's capital city, two separate surveys were conducted to evaluate the effects of time- and duration-based pricing strategies. The surveys included 1,388 participants from the congestion pricing zone (CBD) and 983 participants from the odd-even traffic rationing zone. The error component logit model was calibrated using stated preference (SP) scenarios for both the congestion pricing zone and the odd-even traffic zone; These models aimed to analyze modal shift, route choice, and time of travel in a day. Additionally, the mode choice behavior in the CBD was examined using the generalized mixed logit (GMXL) model, which was calibrated using both SPs and RPs. The findings indicate that implementing a duration-based scenario would result in a modal shift, changes in trip patterns, and even trip cancellations. On the other hand, the time-based scenario would primarily lead to changes in travel timing or destination choices. GMXL results show that duration-based pricing is more effective in shifting private vehicle trips to other modes. Furthermore, on-demand ride-hailing is less significant as a competitor mode within these zones.

Keywords

Congestion pricing; Odd-even scheme; Travel behavior; Mode choice; Generalized mixed logit model; Error component logit model.

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1. Introduction

Surcharging private car users is the most straightforward and fastest controlling measure to curb the effects of traffic congestion. Cordon congestion charging around the central business district (CBD) area is one method of surcharging private car users implemented in some cities in recent decades, such as Stockholm, London, Singapore, and Tehran. Global experiences suggest that congestion charging permanently changes travel behavior and positively contributes to the growth of public and shared transport modes (Milenković et al., 2019) and the health benefits of increased physical activities (Brown et al., 2015).
Like many major cities, Tehran, the capital city in Iran, has encountered challenges due to population growth, social development, and urban expansion. These challenges have led to increased traffic congestion, reduced travel speed, and problems with noise and air pollution. As a response to these issues, Tehran has executed a traffic congestion charging system for entering certain areas of the city during particular hours (Saffarzadeh et al., 2021; Bakhshi Lomer et al., 2023). In addition, A significant number of people who live in the suburbs of Tehran travel to the city center for work every day and return home in the evening, which leads to a greater population in Tehran during the day compared to at night. This results in over 15 million daily commuters (Jozdani et al., 2013; Rezaei et al., 2023; Mamdoohi et al., 2022). Tehran was the first developing country to use a traffic congestion zone in the central business district; The implementation of the congestion pricing scheme in Tehran started in 1980. since then, the entry of private cars to the central business district has been limited, and only drivers with permits have had access to the area. This policy was in place for almost 40 years and in 2010, the enforcement for this restriction was improved by the Automatic Number Plate Recognition (ANPR) technology. The Tehran Traffic Control Company (TTCC) has reported that as a result of this policy, the city has seen a reduction in congestion and air pollution due to decreased private car usage (Vossoughi & Aminzadeh, 2021; Siddique & Choudhury, 2017).
Despite notable investments in expanding and improving public and active transport systems, the central business district of Tehran still encounters traffic congestion, air and noise pollution, and delays. Additionally, there is a considerable number of annual permit requests from which only a few percentages are issued every year. In the quest to provide a more equitable and effective scheme, city managers seek to modify the congestion pricing scheme. Hence, this study investigates the travel behaviors under time-based and duration-based methods with variable fee scenario. Accordingly, in these hypothetical scenarios, the user is charged based on the number of hours spending in the pricing zone, and the charging fee is cheaper if the trip starts during non-peak hours.
This paper concerns Tehran's congestion charging scheme and examines the trip behavior changes after changing the schemes from a flat-based to a time-based and duration-based method. This study differs from previous studies because it compares the effectiveness of time-based and duration-based congestion pricing schemes. This paper also concerns the trip behavioral changes of users who have already been accustomed to the congestion-controlling regimes for many years. Furthermore, Tehran is one of the few cities in the world where two cordon-based congestion-controlling regimes are in place. The smaller CBD area has a flat-based charging scheme, and another outer cordon restricts traffic access for vehicles with license plate numbers ending in certain digits or a so-called odd-even rationing scheme. The CBD congestion charging scheme issues daily, weekly, and annual permits where permit holders can commute in or out of the zone in unlimited daily journeys. An odd-even rationing scheme is in place in many capital cities of developing countries, such as Delhi, Jakarta, and Mexico City, as a low-cost and easy enforcement traffic control measure. In Tehran, these two cordons have been automatically controlled by automatic number plate recognition (ANPR) cameras since 2014, and manual enforcement is only applied on ad-hoc bases and as a complementary checking method where the non-permit plate numbers are blocked intentionally. Hence, implementing a variable charge is now easily doable. Furthermore, the persistent problem of traffic congestion in the CBD motivated the city managers to revise these two congestions rationing schemes more efficiently.

Two scenarios were considered for the revised CBD congestion charging scheme: time- and duration-based. In a time-based scheme, the private cars are charged based on the time of the day entering and exiting the charging zone if it happens during peak or off-peak hours.

In the duration-based scheme, private car users are also charged based on the number of hours spent in the zone and the fixed price of entrance, which varies between peak and off-peak hours. However, only a duration-based scenario was considered for the odd-even rationing scheme due to the land use dominated by office businesses.

Tehran City Council conducted two sets of paper-based surveys in 2018, separately for each traffic rationing scheme. The CBD congestion pricing questionnaire targeted all transport mode users, whereas the odd-even questionnaire only targeted private car users. Each set of surveys consisted of three different paper-based forms with varying prices of permits designed by the fractional factorial design method. First, the interviewee's current trip specifications, such as departure time, duration, transport mode, origin, and destination, were asked. According to the trip specifications, the interviewer calculated and presented the price for the same trip's hypothetical pricing scenario (e.g., time-based or duration-based).

Then the interviewee was asked to choose among various alternatives as follows: (i) no change; (ii) changing entry time; (iii) changing exit time; (iv) changing the destination; (v) canceling the trip; (vi) shifting the trip to the weekend, and (vii) modal shift. If a modal shift had been selected, the alternative transport mode was asked in the following question: private car, public transport, pooled taxi, Snap (a shared-economy ride-hailing transport mode in Iran), and motorcycle.

Using this dataset, we first apply the error component logit model to explore the travel behavior changes as a result of time-based and duration-based schemes. Accordingly, the effects of pricing on route and mode shift, departure time, and trip cancellation are investigated. The error component logit (EClogit) model is used for this purpose where the latent error component effects and the non-IID part are associated with the unobserved variance nests (see, e.g., Guo et al., 2018).

Furthermore, this paper combines SP and RP data of CBD pricing users to investigate the mode choice, considering the scale and taste heterogeneity. While the previous studies used the nested logit (NL) model for combining SP and RP data (Hensher et al., 2008; Dissanayake & Morikawa, 2001), this study applies the generalized mixed logit model (GMXL), proposed by Greene and Hensher (2010), to account for unobservable scale and taste heterogeneity and the correlations among alternatives and preferences in SP and RP data. Scale heterogeneity is defined as variation through decision-makers in the impact of factors not included in the model relative to the effects of included factors (Hess & Train, 2017).

Notably, in the presence of scale heterogeneity in the data, GMXL models result in slightly better goodness of fit and more robust estimation of willingness to pay (WTP) (Hensher & Greene, 2011; Hensher et al., 2015; Kragt, 2013).

The paper's organization is as follows. Section 2 describes the methodology and survey data. Section 3 presents the model results, and finally, section 4 concludes the study.

2. Literature Review

A brief analysis of the literature indicates that the Congestion charging is a well-studied area in the transportation literature. Focusing on the public acceptance, (Milenković et al., 2019) indicated that various factors, such as socio-demographic characteristics, movement patterns, perception of traffic issues, familiarity with congestion pricing, preferences for pricing policies and revenue allocation, affect the acceptability of congestion pricing. In another study, (Janusch et al., 2020) conducted a laboratory experiment using heterogeneous users to explore the effectiveness and acceptability of a toll in a six-player-two-route congestion game. The results obtained from this study show that congestion pricing policy effectively reduces congestion; this study also collected data on worldviews and beliefs to understand how experience influences public acceptability. More recently, (Abulibdeh, 2022) conducted a study that examined the public acceptability of two congestion pricing strategies, namely high-occupancy toll (HOT) lanes and cordon pricing in Abu Dhabi city, United Arab Emirates (UAE); The study found that trip conditions, demographics, and toll fees affect the public acceptability of HOT lanes, while income, age, employment, car ownership, and travel time savings influence the acceptability of cordon pricing. Furthermore, previous studies suggest that the public acceptability of congestion charging depends on various factors, including the complexity of the charging scheme (Gu et al., 2018; Grisolía et al., 2015). Link (2015) suggests that charge complexity decreases people's resistance to considering trip behavioral changes.

