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(Citation)
Transportation,47(2):555-583

(Issue Date)
2020-04

(Resource Type)
journal article

(Version)
Accepted Manuscript

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Decisions on Truck Parking Place and Time on Expressways: An Analysis Using Digital Tachograph Data

Abstract: With the objective of deriving useful insights into measures against traffic congestion at service areas (SAs) and parking areas (PAs) on expressways and ensuring efficient use of SAs/PAs, this study investigated the decisions on where a truck is parked (i.e., choice of an SA or a PA), how long it is parked (i.e., parking time), and their influential factors. To this end, this study used the trajectory data of 1,600 trucks recorded in six-minute intervals by in-vehicle digital tachographs on the Sanyo and Chugoku Expressways in Japan from October 2013 to March 2014. First, the aspect of repeated choice of each truck (i.e., habitual behavior) toward a specific SA/PA was clarified. Next, a multilevel discrete-continuous model (Type II Tobit model) was developed to reveal the factors affecting the above decisions. The modeling results confirmed the existence of habitual behavior and showed that trucks were more likely to be parked a longer time at an SA/PA when it is closer to the destination. It appears that truck drivers may adjust their time at the SA/PA close to the destination to comply with the arrival time, which is often predetermined by the owner of the transported goods. Furthermore, the availability of restaurants and shops, and the number of parking spaces available for trucks and trailers are important determinants of parking time, whereas the existence of a convenience store is important to the choice of the SA/PA. Parking experience has an extremely strong positive effect on the parking choice and use. Moreover, increasing the number of parking lots may induce its longer use.

Keywords: *truck, rest area, habitual behavior, discrete-continuous model, expressways in Japan*

1. Introduction

A rest area (i.e., a parking area (PA) or a service area (SA)) located alongside an expressway or freeway is a facility where road users can take rest, use the restroom, refuel their vehicles, and so on. The existence of rest areas improves the comfort and convenience of road users (Campbell, 2014), minimizes travel diversions (Gates et al., 2013), and reduces fatigue-related crashes (McArthur et al., 2013). The distance interval and quality of rest areas vary from country to country. For instance, Gates et al. (2013) reported that in the US, rest areas are typically non-commercial facilities and the maintenance of the rest area networks has become increasingly challenging for the states. Rest areas on expressways in Japan are generally safe and operated by private companies. SAs in the Japanese expressways are usually placed every 50 km and typically equipped with restrooms, restaurants, food courts, and gas stations, whereas the PAs are smaller in terms of both size and amenities, and are typically placed every 15 km with restrooms, vending machines, and/or small kiosks. Although SAs/PAs can be an important factor that affects truck route choices on expressways, little is known regarding the choice of truck parking and decisions on parking time at SAs/PAs in Japan, mainly due to data unavailability.

The Sanyo Expressway (S-EXPWY) and Chugoku Expressway (C-EXPWY), the target expressways in this study, are inter-regional expressways connecting the western Kyushu region and eastern Kansai region (Figure 1). According to the 2010 Road Traffic Census (MLIT, 2010), C-EXPWY has an average 24-h traffic volume of 15,431 cars per day, whereas the average traffic volume of S-EXPWY is 37,787 cars per day. Clearly, the traffic volume of C-EXPWY is less than half that of S-EXPWY. Since the opening of all lanes of S-EXPWY in 1997, an obvious decline in users of C-EXPWY has been observed, leading to many PAs on C-EXPWY having to close or reduce their opening hours (see Table 1[1]). For example, the distance between gas stations is more than 150 km at some sections of C-EXPWY. In contrast, because the traffic volume on S-EXPWY is approximately 2.5 times higher than that on C-EXPWY, many parking lots are occupied by trucks, especially during late night. This often results in severe congestion in SAs/PAs. Therefore, the improvement of this unbalanced use of the expressways in this region has become an increasingly important policy issue. However, it should be noted that over-crowdedness by trucks on expressways is not a phenomenon that is specific to Japan. Similar situations prevail in Europe (Heinitz and Hesse, 2009; Carrese et al., 2014), in the US (Higgins et al., 2015), and developing countries such as India (Swamy et al., 2014).

[Figure 1: S-EXPWY and C-EXPWY] around here

[Table 1: Trends in closure and reduced opening hours of PAs on C-EXPWY] around here

Despite the urgent need to obtain fundamental knowledge that will help to solve the above issue, obtaining large-scale data on the parking time of trucks proved difficult. Relevant analysis can be conducted based on questionnaire surveys; however, such questionnaire-based methods suffer from the issue of population representativeness. Further, recalling and stating all the SA/PA choices and parking times made over a long period is burdensome for respondents. This study attempts to make use of Big Data to explore decisions on parking place choice and parking time as well as their influential factors. Recently, Big Data has been increasingly attracting attention from researchers in many disciplines. Examples of Big Data in the transportation field include IC cards of public transportation systems (e.g., Pelletier et al., 2011), person probe data with individual trajectories (e.g., Asakura and Hato, 2004), and in-vehicle car navigation data (including GPS-enabled smartphone usage for navigation) (e.g., Jiang and Zhang, 2017a). Such Big Data do not contain detailed factors related to the travelers' choices, but they include much detailed temporal and spatial information across much wider spaces and over a much longer period than questionnaire surveys. Considering the relative advantages of Big Data, this study used the trajectory data of 1,600 trucks recorded in six-minute intervals by in-vehicle digital tachographs[2] on S-EXPWY and C-EXPWY in Japan from October 2013 to March 2014.

[1] The information in Table 1 is further used to specify some SA/PA-specific variables used in the later analysis.
[2] The installation of digital tachographs has become mandatory in Japan for trucks having the vehicle total weight of seven ton or more or trucks having the maximum loading capability of four ton or more since April 2017.

This paper first clarifies the aspect of repeated choices of SAs/PAs; it then reveals the factors affecting the choices of the SAs/PAs and parking time at the SAs/PAs by developing a multilevel discrete-continuous model. Finally, discussions on the policy implications of the empirical analysis results are summarized with respect to traffic congestion at SAs/PAs on expressways and ensuring the efficient use of the SAs/PAs.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 introduces the digital tachograph data used here, explains the data processing, and presents the results of aggregate analyses. Section 4 describes the multilevel discrete-continuous model developed in this study. Section 5 explains the estimation results of the model. Section 6 provides discussion and conclusions of this study.

2. Literature review

In Japan and other countries, only a few studies on SA/PA choice and usage behavior can be found. Chatterjee and Wegmann (2000) noted that in the US, truck parking spaces in public rest areas and pull-out areas along Tennessee's Interstate highways are fully occupied at night, causing large trucks to be parked along the shoulders of the ramps leading to these areas. Based on interview survey conducted with truck drivers, they found that although there are facilities for resting and sleeping at public rest areas along major highways, many truck drivers cannot take advantage of these facilities because of unavailability of truck parking especially during peak resting hours. Al-Kaisy et al. (2012) stated that existing studies on rest areas are either outdated or used limited samples. By using data collected from surveillance camera sets overlooking the overall parking area for 1 week at 44 study sites, they found that in the US, the mean dwell time of trucks is longer than that of passenger cars on low-volume interstate freeways, that is, approximately 38 min during daytime and approximately 3 h and 22 min during nighttime. These reported dwell times are much longer than those in Japan are (as summarized in the latter part of this paper). Muramatsu and Oguchi (2017) recommended a first-in first-out (FIFO) condition to alternate the electronic toll collection (ETC) data combined with probe data in describing the performance of parking areas on expressways. They assessed the performance by only measuring the number of vehicles entering and exiting the parking areas; however, the duration of stay at each rest area was not analyzed in their study. A study conducted by Jung et al. (2017) in Korea showed that supplemental rest areas, which are relatively small road facilities installed between regular rest areas to provide resting spaces for drowsy drivers, could reduce the number of crashes due to drowsy driving by approximately 14%, particularly on freeway sections with 2–3 traffic lanes or ramps. Kay et al. (2014) presented the results of binary logistic regression and negative binomial regression on the demand characteristics of 47 roadside rest areas in Michigan. They found that the greater the distance between a rest area and the nearest upstream rest area, the greater the number and proportion of vehicles entering a roadside rest area. They used an online data queried from the Traffic Monitoring Information System of the Michigan department of transportation. However, none of the above studies considered simultaneous decisions on rest area stops and parking time.

In Japan, Shiino et al. (2011) analyzed the characteristics of rest facility visit behavior based on data from logs of radio antennas installed at the entrances and exits of SAs/PAs and a questionnaire survey on the actual use of the SA/PA facilities. They revealed that based on aggregate analyses, the (1) SA/PA facilities, (2) sizes and characteristics of the upstream and downstream SA/PA facilities, and (3) occurrence of road congestion influence the visiting probability. Matsushita et al. (2011) conducted an SA/PA user attitude survey, and developed an SA/PA choice model (a binary logit model) and an SA/PA attractiveness evaluation model (a multiple regression model). Their results showed that travel time, SA/PA attractiveness, and number of travelers aged over 65 years positively influence the SA/PA choice, whereas the available spaces in parking lots, restroom cleanliness, and availability of restaurants, convenience stores, and vendor stands contribute to a higher evaluation of the SA/PA attractiveness. The importance of information provision regarding an SA/PA was also highlighted (Muramatsu and Oguchi, 2017). Furthermore, by using two types of questionnaire surveys (a paper-based survey and a web survey), Nishii et al. (2014) constructed a nested logit model, where the upper level considers whether to stop at an SA/PA (binary choice) or not, and the lower level presents the choice of a specific SA/PA on S-EXPWY and C-EXPWY (multinomial choice). Nishii et al. confirmed that the degree of recognition of SAs/PAs and distance from the entry interchange (IC) affect the decision to make a stop, whereas driver satisfaction has a significant and positive effect on the choice of a particular SA/PA. Unexpectedly, they reported that the distance from the entry interchange (IC) has a negative effect on the decision to make a stop.

