Modeling Dockless Shared E-scooter Demand by Time of Day: A Case Study of Austin

Nami Alsulami
Doctoral Student
Department of Civil, Environmental and Construction Engineering
University of Central Florida
12800 Pegasus Drive, Room 213 D, Orlando, Florida 32816, USA
Tel: 1-813-503-3775
Email: nami.alsulami@knights.ucf.edu
Faculty member
Civil Engineering Department
Albaha University
Alaqiq, 65779 - 7738, Saudi Arabia
Email: nalsulami@bu.edu.sa
ORCiD number: 0000-0001-5991-3101

Sudipta Dey Tirtha*
Post-Doctoral Scholar
Department of Civil, Environmental & Construction Engineering
University of Central Florida
12800 Pegasus Drive, Room 327, Orlando, Florida 32816, USA
Tel: 1-407-543-7521
Email: sudiptadeytirtha2018@knights.ucf.edu
ORCiD number: 0000-0002-6228-0904

Shamsunnahar Yasmin
Senior Lecturer/Senior Research Fellow
Queensland University of Technology (QUT)
Centre for Accident Research & Road Safety – Queensland (CARRS-Q)
Brisbane, Australia
Email: shams.yasmin@qut.edu.au
Telephone: +61731384677
ORCiD number: 0000-0001-7856-5376

Naveen Eluru
Professor
Department of Civil, Environmental and Construction Engineering
University of Central Florida
12800 Pegasus Drive, Room 301D, Orlando, Florida 32816, USA
Tel: 1-407-823-4815; Fax: 1-407-823-3315
Email: naveen.eluru@ucf.edu
ORCiD number: 0000-0003-1221-4113

Submitted to: Journal of Advanced Transportation

*Corresponding Author

Abstract
The goal of the current study is to identify and quantify the influence of various contributing factors on dockless e-scooter demand. Drawing on high-resolution e-scooter trip level data for 2019 from Austin, Texas, we develop Census Tract (CT) level demand data for four time periods of the day. The time-period specific data is partitioned for weekdays and weekends. Using the prepared datasets, we develop a joint panel linear regression (JPLR) model framework that accommodates for the influence of unobserved factors at multiple levels – CT, month, day, and time period levels. The analysis results indicate that the proposed JPLR models outperform the independent linear regression models for both weekdays and weekends. The results also manifest a significant association between e-scooter demand and several independent variables including sociodemographic attributes, transportation infrastructure variables, land use and built environment variables, meteorological attributes, and situational attributes. Further, several panel-specific correlation effects are found to be significant across four dimensions highlighting the importance of accommodating the influence of common unobserved factors on e-scooter demand across different time-of-day dimensions. Model validation exercise results revealed that the proposed models perform well compared to the independent models. Finally, the estimated models are employed to conduct a policy exercise illustrating the value of the estimated models for understanding CT level e-scooter demand on weekdays and weekends. The results indicate that land use mix, proportion of commuters, and season are some of the most influential factors for e-scooter demand.

Keywords: Dockless e-scooter demand, Time of the day, Weekday, Weekend, Joint panel linear regression

Introduction

Shared micromobility – low speed modes of transportation such as bike share systems and e-scooters - has been burgeoning across the world in recent years. The emergence of shared mobility started with station-based bicycle sharing systems (BSS) in major urban regions worldwide. In recent years, these station-based systems have given rise to dockless shared mobility systems with e-bikesharing and e-scooters (Shaheen et al., 2020). In 2019, shared micromobility accounted for 136 million trips in the US. Among these trips, about 30% are attributed to station-based BSS while 70% of the trips are attributed to dockless systems (NATCO, 2019). Within dockless systems, e-scooters account for 90% of the trips. In 2019, the number of cities with dockless e-scooters increased by 45% compared to the number of such cities in 2018. Dockless e-scooters can potentially contribute to transportation planning goals of reducing automobile dependency and its ensuing negative consequences (such as congestion, crashes, and air pollution). E-scooters have elicited a positive response from riders and presented a robust alternative to private vehicles for trips between half and two miles (Clewlow, 2019; Smith & Schwieterman, 2018). Early studies across the world investigating e-scooter mode have generally offered positive conclusions on the role of e-scooters in improving the transportation systems, particularly for short trips (James et al., 2019; Noland, 2019; Wang et al., 2022). There is evidence indicating that e-scooters can offer increased access to economic opportunities and services in a short time frame relative to traditional transportation alternatives (Milakis et al., 2020). At the same time, there are several challenges associated with e-scooter deployment across urban regions. The sharing of sidewalk space with pedestrians and possible e-scooter speeding can result in pedestrian and e-scooter conflicts and associated safety concerns. Several urban regions have also found e-scooter parking on sidewalks and street intersections as a potential hassle for operations (Fang et al., 2018; James et al., 2019). As e-scooter deployment across urban regions speeds up, it is important that these challenges are addressed by local officials to ensure that the potential benefits of this mode are realized.

The current study builds on our understanding of dockless e-scooter systems by examining the relationship between e-scooter demand and various contributing factors. The study employs a high-resolution spatio-temporal e-scooter trip level data from Austin, Texas including around 5 million trips recorded in 2019. E-scooter demand for dockless systems is aggregated at a census tract (CT) level to examine spatial demand patterns. Given significant variation of e-scooter usage patterns across different time periods and weekday/weekend, we analyze e-scooter demand for four time periods of the day (Morning: 6am-11am, Midday: 11am-4pm, Evening: 4pm-9pm, Nighttime: 9pm-6am) separately for weekdays and weekends. The spatio-temporal e-scooter demand is studied employing a comprehensive set of independent variables including sociodemographic attributes, transportation infrastructure variables, land use and built environment variables, meteorological attributes, and situational attributes. Further, recognizing the presence of multiple repetitions of the CT level dependent variable, we employ a panel regression framework that accommodates for the influence of unobserved factors at multiple levels – CT, month, day, and time period levels (see Bhowmik et al., 2019 for unobserved effects at multiple levels). The model framework is rigorously tested to identify the appropriate factors influencing demand. A policy exercise is conducted to illustrate the value of the proposed models for understanding CT level e-scooter demand. The framework will allow local agencies to identify e-scooter demand hotspots and build adequate infrastructure and signage to reduce pedestrian and e-scooter conflicts. Further, understanding demand imbalances might also allow local agencies to address potential issues associated with e-scooter parking for longer time intervals. The model will also allow e-scooter agencies to develop a robust rebalancing plan (to move unused e-scooters to locations with higher demand).

Literature Review

Prior research on e-scooters can broadly be classified along three directions: (a) survey-based studies of e-scooter systems, (b) comparative analysis of e-scooter and other transportation modes, and (c) e-scooter trip data analysis. In this section, we present a summary of the relevant studies focusing on these three dimensions.

With regard to the *first stream of studies*, earlier e-scooter research efforts followed survey based approaches to investigate and understand dockless e-scooter shared systems (Almannaa et al., 2021; Campisi et al., 2021; Clewlow, 2019; Nikiforiadis et al., 2021; Sanders et al., 2020). Most of these studies focused on understanding perceptions of e-scooter riders and non-riders (Almannaa et al., 2021; James et al., 2019), differences in e-scooter renters and owners (Laa & Leth, 2020), impact of age, gender and level of education on e-scooter usage (Huang & Lin, 2019; Laa & Leth, 2020), relation of e-scooter with transit (Nikiforiadis et al., 2021), differences in the knowledge of rules and regulations among e-scooter riders and non-riders (James et al., 2019), and behavior of long term users (Huang & Lin, 2019). An extensive survey was conducted across eleven major US cities, and the study found that most of the people perceived e-scooters in a positive way (Clewlow, 2019). In another study, surveying employed professionals at University of Arizona, the authors identified safety concerns among women (Sanders et al., 2020).

Within the *second stream of research*, a number of studies compared docked bikes and dockless e-bikes or e-scooters in several US cities including Washington, D.C., San Francisco, Louisville, Chicago and Austin (Almannaa et al., 2020; Guo & Zhang, 2021; Hosseinzadeh, Karimpour, et al., 2021; Lazarus et al., 2020; McKenzie, 2019; Wang et al., 2022; Yang et al., 2021; Younes et al., 2020; Ziedan et al., 2021). In terms of the interaction between e-scooter and transit modes, previously published papers suggest that public transit and scooter complemented each other (Baek et al., 2021; Nawaro, 2021; Yan et al., 2021). With regard to docked bikes and dockless e-bikes or e-scooters, research studies found that the main difference between the two modes is that the docked shared bikes are more likely to be used for commuting (Faghih-Imani et al., 2017; Faghih-Imani & Eluru, 2015) while dockless e-scooters are less likely to be used for commuting (McKenzie, 2019). Moreover, average dockless e-scooter trips were longer in terms of travel distance by a third and approximately twice as long in terms of travel time than average docked shared bike trips (Lazarus et al., 2020). Another study in Chicago found that the average travel time of scooter trips is shorter than bike trips (Yang et al., 2021). Surprisingly, earlier work found that dockless shared e-scooters are less sensitive to weather conditions than docked shared bikes (Younes et al., 2020). The investigation in Washington, D.C. identified potential competition between e-scooter and bikeshare use for non-members while complementarity was observed for members. The result is interesting and indicates occasional users choose between the modes while regular members combine the mode usage to improve their accessibility needs (Younes et al., 2020). Other studies also compared e-bike and e-scooter usage patterns and concluded that e-bikes are relatively faster than e-scooters (Almannaa et al., 2020; Nawaro, 2021). Also, temporal attributes were found to be crucial factors that influence e-scooter demand (Almannaa et al., 2020). In terms of data analysis approaches, several methodologies were adopted for modelling these systems including descriptive analysis (McKenzie, 2019), negative binomial count models (Younes et al., 2020), and multi-objective clustering algorithms (Almannaa et al., 2020).

The current study falls within the *third stream of research*. This group of research efforts focused on analyzing real-world dockless shared e-scooter trip data (Bai & Jiao, 2020; Caspi et al., 2020; Hawa et al., 2021; Hosseinzadeh, Algomaiah, et al., 2021; Huo et al., 2021; Li et al., 2022; Mehzabin Tuli et al., 2021; Noland, 2019). Previous studies in this stream of research investigated the primary purpose of using e-scooter and found that these emerging mobility systems are mostly used for leisure rather than for commuting purposes (Caspi et al., 2020; Noland, 2019). In addition, several studies found that this mode is popular for short trips and for first- and last-mile connectivity (Mathew et al., 2019; Milakis et al., 2020; Shaheen et al., 2020). Analyzing data from Austin, contrary to expectations, authors found that e-scooters are not employed to address first- and last-mile connections, but are shifting demand from transit to e-scooter mode (Zuniga-Garcia & Machemehl, 2020). Previously published studies on shared dockless e-scooters found that many factors increased e-scooter demand including commercial and industrial presence, population density, land use mix, access to transit, bike score, central business district locations, student populated regions and weather conditions (Bai & Jiao, 2020; Caspi et al., 2020; Cheng et al., 2020; Hosseinzadeh, Algomaiah, et al., 2021; Jiao & Bai, 2020). The methodological approaches employed to study e-scooter data include negative binomial count models, linear mixed models and spatial regression models (and variants such as spatial error and autoregressive error models) (Bai & Jiao, 2020; Caspi et al., 2020; Cheng et al., 2020; Hosseinzadeh, Algomaiah, et al., 2021; Huo et al., 2021; Jiao & Bai, 2020).