Several researchers have explored the impact of congestion pricing on equity and welfare implications. Using data from the Household Travel Survey in South East Queensland, Australia, (Sen et al., 2022) investigated the equity and welfare implications of a hypothetical usage-based road pricing scheme. The results revealed that such a scheme would lead to both horizontal and vertical inequities, disproportionately affecting disadvantaged commuters. In another research study (Feldman et al., 2022), congestion pricing led to a more than 4% increase in consumer and social welfare. Additionally, it significantly reduced search traffic by over 10% in congested regions compared to fixed pricing. A Natural Experiment conducted in Beijing provided evidence that implementing road pricing would result in an 11 percent increase in traffic speed within the city center. This would lead to an annual welfare gain of ¥1.5 billion due to reduced congestion, along with revenue of andn (Yang et al., 2020).

Congestion pricing effectively may reduce air pollution by discouraging unnecessary trips and promoting alternative transportation modes, thereby improving air quality and public health (Kazemi Garajeh et al., 2023). According to a study conducted by (Simeonova et al., 2021) in Stockholm, implementing a congestion pricing policy showed significant results in reducing ambient air pollution by 5-15 percent. Additionally, the study found a corresponding decrease in the rate of acute asthma attacks among young children. Reliability is a important subject in the literature, as it significantly impacts how congestion pricing affects various types of travelers. The valuation of reliability by network users plays a vital role in determining the effectiveness and outcomes of congestion pricing strategies (Fakhrmoosavi et al., 2021).

While congestion pricing policies may have advantages, it is important to acknowledge that some researchers have identified negative impacts. Experiences from cities that have implemented road congestion pricing policies provide evidence that this approach may adversely affect regional land use systems. Specifically, it has been observed that such policies can lead to a decrease in regional accessibility and a reduction in the diversity of land use patterns (see, e.g; Zhong et al., 2021; Tillema et al., 2010; Sarker et al., 2023). For instance, a study by (Zhong & Bushell, 2013) highlighted that the implementation of road pricing can potentially reduce job accessibility in the periphery area of the toll ring. More recently, (Chen et al., 2022) revealed that the implementing charging mode policy in congestion pricing can have unintended consequences, such as a rebound effect resulting in increased vehicle trips. This finding emphasizes the importance of carefully considering potential side effects when designing and implementing congestion pricing measures.

In the literature, congestion pricing policies have been extensively studied in terms of their feasibility and political considerations (Özgenel & Günay, 2017; Manville & King, 2013). Political feasibility is the main obstacle to achieving ecological sustainability in transportation. Effective policies often face strong public opposition as they disrupt people's daily lives, creating a dilemma between political feasibility and environmental effectiveness (Wicki et al., 2019; Soltaninejad et al., 2021). While congestion pricing is widely recognized as the most efficient approach to address urban congestion, its implementation remains limited worldwide. Numerous attempts have encountered failure, often attributed to various factors, with the lack of public and political support being the most commonly cited obstacle (Krabbenborg et al., 2021).

The implications of congestion charging in travel behavior have also been examined in terms of mode choice (Li & Lu, 2019; Abulibdeh & Zaidan, 2018; Yamamoto et al., 2000; Whitehead et al., 2014; Bakkar & Charisma, 2017), departure time and route choice behavior (Hasnine et al., 2019; Ramos & Cantillo, (2017), where congestion charging was still non-existent, and a hypothetical flat pricing scheme was assumed. Notably, these studies were limited to state preference (SP) data. Only a few studies examined the mode shift behavior due to congestion pricing using revealed preference (RP) data (Brownstone et al., 2003; Ghosh, 2001). Since decisions may differ in hypothetical and actual situations, SP data may not entirely reveal the traveler's actual behavior (Hensher et al., 1998). The overall response scale may be distorted (Börjesson, 2008). Hypothetical bias in stated choice (SC) experiments has been frequently investigated in the literature (e.g., Ben-Akiva et al., 1992). Previous studies have examined further evidence of hypothetical bias as well as status quo bias in transport choices (see e.g., Fifer et al., 2014), or so-called asymmetric preferences for a policy before and after implementation, which is caused by loss aversion or cognitive dissonance (see e.g., Börjesson et al., 2016). One of the advantages of combining SP and RP data is reducing hypothetical bias (Hensher, 2010; Whitehead & Lew, 2019), maximizing benefits from contradictory strengths of RP and SP data, and minimizing their weaknesses (Brownstone et al., 2000).

Evaluation of different charging schemes is imperative even after the scheme implementation. Public attitudes to congestion pricing could also gradually change depending on the system characteristics (Zhang et al., 2016). For example, the general attitudes towards congestion charging in Stockholm became gradually more negative than the scheme's start (Eliasson, 2014). Additionally, new challenges may arise as a result of trip behavior changes. For example, the peak traffic period may shift before or after the charging period in a flat-based charging scheme (Ge et al., 2016). Rouhani (2018) concluded that a flat daily charge could decrease the system efficiency even in an off-peak hour and that time-varying charging schemes could be applied as an alternative mitigation strategy. Time-varying charging scenarios are deemed more suitable due to the time-dependent nature of traffic flow and the dynamics of travelers' departure time decisions.

There are three main types of congestion pricing schemes: (i) time-distance and/or distance-based pricing, (ii) cordon pricing and (iii) zonal pricing. The first approach adjusts charges based on either the distance travelled or time of day or a combination of both. In the second approach—cordon pricing – the vehicle is charged every time that passes a boundary into and out of a charged zone. In the third approach – the zonal system – drivers can make unlimited trips into and within the zone with a fixed (flat) fee. Pricing schemes are carried out in three ways: (i) flat, (ii) variable (time of day), and (iii) responsive modes (de Palma & Lindsey 2011, Nohekhan et al., 2021). It hardly can be said which method suits better, since the effectiveness of each method is various among different cases (Ecola & Light 2009; Bakhtiari et al., 2023).

The overview above indicated that earlier studies have contributed to our understanding of congestion pricing impacts on travel behavior and mode choice, yet there remain some unanswered research questions. First, it is unclear how much different pricing schemes can affect travel behaviors including modal choices, and there has been little discussion directed to the examination of hourly-based versus flat pricing scheme. Second, it is important to investigate the determinants of modal choice as a result of changes in pricing and also to assess how much the demand for private cars is elastic with respect to the pricing fee. Third, it is likely that the effects of pricing in cities differ, particularly cities with high levels of congestion and car dominance like Tehran. Thus, undertaking analysis is important for different cities. Finally, the majority of studies have examined the impact of pricing before the implementation phase. Considering that in our study, the participants have a better understanding of the associated costs and benefits of purchasing the permit and using private vehicle, the research efforts in this stage are essential.

3. Methodology

This section presents the study area, data, formulation and more description regarding the methodology in the following subsections.

3.1 Study area

Fig.1 presents two management schemes that are in place in Tehran's downtown intending to reduce air pollution and private car usage. The congestion pricing and odd-even zones are about 32 and 88 square kilometers, respectively (4.1% and 11.3% of the total area of Tehran city, respectively).