With the exception of the above study by Shiino et al. (2011), the existing studies in Japan only focused on questionnaire survey data obtained from non-business trips and passenger cars. In other words, no studies on trucks in Japan can be found. To fill this research gap, the present study (i) focuses on the parking behaviors of truck drivers, (ii) uses a six-month vehicle trajectory data (i.e., digital tachograph data), and (iii) represents SA/PA choice and usage behavior simultaneously by developing a multilevel discrete-continuous model. Because digital tachograph data include both temporal and spatial information of trucks, it is possible to analyze not only the SA/PA choice behavior, but also the usage behavior (parking time in this study). The analysis based on vehicle trajectory data makes it possible to more accurately ascertain the state of long-term parking than questionnaire surveys. It is also possible to analyze the repeat choices (i.e., habitual behavior) of each individual vehicle. Recently, Hirai et al. (2016) analyzed the parking time of cars by using the ETC data. They estimated the parking time at an SA/PA based on the entry/destination time to the ICs. However, it is difficult to use such ETC data to capture how many SAs/PAs were visited and the particular SAs/PAs where a vehicle stopped.

3. Data and features of SA/PA choice and usage behavior

3.1 Digital tachograph data

The digital tachograph data used in this study are trajectory data spanning a period of six months from October 2013 to March 2104[3], transmitted from 1,600 trucks equipped with digital tachographs manufactured by Kouei System Ltd.[4,5] The information is available at each truck (vehicle) level. Unfortunately, the size of the truck was known only for 32.5% of the trucks because of which we discarded this information. The original data were second-by-second data; however, they were stored every six minutes and the original data are not available to the public. The data available to this study included the date of the trip and the GPS information (longitude and latitude) (vehicle location, odometer value (km), number of engine revolutions, and trigger class (distinguishing between regular data in six-minute intervals and data at the time of engine start/stop)). This dataset also included the logistics company ID of each truck, and the type of business performed by each company. The total number of companies considered in this study was 78. For our research purpose, this study extracted all data associated with S-EXPWY and C-EXPWY (see Figure 1).

3.2 Data processing

In this study, the digital tachograph data were processed in the following manner:

i. Data from 140,288 original csv files (date + vehicle ID) were grouped into units of 1,600 vehicles by using the vehicle ID.
ii. The latitudes and longitudes in the original csv files were converted from the decimal format to the degree/minute/second (DMS) format.
iii. The following processes were conducted using ArcGIS ver 10.3.1 (ModelBuilder function) and code developed by us (the following was repeated for 1,600 vehicles):
    A) The csv files were converted to shapefiles.
    B) The coordinate system of the shapefiles was changed from the old definition (Tokyo Datum) to the recent definition (Japanese Geodetic Datum 2000).

[3] During the period covered by the data, the midnight discount rate of the expressways was 50%, although it is now reduced to 30% (December 2017). At that time, the SA/PA parking congestion was very severe and therefore it is worthwhile to focus on this period.

[4] https://www.kouei.co.jp/products/operation/

[5] We need to admit the possibility of the selection bias due to the use of the data from this particular digital tachographs system.

C) Data for travel on S-EXPWY and C-EXPWY were extracted.
D) Information on the closest SA/PA from the current driving location (separated by driving direction: West to East (upstream) and East to West (downstream)) was added.
E) Information on the closest IC from the current driving location was added.
F) Information on the time of passing each SA/PA was added, where the definition of passing is the moment when the distance from the current driving location to each SA/PA became less than 300 m[6].
G) Information on the time and odometer value when passing the first and the last IC on C-EXPWY or S-EXPWY were added.

iv. Calculation of parking time at SAs/PAs (the following were repeated for the 1,600 vehicles):
A) The trigger class "28 (onboard device stop)" data were extracted (it was assumed that the trip will change over) and the trip ID was added[7].
B) In the trigger class "37 (regular data)," if the average velocity was zero for six minutes and the distance from the current driving location from any SA/PA was less than 300 m, it was considered as a stop. The stopping time was counted as the parking time as long as the above conditions were met.

3.3 Analysis unit, sample, and choice set

The analysis unit in this study is each GPS dot representing a truck. The samples were these dots, which first enter the catchment areas of the SAs/PAs, where an SA/PA can be chosen for each trip. Figure 2 briefly illustrates how we selected the samples. In the figure, a truck goes from East to West along the expressway. The point marked in black is the GPS dot that first enters the catchment area of the SA for this trip (we assumed a 300-m radius). Therefore, the dot is included in our analysis as a sample. The dots marked in gray are excluded (i.e., not regarded as a sample) because they are not located within the 300-m radius. The dot marked in white was also excluded because it is not the "first" sample entering the catchment for this trip (i.e., it just keeps taking a rest at the SA and no choice is made). The samples are indexed by i ($i = 1, \ldots, I$).

The choice set is binary; that is, whether to stop at the SA/PA or not to stop at the SA/PA. The parking time was obtained by taking the difference between the clock times corresponding to the entrance and departure to/from the catchment area. The actual SA/PA arrival and departure times are unavailable because the original data provided by Kouei System Ltd. are stored as six-minute intervals. Therefore, we obtained the above actual times based on the following assumption. We assumed a random (uniform) distribution of arrival and departure times for each six-minute period, and calculated the actual parking time by combining the first three minutes and the last three minutes (thus, the minimum parking time is six minutes).

[Figure 2: Samples used in our analyses] around here

3.4 Features of parking choices and distributions of parking time

Before moving into the model analysis, the results of the aggregate analysis are presented to summarize the basic parking choice and parking time information. First, we focus on the overall distribution of parking choice/time (Subsection 3.4.1). Next, because we are interested in spatio-temporal differences in the parking time at each SA/PA, we conduct an aggregate analysis by answering the following two questions: (1) does the parking time differ between S-EXPWY and C-EXPWY, and between SA and PA? (2) Does the parking time differ among time periods? Then, in order to understand the nature of the habitual behavior, we further raised the following question: (3) does the parking time depend on past usage experiences?

[6] Threshold values of 300 were set via a trial and error process by checking the locations of stopping trucks around the SAs/PAs on GIS.
[7] Because onboard devices sometimes do not stop, a trip was considered to have ended if there were no observations for three hours.

3.4.1 Overall parking time distribution

Table 2 presents the descriptive statistics for parking time except for zeros (i.e., nonstop) by the expressway (S-EXPWY or C-EXPWY) and the driving direction (upstream or downstream). Compared to the median values, the mean values are larger by 5 to 11 minutes, meaning that the distribution is right-skewed. It can be seen that the maximum value exceeded 9 h for all cases. Such a long parking may involve sleeping or time adjustments, where early arrival may be necessary to avoid any delivery delay caused by traffic congestion, and time adjustment may be needed to reach the destination on time. The shape of the distribution does not actually follow a normal distribution (see Figure 3, where zero parking times are excluded). Therefore, the parking time is log-transformed when the Type II Tobit model is used. The frequency of large values is extremely low and they rarely appear (Figure 3).

Regarding the parking choice, the information on the stop and nonstop samples is summarized in Tables 2 and 3. Overall stop rates (in percentage) range between 39% and 45% (Table 2), which does not indicate a significant difference between S-EXPWY and C-EXPWY, and between upstream and downstream driving directions. Figure 4 represents the stop rate for each SA/PA. The stop rates are higher for Ougo PA on S-EXPWY (71%), Nanatsukahara SA (72%), and Oosa SA (76%) on C-EXPWY. The rates are however lower for the following three PAs on C-EXPWY: Nioroshitouge PA (4%), Yuda PA (14%), and Asakura PA (18%). As shown in Figure 4, the average stop rate for PAs (41%) is smaller than that of SAs (45%). In addition, the average stop rate for S-EXPWY is 43%, whereas that for C-EXPWY is 41%. The small difference between S-EXPWY and C-EXPWY suggests that the stop rate may not be so sensitive with respect to traffic volume on the expressways.

[Table 2: Descriptive statistics for parking time (except for zeros)] around here

[Figure 3: Frequency distribution of parking time (except for zeros)] around here

[Figure 4: Stop rate for each SA/PA (IDs for SA/PA are shown in Table 3. C/S after the ID represents Chugoku Expressway and Sanyo Expressway, respectively).] around here

[Table 3-1: Stop rate for each SA/PA (Chugoku Expressway)] around here

[Table 3-2: Stop rate for each SA/PA (Sanyo Expressway)] around here

3.4.2 Parking times on S-EXPWY and C-EXPWY, and at SAs and PAs

Figures 5(a) and 5(b) show the cumulative proportions of parking time by expressway and by the type of rest area (SA vs PA), whereas Figures 5(c) and 5(d) display the boxplots of parking time by expressway and by type of rest area, respectively. In Figures 5(c) and 5(d), only the samples with less than 100 min are shown for readability, although all samples were used to draw these figures[8]. These figures show that the parking times are longer on C-EXPWY than on S-EXPWY, and longer at SAs than at PAs. Figure 6 further shows the average parking time separated by type of rest area. It can be seen that the average parking time at SAs is longer, especially on C-EXPWY, although the overall stop rate of PAs and SAs is comparable (41% for PAs vs 45% for SAs).