Current Study in the Context

While earlier studies enhance our understanding of the factors influencing shared e-scooter demand, there are still significant gaps in our knowledge of factors influencing e-scooter demand. To that extent, the current study makes twofold contributions to shared micromobility literature using 2019 e-scooter trip level data from Austin. The first contribution of the study stems from our recognition that the impact of independent variables varies across the day. The recognition allows us to incorporate the impact of independent variables accurately. For example, higher employment density might contribute to higher demand for e-scooter in the morning peak period while not having a significant influence during midday. In a model examining e-scooter demand as a daily variable, the variation of the parameter impact across the day is lost. In addition to time of day, we also recognize that e-scooter demand profiles are likely to be different for weekdays and weekends. Thus, our study develops a time-of-day model with four time periods: Morning peak (6am-11am), Midday (11am-4pm), Evening peak (4pm-9pm), and Nighttime (9pm-6pm). The daily trip level data is aggregated to its census tract origin for each time period separately. The aggregate time period data is partitioned for weekdays and weekends[1].

The second contribution of our study arises from the flexible methodology employed for our analysis in data samples with high number of repeated observations. The nature of the e-scooter demand data offers multiple dimensions of unobserved impacts: CT level, Time of day, CT -Time of day, day of the week, spatial factors, and observation resolution. In multiple studies modeling such data, researchers have adopted spatial models such as spatial error and spatial lag models (Faghih-Imani & Eluru, 2016; Rahman et al., 2021). While spatial factors are quite important, in the presence of large number of repetitions such as is the case in our dataset, other dimensions of unobserved effects are also important. For example, in our case, our data provides for repetitions of demand at the CT level by four time periods for every day in the year. In the presence of such

[1] The reader would note that recent studies (such as Hawa et al., 2021) have considered hourly e-scooter presence. However, the presence variable represents the e-scooter availability and not actual trips made by e-scooter.

large panels, the adoption of spatial models reduces the flexibility of the model system due to the inherent complexity of developing spatial models. To elaborate, it is not readily possible to estimate multi-level random effects while also accommodating for the spatial unobserved effects. Further, as the size of the panel (repeated measure per CT) increases, estimating and interpreting spatial models are not straightforward. Resorting to spatial model development will restrict the model system to considering spatial unobserved factors while not considering for the presence of multi-level unobserved dependencies identified. Towards addressing these challenges, in this study, a viable middle ground is considered. Specifically, a multi-level mixed linear regression framework that offers flexibility in accommodating for several types of unobserved dependencies such as CT level, CT- Time of the day, day of the week and observation level is developed. The mixed linear regression model framework is developed separately for weekdays and weekends using an extensive set of independent variables including sociodemographic attributes, transportation infrastructure variables, land use and built environment variables, meteorological attributes, and situational attributes[2]. The performance of the estimated model is validated using a holdout sample. A policy analysis is conducted to illustrate the applicability of the proposed model system.

The rest of the paper is organized as follows: Section 3 presents data processing procedures and summarizes the data employed for model estimation. Section 4 provides a discussion of the econometric models employed in this study. The results from the models are discussed in Section 5. Section 6 presents model validation, and Section 7 presents policy analysis. Finally, the conclusion section summarizes the findings and concludes the paper.

Data

Data Sources

E-scooter trips were derived from City of Austin's open-source data platform. The e-scooter data was augmented with built environment attributes, sociodemographic data and meteorological data which were sourced from the City of Austin open data source (https://data.austintexas.gov/), American Community Survey (https://www.census.gov/programs-surveys/acs) and National Climatic Data Center data sources (http://www.ncdc.noaa.gov/data-access)

Dependent Variables

The major focus of this study is to examine aggregate level e-scooter demand at a census tract level across different times of the day for weekdays and weekends. Before aggregating the data at a census tract level by time of day, the following steps were followed to process the trip level e-scooter data. First, e-scooter trip records with missing information were deleted (approximately 730 records). Second, to avoid including inaccurate or incorrect data in the analysis, we consider the City of Austin official trips report criteria. Therefore, we delete any trips that do not meet the following criteria:

- Trip distance greater than or equal to .1 miles and less than 500 miles
- Trip duration less than 24 hours

[2] The e-scooter demand variables can also be studied using count regression models such as Negative Binomial regression (Mehzabin Tuli et al., 2021). However, when count values are relatively high such as above 100 (as is the case in our study), the model probability values become very small and lead to estimation complexities. Further, in our case, considering the logarithm of the e-scooter demand variable resulted in a close to normal dependent variable form. Hence, a log-linear regression approach was preferred.

After applying the above-mentioned criteria around 600 thousand trips were deleted. Third, the data was processed to eliminate CTs with very small number of records. Among the 265 CTs, 48 CTs account for 99.2% of total trips. For our analysis, we selected trips from these 48 CTs. Finally, after cleaning the database based on the abovementioned criterion, the final e-scooter database had approximately 4.98 million trips. The spatial distribution of the yearly e-scooter trips originating in the selected 48 census tracts for the year 2019 is presented in Figure 1. From Figure 1, it is evident that most of the e-scooter trips started near the city's center in close proximity to downtown Austin and the University of Texas Campus. The time-of-day distribution of the yearly e-scooter trip patterns are presented in Figure 2. From Figure 2, it can be observed that there are significant differences in e-scooter demand across different times of the day. Furthermore, it is clear that e-scooter usage is considerably higher during midday and evening periods compared to morning and nighttime periods. Therefore, in developing the e-scooter trip demand model, we consider four time periods– Morning peak (6am-11am), Midday (11am-4pm), Evening peak (4pm-9pm), and Nighttime (9pm-6pm). Further, to explore the trip patterns across different day-of-week, the day specific trip distributions for the year 2019 are plotted in Figure 3. Figure 3 provides a representation of e-scooter trips for weekdays and weekends. Figure 3 demonstrates that e-scooter demand pattern remains stable across the weekdays (Monday–Friday) but varies on weekends (Saturday–Sunday). Hence, we consider splitting the data into weekday and weekend samples for each time period. Consequently, the e-scooter trips are aggregated by different times of day (4) and days-of week (2) at the census tract level resulting in 8 dependent variables.

[Figure 1 near here]

[Figure 2 near here]

[Figure 3 near here]

To obtain a reasonable sample for estimation purposes from the abovementioned samples, we randomly select, for each census tract, 40 weekdays and 20 weekend days. Therefore, for weekday samples we have 1920 records [48*40], while weekend samples resulted in 920 [48*20] records. The descriptive stats of the dependent variables are presented in the first-row panel of Table 1. The data compilation procedure including dependent and independent variables are presented in Figure 4 for weekdays and weekends.

[Figure 4 near here]

Independent Variables

The independent variables considered in this study can broadly be categorized as: 1) Sociodemographic attributes, 2) Land use and Built environment attributes, 3) Transportation infrastructure attributes, 4) Meteorological variables, and 5) Situational attributes. The sociodemographic, land use and built environment, transport infrastructure attributes are computed at census tract level. The meteorological variables are generated specific to the time-of-day and day-of week for which the e-scooter demand is computed.

The sociodemographic attributes include population density, employment density, the proportion of students, the proportion of females, proportion of commuters, proportion of commuters by mode (drive, carpool, public transport, walk and other modes) and median income. Several land use and built environment variables are considered including the density of the single-family area, density of the multi-family area, density of commercial area (mixed-use houses, retail, and wholesale), the density of office area, density of the industrial area, density of educational area (colleges, universities, primary and secondary school), density of parking area (parking garage, and parking lots), and density of parks and open space area, the density of other land-use areas (cultural services, hospitals, utilities) and historic landmarks. Finally, land use mix is computed as: "Land-use mix = $\left[\frac{-\sum_{k}(\boldsymbol{p_k}(\boldsymbol{lnp_k}))}{\boldsymbol{lnN}}\right]$", where $\boldsymbol{k}$ is the category of land-use, $\boldsymbol{p}$ is the proportion of the developed land area devoted to a specific land-use, $\boldsymbol{N}$ is the number of land-use categories in a census tract.

The census tract level transportation infrastructure attributes include bus station density (capturing the influence of availability of public transit on e-scooter usage), sidewalk density, bike road density, major street density, and minor street density. The meteorological variables include precipitation, humidity, and average temperature. Situational attributes include the day of the week and seasons. A summary of the independent variables generated for our analysis are included in Table 1. The reader would note that several functional forms such as logarithm and standardized z-score were considered in our model estimation process. The functional form that offered the most intuitive fit was retained in the model. Table 1 provides the definition of the functional form employed in the model for each variable.

[Table 1 near here]

Methodology

This section presents the econometric framework for the JPLR model (see Rahman, 2018 for similar approach). Let us assume that *q* (*q* = 1, 2, …, *Q=48*) be an index to represent census tracts, *t* (*t* = 1, 2, 3, …, *T=40* for weekdays and *20* for weekends) represents the different days, and *r* (*r* =1, 2, …, R=4) represents different times of the day. Let, y_{qtr} represents the observed log-linear demand in census tract *q*, on day *t* and during time period *r*. Thus, the equation for modeling e-scooter demand can be written as:

$$y_{qtr}^{*} = \left(\alpha_r' + \gamma_{qr}'\right)x_{qtr} + (\eta_k)x_{qtr} + \varepsilon_{qtr} \tag{1}$$

where, y_{qtr}^{*} is the predicted demand for census tract *q*, for day *t* and time period *r*. x_{qtr} is a matrix of attributes that influence e-scooter demand (including a scalar constant); α_r is the vector of coefficients corresponding to the attributes for the time of day r and γ_{qr} is a vector of unobserved factors moderating the influence of corresponding element in x_{qtr} in time of day dimension, r. Further, ε_{qtr} is an idiosyncratic random error term assumed to be independently normally distributed with variance λ_r^2.

η_k represents the vector of coefficients representing the impact of common unobserved factors that jointly influence e-scooter demand at different time periods across repetition level *k*. As discussed earlier, in the current study context, we estimate η_k for different levels (*k*) of repetition measures including census tract, census tract-time of the day, day of the week and observation level. In accommodating unobserved effects at different levels, random numbers are assigned to the appropriate observations of the repetition measures. For example, we have a total of 48 census tracts in the estimation set. Thus, in evaluating unobserved effect at the census tract level, 48 sets of different random numbers are generated specific to each census tract and assigned to the data records based on their census tract ID. Similarly, the census tract-time of the day level repetition measure represents unobserved effects across different combination of census tracts and time periods. Thus, the census tract-time of the day combination has a total of 192 (48 census tracts*4 times of the day) records. For evaluating the unobserved effect at the census tract-time of the day, 192 sets of different random numbers are generated and assigned to the data records based on their census tract-TOD combinations. For other combinations considered, the random number are generated and assigned following a similar process.

To complete the model structure of the equations (1), it is necessary to define the structure for the unobserved vectors γ_{qr} and η_k. In this paper, we assume that these vectors are independent realizations from normal distributions as follows: $\gamma_{qr} \sim N(0, \sigma_r^2)$ and $\eta_k \sim N(0, \varrho^2)$.