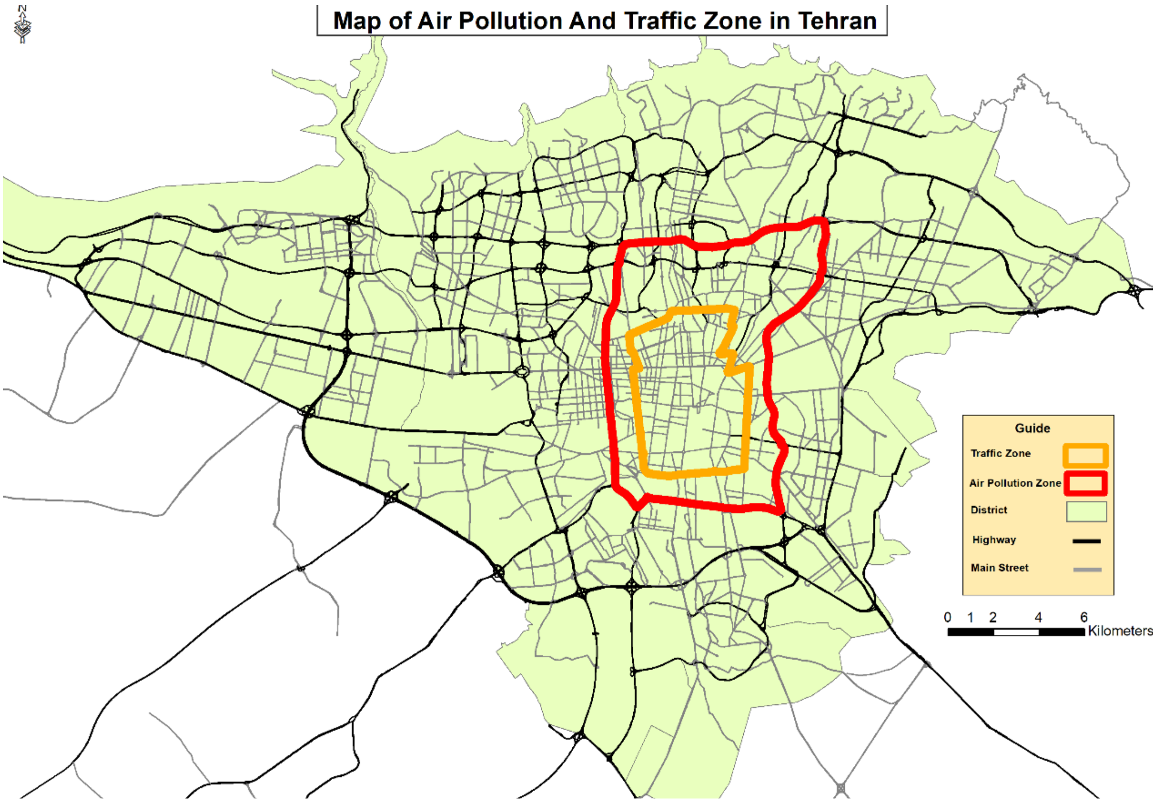

Fig.1 Traffic zone (congestion pricing area) and air pollution zone (odd-even area) in Tehran

Fig.2 presents some additional information according to the Tehran Municipality Urban Planning & Research Center (2019). As shown in Fig.2, while these areas constitute only 4.1% and 11.3% of the total area of Tehran city, they accommodate a wide variety of work and business units.

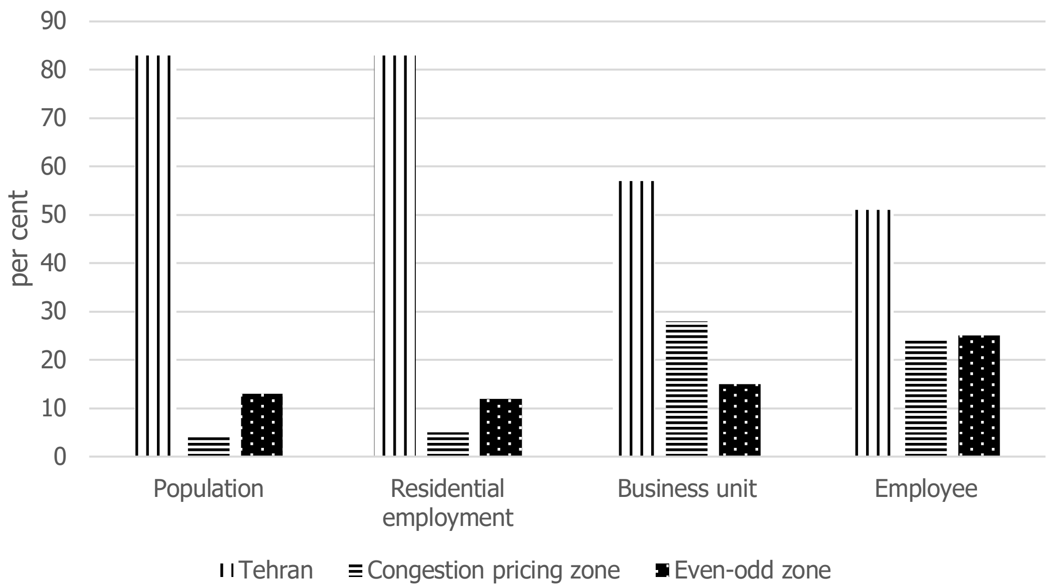

Fig.2 The share of the population, residential employment, business unit, and employee in traffic rationing zones

2.2 Data

We used two separate datasets collected in 2018 for each scheme by Tehran City Council. These two datasets present different sets of individuals. The CBD pricing survey had targeted the multi-modal travelers to this zone, while the odd-even rationing survey only targeted private car users who were observed in the odd-even zone. The CBD survey data consists of 1,388 complete records, while the odd-even survey data contains 983 complete records. The sample characteristics are presented in the Appendix. The questionnaires consist of three primary sections: (i) participants' travel specifications for the very trip to the schemes; (ii) SP choice experiments; and (iii) socio-demographic characteristics of travelers.

To ensure the robustness of data and the developed models, it was vital that we first understand the survey and data collection methods, which are summarized in the following paragraphs. The CBD pricing questionnaire considered two pricing scenarios: time-based and duration-based pricing strategies. In the duration-based scenario, a user is charged two different fees for entering the zone in peak or off-peak, as well as an additional variable fee based on the duration of presence in the zone. Whereas the duration of presence does not matter in the time-based scenario, and the users are charged based on the time of entry and exit in the zone. Notably, they will be charged more during peak hours (6-10 AM and 4-7 PM).

The price ranges in SP experiments had been identified through a prior economic study undertaken by Tehran City Council. The SP experiments were also designed using a fractional factorial design method, and the price levels were evaluated and adjusted after a pilot survey. Tab.1 presents the price levels in both surveys.

Due to the complexity of these new pricing scenarios, the team conducted a multi-step survey. First, the specifications of the current trip of the interviewee had been asked, such as departure time, duration, transport mode, origin and destination. According to the trip specifications, the interviewer calculated and presented the trip's price for the hypothetical pricing scenario (e.g., time-based or duration-based). Then the interviewee was asked to choose among various alternatives as follows: (i) no change (ii) changing entry time, (iii) changing exit time (iv) changing the destination; (v) canceling the trip (vi) shifting the trip to weekend and (vii) modal shift. If a modal shift had been selected, the alternative transport mode was asked in the next question including private car, public transport, pooled taxi, Snap (a shared-economy ride-hailing transport mode in Iran), and motorcycle. Since the odd-even survey only included car users, the private car alternative was dropped from this survey. The odd-even survey focused on car users, and some respondents selected 'no change in trip,' indicating their intention to continue traveling by private car in the SP scenario. Notably, the odd-even survey only considered a time-based pricing scenario. It is mainly because the land uses in the odd-even zone are dominated by business offices, and imposing a fee for the duration of stay will not appeal to the workers and employees who may stay in the zone during working hours. Whereas the CBD pricing zone mainly consists of commercial, market, shopping, and public office land uses. In this regard, the interaction between land use and congestion and odd-even zones would be important in viewpoint of CBD and odd-even zones questionnaires.

CBD zone questionnaire		**Odd-even zone questionnaire**
Time-based scenario	**Duration-based scenario**	**Time-based scenario**
Entry and exit in off-peak: 10, 15	Entry in peak: 15	Entry and exit in off-peak: 4, 7.5, 10
One in peak & another in off-peak: 20, 28	Entry in off-peak: 10	One in peak & another in off-peak: 5.5, 10, 14
Both entry and exit in peak: 36, 45	Hourly fee: 2, 3, 4	Both entry and exit in peak: 7.5, 15, 21.5

Tab.1 Price levels in SP experiments (‘000 Iranian Toman)

The CBD pricing dataset includes 1,388 individuals and 8,328 observations due to each participant's response to three price levels in the duration-based scenario, and two price levels in the time-based approach in addition to the observed transport mode (RP). The odd-even dataset includes 983 individuals and 2,949 observations related to three price levels in the time-based scenario.