[Figure 5: Features of parking time by SA/PA] around here

[Figure 6: Average parking time by SA/PA] around here

3.4.3 Differences in parking time across time periods

Figure 7 shows the cumulative proportion of parking time separated by time period (see Figure 7(a))

[8] The bottom and top of the box are the 25th and 75th percentiles; the band near the middle of the box is the 50th percentile (the median). The dots at the end of the boxplot represent outliers (less than Q1 – 1.5 × IQR; greater than Q3 + 1.5 × IQR, where IQR denotes the interquartile range (Q3–Q1)).

and boxplots of parking time separated by time period, where only samples for less than 100 min are shown for readability, although all the samples were used to draw the boxplot; see Figure 7(b). We defined 00:00–04:00 as “Midnight,” 05:00–09:00 as “Early Morning,” 10:00–13:00 as “Late Morning,” 14:00–16:00 as “Afternoon,” 17:00–20:00 as “Evening,” and 21:00–23:00 as “Night.” These categories roughly correspond to the price discount based on the time period[9]. There are some exceptions depending on regions (e.g., Osaka and Tokyo are excluded), and price discount policies change frequently. For parking time under the cumulative proportion of 0.60, the differences by period are rather small (note: the median for Early Morning is a bit shorter). However, for the range above the cumulative proportion of 0.75, the parking time becomes longer during “Night” and “Midnight.” These results suggest the existence of long parking during these two periods, as is the case in the US (Al-Kaisy et al., 2012).

[Figure 7: Features of parking time by periods] around here

3.4.4 Dependence of parking time on usage experience

Figure 8 illustrates the repeated use of the same trucks over the six-month period. The average frequency is 87.7.

[Figure 8: Frequency distribution of repeated use by the same truck] around here

In order to quantify the habitual behavior of the trucks, Figure 9 shows the repeated choices made by each truck. Figure 9(a) shows the cumulative distribution of the repeated use (usage experience) of the same SA/PA by the same truck, whereas Figure 9(b) displays the boxplots of the parking time separated by repeated use of the same SA/PA by the same truck. It is notable that the increase in parking time associated with the usage experience is clearly identified, suggesting that frequent users park for extended periods.

[Figure 9: Features of repeated use of the same SA/PA by the same truck in the past] around here

4. Multilevel Type II Tobit model

Decisions on parking places and times may be interdependent. If a longer parking time is required for not only taking a nap but also performing other activities (e.g., having a meal or taking a shower), an SA may be more preferred over a PA because an SA has more amenities than a PA. A reverse case may also be observable. For example, upon parking at an SA, when a truck driver discovers the facility of a shower room, he/she may decide to use it, which lengthens the parking time. The above potential interdependence may exist irrespective of who actually made the decisions. It is however unclear whether the company managers and/or drivers actually make the above decisions. Based on a questionnaire survey (covering 52 company managers and 178 drivers) targeting the same region, Jiang and Zhang (2017b) found that approximately 60% of truck routes were decided by company managers and the remaining share refers to other types of decisions (i.e., decisions made by the drivers themselves, jointly by both managers and drivers, or case by case). Although no information is available regarding the decisions made by the drivers themselves or the decisions taken jointly by the drivers and the company managers, it is logical to assume that a similar decision-making pattern may also be applicable to them. Here, to accommodate the above interdependent decisions, this study adopts a Tobit-type model with a new feature.

Precisely speaking, the model is a Type II Tobit model. However, unlike the conventional Type II Tobit model, we introduce random effects at a company/group level within a multilevel modeling framework for controlling possible unobserved heterogeneity, which may lead to correlations

[9] There are several price discount policies on the expressways in Japan based on the time period. For more details on discount policies, visit the East Nippon Expressway Company website (https://www.driveplaza.com/traffic/tolls_etc/etc_dis_night/).

between samples. The resulting multilevel model is formulated as follows.

$$y_{1ij} = \begin{cases} y_{1ij}^{*} & if \quad y_{2ij}^{*} > 0 \\ 0 & if \quad y_{2ij}^{*} \le 0 \end{cases}, \tag{1}$$

$$y_{1ij}^{*} = \boldsymbol{x}_{ij}' \boldsymbol{\beta} + u_{1j} + \varepsilon_{1ij}, \tag{2}$$

$$y_{2ij}^{*} = \boldsymbol{z}_{ij}' \boldsymbol{\gamma} + u_{2j} + \varepsilon_{2ij}, \tag{3}$$

$$\begin{bmatrix} \varepsilon_{1ij} \\ \varepsilon_{2ij} \end{bmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho_1\sigma_1 \\ \rho_1\sigma_1 & 1 \end{pmatrix}\right]; \begin{bmatrix} u_{1j} \\ u_{2j} \end{bmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_1^2 & \rho_2\tau_1\tau_2 \\ \rho_2\tau_1\tau_2 & \tau_2^2 \end{pmatrix}\right]. \tag{4}$$

Here, i and j (j=1, …, J) denote the sample and group (i.e., company), respectively. The variable y_{1ij} is the parking time, which indicates a nonstop journey if it is equal to zero and indicates a stop otherwise. The variables y_{1ij}^{*} and y_{2ij}^{*} are latent variables, which are used to specify whether a nonstop or a stop is observed. To be precise, it is assumed that if y_{2ij}^{*} is positive, a stop is observed, and if y_{2ij}^{*} is non-positive, a nonstop is observed. In the case of a stop, the latent variable y_{1ij}^{*} is used to predict the parking time. $\boldsymbol{z}_{ij}$ and $\boldsymbol{x}_{ij}$ are explanatory variable vectors for y_{1ij}^{*} and y_{2ij}^{*}, and $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ represent their coefficient vectors. Furthermore, ε_{1ij} and ε_{2ij} are correlated error terms that follow a bivariate normal distribution (mean: 0; standard deviations: σ_1 and 1; correlation: ρ_1)[10]. Finally, the most important feature of the above modeling process is that two error components u_{1j} and u_{2j} are introduced to explain the unobserved company-specific heterogeneity, which follows another bivariate normal distribution (mean: 0; standard deviations: τ_1 and τ_2; correlation: ρ_2). The above decisions may show similarities within the same company. The above company-level error terms u_{1j} and u_{2j} are introduced to accommodate the influence of such similarities, which may cause correlations between the samples.

Both parking place choice and parking time are jointly represented in the above model structure. As stated at the beginning of this section, both company managers and drivers can be decision makers for the above two decisions. Irrespective of who makes the above decisions, the above multilevel modeling approach is applicable as long as the decisions are rational.

To estimate the above multilevel model, we apply the maximum likelihood method using the *cmp* module (Roodman, 2011) in Stata (version 14). In general, the studies on unobserved heterogeneity (represented by u_{1j} and u_{2j}) in the context of the Type II Tobit model are rare (Bellio and Gori, 2003; Grilli and Rampichini, 2010). As seen later, our empirical results show that ignoring such heterogeneity may lead to wrong policy implications at worst.

5. Model estimation results

5.1 Dependent variables and explanatory variables

There are two dependent variables: whether to stop at a particular SA/PA (choice of SA/PA) and how long to stop (parking time). The analysis unit and samples in our analysis have already been explained in Figure 2. Parking time was converted into a natural logarithmic value considering its right-skewed distribution (Figure 3). The explanatory variables were categorized into "expressway-specific varia-

[10] Because the deviation resulting from this assumption causes loss of consistency of the estimator (Vella, 1998), a better treatment of error correlation such as employing Copulas may be needed (Marra and Radice, 2013). However, we made this bivariate normal assumption for simplification.

bles," "SA/PA-specific variables," "truck-specific variables," and "sample-specific variables," where the first three types of variables are invariant over time (i.e., temporally fixed) and the last type changes over time (i.e., temporally varying). These explanatory variables are shown in Table 4 and their statistical features are illustrated in Table 5. Note that the SA/PA information included in this part of the analysis reflects the trends in closure and reduced opening hours of PAs on C-EXPWY (Table 1).

Expressway-specific variables include two dummy variables: upstream (to reflect the influence of driving direction) and S-EXPWY (to reflect the influence of expressway type). There are seven SA/PA-specific variables: one dummy variable "SA" indicating the influence of the rest area type, three dummy variables reflecting the influence of different functions (Convenience store, Gas station, and Other shops), one distance variable (i.e., distance from the previous upstream SA/PA), and two continuous variables (i.e., number of parking spaces for trucks and trailers, number of toilets). The number of parking spaces for trucks and trailers are introduced to approximate the supply of parking.

Truck-specific variables contain six dummy variables to indicate the business type of logistics companies: household goods, restaurants, convenience stores, oil (tanker), retails and distribution, and the unidentified type. Sample-specific variables include five variables. The first is the frequency of using the same SA/PA by the same truck in the past, which is used to capture the influence of usage experience. The second refers to whether a driver has driven continuously for four or more hours, which is used to reflect the influence of long driving. This variable is introduced to reflect the fact that in Japan, truck drivers are regulated by a labor law that mandates a break of at least 30 min after a 4-h driving session. The third variable is distance remaining until the destination IC: it is expected that the shorter the distance, the higher the probability of stopping at an SA/PA if the driver has to perform a time adjustment. The fourth variable is introduced to express the influence of open restaurants: whether or not a restaurant is open at the time of stopping at the SA/PA. The last indicates the influence of the time period when the truck passes or enters the SA/PA being studied, and includes 23 dummy variables.

