Analyzing the Impacts of Gasoline Price Change on Nationwide Trip Demand and Drivers' Behavior Using Regression Discontinuity Design

Sepehr Saeidi, Zahra Amini*

Civil Engineering Department, Sharif University of Technology, Tehran, Iran

Highlights

- Analyzing a scenario of an abrupt and substantial surge in gasoline price.
- Investigating a nationwide (rather than city or route-specific) case study.
- Exploring the impact of an increase in gasoline price on demand, speed distribution, and traffic violations.

Abstract

Gasoline is one of the essential commodities in today's societies and its price can affect different aspects of citizens' lives. This article studies the impacts of the sudden increase in gasoline price on the volume of intercity traffic at national and provincial scales, along with the changes in driving speed distribution and the percentage of speeding violations. The studied period includes four months in two consecutive years. Data was collected from more than 2400 loop detectors placed on the roads of 31 provinces of Iran. This data is used for implementing Regression Discontinuity Design (RDD) on traffic volume and speeding violation percentage. Statistical measures of speed distribution are also used to examine changes in driving speed. According to the literature, the optimal driving speed for fuel consumption is about 50 to 70 km/h. This study showed a 7.4% increase in the probability of driving in the 50 to 70 km/h range after the price increase. Also, according to research results, the volume of intercity traffic and the percentage of speeding violations has decreased due to the rise in gasoline price.

Keywords

- Gasoline price change,
- Regression Discontinuity Design,
- Traffic volume,
- Speeding violation percentage,
- Driving speed

* Corresponding author
Tel.: +98 (21) 6616-4238
Mobile: +98 (912) 873 1262
E-mail addresses: Zahra.Amini@sharif.edu (Z. Amini)
Sep.saeidi99@student.sharif.edu (S. Saeidi)

1. Introduction

Gasoline is one of the essential commodities in today's societies. Therefore, the price of gasoline can affect different aspects of citizens' lives. So far, various studies have been conducted on the effects of changing gasoline price on public health [1–3], the automotive industry and car dealership [4,5], and people's daily routines [6]. In addition, gasoline price change affects the demand for different modes of transportation, such as trains and buses [7,8] and bicycles [9]. The present article examines how gasoline price would impact private vehicles’ driving speed and traffic volume.

In Iran, unlike many other countries, the government is responsible for setting a fixed price for gasoline, which is constant all over the country. As a result, the government changes gasoline prices every several years for various reasons, such as fiscal crises [10]. In recent years, these changes have always been aimed at increasing the price of gasoline. During the latest price change, which went into effect on November 16, 2019, the National Iranian Oil Products Distribution Company (NIOPDC) increased gasoline price by 50% for private cars using their 60 liters/month quota, and 200% for their over-quota consumption [10]. This was while CNG[1] and diesel prices were kept unchanged.

Since most vehicles in Iran use gasoline as fuel, the increase in gasoline price has significantly affected different aspects of travel demand. Some of these aspects that receive impact from the change in gasoline price are the number of trips, length of trips, and driver behavior. The vehicle count recorded by loop detectors can be an indicator for measuring changes in the count and length of trips (as the trip length grows, more loop detectors cover the trip). On the other hand, aspects of driver behavior are expected to change due to the change in the gasoline price are driving speed and the number of speeding violations. In this study, changes in driving speed and, as a result, the percentage of speeding violations are used to examine changes in driver behavior. The type and duration of travel in different regions of the country vary according to the occupations of the drivers, geographical locations, and economic class. Such demographic factors control the effects of gasoline price change in different regions of the country. Therefore, this study is conducted at the national and provincial levels to capture the effects of these demographic factors.

According to the statistical yearbook of the Roads and Transportation Organization of Iran, in 2013-2014, 429 million passengers made intercity trips using a class 1 vehicle (cars and vans) for various trip purposes, such as leisure and work [11]. Many ways can be used to collect these traffic data, such as pneumatic road tubes, magnetic loops, and piezoelectric sensors [12]. The investigated intercity trip data is collected by loop detectors installed on Iran's road network. Daily traffic, mean speed, and speeding violation count data collected from more than 2400 loop detectors in 31 provinces of the country for the same periods of 4 months in two consecutive years have been examined. Gathered speed data has an hourly resolution, but traffic data and the number of speeding violations were recorded daily. Since the data used in this study are collected using loop detectors, in some cases, the data was not recorded, or the recorded data had an error. The errors in the data could result from inadequate device installation, inadequate loop sealants, and disconnection of the device wire [13]. Therefore, a correction method in the case study section was used to resolve these errors in order to prepare the data for doing the regression discontinuity analysis.

The rest of the paper is organized as follows: The next section entails a comprehensive literature review. Second, the methodology section will explain RDD and its features. Then, the case study, data source,

[1] Compressed Natural Gas

data processing, and implementation of RDD on data and its results are presented in the case study section. Finally, the conclusion is provided in the final section.

2. Literature Review

Prior to this study, several pieces of research were done on the policies that lead to travel behavior change [14] and the impacts gasoline price has on transportation demand. While gasoline pricing differs from road pricing as a travel demand management (TDM) tool, it can still influence the travel behavior of commuters by increasing the cost of car ownership and diverting some of its demand to public transportation. However, in places where gasoline prices are obscured by external interventions, it may not effectively serve as a TDM option. Additionally, social and political reasons may limit its viability as a TDM option in certain regions, such as Iran. Studies of the effects of rising gasoline price on public transportation demand in the United States [15,16], Taiwan [17], Australia [18], and Malaysia [19] have shown that with increasing gasoline price, public transportation demand in short-term, long-term, or both have grown. Several studies have also examined the effects of changes in gasoline price on the volume of intracity traffic in Flanders-Belgium [20], Indonesia [21], and Klang Valley-Malaysia [19], in which the traffic volume has decreased with an increase in gasoline price. Also, following an increase in fuel taxes in Greece, a similar study was conducted to examine the traffic volume in a single corridor [22].

Another factor that is affected by the price of gasoline is driving speed [23], even though some research shows that the impact of gasoline price change on driving speed is not significant [24]. In general, four main factors affect fuel consumption: acceleration, speed, slope, and payload [25]. Studies in this field show that although the optimum speed is different for each car, fuel consumption at speeds of 50 to 70 km/h will be optimal [26]. Also, The U.S. Department of Energy has announced 80 km/h as the highest fuel-efficient speed [27]. For example, a study by the Federal Highway Administration found that reducing speed from 112 to 104 km/h would reduce gasoline consumption by about 8.2% [28]. Considering the effect of speed on gasoline consumption, the behavioral changes of drivers due to the increase in gasoline price are reasonable and shall be examined.