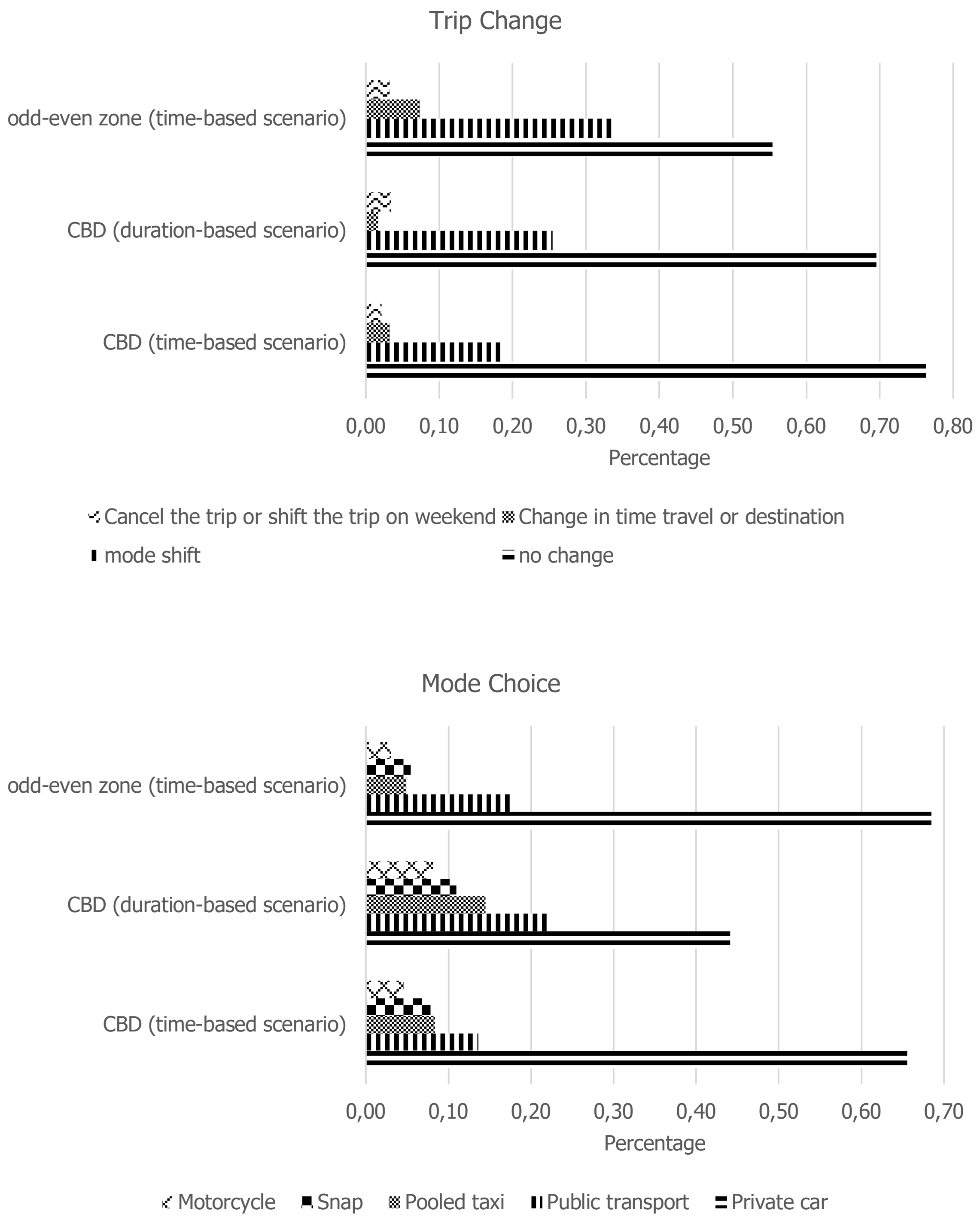

Fig.3 The share of different alternatives in price scenarios in odd-even and congestion pricing areas

EMME/2, a multi-mode urban transportation forecasting system, is being used to evaluate the effectiveness of TDM policies. This system has been calibrated and is currently being used to model Tehran's long-range transportation plans. The demand prediction process includes steps such as trip generation, trip distribution, mode choice forecasting, and freight transportation. The outcome is travel demand in the form of a PCE (passenger-car-equivalent), with public transport vehicles assigned to both the auto and public transport networks. EMME/2 combines an aggregate demand model with equilibrium-type road assignment and transit assignment methods, providing a comprehensive analysis for transportation planning (Baghestani et al., 2023; TCTTS, 2000; Dueker et al., 1985; Mamdoohi & Zarei, 2016). We utilized Tehran's Strategic Multimodal Transport model to calculate some variables related to travel characteristics, including travel distance, travel time between origins and destinations, and car ownership per capita in the origin district.

Fig.3 illustrates the trip changes and mode choices in both surveys. Of these alternatives, since the odd-even sample only includes car users, we witness more intention toward trip changes compared to CBD pricing scenarios. Our sample also suggests that, on average, more travelers intend to change their trip specifications in the duration-based scenarios (31%), compared to the time-based scenario (24%). Also, the percentage of mode shifts increased from 18% in time-based scenarios to roughly a quarter in duration-based scenarios.

The mode choice of odd-even private car users suggests a modal shift from the private car towards other modes, particularly the public transport mode. This data also indicates that the private car share in the congestion pricing area slid away from about 65% in the time-based scenario to around 44% in the duration-based scenario. Meanwhile, the public transport share steadily rose from nearly 13% in the time-based scenarios to over 22% in the duration-based scenarios.

2.3 Formulation

Travel choices were estimated under the assumption that decision-makers were utility maximizers, and there exists a correlation between the RP and SP choice alternatives as well as unobserved heterogeneity across choices. Hence, we employed random error component models to accommodate these assumptions. The utility of travel choice j for decision-maker n in choice task k is expressed as the sum of the observed portion Vnk,j and the unobserved (random) portion of utility ηn,j, as follows (Train, 2009; Greene & Hensher, 2015; Titiloye et al., 2023):

$$U_{nk,j} = V_{nk,j} + \eta_{n,j} = \beta'_{ni} X_{nk,j} + \omega \aleph_{ib} \kappa_{n,j} + \varepsilon_{nk,j} \tag{1}$$

Where βni is the vector of coefficients; Xnk,j is a vector of observed variables relating to alternative j in choice task k for individual n; ω is a vector of random terms with zero mean; and κn,j is error components that, along with εnk,j, defines the stochastic portion of utility and can be correlated over alternatives; and $\aleph_{ib}$ It is a dummy variable, one if i is located in nest b, and otherwise, it is equal to zero.

We also tested a scale heterogeneity across choices based upon the generalized mixed logit model specification. The preceding is then modified as follows (Greene & Hensher, 2010; Rezaei et al., 2021):

$$U_{nk,j} = \beta'_{ni} X_{nk,j} + \varepsilon_{nk,j} = [\sigma_n(\beta + \Delta Z_n) + (\gamma + (1-\gamma)\sigma_n)\Gamma \nu_n] X_{nk,j} + \varepsilon_{nk,j} \tag{2}$$

Where β is a vector of constant parameters; Zn is a set of M characteristics of individual n that influence the mean of the taste parameters; ν_n is a vector of L random variables with zero means, unit variances, and zero covariances; Δ is the L×M matrix of parameters, and Γ is the nonzero elements of the lower triangular Cholesky matrix. The scale of the error term is denoted by σ_n for individual n, which is specified as $\sigma_n = exp\,[\bar{\sigma} + \delta' h_n + \tau \mu_n]$, and explains the individual specific standard deviation of the idiosyncratic error term. Parameter $\bar{\sigma}$ in the scale term denotes the mean parameter in the error variance; δ′ is the parameter in the observed heterogeneity; hn is a set of characteristics of individual n that may overlap with Zn; τ is the coefficient on the unobserved scale heterogeneity; μ_n is the unobserved individual heterogeneity in scale and μ_n~N(0,1). The parameter γ is a weighting parameter that indicates how the variance of residual heterogeneity varies with scale ($\gamma \in [0,1]$). To estimate the GMXL, we assume σ_n is normalized as $\bar{\sigma} = -\frac{\tau^2}{2}$ so $\sigma_n = exp\,[-\frac{\tau^2}{2} + \delta' h_n +$