[Table 4. Explanatory variables] around here

[Table 5. Descriptive statistics of the explanatory variables] around here

5.2 Parameter estimation and discussion

Table 6 shows the results of the parameter estimation. We found that the parameter estimate for ρ_1 and σ_1 are statistically significant at 5% confidence level, both in the conventional model and in the multilevel model ([.], after, for instance, ρ_1, denotes the confidence interval for the estimate of ρ_1). The negative correlation coefficient suggests that the error term for parking choice and the parking time equation have a negative association. The random effects parameters τ_1 and τ_2 are both significant at 5% confidence level, suggesting that the trucks that belong to the same company tend to behave similarly in terms of SA/PA choice and use. The significant parameter ρ_2 indicates that the random effects are not independent and have a positive correlation (5% significance level), which suggest the importance of considering group level heterogeneity. Due to the introduction of random effects terms, goodness of fit in terms of log-likelihood is fairly improved. We further confirmed that the parameters of the variable "Number of parking spaces for trucks and trailers" are negative in the non-multilevel model, but become positive in the multilevel selection model. The availability of parking encourages drivers to access the SA/PA, and therefore the multilevel model produces a much natural result. The estimation results from the multilevel model are summarized for each variable group.

(1) Expressway-specific variables (temporally fixed)
For the two (dummy) variables, i.e., "Sanyo Exp. Way" and "Upstream," "Sanyo Exp. Way" does not affect the SA/PA choices and parking time. Conversely, the driving direction affects the SA/PA choices such that the parameter "Upstream" has a 1% significance level. The parameter signs of "Upstream" indicate that truck drivers driving upstream tend to stop more (the selection model). Note that conventional models produce significant coefficient estimates for both variables for all cases, which may lead to wrong (biased) implications.

(2) SA/PA-specific variables (temporally fixed)

Of the seven relevant variables, all of them except “SA” and “Gas station” affect the SA/PA choices (with at least 10% significance level). Further, the four variables insignificantly affecting the parking time are “SA,” “Gas station,” “Distance from previous SA/PA,” and “Number of toilets”[11]. The SAs/PAs that attract the most truck drivers are those with convenience stores and more parking spaces for trucks, and are located far from the nearest upstream SA/PA because the corresponding parameters are statistically significant. The magnitude of the parameter for the nearest upstream SA/PA in the selection model is large, suggesting that the distance between the SAs/PAs matters when the truck drivers consider accessing the SA/PA. For instance, if the distance between the SAs/PAs is short, a driver may skip the upcoming PA and look for the next SA. However, if the distance between the SAs/PAs is long, the driver may choose the upcoming stop regardless of its type. In contrast, the presence of a shop is associated with fewer stops by truck drivers. This result suggests that installing shops does not necessary attract truck drivers. Note that the difference between the SAs and PAs are negligible in terms of both choice and use. Some of the PAs have similar facilities and space and we may say that the difference for truck drivers are now small.

More parking spaces for trucks and trailers appears to have a significant (at 1% significance level) positive influence on the parking time. Hence, increasing the number of parking lots (i.e., parking affordability) may attract truck drivers and encourage longer use.

(3) Truck-specific variables (temporally fixed)

Compared to trucks transporting household goods (a reference for estimating the variables for other business types), trucks related to other business types have shorter parking time and lower stopping probability. Trucks transporting goods for convenience stores have the shortest parking time (with respect to the coefficient estimate). As regards the stopping probability, those of convenience stores, oil tankers, and retail/distribution trucks are significantly lower than that of the reference trucks. The existence of such “group effects” suggests the possibility of group/company level (but not individual truck level) decision making. However, it is impossible to verify this based on the current data alone. This is left as a future research issue.

(4) Sample−specific variables (temporally varying)

Even though an open restaurant at the time of using the SA/PA does not affect the driver’s SA/PA choices, it surely influences the parking time as it extends the time. This observation may mean that while truck drivers are not concerned about whether a restaurant is open or not when they choose an SA/PA, drivers will increase their parking time if the restaurant is open.

Japanese truck drivers are regulated under “Labor Standards Act,” and one of the important articles of this act is that a driver who drives continuously for 4 h must take a break of not less than 30 min. In order to consider this aspect, we created a variable for long continuous driving (greater than or equal to four hours). The coefficient estimates of this variable suggest that the drivers who have been driving continuously for a long time have a higher probability of stopping at an SA/PA, and staying there longer. Similarly, a shorter distance remaining to reach the destination IC results in a higher probability of stopping at an SA/PA and a longer parking time. This finding implies that truck drivers may adjust their time use before approaching their destination.

The parking usage experience shows an extremely strong positive effect at a 1% significance level on choice and use, suggesting that experiential accumulation has a major influence on the SA/PA choice and usage behavior. In other words, the more the experience, the more they choose and the longer they park. This implies that it may be an effective way to provide information on SAs/PAs with more parking spaces, which consequently leads to them being less congested and encourages more drivers to experience using the SAs/PAs.

[Table 6: Parameter estimation results] around here

[11] The facilities at the SAs/PAs are improved sometimes. Moreover, the number of parking lots would have been determined according to the number of trucks that request for parking. These facts suggest the existence of reverse causalities. However, because the SA/PA facilities are available to all users and not for truck drivers alone, it is natural to assume the causal direction from the facilities or number of parking lots to choice/usage behavior.

6. Discussion and Conclusions

In this case study, we examined the truck drivers' choices of service areas (SAs) and parking areas (PAs) and their parking time with the objective of deriving useful insights into implementing measures against traffic congestion at SAs/PAs on expressways and ensuring the efficient use of SAs/PAs. The study was performed based on the trajectory data of 1,600 trucks recorded in six-minute intervals using in-vehicle digital tachographs on the Sanyo and Chugoku Expressways in Japan from October 2013 to March 2014. A multilevel Type II Tobit model was developed to reveal factors affecting the choices of SAs/PAs and their parking time. The obtained results and possible policy implications can be summarized as follows:

(1) More parking spaces for trucks and trailers seem to have significant (at 1% significance level) positive influence on the parking choice and time in the multilevel selection model. Hence, increasing the number of parking lots (i.e., parking affordability) may attract truck drivers and encourage longer use.

(2) The magnitude of the parameter for the nearest upstream SA/PA in the selection model is large, suggesting that the distance between the SAs/PAs matters when truck drivers consider accessing the SAs/PAs. Such results may suggest the usefulness of flexible relocations of the SAs/PAs. Currently, SAs in the Japanese expressways are usually placed every 50 km, whereas the PAs are typically placed every 15 km. Such rule clearly has merit in terms of fairness, but may not be necessarily efficient.

(3) Parking experience has an extremely strong positive effect on the parking choice and use. This suggests that providing information to companies and drivers regarding SAs/PAs with a large number of parking spaces and the resulting lower level of congestion may be effective in encourage companies and drivers to use those SAs/PAs.

(4) Further, it has been revealed that trucks may perform some time adjustments at some SAs/PAs close to the destination IC. Such time adjustments produce negative externalities for the other users who have higher willingness to pay.

In the future, it is important to gather more long-term data for a deeper understanding of causalities involved in SA/PA choices and parking time decisions due to service level changes. One difficulty in applying the model developed in this study is that in some companies, drivers choose the truck routes by themselves, whereas in other companies, both company managers and drivers may make a joint decision. Such decision-making mechanisms have to be revealed by directly interviewing drivers and company managers. In line with such a consideration, it may be worth exploring methods to combine Big Data and the results of questionnaire surveys. In addition, studies using Big Data and covering a much bigger transport network should be further promoted. Finally, it is surely important to reflect the influence of cost when we discuss congestion mitigation. Although we can calculate the cost based on distance and time period, such calculation cannot reflect reality, for example, some companies have a frequent-user contract with expressway companies. We leave this as an important future research issue.

Acknowledgment

This study was funded by the West Nippon Expressway Company Limited, and JSPS KAKENHI Grant Numbers 15H02271 and 17K18905.

The corresponding author states on behalf of all authors that there is no conflict of interest.

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Table 1: Trends in closure and reduced opening hours of PAs on C-EXPWY

Closure	Yuda PA (Yamaguchi Pref.)	Small restaurant; Small kiosk (2003)
	Kano PA (Yamaguchi Pref.)	Gas station (2005)
		Information center (2007)
	Yoshiwa PA (Hiroshima Pref.)	Gas station (East to West: 2008; West to East: 2009)
	Nanatsukahara PA (Hiroshima Pref.)	Information center (2007)
	Taishakukyo PA (Hiroshima Pref.)	Restaurant; Small kiosk; Gas station (2005)
Reduced opening hours	Kano PA (Yamaguchi Pref.)	Restaurant; Small kiosk (2007)
	Nanatsukahara PA (Hiroshima Pref.)	Small restaurant; Small kiosk (2007)
	Taishakukyo PA (Hiroshima Pref.)	Gas station (2010); Restaurant (2014)

Table 2: Descriptive statistics for parking time (except for zeros)

	Parking time (minutes)			
	Sanyo Expressway		Chugoku Expressway	
	Downstream	Upstream	Downstream	Upstream
Mean	26.95	25.74	28.84	28.53
Minimum	6	6	6	6
1st Quartile	6	6	6	6
Median	18	18	24	18
3rd Quartile	36	30	36	42
Maximum	912	828	582	636
Sample size for stop	10,777	13,187	3,634	2,988
Sample size for nonstop	15,573	16,144	4,832	4,597
Total sample size	26,350	29,331	8,466	7,585
Stop rate	0.41	0.45	0.43	0.39

Table 3-1: Stop rate for each SA/PA (Chugoku Expressway)