With these assumptions, the probability expressions for the observed demand may be derived. Conditional on γ_{qr} and η_k the probability for census tract *q* to have e-scooter demand y_{qtr} in day *t* and time period *r* is given by:

$$P(y_{qtr})|\gamma, \eta = \frac{\phi\left[\dfrac{y_{qtr} - \left((\alpha_r' + \gamma_{qr}')x_{qtr} + (\eta_k)x_{qtr}\right)}{\lambda_r}\right]}{\lambda_r} \tag{2}$$

where ϕ(.) is the standard normal probability distribution function.

The complete set of parameters to be estimated in the multivariate model system of equations (2) are α_r vector and the following standard error terms: σ_r and ϱ. Let Ω represent a vector that includes all the standard error parameters to be estimated. Given these assumptions the joint likelihood for e-scooter demand at four time periods for day-of-week (weekdays/weekends) is provided as follows:

$$L_q|\Omega = \prod_{t=1}^{T} \prod_{r=1}^{R} \left[P(y_{qtr})|\gamma, \eta\right] \tag{3}$$

Finally, the unconditional likelihood function may be computed for census tract *q* as:

$$L_q = \int_{\Omega} (L_q|\Omega) d\Omega \tag{4}$$

Now, we can express the log-likelihood function as follows:

$$\text{LL} = \sum_{q=1}^{Q} \ln L_q \tag{5}$$

The log-likelihood function in Equation (5) involves the evaluation of a multi-dimensional integral of size equal to the number of rows in Ω. We apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function (See Bhat, 2001; Rahman et al., 2019; Yasmin & Eluru, 2013 for more details).

Model Estimations Results

Model Selection

The empirical analysis involves estimation of a series of models. First, the eight simple linear regression models for the eight times of the day are estimated. These independent regression models serve as a benchmark for comparison. Next, we estimate two joint panel linear regression models for weekdays and weekends. The log-likelihood values for independent linear regression (LR) models for weekdays and weekends are -10414.08 (with 96 parameters) and -5259.19 (with 88 parameters), respectively. The log-likelihood values of joint panel linear regression models for weekday and weekend are -7981.75 (with 97 parameters) and -4254.14 (with 89 parameters). The performance of the independent model and the joint panel LR model in terms of data fit are compared by employing Bayesian Information Criterion (BIC). For weekdays, BIC values for LR and JPLR models are 20989.56 and 15946.58, respectively. For weekends, BIC values for LR and JPLR models are 10666.33 and 8657.91, respectively. From the BIC values, it is evident that the JPLR models outperformed the LR models for both weekdays and weekends. In addition, we identify the improvements in the data fit offered by the addition of different variable groups. For this purpose, we plotted the sum of squared error (SSE) by variable subsets such as socio-demographics and land use and other variable combinations. The results of the analysis are presented in Figure 5 and Figure 6 for weekday morning peak and evening peak. In terms of the sum of squared error (SSE), our model results indicate that adding variables gradually reduces SSE of the updated models.

[Figure 5 near here]

[Figure 6 near here]

Panel Linear Regression Results

The results of the JPLR models for weekdays and weekends are presented in Table 2 and Table 3, respectively. The final specification of the model development was based on removing the statistically insignificant variables in a systematic process based on statistical confidence (90% confidence level). The model estimation process followed scientific approach to model estimation. We added the independent variables one at a time and estimated the model. After adding all the variables, we examined the significance of all the variables in the model and dropped insignificant variables one by one. For example, the variable with the lowest t statistic was dropped and the model was re-estimated. The process was continued until no variables were insignificant. The reader would note that potential correlation between the various independent variables were carefully considered prior to model estimation. The variables that exhibited higher correlation values were considered separately and the variable that offered the better fit was retained (while excluding other correlated variables). The specification process was also guided by prior research and parsimony considerations[3]. In estimating the models, several functional forms and variable specifications are explored. The functional form that provided the best result is used for the final model specification. In the estimated models, a positive (negative) coefficient corresponds to increase (decrease) in e-scooter demand. Please note that only the results for weekdays are described in detail for the sake of brevity.

Joint Panel Linear Regression Model for Weekdays

The estimation results of the joint model for weekdays are presented in Table 2. In the joint system, the demand components for morning peak, midday, evening peak and nighttime are presented in the second, third, fourth and fifth column panels of Table 2, respectively. The estimation results of these components are discussed in the following sections by variable groups.

Sociodemographic Attributes

Several sociodemographic attributes at the census tract level are considered in the model. Surprisingly, population density variable has a negative coefficient in morning peak, midday, and evening peak for weekdays. The results imply that the e-scooter demand during weekdays is likely to be less in the census tracts with higher population density. The variable also exhibits significant variation across all time periods as indicated by the random parameter estimated for population density. So, while the average impact might indicate lower demand with increasing population, there is significant variability across census tracts. The reader would note that we retained the same distribution variance across all time periods for maintaining a parsimonious specification. On the other hand, employment density in a census tract is found to increase e-scooter demand at all times (see (Caspi et al., 2020; Jiao & Bai, 2020) for similar findings). The results indicate that as the proportion of females in the CT population increases, there is a reduction in e-scooter demand in morning peak and nighttime. The result might reflect the lower exposure to e-scooters and/or safety concerns among women. The proportion of students affects e-scooter demand positively across all time periods. Thus, it is evident from the results that the e-scooter demand is likely to be higher in census tract for specific cohorts of population rather than across all population categories in a census tract.

The increase in proportion of commuters is likely to increase e-scooter demand across all time periods. The proportion of commuters using public transit is found to affect e-scooter demand negatively in all four time periods. Different trends by mode for commuters are perhaps alluding to the competition between e-scooter and public transportation mode for commuting (see (Zuniga-Garcia & Machemehl, 2020) for a similar finding). With regard to census tract level income, the results show that the census tracts with higher level of median income are likely to have lower level of e-scooter demand across all time points except evening time.

Land Use and Built Environment Attributes

Several land use attributes considered in the study are found to have a significant influence on e-scooter demand. Among land use categories, density of office area, density of commercial area, density of educational area, density of parks and open space and density of other land use area are found to be significant influencers of e-scooter demand. The density of office has negative association with e-scooter demand across the day. In the midday and evening peak demand components, the e-scooter demand is found to be positively associated with higher density of

[3] The model estimation process was guided by parsimony considerations i.e., whenever possible a simpler model was preferred to a complex model with additional parameters while ensuring the model fit was not statistically different.

commercial area, while density of commercial area is not significant in the demand components for morning peak and nighttime as most of the stores are closed in this time of the day. The density of educational area is found to be negatively associated with e-scooter demand during morning peak and nighttime periods. The result is to be viewed in conjunction with the proportion of students' variable. When we consider the net values of proportion of student and density of educational area in the census tract, the net result yields a positive value. The results reveal that parks and open space, and other land use (cultural services, hospitals, utilities) areas in the census tracts are likely to attract more e-scooter riders.

To test the relationship between land use diversity and e-scooter demand, we also consider land-use mix as independent variable in the demand components. The results in Table 2 for weekdays reveal that, land use mix is significant and positive across all time periods (see (Huo et al., 2021) for a similar finding) . The results support the positive influence of diversified land use that encourages an active and livable community. Given that the presence of historical landmarks is a surrogate for recreational activity presence, it is not surprising that they are likely to encourage e-scooter demand across all four time periods.

Transportation Infrastructure Attributes

Among different transportation infrastructure attributes considered, the effect of bus stop density, rail and metro density, sidewalk density, and bike route density are found to be significant indicators of e-scooter demand for weekdays. While proportion of commuters using public transit affects scooter demand negatively, the bus stop density, rail and metro density are positively associated with higher scooter demand. Hence, the results suggest that e-scooter may have a complex relationship with public transit switching from competition to complementarity across the region and by time of day (see (Yan et al., 2021) for a similar finding). Rail and metro density is closely aligned with increasing e-scooter demand. E-scooter clearly serves as a fist- and last-mile connector for rail and metro alternatives. Higher level of sidewalk density and bike route density reflect good infrastructure for riding e-scooter, possibly leading to higher demand.

Meteorological Attributes

Among meteorological attributes considered, precipitation, humidity, and temperature are found to be significant determinants. Precipitation is found to contribute towards lower e-scooter demand during midday and evening peak periods (see (Noland, 2021) for a similar finding). Humidity has a negative coefficient across the time of the day (other than nighttime) indicating that with increasing humidity, the likelihood of e-scooter ridership decreases, perhaps an indication of discomfort resulting from higher humidity. E-scooter demand is found to be higher for the weekdays with temperature higher than 15°C. The temperature>30°C does not have effect on the morning peak and nighttime dimensions. The result may indicate the fact that e-scooter users are likely to be more sensitive to cold weather (see (Noland, 2021) for similar finding).

Situational Attributes

With regard to seasons, spring is found to be associated with higher e-scooter demand for all time periods. Fall is associated with increased e-scooter demand in morning peak and decreased e-scooter demand in the nighttime. With regard to different weekdays, the indicator for Tuesday and Wednesday is found to have significant impact in midday, evening peak and nighttime demand models. The indicator has a negative coefficient revealing that Tuesday and Wednesday are associated with reduced e-scooter demand. Thursday is also associated with lower demand for midday and nighttime periods. The results provide support to our hypothesis that variable impacts vary by time period.

Panel Correlation Effects

In the joint panel model for weekdays, we consider several panel-specific (census tract, census tract-time of the day, day of the week and observation level) correlation effects across four dimensions. Among the different panel level parameters, two parameters were found to be significant. These include (a) common unobserved factors at the CT panel level across all time periods, and (b) CT – normalized population density (discussed earlier in Sociodemographic attributes section). Overall, the results clearly highlight the importance of accommodating for the common unobserved factors influencing e-scooter demand across different time-of-day dimensions.

[Table 2 near here]

[Table 3 near here]

Model Validation

A hold-out sample was created for validation purposes using the same method as the estimation sample. The hold-out sample consists of 221 weekdays and 84 weekends. From these hold-out samples, random samples of days were drawn and employed in repeated model performance evaluation over 30 samples. For weekdays we draw 50 days for each repetition, while for weekends we draw 30 days for each repetition. For each sample, the predicted log-likelihood was estimated employing the independent linear regression model and the proposed joint panel model. The performance of the models were compared using the Bayesian Information Criterion (BIC). The results from the exercise are presented in Figure 7. From Figure 7, we observe that BIC values for the JPLR model improved for a majority of the validation samples (27 out of 30) compared to BIC values for the LR model for both weekdays and weekends. The results clearly illustrate the improved out-of-sample performance of our JPLR model for weekdays and weekends.

[Figure 7 near here]

Policy Analysis

The model specifications in Table 2 and Table 3 demonstrate how parameters affect e-scooter demand. To further illustrate the applicability of the models developed, we perform an elasticity analysis to identify the magnitude of the impacts of the independent variables. To evaluate the impact of exogenous variables on e-scooter demand, we consider changes in aggregate scooter demand in response to a 15 and 25 percent change in independent variables. In this research, we perform elasticity analysis considering a selected set of significant factors. The results of elasticity analysis for weekdays are illustrated in Figure 8 while the results of elasticity analysis for weekends are shown in Figure 9. Regarding the weekday model components, we found proportion of commuters, land use mix, proportion of other land use to be the significant factors that influence the e-scooter demand positively for weekdays. Proportion of transit commuter and density of office area are the most significant factors found to influence the demand negatively. In contrast, weather factors are found to have the least influence on e-scooter demand. For weekend model components, land use mix, density of other land use, medium temperature and proportion of commuters using public transit are the most influential variables for e-scooter demand.