$\tau\mu_n]$. In order to control the variation in σ_n during the simulation, the normal distribution of μ_n is truncated at -1.96 and +1.96 (Greene & Hensher, 2010).
The decision-maker chooses alternative i in choice task k if and only if Unk,i > Unk,j ∀ j ≠ i. The probability of choosing travel choice i is calculated as:

$$P(i|x_{nk}, \beta_{ni}) = \frac{\exp(U_{nk,i})}{\sum_j \exp(U_{nk,j})} \tag{3}$$

The simulated log-likelihood function is calculated as follows (Greene & Hensher, 2010; Saffarzadeh et al., 2022):

$$Log\ L = \sum_{n=1}^{N} log\left\{\frac{1}{R}\sum\nolimits_{r=1}^{R}\prod\nolimits_{k=1}^{K_n}\prod\nolimits_{i=1}^{I_{nk}} P(i|x_{nk}, \beta_{nr})^{d_{nk,i}}\right\} \tag{4}$$

where $\beta_{nr} = \sigma_{nr}(\beta + \Delta Z_n) + (\gamma + (1-\gamma)\sigma_{nr})\Gamma\nu_{nr}$, $\sigma_{nr} = exp\,[\bar{\sigma} + \delta' h_n + \tau\mu_{nr}]$; dnk,i is one if individual n makes a choice i in choice task k and zero otherwise; μ_{nr} and ν_{nr} is the r simulated draws on μ_n and ν_n. Fig.4 represents the model structure. Model specification of the trip change involved three nests for both datasets, including no change, modal shift, and trip alteration, and each nest consists of several alternatives.

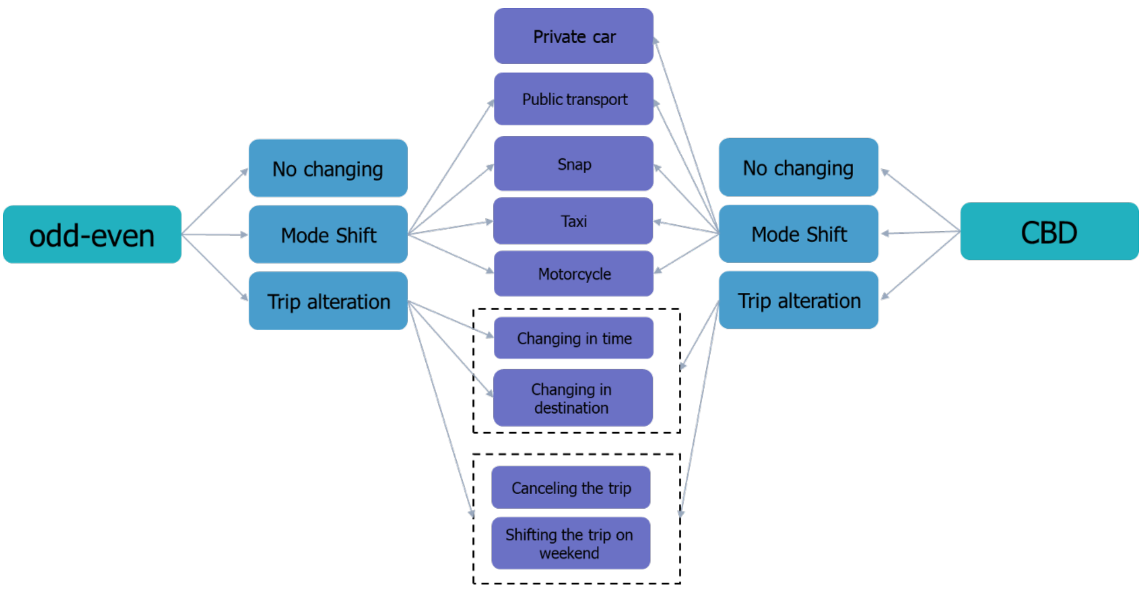

Fig.4 Model structure

3. Results

The modeling results reveal several significant findings. Firstly, pricing has a notable influence on the demand for private car vehicles. Secondly, pricing also affects travel behavior in various ways, including mode shift, trip modifications such as changes in destination or even trip cancellations. These behavioral changes highlight the sensitivity of travelers to pricing adjustments. Thirdly, the impact of pricing varies depending on the purpose of the trip. Different trip purposes, such as commuting or leisure activities, can be influenced differently by pricing strategies. Furthermore, accessibility to public transport plays a crucial role in decision making process (Sarker et al., 2023); Higher accessibility to public transportation options can mitigate the negative effects of pricing changes by providing travelers with viable alternatives to private vehicles. Additionally, the modeling results shed light on the distinct effects of time-based and duration-based pricing strategies on travel behavior. The results reveal that duration and time-based schemes implies a significant decrease in private car use in both CBD and odd-even pricing zones. Fig.5 depicts the impacts of pricing on travel behavior of the odd-even private car users. As is presented, the rate of car users deciding to use other modes will increase. This rate soars to just beyond half in 21,500 Toman from 14% in 4,000 Toman. Similarly, the percentage of trip alteration alternative rises gradually from 5 percent in 4,000 Toman to nearly 20% in 21,500 Toman.

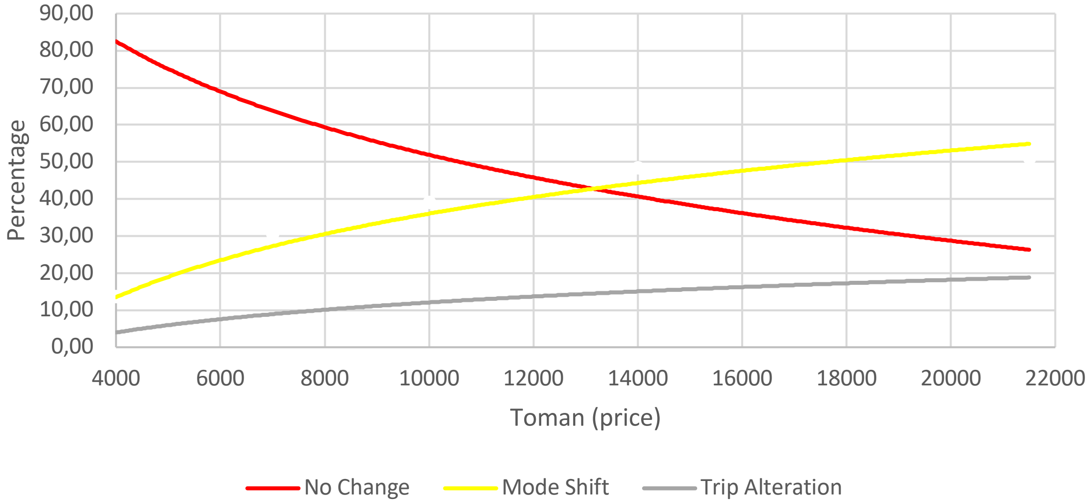

Fig.5 Observed sensitivity of travel behavior changes concerning pricing fees in the odd-even dataset

Fig. provides comparative data on the time and duration-based scenario for the CBD pricing zone, suggesting that the share of private cars decreases and demand shifts to other options. Interestingly, our sample indicates that both duration-based and time-based scenarios result in slightly similar trip changes. Also, the most significant deviation of demand is more likely towards public transport; this deviation is more significant in the time-based scenario than in the duration-based scenario. Moreover, this data suggests that Snap is the less essential competitor since the increase in mode shift to snap is less than other transport modes in both scenarios.