Identifying contributory factors in traffic crashes can be somewhat subjective. Some surveys suggest that one-third of collisions resulting in a fatality involve an element of excessive speed. Moreover, speed is an aggravating factor in all crashes [29]. In 2002, 31% of all fatalities and 17% of all severe injuries in New Zealand were due to speeding, based on police judgments [30]. Therefore, studying car speed distribution can provide helpful information about the changes in car accidents. This study uses driving speed and the ratio of speeding violations to the total traffic volume (speeding violation percentage) to describe alterations in drivers' behaviors. Statistical measures of driving speed have been used to study changes in driving speed.

The regression Discontinuity Design method (RDD) is a quasi-experimental evaluation method [31] that measures the effects of a treatment or an intervention based on the difference between results before and after the intervention. This method was performed in psychology for the first time. It was used to measure the effect of a treatment on a random group of students with different abilities [32]. After that, RDD has been widely used in various fields such as psychology, statistics, and economics [33]. In transportation, RDD has been used to estimate the impact of road pricing on traffic composition in Milan, Italy [34]. Also, the impact of Ride-Hailing on public transport usage in the United States has been investigated using RDD [35]. In this paper, RDD is used to measure the impact of the increase in gasoline price on traffic volume and speed violation percentage.

The present research has some main advantages over previous studies. The first advantage is studying a case with a sudden and significant increase in gasoline price. It shall be noted that the four main components that affect gasoline price are the cost of crude oil, refining costs and profits, distribution and marketing costs, and profits and taxes [36]. The most critical factor in the price of gasoline is the price of crude oil [37]. Due to the oil crisis of 1973, the oil price was liberalized to fluctuate in line with supply and demand [38]. Hence, in all the studied countries, unlike Iran, gasoline price has constantly changed over time. The second advantage is the scale of the data examined. In previous studies, public transport demand or traffic volume of a particular city or even a specific route was studied. In this study, all car/van trips of the whole country are examined. The third, and most important advantage of this paper over previous studies is in examining the effect of gasoline price changes on the speed distribution and speeding violation percentage. These are not noticed in any of the earlier studies. Also, to measure the driving speed variation due to the gasoline price jump, the speed's mean, and variance changes are examined before and after the increase in the gasoline price.

3. Methodology

The label "RDD" actually refers to a set of design variations. The RDD is a pretest-posttest program-comparison group strategy in its most straightforward, traditional form. What makes RDD different from other pre-post group designs is the method by which research participants are assigned to conditions [39].

RDD can be characterized in two main ways:

1. Global strategy (Discontinuity at a cut-point): It focuses on a jump in a specific cutoff point. Magnitude and sign of the jump are the measuring tools for evaluating treatment impacts [40].
2. Local strategy (Local randomization): It is based on the premise that differences between candidates who miss and make a threshold are random [41].

In addition, RDD is being implemented in two main ways:

1. The Sharp design: All subjects receive their assigned treatment or control condition, so the probability of treatment is equal to 1.
2. The Fuzzy design: Some subjects do not receive their assigned treatment or control condition, so the probability of treatment is not equal to 1 [42].

A basic model for executing RDD can be seen in Equation 1. This equation measures the expected value of the post-treatment measurement based on a rating variable $(\tilde{x}_i)$ and a post-treatment measure value [43].

Equation 1

$$E(y_i) = \beta_0 + \beta_1 z_i + \beta_2 \tilde{x}_i + \beta_3 \tilde{x}_i z_i + \cdots + \beta_{n-1} \tilde{x}_i^s + \beta_n \tilde{x}_i^s z_i$$

Where:

$$\tilde{x}_i = pretreatment\ measure\ for\ individual\ i\ minus\ the\ cutoff\ value\left(i.e.,\ \tilde{x}_i = x_i - x_0\right);$$

$$y_i = posttreatment\ measure\ for\ individual\ i;$$

$$z_i = assignment\ variable = \begin{cases} 1 & Observation\ i\ is\ assigned\ to\ the\ treatment\ group \\ 0 & Otherwise \end{cases}$$

$s = the\ degree\ of\ the\ polynomial\ for\ the\ associated\ \tilde{x}_i;$

$\beta_0 = parameter\ for\ comparison\ group\ intercept\ at\ cutoff\ x_0;$

$\beta_1 = treatment\ effect\ parameter;$

$\beta_2 = linear\ slope\ parameter;$

$\beta_3 = linear\ interaction\ parameter;$

$\beta_{n-1} = parameter\ for\ the\ s^{th}\ order\ polynomial;$

$\beta_n = parameter\ for\ the\ s^{th}\ order\ polynomial\ interaction\ term.$

The above model tries to measure the main effects at the intervention point, which are shown as β coefficients. β_1, which represents the fracture at the cutoff point, is the most crucial measure to be considered. RDD has excellent potential for evaluating program-based research. Methodologically, the results of RDD are comparable to the randomized experiments in terms of internal validity. Therefore, RDD can compete with randomized designs when causal hypotheses are examined [39]. RDD evaluates the mean effects of an intervention on a subset of society with the fewest assumptions. One of the advantages of this method is its simplicity. For instance, it only requires a few details on the model specifications, such as variables that should be included in the model and their functional forms [31]. On the other hand, one of the limitations of RDD is its functional scope. RDD examines the effects of treatment for the cut-point locally, where the probability of receiving treatment changes [31]. Since the estimated effects of the treatment are limited to the site of rupture, the external validity of this method cannot be considered very desirable. However, in order to obtain internally valid impact estimates, RDD is recognized as the most rigorous non-experimental approach [44] and is widely used in non-experimental methods for causal inference and program evaluation [45].

4. Case study

Unlike many countries, gasoline price is the same in all regions of Iran and do not fluctuate with time until the government sets a new fee. In the last change, on November 19, 2019, the price of gasoline in Iran increased by 50% after almost four years. In this study, the loop detector's daily data are utilized to investigate the effects of the gasoline price hike in Iran on the volume of traffic and speeding violation percentage. The distribution of loop detectors on roads across the country can be seen in Figure 1. The circle's color indicates the density of loop detectors in each area, and the numbers inside the circles indicate the number of loop detectors in that area. Orange, green, and blue colors correspond to loop detectors' high, moderate, and low densities.