[Figure 8 near here]

[Figure 9 near here]

Conclusions

The current study contributes to our understanding of dockless e-scooter systems by identifying and quantifying the influence of various contributing factors on dockless e-scooter demand. The study recognizes the significant variation of e-scooter usage patterns across different time periods and weekday/weekend. The study employs high-resolution spatiotemporal e-scooter trip level data from Austin, Texas to generate census tract (CT) level e-scooter demand by time period (Morning, Midday, Evening, Nighttime) separately for weekdays and weekends.

As data generated is available for multiple observations per CT (by day and time period), the study develops a framework that accommodates for the influence of unobserved factors at multiple resolutions including CT level unobserved factors, time period level unobserved factors, and potential variation in the influence of various attributes (random parameters). The framework takes the form of a joint panel regression model framework. The model framework is developed separately for weekdays and weekends using an extensive set of independent variables including sociodemographic attributes, transportation infrastructure variables, land use and built environment variables, meteorological attributes, and situational attributes.

The proposed model system is compared with its traditional counterpart - an independent linear regression (LR) model for weekdays and weekends. A comparison of the two model systems based on BIC measures reveals that the JPLR models outperform the LR models for both weekdays and weekends. From the analysis results, we observe a significant association between the dependent variables and various independent variables. The results also highlight variation in parameter effects across time of day. For instance, the influence of public transit stops highlights that e-scooter may have a complex relationship with public transit switching from competition to complementarity across the region and time of day. Multiple panel-specific correlation effects are found to be significant across four dimensions highlighting the importance of accommodating the influence of common unobserved factors on e-scooter demand across different time-of-day dimensions. Finally, the estimated model is employed to conduct a policy exercise illustrating the value of the estimated model for understanding CT level e-scooter demand. The results indicate that land-use mix variable has a significant impact on e-scooter demand for weekdays and weekends. The finding is quite encouraging and suggests mixed land use growth regions can attract higher e-scooter demand potentially reducing auto reliance.

To be sure, the study is not without limitations. E-scooter usage data from multiple years could be employed to enhance our understanding of the temporal variability of the demand. It might also be interesting to compare the proposed model performance with the performance of spatial lag and error models in a future effort (for example see Faghih-Imani & Eluru, 2016; Rahman et al., 2021). The data considered in our analysis is from 2019 and was unaffected by Corona Virus Diseases 2019 (COVID-19). As documented in many recent studies, COVID-19 has significantly transformed transportation systems. Future efforts might consider how the changes have affected e-scooter demand.

Declaration of Interest Statement

There is no competing interest to declare.

Acknowledgment

The authors would like to thank Dr. Bibhas Kumar Dey for initial discussions on the idea of the paper. Also, the authors would like to acknowledge the City of Austin for providing access to their datasets.

Author Contribution Statement

The authors confirm contribution to the paper as follows: study conceptualization and design: Naveen Eluru, Nami Alsulami; data collection: Nami Alsulami, Sudipta Dey Tirtha, Naveen Eluru; model estimation: Nami Alsulami, Sudipta Dey Tirtha, Shamsunnahar Yasmin, Naveen Eluru; analysis and interpretation of results: Nami Alsulami, Sudipta Dey Tirtha, Shamsunnahar Yasmin, Naveen Eluru; draft manuscript preparation: Nami Alsulami, Shamsunnahar Yasmin, Sudipta Dey Tirtha, Naveen Eluru. All authors reviewed the results and approved the final version of the manuscript.

References

Almannaa, M. H., Alsahhaf, F. A., Ashqar, H. I., Elhenawy, M., Masoud, M., & Rakotonirainy, A. (2021). Perception Analysis of E-Scooter Riders and Non-Riders in Riyadh, Saudi Arabia: Survey Outputs. *Sustainability*, *13*(2), 863. https://doi.org/10.3390/su13020863

Almannaa, M. H., Ashqar, H. I., Elhenawy, M., Masoud, M., Rakotonirainy, A., & Rakha, H. (2020). A comparative analysis of e-scooter and e-bike usage patterns: Findings from the City of Austin, TX. *International Journal of Sustainable Transportation*, 1–9. https://doi.org/10.1080/15568318.2020.1833117

Baek, K., Lee, H., Chung, J.-H., & Kim, J. (2021). Electric scooter sharing: How do people value it as a last-mile transportation mode? *Transportation Research Part D: Transport and Environment*, *90*, 102642. https://doi.org/10.1016/j.trd.2020.102642

Bai, S., & Jiao, J. (2020). Dockless E-scooter usage patterns and urban built Environments: A comparison study of Austin, TX, and Minneapolis, MN. *Travel Behaviour and Society*, *20*, 264–272. https://doi.org/10.1016/j.tbs.2020.04.005

Bhat, C. R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research Part B: Methodological*, *35*(7), 677–693. https://doi.org/10.1016/S0191-2615(00)00014-X

Bhowmik, T., Yasmin, S., & Eluru, N. (2019). A multilevel generalized ordered probit fractional split model for analyzing vehicle speed. *Analytic Methods in Accident Research*, *21*, 13–31. https://doi.org/10.1016/j.amar.2018.12.001

Campisi, T., Skoufas, A., Kaltsidis, A., & Basbas, S. (2021). Gender Equality and E-Scooters: Mind the Gap! A Statistical Analysis of the Sicily Region, Italy. *Social Sciences*, *10*(10), Article 10. https://doi.org/10.3390/socsci10100403

Caspi, O., Smart, M. J., & Noland, R. B. (2020). Spatial associations of dockless shared e-scooter usage. *Transportation Research Part D: Transport and Environment*, *86*, 102396. https://doi.org/10.1016/j.trd.2020.102396

Cheng, L., De Vos, J., Zhao, P., Yang, M., & Witlox, F. (2020). Examining non-linear built environment effects on elderly's walking: A random forest approach. *Transportation Research Part D: Transport and Environment*, *88*, 102552. https://doi.org/10.1016/j.trd.2020.102552

Clewlow, R. R. (2019). *The Micro-Mobility Revolution: The Introduction and Adoption of Electric Scooters in the United States* (No. 19–03991). Article 19–03991. Transportation Research

Board 98th Annual MeetingTransportation Research Board. https://trid.trb.org/view/1572549

Faghih-Imani, A., & Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. *Journal of Transport Geography*, *44*, 53–64. https://doi.org/10.1016/j.jtrangeo.2015.03.005

Faghih-Imani, A., Eluru, N., & Paleti, R. (2017). *How Bicycling Sharing System Usage is Affected by Land Use and Urban Form: Analysis from System and User Perspectives*. 18.

Fang, K., Agrawal, A. W., Steele, J., Hunter, J. J., & Hooper, A. M. (2018). *Where Do Riders Park Dockless, Shared Electric Scooters? Findings from San Jose, California*. 6.

Guo, Y., & Zhang, Y. (2021). Understanding factors influencing shared e-scooter usage and its impact on auto mode substitution. *Transportation Research Part D: Transport and Environment*, *99*, 102991. https://doi.org/10.1016/j.trd.2021.102991

Hawa, L., Cui, B., Sun, L., & El-Geneidy, A. (2021). Scoot over: Determinants of shared electric scooter presence in Washington D.C. *Case Studies on Transport Policy*, *9*(2), 418–430. https://doi.org/10.1016/j.cstp.2021.01.003

Hosseinzadeh, A., Algomaiah, M., Kluger, R., & Li, Z. (2021). Spatial analysis of shared e-scooter trips. *Journal of Transport Geography*, *92*, 103016. https://doi.org/10.1016/j.jtrangeo.2021.103016

Hosseinzadeh, A., Karimpour, A., & Kluger, R. (2021). Factors influencing shared micromobility services: An analysis of e-scooters and bikeshare. *Transportation Research Part D: Transport and Environment*, *100*, 103047. https://doi.org/10.1016/j.trd.2021.103047

Huang, F.-H., & Lin, S.-R. (2019). A Survey of User Experience of Two Wheeler Users in Long-Term Interactions. In S. Bagnara, R. Tartaglia, S. Albolino, T. Alexander, & Y. Fujita (Eds.), *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018)* (pp. 1465–1472). Springer International Publishing. https://doi.org/10.1007/978-3-319-96071-5_149

Huo, J., Yang, H., Li, C., Zheng, R., Yang, L., & Wen, Y. (2021). Influence of the built environment on E-scooter sharing ridership: A tale of five cities. *Journal of Transport Geography*, *93*, 103084. https://doi.org/10.1016/j.jtrangeo.2021.103084

James, O., Swiderski, J. I., Hicks, J., Teoman, D., & Buehler, R. (2019). Pedestrians and E-Scooters: An Initial Look at E-Scooter Parking and Perceptions by Riders and Non-Riders. *Sustainability*, *11*(20), Article 20. https://doi.org/10.3390/su11205591

Jiao, J., & Bai, S. (2020). Understanding the Shared E-scooter Travels in Austin, TX. *ISPRS International Journal of Geo-Information*, *9*(2), Article 2. https://doi.org/10.3390/ijgi9020135

Laa, B., & Leth, U. (2020). Survey of E-scooter users in Vienna: Who they are and how they ride. *Journal of Transport Geography*, *89*, 102874. https://doi.org/10.1016/j.jtrangeo.2020.102874

Lazarus, J., Pourquier, J. C., Feng, F., Hammel, H., & Shaheen, S. (2020). Micromobility evolution and expansion: Understanding how docked and dockless bikesharing models complement and compete – A case study of San Francisco. *Journal of Transport Geography*, *84*, 102620. https://doi.org/10.1016/j.jtrangeo.2019.102620

Li, A., Zhao, P., Liu, X., Mansourian, A., Axhausen, K. W., & Qu, X. (2022). Comprehensive comparison of e-scooter sharing mobility: Evidence from 30 European cities. *Transportation Research Part D: Transport and Environment*. https://doi.org/10.3929/ethz-b-000534409

Mathew, J., Liu, M., Li, H., Seeder, S., & Bullock, D. (2019). Analysis of E-Scooter Trips and Their Temporal Usage Patterns. *Ite Journal*, *89*, 44–499.

McKenzie, G. (2019). Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. *Journal of Transport Geography*, *78*, 19–28. https://doi.org/10.1016/j.jtrangeo.2019.05.007

Mehzabin Tuli, F., Mitra, S., & Crews, M. B. (2021). Factors influencing the usage of shared E-scooters in Chicago. *Transportation Research Part A: Policy and Practice*, *154*, 164–185. https://doi.org/10.1016/j.tra.2021.10.008

Milakis, D., Gebhardt, L., Ehebrecht, D., & Lenz, B. (2020). *Is micro-mobility sustainable? An overview of implications for accessibility, air pollution, safety, physical activity and subjective wellbeing* (pp. 180–189). https://doi.org/10.4337/9781789900477.00030

NATCO. (2019). *Shared Micromobility in the U.S.: 2019*. National Association of City Transportation Officials. https://nacto.org/shared-micromobility-2019

Nawaro, Ł. (2021). E-scooters: Competition with shared bicycles and relationship to public transport. *International Journal of Urban Sustainable Development*, *0*(0), 1–17. https://doi.org/10.1080/19463138.2021.1981336

Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Raptopoulou, A., Kostareli, A., & Basbas, S. (2021). Analysis of attitudes and engagement of shared e-scooter users. *Transportation Research Part D: Transport and Environment*, *94*, 102790. https://doi.org/10.1016/j.trd.2021.102790

Noland, R. B. (2019). Trip patterns and revenue of shared e-scooters in Louisville, Kentucky. *Transport Findings*. https://doi.org/10.32866/7747

Noland, R. B. (2021). Scootin' in the rain: Does weather affect micromobility? *Transportation Research Part A: Policy and Practice*, *149*, 114–123. https://doi.org/10.1016/j.tra.2021.05.003

Rahman, M. (2018). Econometric Modeling Analysis of Public Transit Ridership: Application for Orlando Region.