SA/PA Name	SA/PA	Number of with stops			Number of without stops			Ratio: with	Ratio: without
		Downstream	Upstream	Total	Downstream	Upstream	Total		
02.Ouji	PA	525	199	724	145	176	321	0.69	0.31
03.Isa	PA	64	78	142	138	130	268	0.35	0.65
04.Mitou	SA	104	57	161	182	122	304	0.35	0.65
05.Yuda	PA	2	0	2	9	3	12	0.14	0.86
06.Nioroshitouge	PA	1	0	1	5	20	25	0.04	0.96
07.Kano	SA	1	8	9	7	4	11	0.45	0.55
08.Asakura	PA	1	1	2	5	4	9	0.18	0.82
09.Fukaya	PA	5	2	7	4	10	14	0.33	0.67
10.Yoshiwa	SA	3	7	10	10	1	11	0.48	0.52
11.Tsutsuga	PA	8	5	13	9	2	11	0.54	0.46
12.Asa	SA	539	220	759	754	721	1,475	0.34	0.66
13.Hongo	PA	204	137	341	369	351	720	0.32	0.68
14.Gounokawa	PA	142	142	284	321	294	615	0.32	0.68
15.Nanatsukahara	SA	180	51	231	51	38	89	0.72	0.28
16.Honmura	PA	44	15	59	48	51	99	0.37	0.63
17.Taisyakukyo	PA	15	17	32	40	47	87	0.27	0.73
18.Shingo	PA	62	24	86	86	33	119	0.42	0.58
19.Oosa	SA	205	201	406	63	62	125	0.76	0.24
20.Maniwa	PA	165	237	402	427	445	872	0.32	0.68
21.Mimasakaoiwake	PA	40	104	144	167	163	330	0.30	0.70
22.Ninomiya	PA	60	75	135	104	116	220	0.38	0.62
23.Syouou	SA	62	50	112	165	129	294	0.28	0.72
24.Narahara	PA	23	31	54	95	88	183	0.23	0.77
25.Koudsuki	PA	19	71	90	91	92	183	0.33	0.67
26.Ibogawa	PA	20	15	35	28	28	56	0.38	0.62
27.Yasutomi	PA	64	18	82	52	63	115	0.42	0.58
28.Kasai	SA	48	29	77	41	41	82	0.48	0.52
29.Yashiro	PA	70	176	246	118	104	222	0.53	0.47
30.Akamatsu	PA	30	246	276	378	13	391	0.41	0.59
31.Nishinomiyanajio	SA	928	772	1,700	920	1,246	2,166	0.44	0.56

Table 3-2: Stop rate for each SA/PA (Sanyo Expressway)

SA/PA Name	SA/PA	Number of with stops			Number of without stops			Ratio: with	Ratio: without
		Downstream	Upstream	Total	Downstream	Upstream	Total		
01.Suonada	PA	0	6	6	0	10	10	0.38	0.63
02.Sabagawa	SA	204	430	634	28	683	711	0.47	0.53
03.Tonomi	PA	293	330	623	676	583	1259	0.33	0.67
04.Kudamatsu	SA	327	651	978	645	660	1305	0.43	0.57
05.Kuga	PA	379	2177	2556	974	1267	2241	0.53	0.47
06.Miyajima	SA	708	1104	1812	1391	741	2132	0.46	0.54
07.Numata	PA	1388	368	1756	1112	1289	2401	0.42	0.58
08.Okuya	PA	418	329	747	326	1610	1936	0.28	0.72
09.Kodani	SA	685	230	915	1014	1017	2031	0.31	0.69
10.Takasaka	PA	598	310	908	622	722	1344	0.40	0.60
11.Yahata	PA	683	506	1189	745	741	1486	0.44	0.56
12.Fukuyama	SA	807	605	1412	853	887	1740	0.45	0.55
13.Shinosaka	PA	766	521	1287	1024	879	1903	0.40	0.60
14.Michiguchi	PA	323	551	874	600	600	1200	0.42	0.58
15.Kibi	SA	540	610	1150	610	496	1106	0.51	0.49
16.Seto	PA	268	185	453	535	560	1095	0.29	0.71
17.Fukuishi	PA	131	300	431	403	419	822	0.34	0.66
18.Tatsunonishi	SA	224	2652	2876	1885	1188	3073	0.48	0.52
19.Shiratori	PA	370	260	630	847	758	1605	0.28	0.72
20.Gongenko	PA	279	202	481	632	585	1217	0.28	0.72
21.Miki	SA	501	395	896	237	312	549	0.62	0.38
22.Ougo	PA	885	465	1350	414	137	551	0.71	0.29

Table 4. Explanatory variables

Category	Name	Description (type or unit)
Expressway-specific variables (temporally fixed)	Upstream	1: yes; 0: no (dummy)
	S-EXPWY	A dummy variable indicating Sanyo Expressway: 1: yes; 0: no
SA/PA-specific variables (temporally fixed)	SA	1: SA; 0: PA (dummy)
	Convenience store	1: available at the SA/PA; 0: otherwise (dummy)
	Gas station	1: available at the SA/PA; 0: otherwise (dummy)
	Other shops	1: available at the SA/PA; 0: otherwise (dummy)
	Distance from previous SA/PA	Distance from the previous upstream SA/PA (km)
	No. of parking spaces for trucks and trailers	Number of parking spaces for trucks and trailers (actual number)
	No. of toilets	Total number of toilets (actual number)
Truck-specific variables (temporally fixed)	Business type category for trucks	Business type category variable for trucks (Nominal, inputted as dummy) Business type: Household goods Business type: Restaurant Business type: Convenience store Business type: Oil (tanker) Business type: Unidentified Business type: Retail& distribution
Sample-specific variables (temporally varying)	Usage experience	Frequency of using the same SA/PA by the same truck in the past (actual number for six months)
	Long driving	1: Continuous driving time is more than or equals four hours; 0: otherwise (dummy)
	Distance until arrival	Distance remaining until the destination IC (km)
	Restaurant opening	1: if any restaurant is open at the time of stopping at SA/PA; 0 otherwise (dummy)
	Hour (x o'clock)	The time of passing or entering the SA/PA (nominal data, inputted as a dummy variable)

Table 5. Descriptive statistics of explanatory variables

Name	Yes	No	Min.	Med.	Mean	Max.
Upstream	36,916	34,816				
Sanyo Exp. Way	55,681	16,051				
SA	31,342	40,390				
Convenience store	13,367	58,365				
Gas station	31,676	40,056				
Other shop	58,594	13,138				
Distance from previous SA/PA			8	18.90	19.15	38
# of parking spaces for trucks and trailers			4	41	46.51	107
# of toilet			10	33	35.28	71
Business type: Household goods	1,678	70,054				
Business type: Restaurant	689	71,043				
Business type: Convenience store	7,273	64,459				
Business type: Oil (tanker)	23,728	48,004				
Business type: Unidentified	2,044	69,688				
Business type: Retail& distribution	36,320	35,412				
Usage experience			0	0	6.101	144
Long driving	9,369	62,363				
Distance until arrival			0.00	27.71	40.10	425.9
Restaurant opening	54,965	16,767				

Minimum value for “distance until arrival is” not exactly zero, but near to zero.

Table 6-1: Parameter estimation results

Explanatory variables	Without multilevel-term						Multilevel model (company, selection and outcome)					
	Selection (choice) model (Choice of SA/PA)			Outcome model (Parking time)			Selection (choice) model (Choice of SA/PA)			Outcome model (Parking time)		
	coef.	z-score	P>|z|	coef.	z-score	P>|z|	coef.	z-score	P>|z|	coef.	z-score	P>|z|
Constant term	-8.72E-01	-14.56	0.000	3.05E+00	43.77	0.000	-6.65E-01	-6.81	0.000	3.39E+00	31.13	0.000
Upstream	3.07E-02	3.06	0.002	-2.76E-02	-2.78	0.005	4.72E-02	3.72	0.000	9.67E-03	0.77	0.441
Sanyo Exp. Way	6.30E-02	3.60	0.000	-7.86E-02	-4.58	0.000	7.14E-03	0.32	0.750	8.97E-03	0.42	0.678
SA	-3.48E-01	-5.37	0.000	-1.89E-01	-3.28	0.001	-6.41E-04	-0.01	0.995	1.44E-02	0.14	0.886
Convenience store	1.75E-01	11.61	0.000	-4.24E-02	-2.83	0.005	1.21E-01	6.23	0.000	-7.78E-02	-4.13	0.000
Gas station	2.83E-01	4.38	0.000	1.46E-01	2.56	0.011	-2.07E-03	-0.02	0.982	7.38E-02	0.74	0.462
Other shop	-7.10E-03	-0.41	0.680	6.52E-02	3.81	0.000	-5.57E-02	-2.59	0.010	5.96E-02	2.77	0.006
Distance from previous SA/PA	9.19E-03	11.13	0.000	1.38E-03	1.65	0.099	7.82E-03	7.33	0.000	5.92E-04	0.54	0.590
# of parking spaces for trucks and trailers	-2.89E-03	-7.33	0.000	-7.22E-04	-1.94	0.053	2.19E-03	4.05	0.000	1.92E-03	3.90	0.000
# of toilet	7.28E-03	11.88	0.000	8.63E-03	14.56	0.000	1.59E-03	1.75	0.081	-3.47E-04	-0.38	0.703
Business type: Restaurant	-5.53E-02	-0.93	0.352	-8.24E-01	-15.33	0.000	-1.68E-01	-0.84	0.399	-8.36E-01	-3.53	0.000
Business type: Convenience store	-2.89E-01	-8.08	0.000	-5.38E-01	-16.24	0.000	-2.03E-01	-2.60	0.009	-7.83E-01	-9.38	0.000
Business type: Oil (tanker)	-6.13E-02	-1.78	0.075	-2.44E-01	-7.79	0.000	-2.35E-01	-3.09	0.002	-4.51E-01	-5.53	0.000
Business type: Unidentified	-1.39E-01	-3.16	0.002	-4.36E-01	-10.85	0.000	-3.76E-01	-3.46	0.001	-6.70E-01	-5.41	0.000
Business type: Retail& distribution	-3.97E-01	-11.84	0.000	-4.30E-01	-13.80	0.000	-6.08E-01	-8.14	0.000	-6.57E-01	-8.09	0.000
Usage experience	3.53E-02	72.41	0.000	6.13E-03	14.00	0.000	3.65E-02	62.44	0.000	6.07E-03	12.54	0.000
Long driving	1.09E-01	7.42	0.000	6.45E-02	4.57	0.000	1.09E-01	6.04	0.000	8.73E-02	5.36	0.000
Distance until arrival	3.69E-04	2.08	0.037	-9.75E-04	-5.59	0.000	-2.43E-04	-1.07	0.287	-1.00E-03	-4.76	0.000
Restaurant opening	-4.76E-02	-2.48	0.013	1.12E-01	5.89	0.000	4.67E-03	0.19	0.849	6.39E-02	2.59	0.010
Time control	Yes (Table 6-2)											
Log-Likelihood:	-81,142.5						-78,662.6					
Rho_1 [95%C.I.]	-0.1635 [-0.2151, -0.1109]						-0.1656 [-0.2134, -0.1170]					
$Sigma_1$ [95%C.I.]	0.8226 [0.8147, 0.8310]						0.7803 [0.7727, 0.7879]					
Tau_1 or Tau_2 [95%C.I.]	-			-			0.1783 [0.1673, 0.1901]			0.2185 [0.2054, 0.2324]		
Rho_2 [95%C.I.]							0.4525 [0.3708, 0.5273]					
Sample size (total)	71,732											
Sample size (stop)	30,586											