Each detector can relegate passing vehicles into five different classes:
Class 1: passenger cars and vans;
Class 2: vans, small trucks, and minibusses;
Class 3: ordinary trucks less than 10 meters in length and three axles;
Class 4: buses;
Class 5: trailers and porters with more than three axles.

To start the analysis, at the first step, class 1 vehicles were filtered to be used. In the initial data analysis, less than 5 percent of the data were detected as errors. These errors can be divided into two general categories: First, no data was recorded for a specific day or period; Second, a significant difference was observed between the data variations on the same days in two consecutive years. The data was adequately estimated by applying the historical background in order to resolve these errors.

Based on previous studies, people tend to travel more during holidays and weekends than on workdays [46]. Also, according to real-life experiences, most people start their trip the day before the holiday starts and return one day after the holiday finishes to take advantage of their vacation as much as possible. In the present research, weeks are divided into two parts to achieve more accurate results: holidays/weekends and workdays. For better realization, traffic data are normalized using equation $y_{normalized_i} = (y_i - y_{\min}) / (y_{\max} - y_{\min})$. In this equation, y_i and $y_{normalized_i}$ represent the original, and the normalized value of traffic volume/speeding violations count per day. Also, y_{min} and y_{max}, respectively, are the minimum and maximum values in the studied four-month period.

The rating variable is a continuous variable that is measured before treatment, determining whether or not a group or individual is assigned to the treatment. To start establishing RDD analysis, time which is considered the rating variable, must be transferred to the origin of the coordinates. This sets the intercept equal to the cutoff. In RDD analysis, when the rating variable is time, the intervention time is considered the cutoff point [31]. So, the gasoline price change date is considered the intervention point in this case. The data belong to 120 days, from 23rd September to 20th January, for two consecutive years (September 2018 to January 2019 and September 2019 to January 2020). Each day is considered an RDD bin for implementing the models. The intervention occurred on 16th November 2019. For convenience, numbers 1 to 120 are assigned to the studying days in order. Thus, number 55 corresponds to the intervention day, x_0. In order to centralize time and be used as the rating variable for the model, the intervention time is subtracted from all times ($\tilde{x}_i = x_i - x_0$).

The change in the price of gasoline was done without any prior notice. Hence, a psychological shock hits the country. Since people needed time to adjust to the new conditions, the workdays of the first week after the intervention were excluded from the analysis. As a result, the duration of the post-test part was considered longer than the pretest part to neutralize the shock effect.

Three fundamental assumptions are needed to implement the RDD model [47]:

1. Data are derived from a single group. This means no factor can be considered as an intervention other than treatment. Here, although the data are from 31 provinces and two seasons, the change in gasoline price is the dominant factor for results. This assumption is discussed later in this section.
2. All used data received the same treatment.
3. There is only one intervention in the studied period.

Since the data was available in this case, it was decided to follow the parametric RDD strategy to establish the model. Considering that the parametric/global approach uses all available data to estimate treatment effects, it can offer greater precision. But also, it shall be noticed that over such a broad range of data, it can be challenging to specify the functional form of the relationship between the conditional mean of the outcome and the rating variable. As a result, there is an augmented risk of bias [42]. Six models (from linear to cubic) were fitted to the data set to find the most appropriate model.

The main challenge of the RDD implementation is choosing the model which describes data behaviors in the best way. There are two main performance measures to test the models [42]:

A. F-Test Approach: This method checks whether the selected model is able to accurately measure the relationships between data. A P-value corresponding to the F-statistic value is also obtained, which displays the significance of the test. F-Statistic value can be calculated using Equation 2, where n is the number of observations, k is the model's bin indicators count, and R^2 is the regression's R-squared value. Also, subscripts r and u correspond to two different models which are being compared.

Equation 2

$$F_{statistic} = \frac{\frac{R_u^2 - R_r^2}{k}}{\frac{1 - R_u^2}{n-k-1}}$$

B. Akaike Information Criterion (AIC) Approach: AIC is also a measure of the accuracy of a function fitted to data relative to another function. It should be noted that this method alone is not a measure of the goodness of a model and is used only for analogy. Any model with a lower AIC will better describe the data. AIC value can be calculated using Equation 3, where σ_b^2 is the estimated residual variance based on a model with p parameters (order of the polynomial plus one for the intercept).

Equation 3

$$AIC = N \ln\left(\sigma_b^2\right) + 2p$$

All RDD models are implemented using the *statsmodels* package [48] in Python. Traffic volume data from all the detectors for the mentioned time interval, including weekdays, weekends, and holidays were used for model implementation. The results of the above tests for the six mentioned models are given in Table 1 and Table 2. The RDD method is inherently a dual fit on the test data. Therefore, the value of R-squared, an evaluation method for fitting accuracy, is also reported in these tables. As can be seen in Table 1 and Table 2, there is no significant difference between the models' R-squared values. On the other hand, the F-statistic value for all models is statistically significant, so the data from each bin adds additional information to the model. This indicates that the tested model is over-smoothing the data. Nevertheless, due to the short time intervals in the data, the temporal nature of the data, and the absence of significant differences between the different models' P-values, the linear model in Equation 4 is the most optimal choice.

Equation 4

$$y_i = \beta_0 + \beta_1 z_i + \beta_2 \tilde{x}_i + \varepsilon_i$$

Where:

$$\tilde{x}_i = \textit{The rating variable for observation } i, \textit{ centered at the cut} - \textit{point};$$

$$y_i = \textit{Posttreatment measure for individual } i;$$

$$z_i = \textit{Assignment variable} = \begin{cases} 1 & \textit{Observation } i \textit{ is assigned to the treatment group} \\ 0 & \textit{Otherwise} \end{cases}$$

$$\beta_0 = \textit{Intercept};$$

$$\beta_1 = \textit{Represents the marginal impact of the change at the cut} - \textit{point};$$

$$\beta_2 = \textit{Line slope};$$

This study was performed in two separate groups on the data of workdays and weekends/holidays (in the rest of the article, referred to as holidays). To examine each group, a separate linear RDD model was implemented. The validity test results of these models are given in Table 3 and Table 4.

As mentioned in the first hypothesis of the RDD method, the basic premise in implementing the RDD is that the change in gasoline price has been the only practical factor. This study is performed for the same period of two consecutive years to validate this hypothesis. As shown in Figure 2 and Figure 3, no sharp change in either chart of the previous year's data can't be seen. So, it can be concluded that any change in the studied parameters is only due to changes in the gasoline price, and other factors have no significant impacts.