Rahman, M., Yasmin, S., & Eluru, N. (2019). Examining determinants of rail ridership: A case study of the Orlando SunRail system. *Transportation Planning and Technology*, *42*(6), 587–605. https://doi.org/10.1080/03081060.2019.1622252

Sanders, R. L., Branion-Calles, M., & Nelson, T. A. (2020). To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. *Transportation Research Part A: Policy and Practice*, *139*, 217–227. https://doi.org/10.1016/j.tra.2020.07.009

Shaheen, S., Cohen, A., Chan, N., & Bansal, A. (2020). Chapter 13 - Sharing strategies: Carsharing, shared micromobility (bikesharing and scooter sharing), transportation network companies, microtransit, and other innovative mobility modes. In E. Deakin (Ed.), *Transportation, Land Use, and Environmental Planning* (pp. 237–262). Elsevier. https://doi.org/10.1016/B978-0-12-815167-9.00013-X

Smith, C. S., & Schwieterman, J. P. (2018). *E-Scooter Scenarios: Evaluating the Potential Mobility Benefits of Shared Dockless Scooters in Chicago*. https://trid.trb.org/view/1577726

Wang, K., Qian, X., Fitch, D. T., Lee, Y., Malik, J., & Circella, G. (2022). What travel modes do shared e-scooters displace? A review of recent research findings. *Transport Reviews*, *0*(0), 1–27. https://doi.org/10.1080/01441647.2021.2015639

Yan, X., Yang, W., Zhang, X., Xu, Y., Bejleri, I., & Zhao, X. (2021). A spatiotemporal analysis of e-scooters' relationships with transit and station-based bikeshare. *Transportation Research Part D: Transport and Environment*, *101*, 103088. https://doi.org/10.1016/j.trd.2021.103088

Yang, H., Huo, J., Bao, Y., Li, X., Yang, L., & Cherry, C. R. (2021). Impact of e-scooter sharing on bike sharing in Chicago. *Transportation Research Part A: Policy and Practice*, *154*, 23–36. https://doi.org/10.1016/j.tra.2021.09.012

Yasmin, S., & Eluru, N. (2013). Evaluating alternate discrete outcome frameworks for modeling crash injury severity. *Accident Analysis and Prevention*, *59*, 506–521. https://doi.org/10.1016/j.aap.2013.06.040

Younes, H., Zou, Z., Wu, J., & Baiocchi, G. (2020). Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, D.C. *Transportation Research Part A: Policy and Practice*, *134*, 308–320. https://doi.org/10.1016/j.tra.2020.02.021

Ziedan, A., Shah, N. R., Wen, Y., Brakewood, C., Cherry, C. R., & Cole, J. (2021). Complement or compete? The effects of shared electric scooters on bus ridership. *Transportation Research Part D: Transport and Environment*, *101*, 103098. https://doi.org/10.1016/j.trd.2021.103098

Zuniga-Garcia, N., & Machemehl, R. (2020). *Dockless Electric Scooters and Transit Use in an Urban/University Environment*.

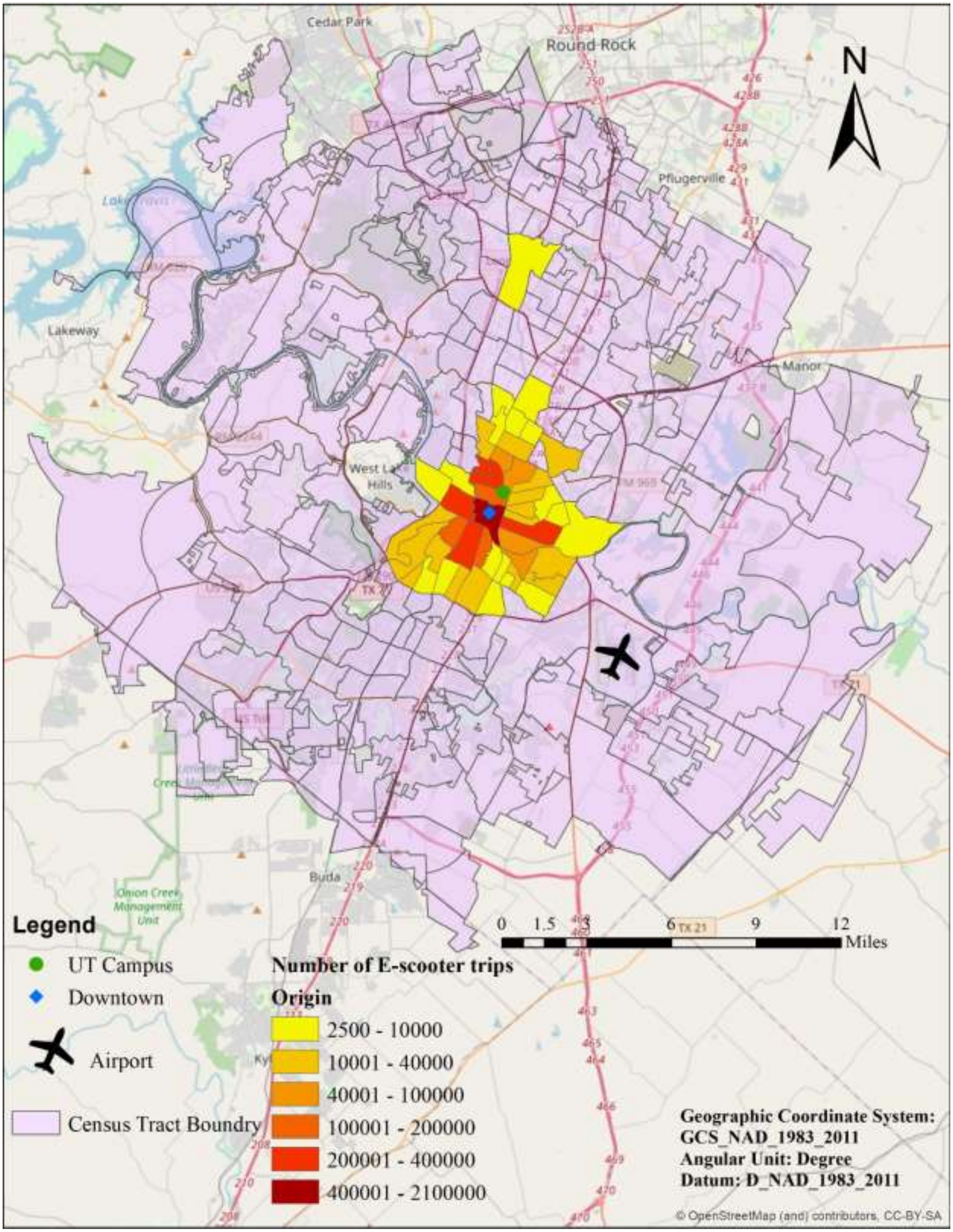


FIGURE 1 Total number of E-scooter trips in thousand in Austin at the census tract level for the year 2019 (Data source: City of Austin open data portal)

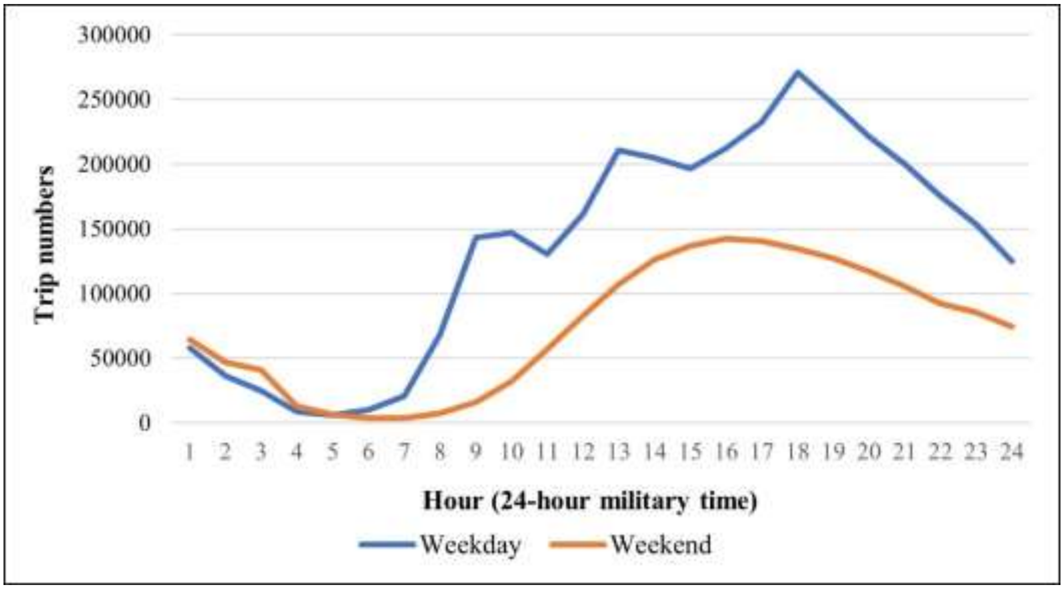


FIGURE 2 Hourly trips based on the day-of-week for the year 2019

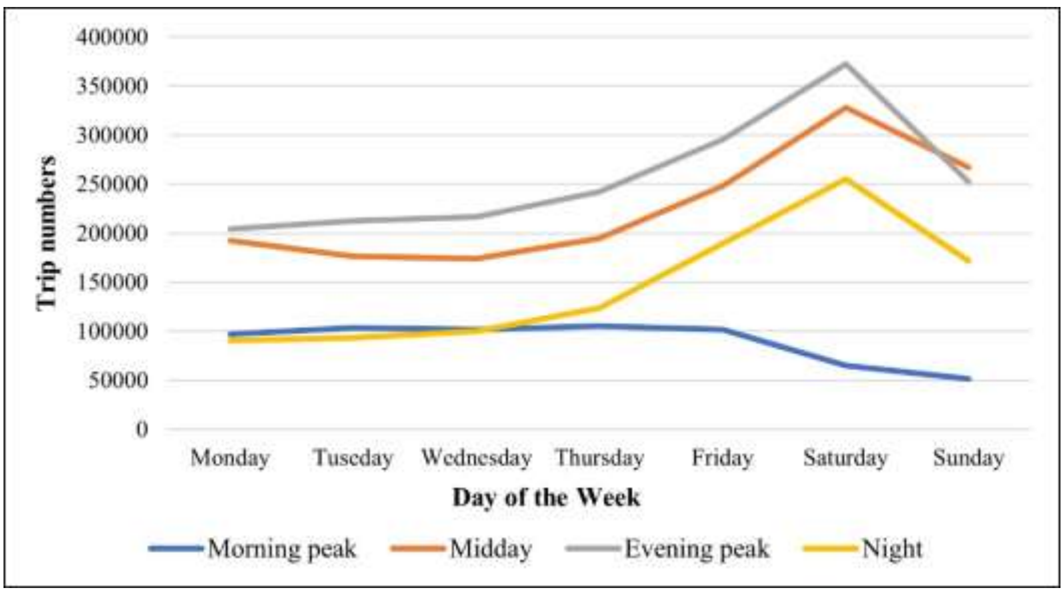


FIGURE 3 Trip patterns based on the day-of-week and time-of-day for the year 2019