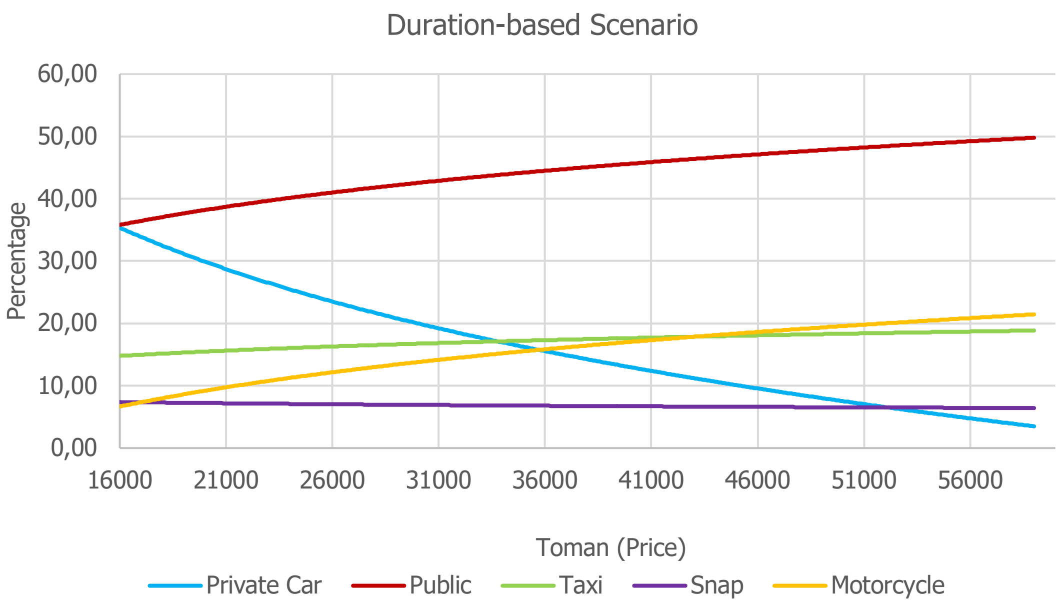

Fig.6 Observed sensitivity of modal shift concerning pricing fee in CBD dataset (Duration-based scenario)

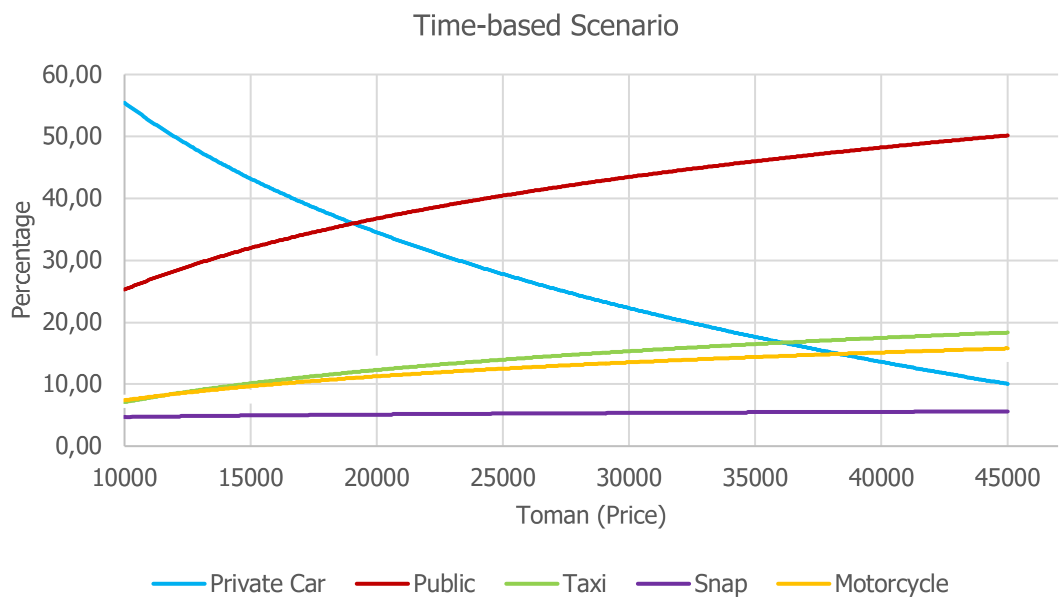

Fig.7 Observed sensitivity of modal shift concerning pricing fee in CBD dataset (Time-based Scenario)

3.1 Changes in trip specifications to CBD and Odd-even Pricing Zone (SP data) – an error component model

Tab.2 and Tab.3 present the best model specifications are resulting from the random error component model for both CBD and odd-even sample data. All the observed variables were tested stepwise and remained in the model if they were statistically significant at 10%. We tested several types of error components throughout the modeling exercise. Regarding the error component, a negligible difference across the nests was revealed in both models of CBD and odd-even data.

Interestingly, the estimates show that all three alternative-specific error components in both models of CBD and Odd-even schemes are statistically significant, suggesting unobserved heterogeneity. The estimates of the binary variables of time-based and duration-based pricing scenarios in the CBD modal suggest that the duration-based scenario will more likely lead to modal shift or trip alteration and trip cancellation, while the time-based scenario will more likely lead to only a change in the time of travel or destination.

Expectedly, the estimates indicate that with the increase in pricing fee, individuals are more likely to change their travel behavior either as a modal shift or trip alteration and are unlikely to opt for private cars. Since the odd-even dataset is only restricted to the current private car drivers, the pricing fee is doomed to be more effective than in the CBD model.

The estimates of the CBD model show that if the trip ends at off-peak, the probability of modal shift to motorcycle increases, while if the start of the trip is at peak hours, the probability of mode shift to Snap and pooled taxi increases.

With respect to the purpose of a trip, individuals with work trip purposes are less likely to change their trip to the CBD pricing zone. Expectedly, those individuals with educational trip purposes are less likely to change the time or destination of their trips, while are more likely to pot for public transportation. Interestingly, those with a medical trip purpose are more likely to shift their transport mode and opt for Snap.

The estimates of the odd-even model also indicate that individuals with personal trip purposes are unlikely to change their trip.

The results show that as the number of entries to the CBD zone per day increases, the introduction of new pricing scheme leads to a modal shift to the public transport alternative. However, it is the opposite in odd-even model so that the individuals with higher number of entries to odd-even zone are unlikely to switch their transport mode from cars to public transport, pooled taxi and Snap. This contradiction may stem from the fact that the sample in the odd-even zone is limited to private car users and has lower public transport accessibility in this zone. Looking at the odd-even model, as car ownership per capita in the origin district increases, individuals are less likely to make any changes in their trip to odd-even zone.

The results also suggested that owning a car would less likely lead to changes in the destination or route. However, the individual's car ownership variable was not statistically significant in the CBD model, perhaps due to better public transport coverage and service in the CBD area.

		Mode shift					**Trip change**	
Alternatives	**No change**	**Private car**	**Public transport**	**Pooled Taxi**	**Snap**	**Motorcycle**	**Change in time of travel or destination**	**Trip cancelation or shift the trip to weekend**
Mean value of constant		-8.385 (-12.26)	-5.391 (-8.89)	-5.754 (-9.29)	-5.371 (-8.81)	-7.363 (-11.84)	-11.344 (-11.02)	-10.602 (-10.71)
Error component parameter	4.323 (14.25)			5.562 (16.40)				-6.511 (-13.04)
Pricing characteristics								
β_{TCost}	-0.941 (-6.44)							
β_{DCost}							1.995 (9.85)	
β_{Cost}	-0.069 (-10.35)	-0.204 (-18.25)						
Trip characteristics								
$\beta_{Distance}$	-0.081 (-2.48)	0.066 (5.60)	-0.012 (-2.17)					
$\beta_{EndOffpeak}$	1.666 (3.74)							
$\beta_{Endpeak}$						0.364 (4.10)		
$\beta_{startpeak}$				0.425 (5.12)	0.276 (3.42)			
$\beta_{startoffpeak}$							-0.340 (-1.66)	0.710 (4.06)
β_{time}						-0.012 (-3.52)		
β_{work}	1.168 (3.25)			-0.360 (-4.75)				
$\beta_{educational}$			0.614 (5.68)				-2.488 (-4.42)	
β_{entry}			0.321 (4.89)					
β_{Annual}							6.726 (9.56)	
$\beta_{No\ permit}$			-6.487 (-18.40)	-6.487 (-18.40)	-6.487 (-18.40)	-6.487 (-18.40)		-6.487 (-18.40)
β_{Public}			0.775 (9.61)					
Traveler characteristics								
$\beta_{Bachelor}$			0.324 (5.38)					

$\boldsymbol{\beta_{Selfemployed}}$		0.923 (6.49)				1.202 (12.89)		
$\boldsymbol{\beta_{18-55}}$						0.924 (6.41)	-2.981 (-3.92)	-2.981 (-3.92)
$\boldsymbol{\beta_{Male}}$			0.625 (7.14)	0.452 (4.46)			-0.495 (-2.40)	
$\boldsymbol{\beta_{single}}$		0.612 (0.144)	-0.295 (-3.41)		-0.297 (-3.53)	-0.297 (-3.53)		-1.050 (-5.32)