In Figure 2 and Figure 3, 2019-2020 data are represented with purple circles, while red circles show the comparison cases in 2018-2019. Also, the green points in Figure 2 represent the shock effect which is not included in the analysis. The cutoff value in this example occurs on the 55^{th} day, which is corresponded to zero and is indicated by the green vertical line. All data for days before 0 are recorded while the gasoline price has not been changed; the remainder (i.e., those to the right of the cutoff) are assigned to days on which the price was increased. The solid lines represent the linear regression of the pretest and post-test for each year. In the absence of a treatment effect, the critical assumption is that the regression line would continue to the other side of the cutoff line (i.e., like the 2018-2019 RDD estimation).

The effect of changing gasoline price on the volume of intercity traffic is studied for the whole country and each province separately. Also, the effects of gasoline price variation on changing drivers' behavior have been investigated from two aspects, driving speed, and the number of speeding violations.

4.1. Nationwide Traffic Volume Changes Results

As mentioned in the previous sections, this study is conducted in two separate sections for workdays and holidays. The primary measure of the impact is the jump magnitude in the chart or the β_1 coefficient in Equation 4. RDD model outputs confirm the previous claim about the discontinuity in the graph. As is evident in Figure 2 and Figure 3, there are no jumps in the chart during 2018-2019, but a significant change in the traffic volume can be seen as the result of the gasoline price change. The β_1 value of implemented model describing country traffic volume in 2018-2019 is -0.0002 for workdays and -0.02648 for holidays. These numbers are close to zero and confirm the hypothesis that the gasoline price change is the only factor influencing the changes in traffic volume. The results of the β_1 values for nationwide traffic volume are presented in Table 5. It is shown that the β_1 value for the 2019-2020 period is -0.1423 for working days and -0.2648 for holidays. These results show that the change in gasoline price has a more significant effect on the volume of holiday trips than on workday trips. Since most holiday trips have recreational purposes, this reduction was expected.

4.2. Provincial Traffic Volume Changes Results

The traffic volume on the roads of different provinces in the country showed varying patterns. Although initial steps to select the best RDD model were not taken for provincial data, local traffic patterns were assumed to be similar to those of the entire country. Therefore, linear modeling was performed on provincial data based on holidays and workdays, and the findings are presented in Figure 4. In the upper part of Figure 4, the β_1 values for the provinces of Iran are shown and the β_1 value for the whole country in 2019-2020 is shown in the lower part of Figure 4 separately for workdays and holidays. However, analyzing light traffic volume data at the provincial level is more complex than at the national level since traffic may take different paths from their origin to their destination, leading to multiple counting of the same trips. As a result, the β_1 observations may be affected, and caution must be exercised when interpreting the results. This phenomenon may contribute to the positive β_1 values observed in some provinces (e.g., Hormozgan) and negative values in others during workdays or holidays.

4.3. Speed Distribution Changes Results

In the previous sections of the article, it was mentioned that the statistical measures of the distribution would be used to study the effects of gasoline price change on driving speed distribution. For this purpose, mean hourly speed data was divided into two parts, 55 days before and 55 days after the change in gasoline price. Then, the probability of driving at each speed was examined. The results are shown in Figure 5 where red and blue colors correspond to the days before and after the intervention. Table 6 represents the statistical measures of driving speed distribution. As can be seen from the data in Table 6, drivers have tended to reduce their driving speed as the gasoline price increases. Although, this reduction in mean speed is not significant.

Meanwhile, the number of vehicles moving in the optimal fuel-efficient speed range (50 to 70 km/h) was examined. According to the results, the probability that a vehicle would drive at the range of 50 to 70 km/h was 21.7% ($0.288-0.071=0.217$) before the change. After the price change, this probability increased to 23.3% ($0.311-0.078=0.233$). As a result, the probability of vehicles traveling in the fuel-efficient speed range has increased by 7.4% ($(23.3-21.7)/21.7=0.074$). It should be noted that no similar increase was observed in the previous year's speed data.

4.4. Speeding Violation Percentage Changes Results

As the final part, the effects of gasoline price change on the speeding violation percentage are investigated. Speed violation percentage is the number of vehicles that have exceeded the permitted speed divided by the total traffic in a specific period. Speeds are recorded by loop detectors and compared with the highest permitted speed on each road. Speed violation percentage change is examined only throughout the country. Performing a model similar to what was done for the traffic volume showed a decrease in the number of violations across the country. According to the output of the RDD model for workdays, the β_1 coefficient is -0.1655 and the β_1 coefficient for holidays is -0.3066. Similar to the traffic volume, the speeding violation percentage on holidays has been more affected by the gasoline price change than the workdays.

5. Discussion

5.1. Summary

In this article, the effects of increasing gasoline price on the characteristics of people's travel and their driving behavior are investigated. The traffic volume has been selected and studied as an indicator of the trip length and trip count, as well as driving speed and the number of speeding violations as indicators of people's driving behavior. To study the effects, with the help of the Regression Discontinuity Design (RDD) method, daily traffic volume data of loop detectors on Iran's road network in two national and provincial scales were examined.

Also, due to the difference in people's behavior on different days of the week, experiments were conducted in two subgroups of working days and holidays to increase accuracy. According to RDD results, a significant decrease in traffic volume can be seen (the value of the β_1 coefficient in the RDD model is -0.1423 for workdays and -0.2648 for holidays). RDD at the provincial level also showed a reduction (except for one case) in traffic volume. Also, the volume of unauthorized speeding violations decreased according to RDD results (the β_1 coefficient in the RDD model was equal to -0.1655 for workdays and -0.3066 for holidays). Statistical indicators of the average hourly speed distribution on the roads also assessed the speed of vehicles on the roads. Although there were no significant changes in the statistics according to the previous studies in the literature, the probability of vehicles traveling at a fuel-efficient speed (50 km/h to 70 km/h) increased by 7.4%. According to the results obtained, it can be said that the change in gasoline price, in addition to the overall effects that will have on various aspects of the lives of commuters, will also have effects in the field of transportation. These effects include a reduction in the volume of traffic and the number of speeding violations.