TABLE 1 Descriptive Summary of Sample Characteristics

Variables Names	Definitions	Descriptive Statistics		
		Minimum	Maximum	Mean
DEPENDENT VARIABLES				
Share E-scooter Trip Demand for Weekdays				
Morning Peak Trips	Ln (Total number of weekday morning peak trips in each CT)	0.000	7.504	2.229
Midday Trips	Ln (Total number of weekday midday trips in each CT)	0.000	8.873	2.683
Evening Peak Trips	Ln (Total number of weekday evening peak trips in each CT)	0.000	9.147	2.893
Nighttime Trips	Ln (Total number of weekday nighttime trips in each CT)	0.000	8.492	2.139
Share E-scooter Trip Demand for Weekends				
Morning Peak Trips	Ln (Total number of weekend morning peak trips in each CT)	0.000	7.391	1.919
Midday Trips	Ln (Total number of weekend midday peak trips in each CT)	0.000	9.016	3.121
Evening peak Trips	Ln (Total number of weekend evening peak trips in each CT)	0.000	9.304	3.117
Nighttime Trips	Ln (Total number of weekend nighttime trips in each CT)	0.000	8.536	2.496
INDEPENDENT VARIABLES				
Sociodemographic Attributes				
Population Density	Z-score ((Population in each CT / Total area of each CT)/1000)	-0.911	3.769	0.000
Employment Density	Z-score ((Number of jobs in each CT/ Total area of each CT)/1000)	-1.327	3.363	0.000
Proportion of Students	Number of high school and university students in each CT/ Total population in each CT	0.034	0.977	0.204
Proportion of Female	Number of females in each CT/ Total population in each CT	0.352	0.597	0.477
Proportion of Commuters	Number of individuals who commute to work in each CT/ Total population in each CT	0.283	0.816	0.627
Proportion of commuters who drive to work	Number of individuals who drive (drive alone) to work in each CT/ Total number of commuters in each CT	0.391	0.795	0.656
Proportion commuters who take public transport to work	Number of individuals who use public transit to work in each CT/Total number of commuters in each CT	0.006	0.205	0.067
Proportion commuters who carpool to work	Number of individuals who use share ride (carpool) to work in each CT tract /Total number of commuters in each CT	0.006	0.153	0.067
Proportion commuters who walk to work	Number of individuals who walk to work in each CT/Total number of commuters in each CT	0.000	0.458	0.060
Proportion of commuters who use other modes to work	Number of individuals who use other modes to commute in each CT/Total number of commuters in each CT	0.015	0.156	0.057
Median Income	Z-score (Median income in each CT/1000)	-2.188	2.525	0.000
Land use and Built Environment Attributes				

Density of Single-Family Area	Defined as ratio of the area of the variable and total area of CT	0.000	0.548	0.252
Density of Multi-family Area		0.006	0.631	0.134
Density of Commercial Area		0.001	0.283	0.066
Density of Office Area		0.000	0.203	0.046
Density of Industrial Area		0.000	0.280	0.030
Density of Educational Area		0.000	0.162	0.027
Density of Parking Area		0.000	0.066	0.008
Density of Park and Open space Area		0.000	0.705	0.110
Density of Other Land Use Area		0.000	0.970	0.327
Land use mix	Land use mix = $\left[\frac{-\sum_k (\boldsymbol{p_k}(\boldsymbol{lnp_k}))}{\boldsymbol{lnN}}\right]$, where k is the category of land-use, p is the proportion of the developed land area devoted to a specific land-use, N is the number of land-use categories in each CT	0.081	0.832	0.657
Historic Landmarks	Z-score (Number of Historic landmarks in each CT)	-0.487	5.664	0.000
Transportation Infrastructure Attributes				
Bus Station Density	Z-score (Total number of bus stops in each CT/Total area of each CT)	-1.744	2.890	0.000
Sidewalk Density	Z-score (Total sidewalk length in each CT in mile /Total area of each CT)	-2.073	1.672	0.000
Rail and MetroRapid Density	Z-score (Total number of rail and MetroRapid stops in each CT /Total area of each CT)	-0.627	4.589	0.000
Bike Road Density	Z-score (Total bike roads length in each CTin mile /Total area of each CT)	-1.718	3.680	0.000
Meteorological variables				
Precipitation	Amount of Precipitation for the day the demand is under consideration (in mm)	0.000	8.041	0.100
Humidity	Z-score (Relative Humidity for the day the e-scooter demand is under consideration (in %))	-2.429	1.650	0.000
Categorical Variables	**Definitions**	**Frequency (%)**		
Temperature	Low Temperature (<=15 C)	19.500		
	Medium Temperature (15.1 - 30 C)	57.800		
	High Temperature (>30 C)	22.700		
Situational Attributes				
Categorical Variables	**Definitions**	**Frequency (%)**		
Seasons	Spring (March-May)	32.825		
	Summer (June-August)	24.840		
	Fall (September-November)	25.286		
	Winter (December-February)	17.049		

Weekdays	Monday	17.892
	Tuesday	17.921
	Wednesday	18.174
	Thursday	20.414
	Friday	25.599
Weekends	Saturday	57.925
	Sunday	42.075

1 **TABLE 2 Panel Linear Regression Model Results for Weekdays**

Variables	Morning Peak		Midday		Evening Peak		Nighttime	
	Estimate	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Constant	-5.304	-13.474	-5.312	-15.711	-4.715	-13.864	-3.879	-9.230
Sociodemographic Attributes								
Population Density	-0.558	-1.650	-1.247	-3.878	-0.679	-2.077	--	--
Standard Deviation of Population Density	-4.426	-52.291	-4.426	-52.291	-4.426	-52.291	-4.426	-52.291
Employment Density	0.161	6.160	0.208	7.892	0.215	7.867	0.171	6.186
Proportion of Female	-0.873	-2.149	--	--	--	--	-1.454	-3.554
Proportion of students	2.807	17.211	3.222	20.530	2.874	18.537	2.488	15.125
Proportion of Commuters	6.386	23.527	5.484	18.816	4.562	18.477	4.985	15.326
Mode of commuting to work (Base: other modes)								
Proportion public transport	-13.740	-26.361	-14.443	-29.822	-12.608	-26.463	-11.933	-22.068
Median Income	-0.461	-12.199	-0.251	-6.499	--	--	-0.293	-7.154
Land use and Built Environment Attributes								
Land use (Base: Density of Single-Family Area, Density of Multi-family Area, and Density of Industrial Area)								
Density of Office Area	-12.418	-23.639	-11.299	-21.112	-10.909	-20.352	-11.335	-20.297
Density of Commercial Area	--	--	1.815	4.603	1.857	4.659	--	--
Density of Educational Area	-4.020	-7.816	--	--	--	--	-4.417	-6.862
Density of Park and Open space Area	5.115	19.642	6.968	27.125	6.657	25.069	4.960	18.805
Density of Other Land Use Area	3.172	16.739	3.207	16.914	3.003	15.518	2.669	14.000
Land use mix	4.888	20.169	5.102	20.351	5.271	20.279	4.935	18.872
Historic Landmarks	0.401	15.172	0.326	12.626	0.291	11.199	0.384	14.236
Transportation Infrastructure Attributes								
Bus Station Density	0.124	4.594	0.245	9.485	0.252	11.456	0.192	7.065
Rail and Metro MetroRapid Density	0.205	8.017	0.320	11.852	0.261	9.566	0.243	8.388
Sidewalk Density	0.440	13.309	0.379	11.554	0.277	9.196	0.285	8.499
Bike Road Density	0.509	18.910	0.534	19.988	0.536	19.707	0.519	18.378
Meteorological variables								

Precipitation	--	--	-0.207	-7.215	-0.286	-4.699	--	--
Humidity	-0.243	-4.991	-0.041	-2.347	-0.065	-3.488	--	--
Temperature (Base: Low Temperature)								
Temperature (Medium)	0.317	9.621	0.179	4.334	0.241	5.660	0.308	6.948
Temperature (High)	--	--	0.250	5.385	0.429	8.430	--	--
Situational attributes								
Seasons (Base: Summer)								
Spring	0.237	6.099	0.373	9.118	0.503	11.910	0.086	1.834
Fall	0.106	2.656	--	--	--	--	-0.206	-4.194
Winter	--	--	--	--	--	--	-0.294	-4.921
Weekdays (Base: Monday, Friday)								
Tuesday and Wednesday	--	--	-0.183	-5.070	-0.092	-2.732	-0.233	-6.501
Thursday	--	--	-0.158	-3.662	--	--	-0.105	-2.438
Variance Component								
Constant	0.671	60.404	0.673	60.465	0.700	60.820	0.675	60.044
Panel Correlation Effect								
	Estimate				**t-statistic**			
Census Tract (Constant)	-0.298				-27.462			

1 **TABLE 3 Panel Linear Regression Model Results for Weekends**

Variables	Morning Peak		Midday		Evening Peak		Nighttime	
	Estimate	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Constant	-2.699	-5.971	-2.768	-7.063	-1.687	-5.792	-2.766	-5.818
Sociodemographic Attributes								
Population Density	-1.055	-7.774	-0.817	-5.198	-1.061	-9.23	-0.868	-5.495
Standard Deviation of Population Density	0.723	29.249	0.723	29.249	0.723	29.249	0.723	29.249
Employment Density	1.275	12.043	1.126	8.987	1.309	13.828	1.178	9.146
Proportion of students	1.411	4.068	0.523	1.751	0.666	2.327	1.025	3.267
Proportion of Female	--	--	--	--	-2.117	-3.179	-1.488	-2.608
Proportion of Commuters	--	--	1.322	2.851	--	--	1.032	1.857
Proportion of modes of commuting to work (Base: other modes)								
Proportion commuters public transport	-10.608	-11.186	-14.679	-19.317	-14.972	-19.976	-12.196	-15.966
Median Income	--	--	--	--	--	--	-0.178	-3.493
Land use and Built Environment Attributes								
Land use (Base: Density of Single-Family Area, Density of Multi-family Area, and Density of Industrial Area)								
Density of Commercial Area	1.901	3.232	2.163	3.708	1.963	3.504	2.695	4.577
Density of Office Area	-8.125	-8.78	-9.468	-11.638	-9.197	-11.912	-10.348	-12.758
Density of Park and Open space Area	6.809	15.199	9.828	23.593	9.622	23.397	8.197	20.129
Density of Other Land Use Area	4.001	11.423	5.24	15.97	4.81	14.81	5.122	16.392
Land use mix	4.903	14.357	5.295	17.432	5.112	16.969	5.594	17.971
Historic Landmarks	0.184	4.434	0.075	1.988	0.073	1.929	0.264	7.036
Transportation Infrastructure Attributes								
Bus Station Density	--	--	0.156	4.878	0.104	3.31	--	--
Rail and Metro MetroRapid Density	0.322	8.286	0.442	12.125	0.488	13.475	0.431	12.11
Sidewalk Density	0.381	8.704	0.528	13.143	0.457	11.469	0.458	11.664
Bike Road Density	0.56	12.328	0.744	18.553	0.758	19.045	0.696	17.635
Meteorological variables								