Note: Transporting household goods is used as a reference for estimating business type parameters.

Table 6-2: Parameter estimation results (continued)

Explanatory variables	Without multilevel-term						Multilevel model (individual truck)					
	Selection (choice) model (Choice of SA/PA)			Outcome model (Parking time)			Selection (choice) model (Choice of SA/PA)			Outcome model (Parking time)		
	coef.	z-score	P>|z|	coef.	z-score	P>|z|	coef.	z-score	P>|z|	coef.	z-score	P>|z|
1 o'clock	3.13E-01	5.22	0.000	-1.01E-01	-1.55	0.120	3.10E-01	4.14	0.000	-2.06E-01	-2.51	0.012
2 o'clock	1.27E-01	2.09	0.037	-6.38E-02	-0.98	0.326	1.81E-02	0.24	0.812	-2.81E-01	-3.21	0.001
3 o'clock	-1.91E-02	-0.34	0.733	-2.35E-02	-0.36	0.720	-9.41E-02	-1.36	0.174	-1.49E-01	-1.82	0.068
4 o'clock	3.21E-01	5.90	0.000	6.52E-01	10.67	0.000	1.07E-01	1.49	0.136	4.33E-01	5.10	0.000
5 o'clock	1.96E-01	3.90	0.000	-1.30E-01	-2.28	0.023	7.62E-02	1.19	0.234	-3.18E-01	-4.40	0.000
6 o'clock	3.52E-01	7.31	0.000	-1.80E-01	-3.30	0.001	2.67E-01	4.32	0.000	-2.91E-01	-4.22	0.000
7 o'clock	4.66E-01	9.65	0.000	-1.59E-01	-2.92	0.003	4.40E-01	7.16	0.000	-2.17E-01	-3.19	0.001
8 o'clock	4.30E-01	8.77	0.000	-2.02E-01	-3.67	0.000	4.08E-01	6.52	0.000	-3.12E-01	-4.56	0.000
9 o'clock	3.12E-01	6.33	0.000	-2.32E-01	-4.19	0.000	3.09E-01	4.91	0.000	-3.01E-01	-4.35	0.000
10 o'clock	4.07E-01	8.45	0.000	-1.63E-01	-3.00	0.003	3.41E-01	5.59	0.000	-2.33E-01	-3.44	0.001
11 o'clock	5.23E-01	11.04	0.000	-7.49E-02	-1.40	0.163	4.62E-01	7.68	0.000	-1.50E-01	-2.24	0.025
12 o'clock	6.11E-01	12.74	0.000	-5.87E-02	-1.08	0.278	6.14E-01	10.04	0.000	-7.94E-02	-1.18	0.238
13 o'clock	5.60E-01	11.63	0.000	-4.11E-02	-0.76	0.448	5.50E-01	9.00	0.000	-6.00E-02	-0.89	0.374
14 o'clock	6.37E-01	13.24	0.000	1.37E-01	2.52	0.012	5.92E-01	9.67	0.000	3.47E-02	0.52	0.606
15 o'clock	4.52E-01	9.38	0.000	-4.21E-02	-0.77	0.439	4.06E-01	6.67	0.000	-1.25E-01	-1.84	0.065
16 o'clock	3.59E-01	7.39	0.000	-1.85E-01	-3.38	0.001	3.26E-01	5.31	0.000	-2.38E-01	-3.49	0.000
17 o'clock	3.27E-01	6.59	0.000	-1.53E-01	-2.77	0.006	2.66E-01	4.24	0.000	-2.05E-01	-2.93	0.003
18 o'clock	3.39E-01	6.66	0.000	-1.98E-01	-3.50	0.000	2.95E-01	4.61	0.000	-2.37E-01	-3.36	0.001
19 o'clock	2.27E-01	4.30	0.000	4.01E-02	0.68	0.494	1.94E-01	2.92	0.004	3.85E-02	0.53	0.599
20 o'clock	1.06E-01	2.03	0.042	-5.27E-02	-0.90	0.370	1.18E-01	1.81	0.071	-5.16E-02	-0.71	0.480
21 o'clock	4.96E-02	0.94	0.349	-1.28E-01	-2.13	0.033	5.30E-02	0.80	0.422	-1.63E-01	-2.20	0.028
22 o'clock	9.26E-02	1.66	0.096	-7.01E-02	-1.15	0.248	8.96E-02	1.21	0.227	-1.60E-01	-1.84	0.066
23 o'clock	1.62E-01	2.82	0.005	-1.85E-01	-2.92	0.004	1.40E-01	1.85	0.064	-1.58E-01	-1.87	0.061

Note: 0 o’clock is used as a reference for time periods.