5.2. Future work

- The duration of leisure trips, which include most holidays, varies. Therefore, dividing the holiday interval into two parts, consecutive long and short holidays, can also show the effect of changing the price of gasoline on two different types of short-term and long-term leisure trips.
- The impacts of price change on different vehicle classes and geographical locations can be examined in another study.
- In this article, a general overview of vehicle speed distribution was investigated daily. A similar study can be performed for different parts of the day (AM and PM peak hours) to observe the changes with better resolution.
- Investigating the impacts of gasoline price on traffic volume in various provinces of Iran has revealed a general decline. However, certain provinces do not conform to this overall trend. Further research examining the influence of factors such as external traffic influx, commercial versus non-commercial gasoline-powered vehicles, and potential double-counting of vehicles en route to their destination, on the results of an RDD analysis, may provide insight into the variability observed in smaller regions like Hormozgan Province, as illustrated in Figure 4.
- While this study sheds light on the impact of gas price hikes on Class 1 vehicle drivers in terms of volume and speed violations, some future directions for research could further contribute to this topic. One potential avenue would be to conduct a similar RDD analysis comparing the post-gas price hike period (2020-2021) with two other periods: a pre-gas price hike (2019-2020) and a more distant past (2018-2019). This would allow examining whether the observed rebound in volume and speed violations is sustained or if it returns to its original level before the price hike.
- Moreover, it would be interesting to investigate the impact of alternative transportation means on drivers' behavior. Specifically, exploring how the provision of public transportation options could act as a buffer against gas price increases and prevent the transfer effect of the price difference to other goods and services. This could potentially lead to a better equilibrium for both the drivers and the overall transportation system.

References

1. Boyd-Swan, C. and Herbst, C. M., “Pain at the pump: Gasoline prices and subjective well-being”, *J Urban Econ*, **72**(2–3), pp. 160–175 (2012).

2. Courtemanche, C., “A silver lining? The connection between gasoline prices and obesity”, *Econ Inq*, **49**(3), pp. 935–957 (2011).

3. Sen, B., “Is There an Association Between Gasoline Prices and Physical Activity? Evidence from American Time Use Data”, *Journal of Policy Analysis and Management*, **31**(2), pp. 338–366 (2012).

4. Langer, A. and Miller, N. H., “Automakers’ short-run responses to changing gasoline prices”, *Review of Economics and Statistics*, **95**(4), pp. 1198–1211 (2013).

5. Busse, M. R., Knittel, C. R., and Zettelmeyer, F., “Who is Exposed to Gas Prices? How Gasoline Prices Affect Automobile Manufacturers and Dealerships”, *Quantitative Marketing and Economics*, **14**, pp. 41–95 (2016).

6. Ma, Y., Ailawadi, K. L., Gauri, D. K., and Grewal, D., “An Empirical Investigation of the Impact of Gasoline Prices on Grocery Shopping Behavior”, *J Mark*, **75**(2), pp. 18–35 (2011).

7. Currie, G. and Phung, J., “Transit ridership, auto gas prices, and world events new drivers of change?”, *Transp Res Rec*, (1992), pp. 3–10 (2007).

8. Mattson, J., Peterson, D., Ripplinger, D., Thoms, W., and Hough, J., “An assessment of demand for rural intercity transportation services in a changing environment”, *Transp Res Rec*, (2145), pp. 108–114 (2010).

9. Rashad, I., “Associations of cycling with urban sprawl and the gasoline price”, *American Journal of Health Promotion*, **24**(1), pp. 27–36 (2009).

10. Atamanov, A., Mostafavi Dehzooei, M., and Wai-Poi, M. G., “Welfare and Fiscal Implications from Increased Gasoline Prices in the Islamic Republic of Iran”, *World Bank Policy Research Working Paper*, (9235) (2020).

11. Central Bank of the Islamic Republic of Iran, “Transportation statistics”, In *Statistical Yearbook of the Roads and Transportation Organization of Iran* (2014).

12. Leduc, G. and others, “Road traffic data: Collection methods and applications”, *Working Papers on Energy, Transport and Climate Change*, **1**(55), pp. 1–55 (2008).

13. J Li and Zuylen, H. van, “Loop detector error and its impacts on traffic control scheme: SCATS case study in Changsha”, *11th TRAIL Congress, Connecting People-Integrating Expertise*, TRAIL Research School, pp. 1–4 (2010).

14. Piras, F., Sottile, E., Tuveri, G., and Meloni, I., “Does the joint implementation of hard and soft transportation policies lead to travel behavior change? An experimental analysis”, *Research in Transportation Economics*, **95** (2022).

15. Lane, B. W., “A time-series analysis of gasoline prices and public transportation in US metropolitan areas”, *J Transp Geogr*, **22**, pp. 221–235 (2012).

16. Mattson, J., “The Effects of Gasoline Prices on Bus Ridership for Different Types of Transit Systems”, *Journal of the Transportation Research Forum*, **47**(3) (2012).

17. Chao, M. C., Huang, W. H., and Jou, R. C., “The asymmetric effects of gasoline prices on public transportation use in Taiwan”, *Transp Res D Transp Environ*, **41**, pp. 75–87 (2015).

18. Currie, G. and Phung, J., “Exploring the impacts of fuel price increases on public transport”, *29th Australasian Transport Research Forum* (2006).

19. Khoo, H. L., Ong, G. P., and Khoo, W. C., "Short-term impact analysis of fuel price policy change on travel demand in Malaysian cities", *Transportation Planning and Technology*, **35**(7), pp. 715–736 (2012).

20. Kochan, B., Bellemans, T., Janssens, D., and Wets, G., "Assessing the impact of fuel cost on traffic demand in Flanders using activity-based models", *Vienna, Austria: TDM* (2008).

21. Burke, P. J., Batsuuri, T., and Yudhistira, M. H., "Easing the traffic: The effects of Indonesia's fuel subsidy reforms on toll-road travel", *Transp Res Part A Policy Pract*, **105**, pp. 167–180 (2017).

22. Musso, A., Godard, G., Lapeyre, A., Papandreou, K., Piccioni, C., and Tozzi, M., "The impact of fuel price changes on traffic demand: The case of a Greek motorway corridor", *13th the World Conference on Transport Research-WCTR, July*, pp. 15–18 (2013).

23. Austin, D., *Effects of Gasoline Prices on Driving Behavior and Vehicle Markets*, Government Printing Office (2008).

24. Burger, N. E. and Kaffine, D. T., "Gas prices, traffic, and freeway speeds in Los Angeles", *Review of Economics and Statistics*, **91**(3), pp. 652–657 (2009).

25. Klein, J., Shen, X., and Barati, K., "Optimum driving pattern for minimizing fuel consumption of on-road vehicles", *ISARC 2016 - 33rd International Symposium on Automation and Robotics in Construction*, International Association for Automation and Robotics in Construction I.A.A.R.C), pp. 555–562 (2016).

26. Wang, H., Fu, L., Zhou, Y., and Li, H., "Modelling of the fuel consumption for passenger cars regarding driving characteristics", *Transp Res D Transp Environ*, **13**(7), pp. 479–482 (2008).