Precipitation	-0.155	-3.909	-0.165	-4.311	--	--	--	--
Humidity	-0.094	-3.821	-0.139	-5.322	-0.134	-5.379	-0.112	-4.613
Temperature (Base: Low Temperature)								
Temperature (Medium)	0.272	5.542	--	--	--	--	0.4	6.621
Temperature (High)	--	--	--	--	0.195	3.303	--	--
Situational attributes								
Seasons (Base: Summer)								
Spring	0.295	5.259	0.526	8.872	0.679	11.476	0.29	4.931
Fall	0.161	2.713	0.122	1.904	--	--	--	--
Winter	--	--	--	--	--	--	-0.193	-2.594
Weekdays (Base: Saturday)								
Sunday	-0.236	-5.17	-0.313	-6.438	-0.383	-7.971	-0.432	-9.218
Variance Component								
Constant	0.667	41.562	0.715	42.685	0.709	42.712	0.69	42.408
Panel Effect								
	Estimate				**t-statistic**			
Census Tract (Constant)	-0.563				-33.738			
Census Tract (Morning peak)	-0.124				-4.597			

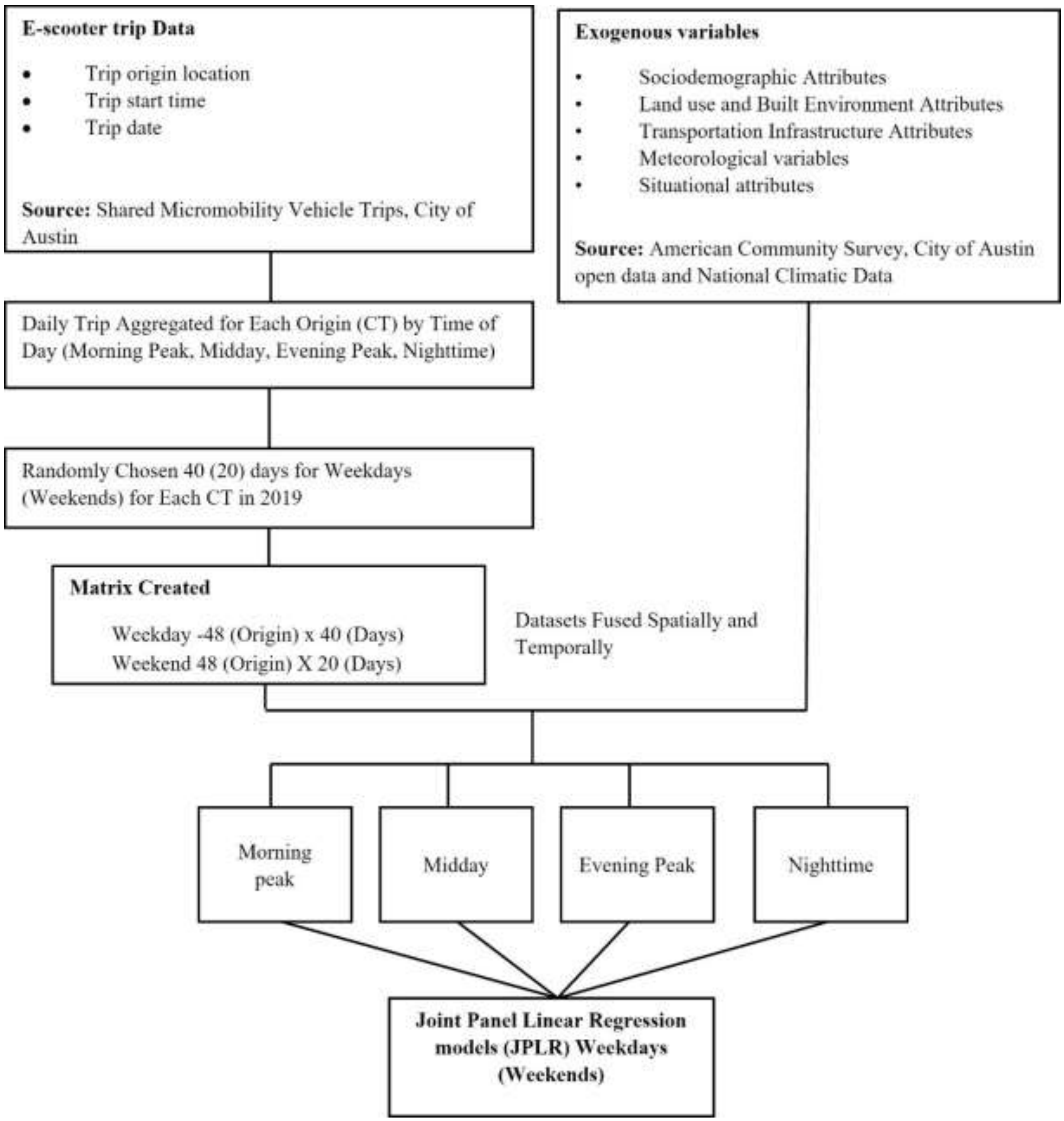


FIGURE 4 Flow chart demonstrating data preparation procedure for weekdays and weekends