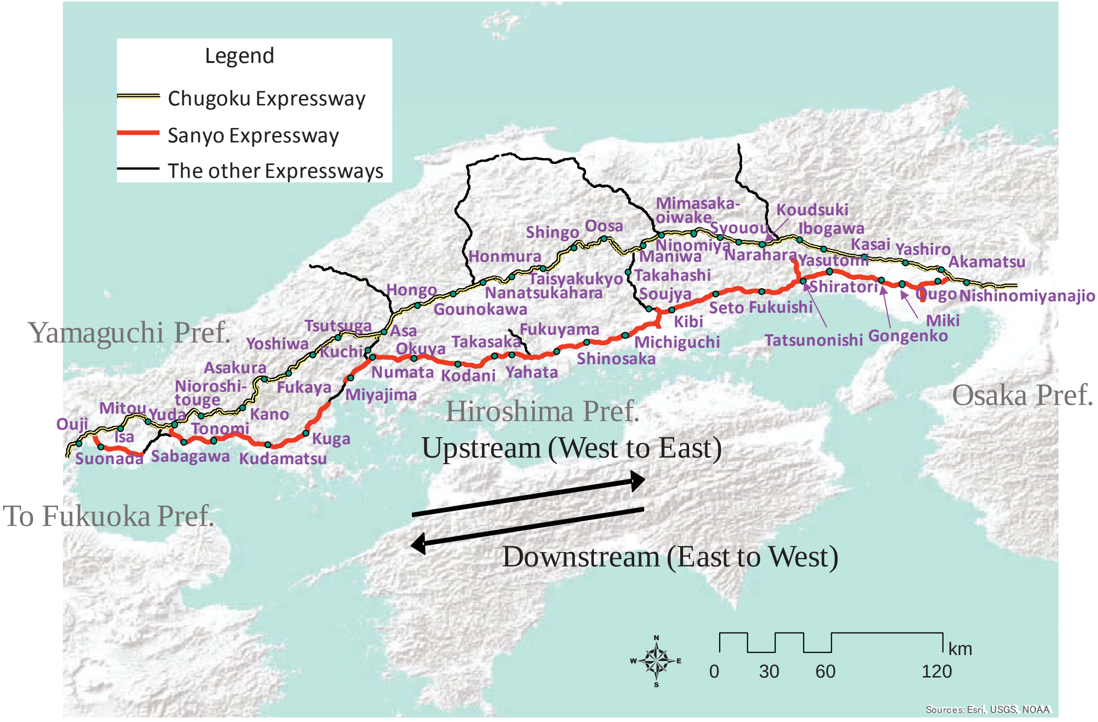


Figure 1: S-EXPWY and C-EXPWY

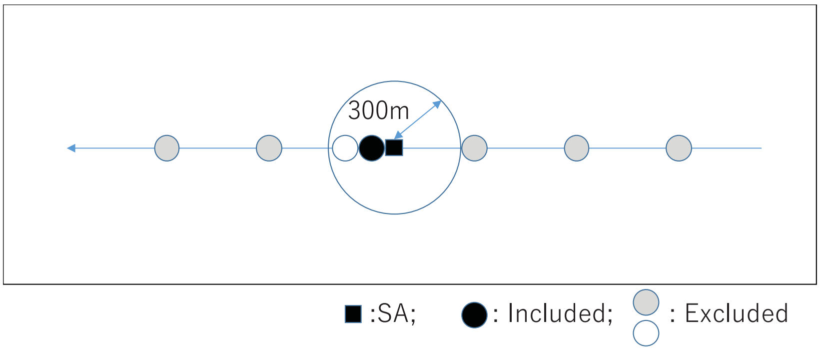


Figure 2: Samples used in our analyses

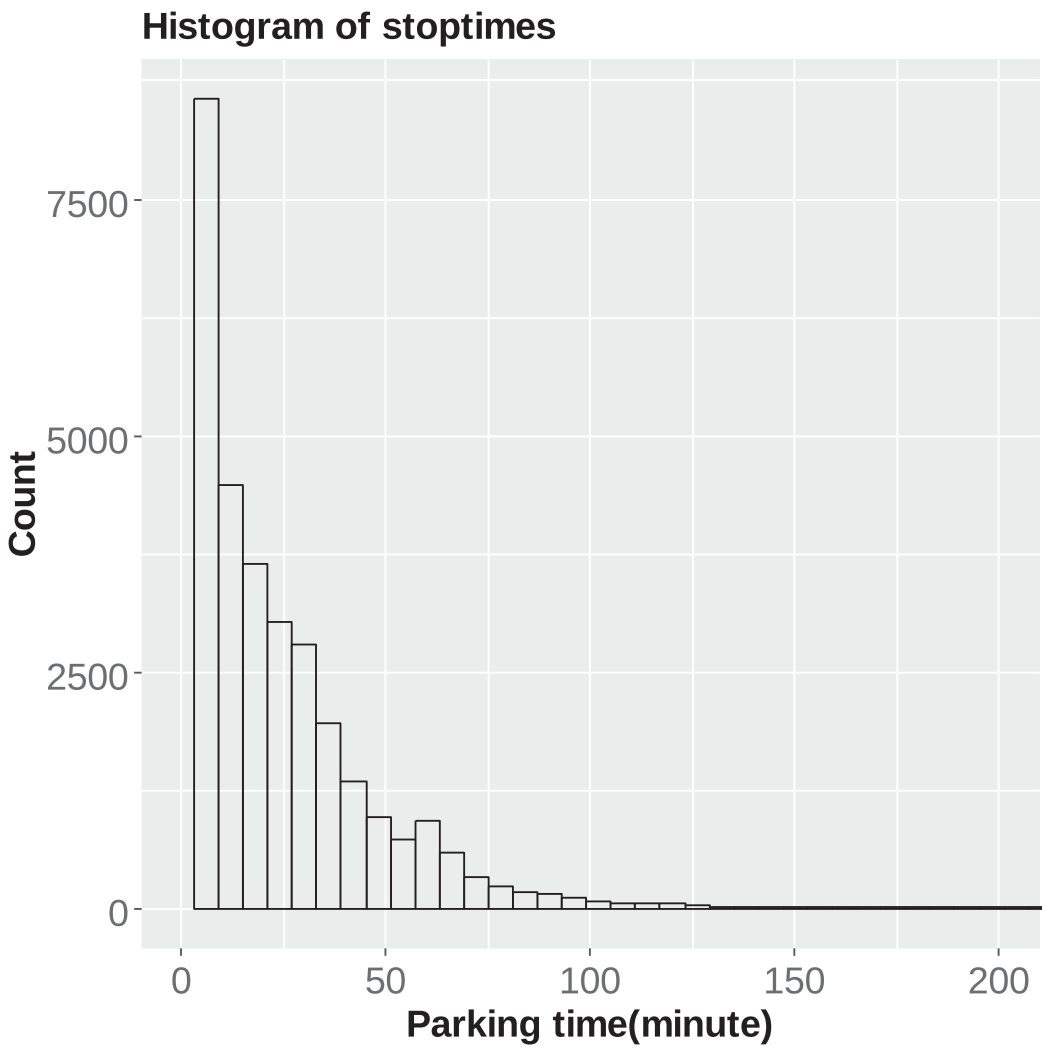


Figure 3: Frequency distribution of parking time (except for zeros)

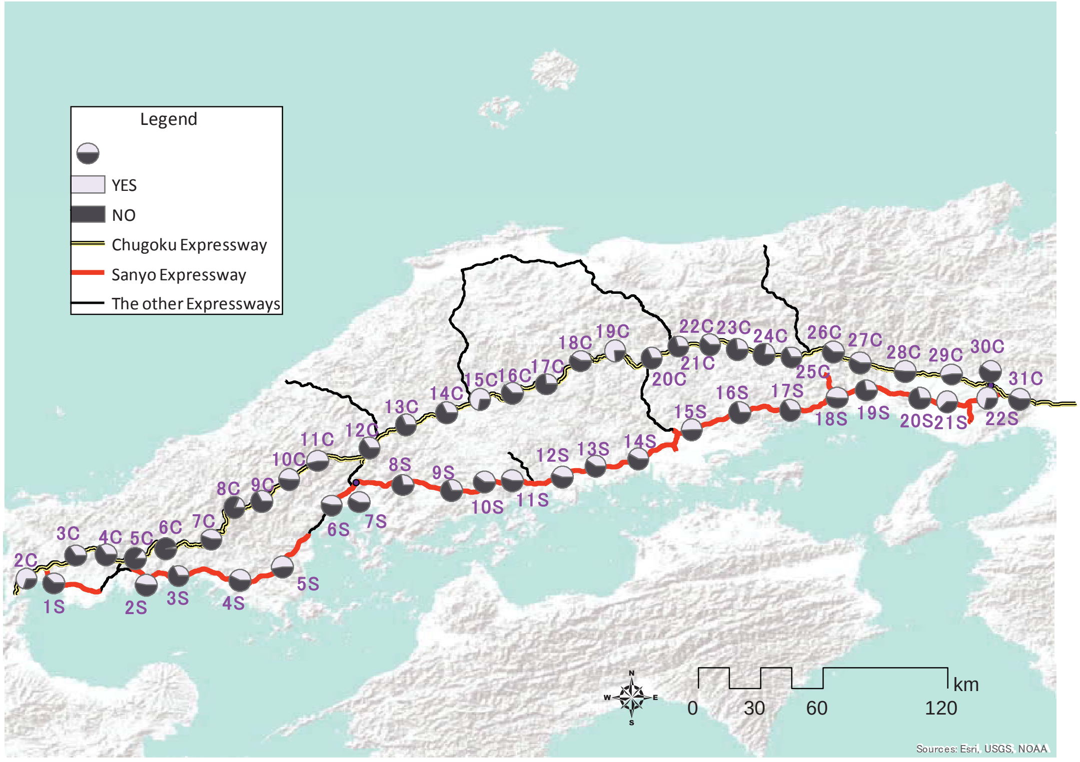
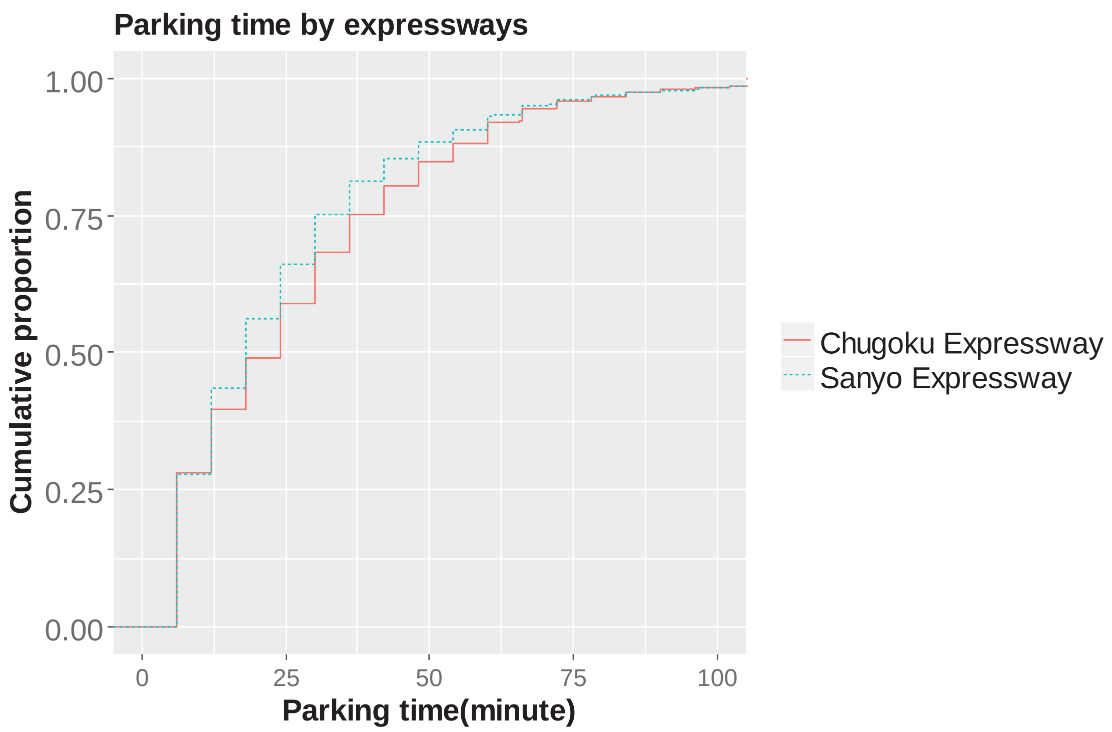
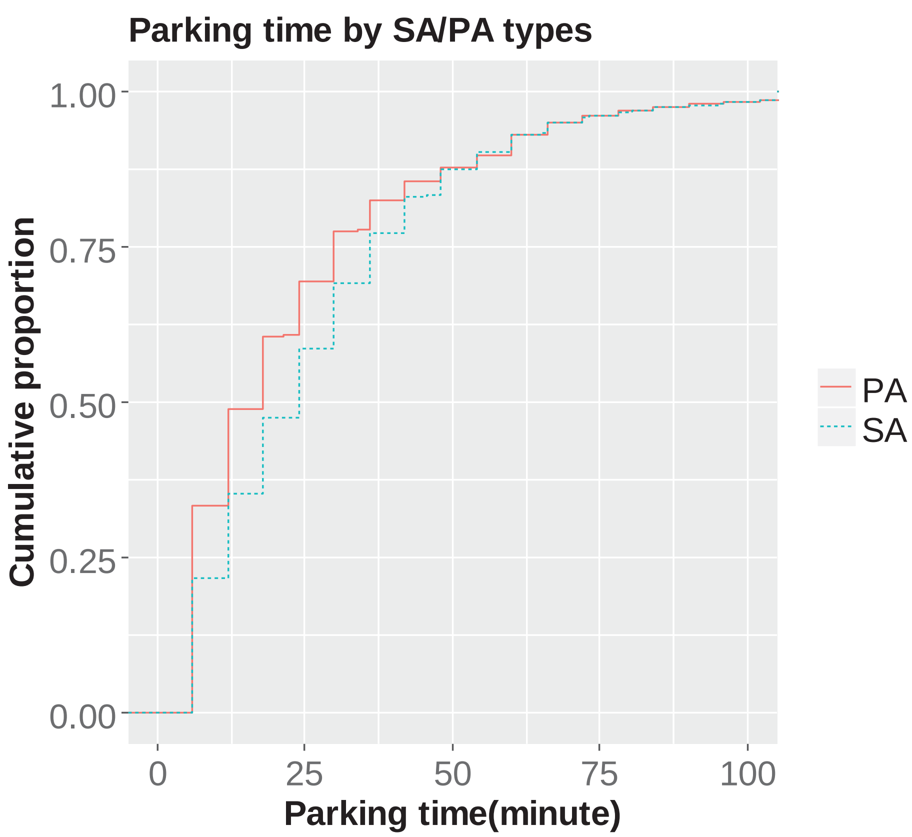