27. John Thomas, Hwang, H.-L., West, B., and Huff, S., "Predicting Light-Duty Vehicle Fuel Economy as a Function of Highway Speed", *SAE International Journal of Passenger Cars - Mechanical Systems*, **122** (2013).

28. West, B. H., McGill, R. N., and Sluder, S., *Development, and Validation of Light-Duty Vehicle Modal Emission and Fuel Consumption Values for Traffic Models* (1999).

29. Pan American Health Organisation, *Speed and Road Crashes*, Washington DC (2018).

30. FIA Foundation for the Automobile and Society, the Global Road Safety Partnership, the W. and Organisation, B. and W. H., *Speed Management : A Road Safety Manual for Decision-Makers and Practitioners* (2009).

31. Hahn, J., Todd, P., and Klaauw, W. Van der, "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design on JSTOR", *Econometrica*, **69**, pp. 201–209 (2001).

32. Villamizar-Villegas, M., Pinzón-Puerto, F. A., and Ruiz-Sánchez, M. A., "A Comprehensive History of Regression Discontinuity Designs: An Empirical Survey of the last 60 Years", *J Econ Surv* (2020).

33. Hausman, C. and Rapson, D. S., "Regression Discontinuity in Time: Considerations for Empirical Applications", *Annu Rev Resour Economics*, **10**, pp. 533–552 (2018).

34. Percoco, M., “The effect of road pricing on traffic composition: Evidence from a natural experiment in Milan, Italy”, *Transp Policy (Oxf)*, **31**(January 2012), pp. 55–60 (2014).

35. Sadowsky, N. and Nelson, E., “The Impact of Ride-Hailing Services on Public Transportation Use: A Discontinuity Regression Analysis”, *Economics Department Working Paper Series*, p. 28 (2017).

36. U.S. Energy Information Administration, “U.S. Energy Information Administration (EIA)”, https://www.loc.gov/item/lcwaN0015422/.

37. U.S. Government Accountability Office, *Motor Fuels: Understanding the Factors That Influence the Retail Price of Gasoline* (2005).

38. Kirikkaleli, D. and Güngör, H., “Co-movement of commodity price indexes and energy price index: a wavelet coherence approach”, *Financial Innovation*, **7**(1), pp. 1–18 (2021).

39. Trochim, W. M., “The Regression-Discontinuity Design”, *Research methodology: Strengthening causal interpretations of nonexperimental data*, pp. 119–130 (1990).

40. Cook, T. D., “‘Waiting for Life to Arrive’: A history of the regression-discontinuity design in Psychology, Statistics and Economics”, *J Econom*, **142**(2), pp. 636–654 (2008).

41. Cattaneo, M. D., Titiunik, R., and Vazquez-Bare, G., “Chapter 44: The Regression Discontinuity Design”, In *The SAGE Handbook of Research Methods in Political Science and International Relations*, SAGE Publications Ltd, 55 City Road (2020).

42. Jacob, R., Zhu, P., Somers, M.-A., and Bloom, H., “A practical guide to regression discontinuity”, *MDRC* (2012).

43. Cappelleri, J. C., “Regression discontinuity design”, *Psychology* (2015).

44. Chaplin, D. D., Cook, T. D., Zurovac, J., Coopersmith, J. S., Finucane, M. M., Vollmer, L. N., and Morris, R. E., “The Internal and External Validity of the Regression Discontinuity Design: a Meta-Analysis of 15 Within-Study Comparisons”, *Journal of Policy Analysis and Management*, **37**(2), pp. 403–429 (2018).

45. Cattaneo, M. D. and Titiunik, R., “Regression Discontinuity Designs”, *Annu Rev Econom*, **14** (2022).

46. Liu, Z. and Sharma, S., “Statistical Investigations of Statutory Holiday Effects on Traffic Volumes”, *Transp Res Rec*, **1945** (2006).

47. Cattaneo, M. D., Idrobo, N., and Titiunik, R., *A Practical Introduction to Regression Discontinuity Designs*, Cambridge University Press (2019).

48. Seabold, S. and Perktold, J., “statsmodels: Econometric and statistical modeling with python”, *9th Python in Science Conference* (2010).