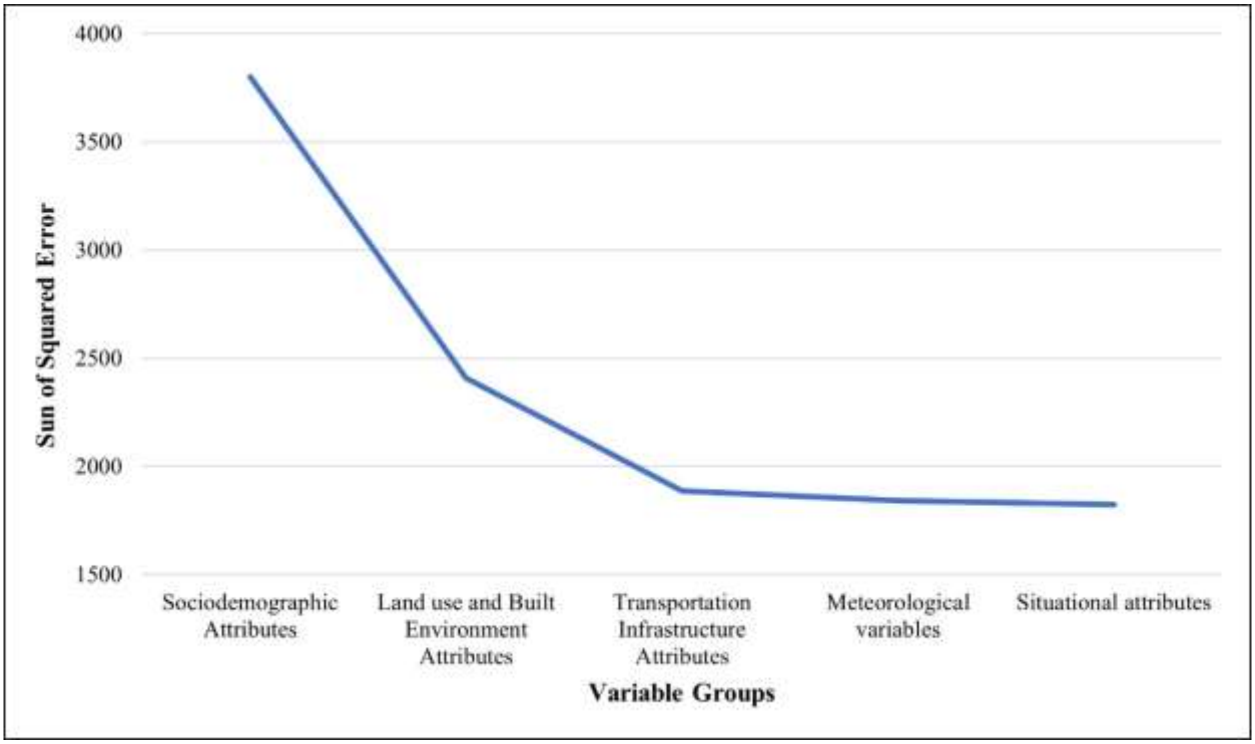


FIGURE 5 Sum of squared error for weekday morning peak

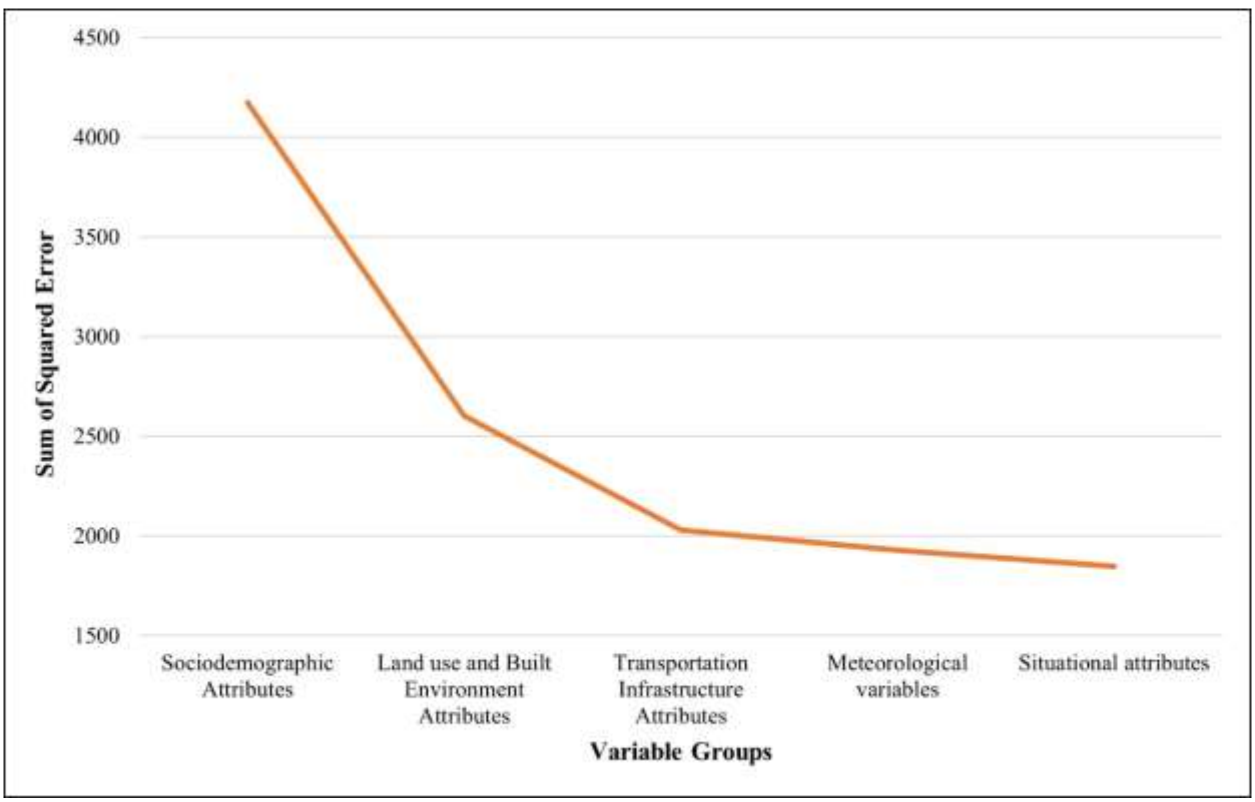


FIGURE 6 Sum of squared error for weekday evening peak

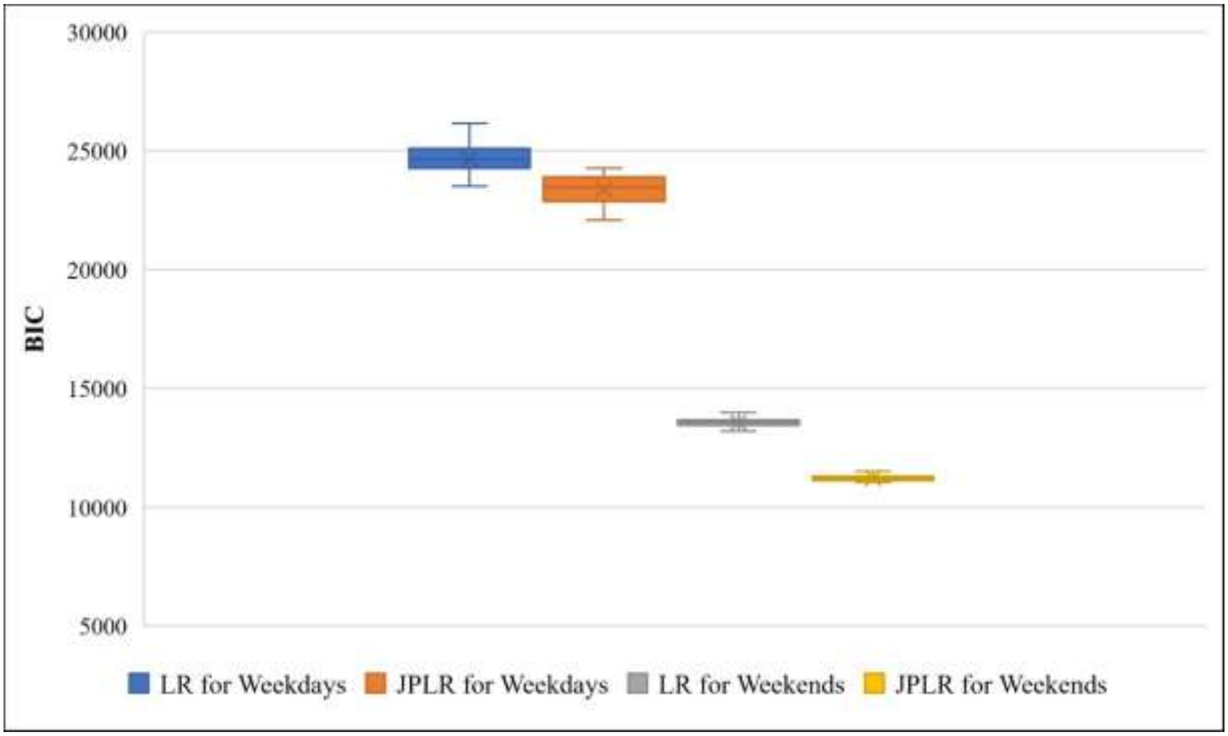
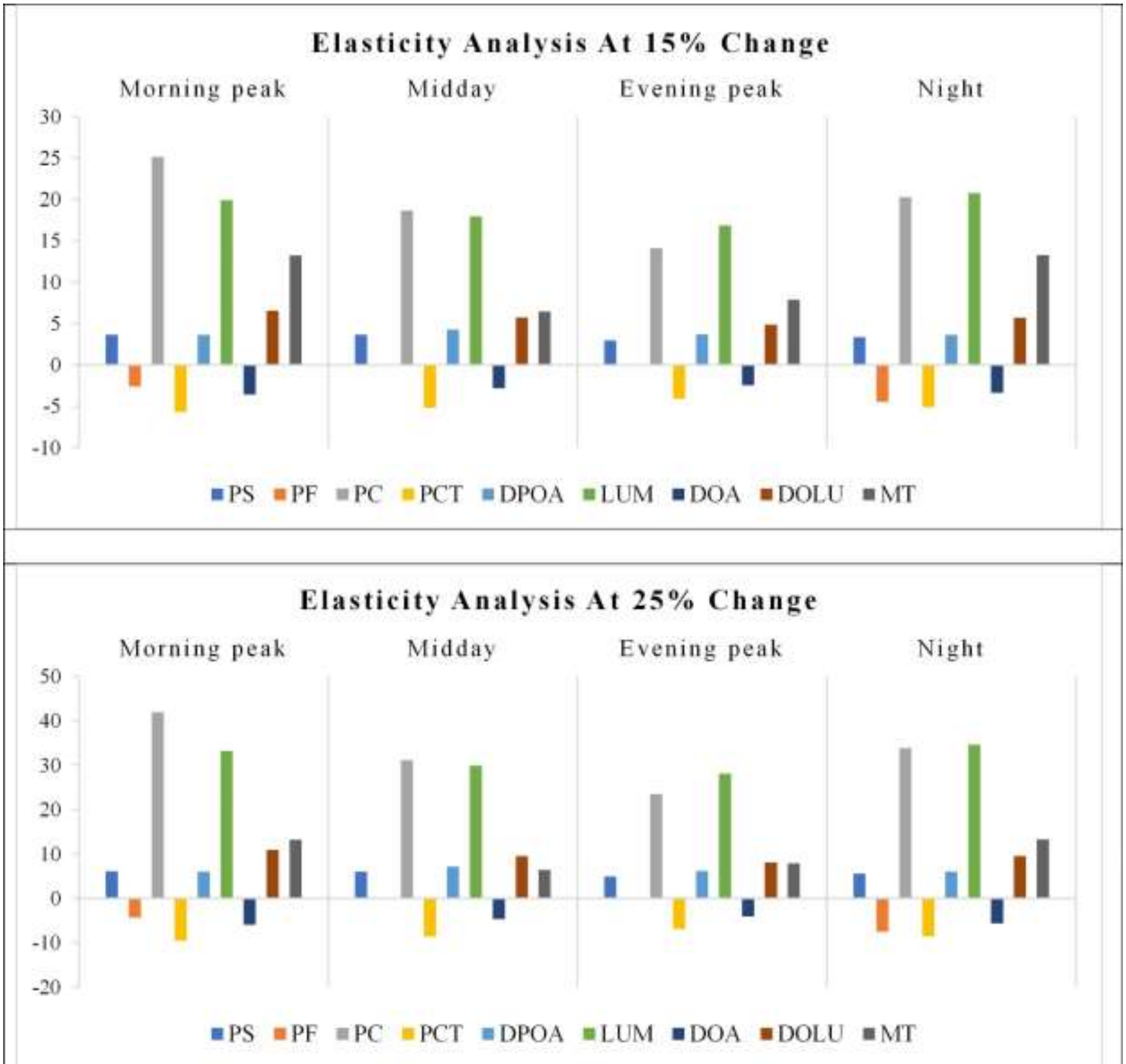
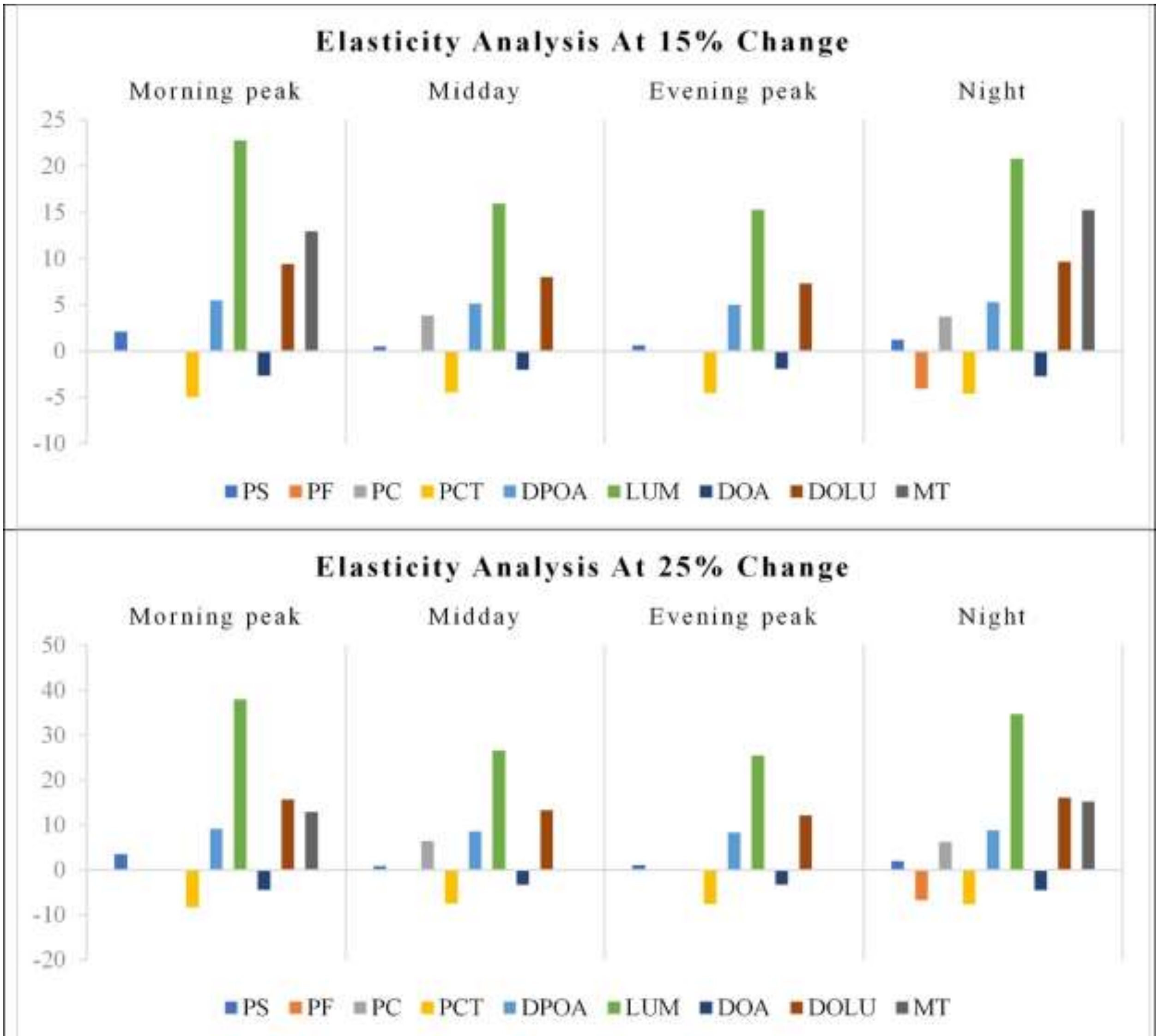


FIGURE 7 Model validation



Note: PS= Proportion of Students, PF=Proportion of Female, PC= Proportion of Commuters, PCT= Proportion of Commuters using who public transit, DPOA= Density of Park and Open space Area, LUM= Land Use Mix, DOA= Density of Office Area, DOLU= Density of Other Land Use Area, MT= Medium Temperature

FIGURE 8 Elasticity analysis for weekdays



Note: PS= Proportion of Students, PF=Proportion of Female, PC= Proportion of Commuters, PCT= Proportion of Commuters using who public transit, DPOA= Density of Park and Open space Area, LUM= Land Use Mix, DOA= Density of Office Area, DOLU= Density of Other Land Use Area, MT= Medium Temperature

FIGURE 9 Elasticity analysis for weekends