Number of parameters = 45

Number of respondents and observations = 1388, 6940

Null and final log likelihood = -13379.127, -4290.210

Adjusted ρ2 and AIC = 0.6793, 1.348

Tab.2 Estimation results of CBD model (t-statistics are presented in the parenthesis)

Alternatives	**No change**	**Mode shift**				**Trip alteration**		
		Public transport	**Pooled Taxi**	**Snap**	**Motorcycle**	**Change in time travel**	**Change in destination/ route**	**Trip cancelation/shift the trip to weekend**
Mean value of constant		-5.170 (-3.75)	-4.709 (-3.41)	-8.071 (-5.72)	-6.890 (-4.91)	-11.542 (-7.01)	-10.879 (-6.39)	-9.699 (-5.92)
Error component parameter	3.748 (6.28)		6.028 (9.24)				8.171 (18.47)	
Pricing characteristics								
β_{cost}	-0.756 (-11.53)							
Trip characteristics								
$\beta_{Carowenership\_district}$	7.780 (2.78)			3.920 (5.09)		-6.925 (-1.71)	-6.925 (-1.71)	-6.925 (-1.71)
$\beta_{INdividualCarowenership}$							-0.901 (-2.45)	
$\beta_{Distance}$					-0.092 (-6.68)			
$\beta_{Endpeak}$				1.305 (4.06)	0.387 (2.28)	0.929 (4.60)	1.620 (3.69)	1.256 (2.61)
$\beta_{startpeak}$						1.046 (5.15)		
β_{time}		-0.015 (-4.63)	-0.030 (-7.99)					
β_{work}				-0.893 (-5.84)				
$\beta_{Medical}$				1.120 (4.98)				
$\beta_{Personal}$						-1.105 (-3.93)	-1.105 (-3.93)	
$\beta_{Previous\ day}$		0.996 (5.98)	0.996 (5.98)		0.896 (3.92)			
β_{Entry}		-0.781 (-3.71)	-0.781 (-3.71)	-0.748 (-2.41)				-1.671 (-3.77)
β_{Enter_month}								-0.701 (-3.04)
β_{Public}		0.765 (6.75)	0.765 (6.75)					

Traveler characteristics								
$\beta_{Bachelor}$					-1.120 (-3.84)			
$\beta_{Diploma}$						0.507 (2.51)		
$\beta_{Selfemployed}$		-0.688 (-5.87)	-0.688 (-5.87)					
β_{18-55}					0.529 (1.77)			
β_{Male}	2.430 (2.80)							-0.900 (-3.01)
β_{Single}							-1.049 (-4.81)	

Number of parameters = 41
Number of respondents and observations = 983, 2949
Null and final log likelihood = -5400.309, -2734.295
Adjusted ρ2 and AIC = 0.494, 2.137

Tab.3 Estimation results of odd-even model (t-statistics are presented in the parenthesis)

	Private car		**Public transport**		**Pooled taxi**		**Snap**		**Motorcycle**	
	ML	**GMXL**	**ML**	**GMXL**	**ML**	**GMXL**	**ML**	**GMXL**	**ML**	**GMXL**
Mean value of constant	-	-	-5.537 (-16.65)	-1.547 (-13.11)	-15.808 (-14.17)	-25.387 (-11.51)	-12.174 (-16.21)	-14.065 (-31.41)	-17.198 (-17.46)	-18.789 (-31.82)
St. dev.			14.522 (17.69)	12.423 (18.80)	15.595 (12.44)	17.128 (22.52)	8.339 (11.43)	10.447 (12.86)	17.528 (16.34)	22.523 (24.93)
Pricing attributes										
β_{DCost}	-4.266 (-14.25)	-2.180 (-3.42)								
St. dev.	1.756 (6.25)	5.621 (8.95)								
β_{TCost}	-2.338 (-6.01)	-1.928 (-7.82)								
St. dev.	8.319 (15.54)	6.363 (21.63)								
β_{Cost}	-0.129 (-9.01)	-0.109 (-12.18)								
St. dev.	0.032 (4.27)	0.059 (33.08)								

Variance Parameter in Scale (τ) in GMXL: 0.324 (17.80)
Heterogeneity in GMXL scale factor (SP): 0.119 (2.57)
Sample mean (σ) in GMXL: 0.919 (1.90)
Number of parameters: ML (14); GXML (16)
Number of observations: 8328
Null LL: -13403.399
Final LL: ML (-5098.741); GMXL (-4205.320)
Adjusted ρ2: ML (0.648); GMXL (0.686)

Tab.4 ML and GMXL results for mode choice in CBD pricing zone (t-statistics are presented in the parenthesis)

3.2 Mode Choice in CBD Congestion Charging Zone (combined SP and RP data) – a GMXL model

We also explored if there is a scale and taste heterogeneity across the transport modes. Combining RP and SP data of the current travelers to the CBD pricing, we applied GMXL framework to model the choice of transport modes.

Tab.4 presents the best model specification of GMXL model alongside a mixed logit (ML) model, where all variables with statistically significance at 10% have been considered.

Comparing the results of GMXL and ML, some parameters were statistically significant in GMXL namely gender, the binary variable of having a permit, and the shopping trip purpose. Comparing the goodness of fit, both models are relatively similar with GMXL model having a slightly lower AIC. However, the scale heterogeneity parameter in the GMXL model turned out to be statistically significant (t-statistics of 18.99), revealing that the individuals pay attention to some attributes more than others. Hence, GMXL model framework enabled us to examine the existence of preference heterogeneity in the sample and taste heterogeneity with regard to some parameters, while accounting for correlation across travel modes and the panel effect across individuals.

The coefficients of the GMXL model are slightly different from the ML model. Despite statistically different estimations for constants in public transport and pooled taxi, the constant parameters of Snap and motorcycle alternatives turned out to be statistically indifferent. Notably, the statistically significant standard deviations of the alternative specific contants indicate a considerable preference heterogeneity among travelers.

Looking at the sign of two dummy variable of pricing schemes, the respondents are less likely to opt for private cars in the revised pricing scheme compared to the status quo (RP data). However, the respondents are least likely to use private cars in the duration-based pricing scenario than in the time-based scenario. Looking at the estimates of the variable of permit price in GMXL model, the results suggest that the duration-based approach will more likely be effective than the time-based approach in discouraging the use of private car alternatives.

4. Conclusion

This paper strives to shed light on travel behavior affected by revising the pricing scheme in congestion charging and odd-even traffic rationing schemes. Five transport modes, including private cars, public transportation, pooled taxis, on-demand ride-hailing services (so-called Snap), and motorcycles, were considered in mode choice models. We applied an error component model to explore the trip changes in both scenarios and in both the CBD and the odd-even zone. This model structure enables us to consider the correlation between the alternatives in each nest. The results of the error component logit model suggest that the duration-based scenario will more likely lead to a modal shift or trip alteration and trip cancellation, while the time-based scenario will more likely lead to only a change in the time of travel or destination.

We also applied a GMXL model to investigate the effectiveness of these scenarios on mode choice behavior. The results of the mode choice model (GMXL model) on combined RP and SP data suggest that a hypothetical duration-based pricing scenario in congestion pricing would more likely be effective in discouraging private cars' use. The greatest demand deviation is more likely to be toward public transport, and this deviation is more significant in the time-based scenario than in the duration-based scenario. Moreover, this data suggests that the on-demand ride-hailing option is the less essential competitor since the mode shift to snap is less than other transport modes in both scenarios. By presenting the GXML model structure, we were also able to capture the correlation between RP and SP data as well as the transport mode alternatives. The random parameter entered in the mode choice model also accounted for the heterogeneity in taste and scale.