49. Iran’s Road Maintenance & Transportation Organization, “Loop Detectors Data”, https://141.ir/trafficcounterfiles.

List of captions

Figures

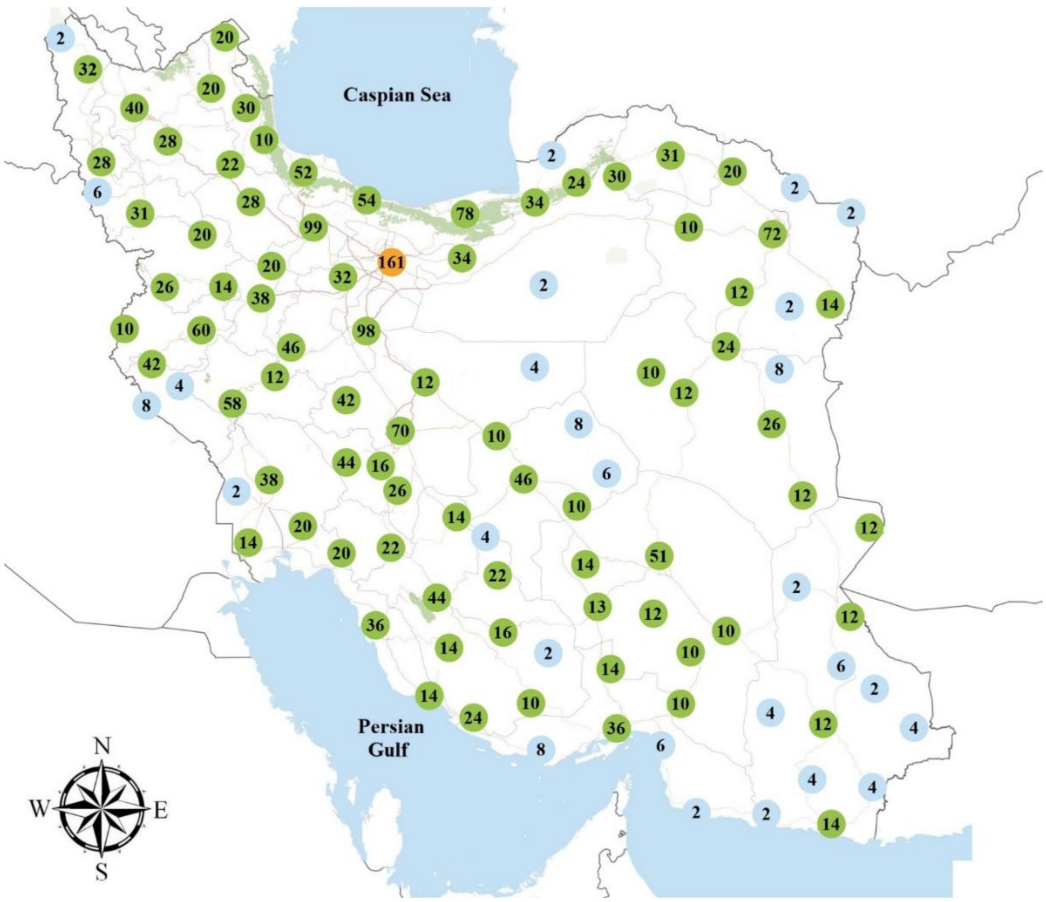

Figure 1. Loop detectors distribution map across Iran [49]

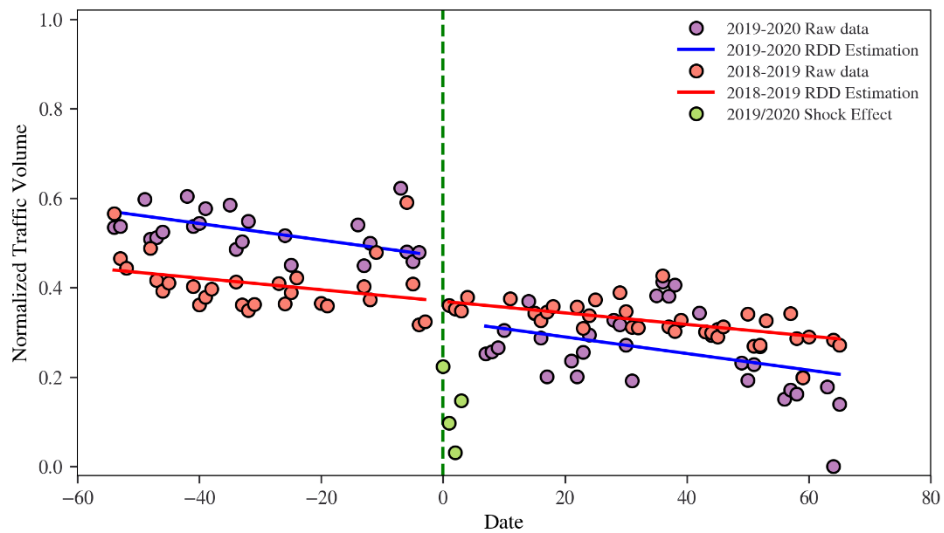

Figure 2. RDD implementation on normalized traffic volume for two consecutive years - workdays

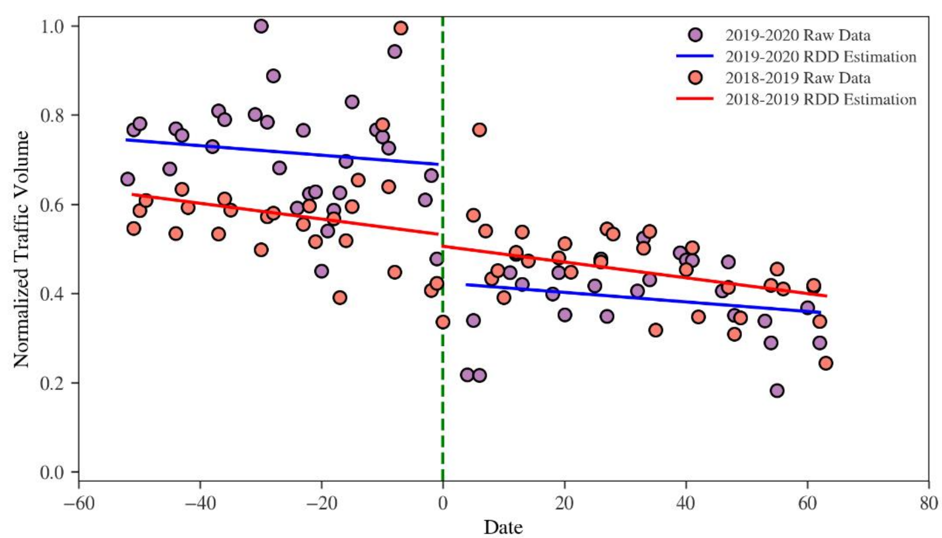

Figure 3. RDD implementation on normalized traffic volume for two consecutive years – holidays

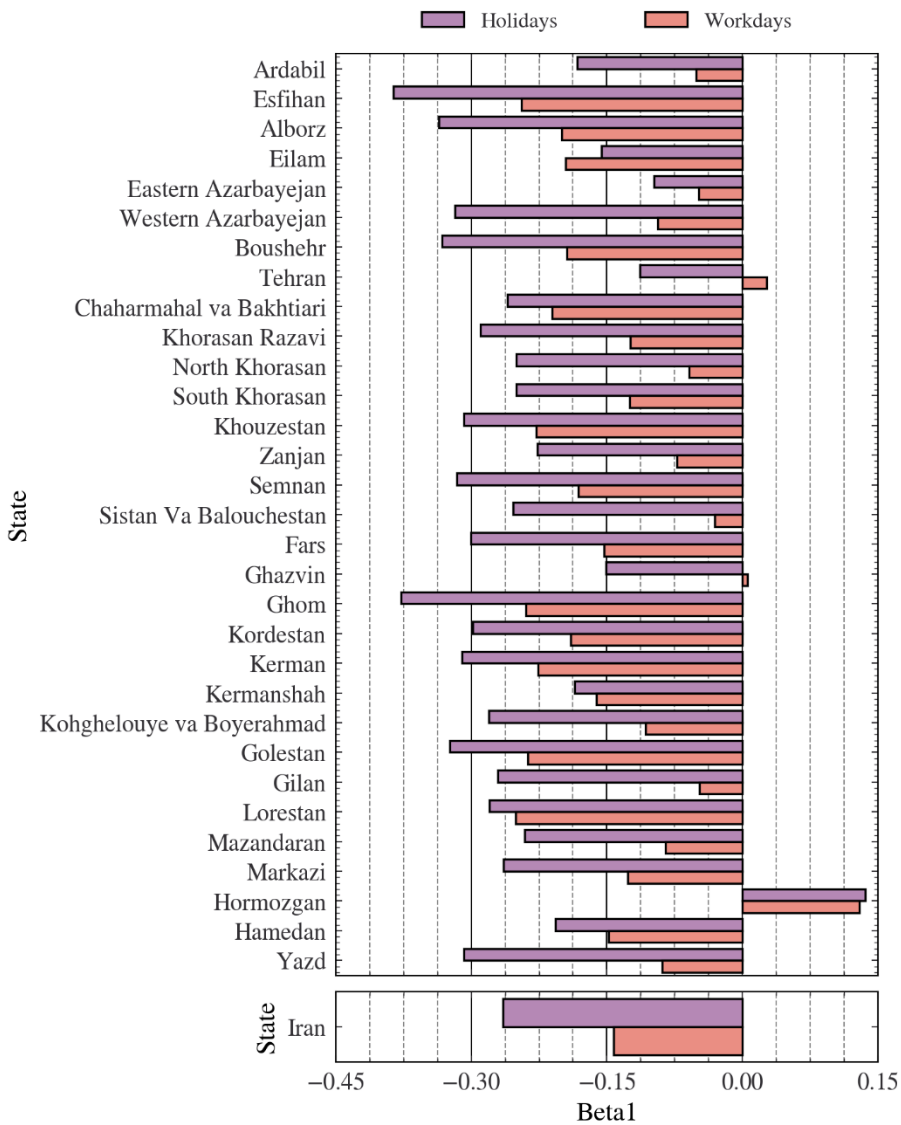

Figure 4. RDD measured β_1 *for different provinces' traffic volume change in 2019-2020*

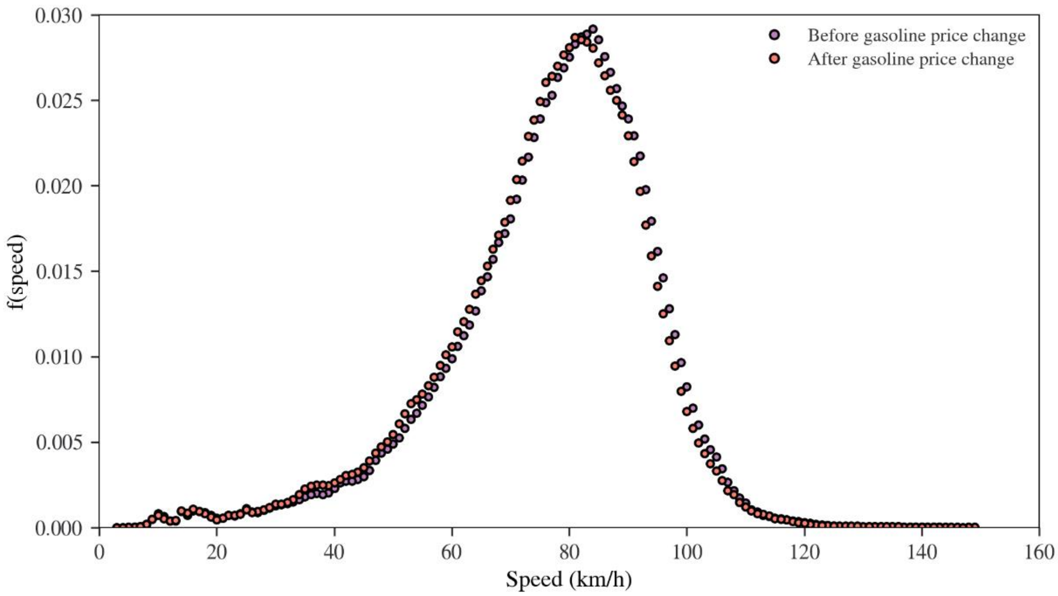

Figure 5. Driving speed distribution based on hourly data in 2019-2020

Tables

Table 1. Statistical measures for 6 different RDD models to find out the best fit for country traffic volume data in 2018-2019

	R-squared	F-statistic	P-value	AIC
Linear	0.35	17.75	6.79E-07	2066
Linear Interaction	0.374	12.94	1.00E-06	2065
Quadratic	0.365	12.46	1.56E-06	2066
Quadratic Interaction	0.432	9.594	7.66E-07	2063
Cubic	0.387	10.12	2.08E-06	2066
Cubic Interaction	0.52	9.432	7.17E-08	2055

Table 2. Statistical measures for 6 different RDD models to find out the best fit for country traffic volume data in 2019-2020

	R-squared	F-statistic	P-value	AIC
Linear	0.755	95.66	1.12E-19	1984
Linear Interaction	0.757	63.34	1.01E-18	1986
Quadratic	0.764	65.82	4.15E-19	1984
Quadratic Interaction	0.814	51.56	2.79E-20	1973
Cubic	0.785	54.64	2.43E-19	1980
Cubic Interaction	0.818	36.61	7.57E-19	1975

Table 3. Statistical measures of linear RDD model for country traffic volume data on workdays and holidays in 2018-2019

	R-squared	F-statistic	P-value	AIC
Workday	0.5	29.99	9.37E-10	-200.8
Holiday	0.31	12.15	4.38E-05	-91.39

Table 4. Statistical measures of linear RDD model for country traffic volume data on workdays and holidays in 2019-2020

	R-squared	F-statistic	P-value	AIC
Workday	0.805	113.7	2.92E-20	-145
Holiday	0.707	66.25	2.25E-15	-90.1

Table 5. β_1 values for nationwide traffic volume

	2018-2019	2019-2020
Workdays	-0.0002	-0.1423
Holidays	-0.0258	-0.2648

Table 6. Speed distribution statistical measures

	Mean	Variance	Mode	Median
Before price change	77.09	285.89	84	80
After price change	75.98	286.73	81	78

Biographies

Sepehr Saeidi is a civil engineer. He received his BSc degree in civil engineering in 2021 from the Sharif University of Technology. He is currently an MSc student at the Department of Civil Engineering, Sharif University of Technology, Iran. His research interests are data analytics, machine learning, and deep learning algorithms and their applications across civil engineering disciplines or the intersection of civil and other research fields.

Zahra Amini is a Professor of Civil Engineering at the Department of Civil Engineering, Sharif University of Technology in Iran. She obtained her BSc, MSc, and Ph.D. degrees from the University of California, Berkeley, Berkeley, USA. Her research focuses on subjects such as Intelligent Transportation Systems, Smart Cities, Traffic Flow Theory, and Traffic Control Strategies within the field of transportation engineering.