The suggestive results provide further insights and policy implications. For example, looking at the estimates of peak and off-peak trips, the pooled taxi and motorcycle alternatives turn out to be the most preferred transport modes for trips made during peak hours, while private cars are the most preferred alternative for off-peak return trips. This would suggest the need for investment in public transport infrastructure in our case study to accommodate more trips during peak hours. Furthermore, work-related trips are more likely to remain unchanged in the CBD area, and the existing car users of the odd-even zone are less likely to shift towards an on-demand ride hailing service (Snap) for work-related trips, perhaps due to the surcharge of such trips that often occur during peak hours. However, Snap is more likely the first alternative for medical trips to the odd-even zone in the new revised pricing scheme. Providing better public transport services in the medical centers located in this zone should be considered as an option to mitigate the externalities of such services. The frequent user of the odd-even zone will most likely switch to motorcycle transportation, whereas the frequent user of the CBD zone will most likely use public transportation. This difference may stem from the fact that the sample size of the odd-even zone only covers private car users, while the CBD questionnaire respondents are pooled from various transport modes. This argument makes us highlight a few limitations in this study, namely the limited sample size, not directly observing the alternative attributes (e.g., travel time and price), and the limited sample of odd-even users, which are only restricted to private car users. Overall, The implications of this study extend to both practical applications and policy changes. By providing a comprehensive understanding of the impact of time-based and duration-based strategies, policymakers gain valuable insights into the effectiveness of pricing strategies in influencing travel behavior. This study's focus on Tehran as a unique case study is particularly noteworthy. With the simultaneous implementation of two pricing zones and travelers' familiarity with congestion policies, Tehran offers a rich context for examining the effects of pricing strategies. Additionally, the study highlights the potential benefits of combining revealed preference (RP) and stated preference (SP) data in GMXL models, a novel approach that has not been extensively explored in this context before. This integration of data sources can enhance the accuracy and robustness of modeling results.

Appendix

<table>
<tr><th colspan="2" rowspan="2">Variables</th><th rowspan="2">Degree</th><th colspan="2">Percentage</th></tr>
<tr><th>CBD pricing scheme</th><th>Odd-even rationing scheme</th></tr>
<tr><td rowspan="22">socio-demographic characteristics</td><td rowspan="2">Gender</td><td>Male</td><td>83.04%</td><td>90.43%</td></tr>
<tr><td>Female</td><td>16.96%</td><td>9.57%</td></tr>
<tr><td rowspan="2">Marital Status</td><td>Single</td><td>32.07%</td><td>72.10%</td></tr>
<tr><td>Married</td><td>67.93%</td><td>27.90%</td></tr>
<tr><td rowspan="2">Age</td><td>18-55 years old</td><td>90.88%</td><td>88.03%</td></tr>
<tr><td>Over 55 years old</td><td>9.12%</td><td>11.97%</td></tr>
<tr><td rowspan="5">Education</td><td>High school</td><td>8.76%</td><td>7.44%</td></tr>
<tr><td>High school diploma</td><td>36.24%</td><td>22.11%</td></tr>
<tr><td>Bachelor's degree</td><td>42.43%</td><td>45.56%</td></tr>
<tr><td>Master's degree</td><td>11.41%</td><td>19.32%</td></tr>
<tr><td>Doctorate degree</td><td>1.16%</td><td>5.57%</td></tr>
<tr><td rowspan="5">Occupation</td><td>Self-employed</td><td>58.29%</td><td>59.36%</td></tr>
<tr><td>Employee</td><td>13.67%</td><td>11.76%</td></tr>
<tr><td>Engineer</td><td>3.72%</td><td>2.67%</td></tr>
<tr><td>College-student</td><td>9.80%</td><td>3.85%</td></tr>
<tr><td>Others</td><td>14.52%</td><td>22.36%</td></tr>
<tr><td rowspan="4">Household size (the number of people in household)</td><td>1 or 2</td><td>15.16%</td><td>23.57%</td></tr>
<tr><td>3</td><td>28.06%</td><td>30.71%</td></tr>
<tr><td>4</td><td>36.98%</td><td>34.29%</td></tr>
<tr><td>5 and above</td><td>19.80%</td><td>11.43%</td></tr>
</table>

	Number of people in households with driving license	1	16.01%	17.38%
		2	44.38%	50.82%
		3 and above	39.61%	31.8%
	Being the head of household (the eligible person to apply for annual permit)	Yes	61.86%	27.65%
		No	38.14%	72.35%
	Number of cars in household	1	80.49%	56.21%
		2	16.84%	34.73%
		3 and above	2.67%	9.06%
Travel characteristics	Purpose of a typical trip to the congestion pricing zone	Shopping	10.37%	5.77%
		Educational	8.86%	3.46%
		Medical treatment/hospital	3.03%	5.46%
		Work	66.86%	51.84%
		Recreational	1.66%	1.15%
		Personal affairs	5.84%	25.29%
		Visiting relatives	2.09%	4.30%
		Other	1.29%	2.73%
	Specifications of a typical trip to the congestion pricing zone	Start of trip at non-peak hour	33.86%	45.29%
		End of trip at non-peak hour	32.64%	34.60%
		Average number of times entering the congestion pricing zone per day	1.23 (min: 0, max:50)	1.30 (min:0, max:20)
	Network specifications	Lack of public transportation accessibility	10.88%	43.82%

Tab.6 Sample statistics

	Variables	Description	Data Type
Pricing characteristics	β_{TCost}	Binary variable of time-based pricing strategy	Binary
	β_{DCost}	Binary variable of duration-based pricing strategy	Binary
	β_{Cost}	Pricing fee for cars entering the pricing zone (thousands Toman)	Real
Trip characteristics	$\beta_{Car\ Time}$	Private car travel time (minutes)	Real
	$\beta_{Distance}$	Travel distance	Real
	$\beta_{EndOffpeak}$	End of trip at Off-peak hour	Binary
	$\beta_{Endpeak}$	End of trip at peak hour	Binary
	$\beta_{StartOffpeak}$	Start of trip at Off-peak hour	Binary
	$\beta_{Startpeak}$	Start of trip at peak hour	Binary
	β_{time}	Mode-specific travel time (min)	Real
	β_{work}	Trip purpose: work	Binary
	$\beta_{educational}$	Trip purpose: educational	Binary
	$\beta_{Medical}$	Trip purpose: Medical	Binary
	$\beta_{Personal}$	Trip purpose: Personal	Binary
	β_{Enter}	Average number of entries to the zone per day	Real
	$\beta_{Previous\ day}$	The way of traveling in previous day, in case of traveling in accordant day; using any vehicle except private car	Binary
	β_{Enter_month}	Frequent odd-even user (i.e., the number of entries to the zone per month greater than ten times)	Binary
	β_{Annual}	Having Annual pricing permit	Binary

Traveler characteristics	$\beta_{No\ permit}$	No permit possession	Binary
	β_{Public}	High accessibility of PT for the typical trip	Binary
	$\beta_{Carowenership\_district}$	Car ownership Per capita in the origin district	Real
	$\beta_{INdividualCarowenership}$	Individual's car ownership	Real
	$\beta_{Diploma}$	Education: Diplomas' degree	Binary
	$\beta_{Bachelor}$	Education: Bachelor's degree	Binary
	$\beta_{Selfemployed}$	Job: self-employed	Binary
	β_{18-55}	18-55 years old	Binary
	β_{Male}	Gender: male	Binary
	β_{Single}	Marital status: single	Binary

Tab.7 Sample Data and Variable description

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Image Sources

Fig.1: Tehran Municipality;

Fig.2 to Fig.6: Authors.

Author’s profiles

Amir Reza Mamdoohi

Dr. Amir Reza Mamdoohi defended his PhD thesis in Civil Eng. Faculty of Sharif University of Technology (SUT) with an excellent degree in 2005 and started his career as a faculty member in the Institute for Management and Planning Studies (IMPS). In 2006, he was appointed as the Director General of Educational Planning and Modeling Office, and in 2007 as the Director General of Research Planning and Coordination Office at IMPS. He was transferred in 2009 to the Highway Engineering Department of the Civil and Environmental Engineering Faculty of Trabiat Modares University (TMU) where his collaboration resulted in the establishment of Transportation Planning Course at the Masters degree in the same year. He held the position of the Head of Highway Engineering Department (2010-2013) where he managed to recruit four new faculty members, establish Transportation Planning Department in 2013, and hold the responsibility of this newly established department for six years until 2018.

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Dr Elnaz (Elli) Irannezhad is as a Senior Lecturer of transport in the School of Civil and Environmental Engineering. Elli's research contributes to the advancement of science in cross-disciplinary fields, including logistics, supply chain and freight transportation, agent-based modelling, Mobility and Logistics as a Service, automated vehicles, and blockchain technology. Elli endeavours her research closely with the industry to ensure a good alignment with the real-world needs and industry uptake.

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