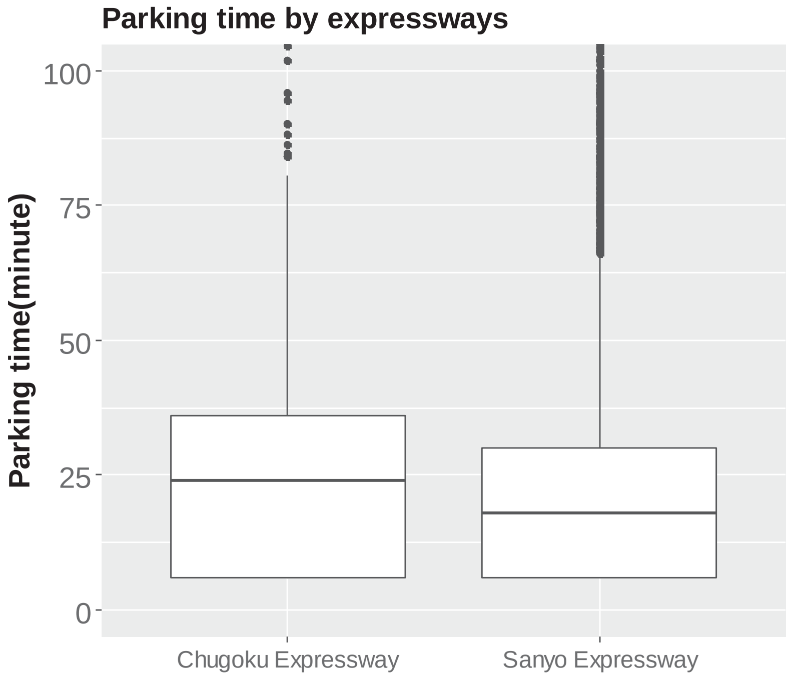
Figure 4: Stop rate for each SA/PA (IDs for SA/PA are shown in Table 3. C/S after the ID represents Chugoku Expressway and Sanyo Expressway, respectively).



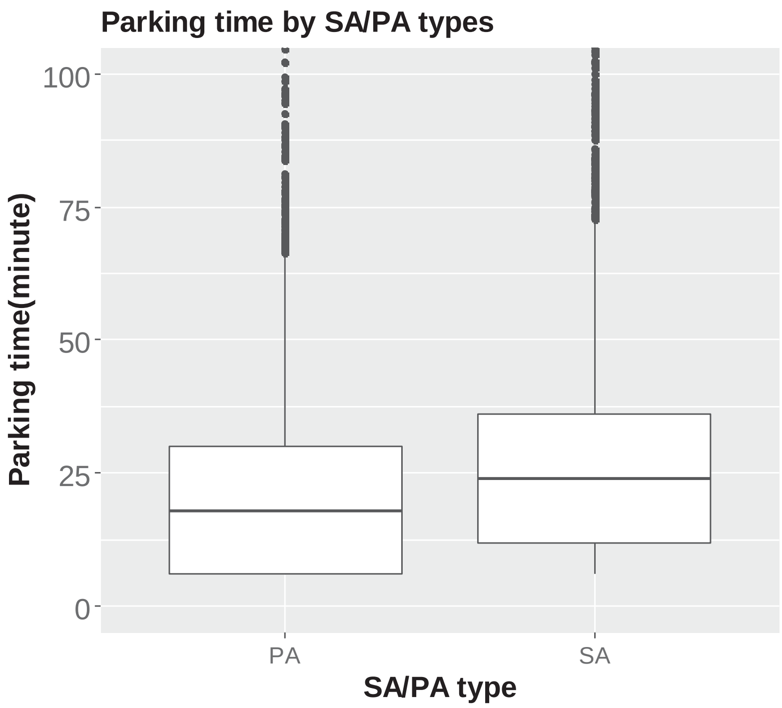
(a) Cumulative proportion of parking time by expressway



(b) Cumulative proportion of parking time by SA/PA



(c) Boxplots of parking time by expressway



(d) Boxplots of parking time by SA/PA

Figure 5: Features of parking time by SA/PA

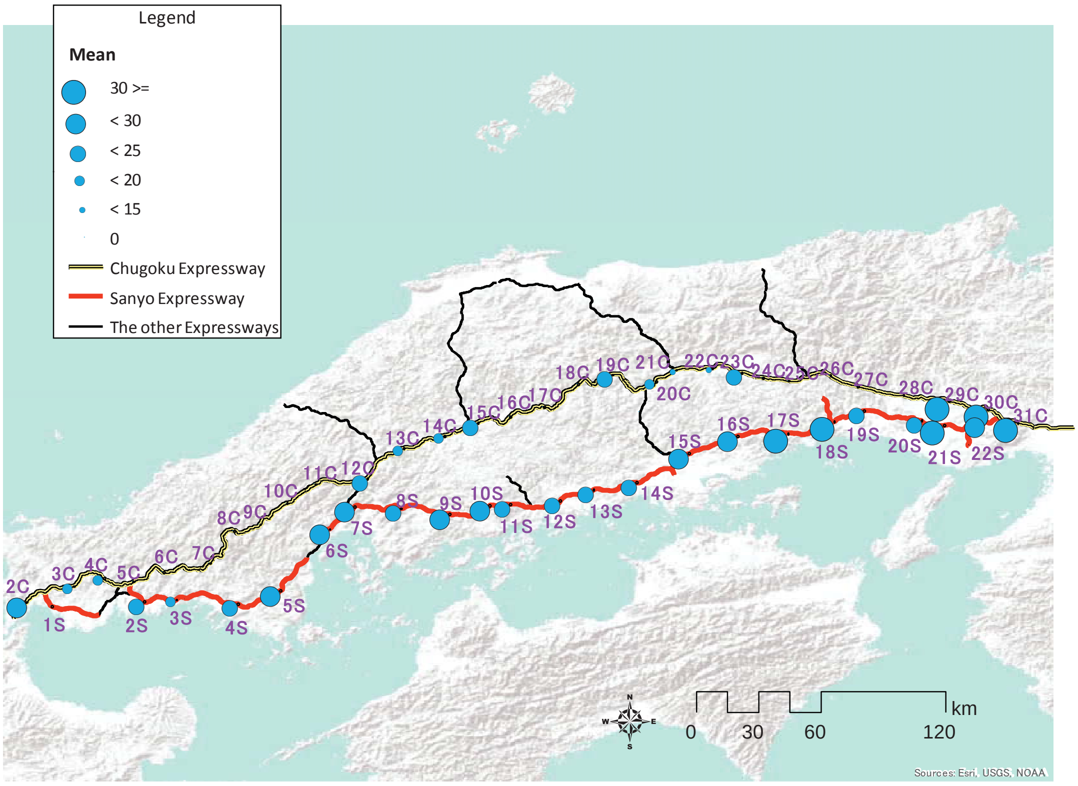
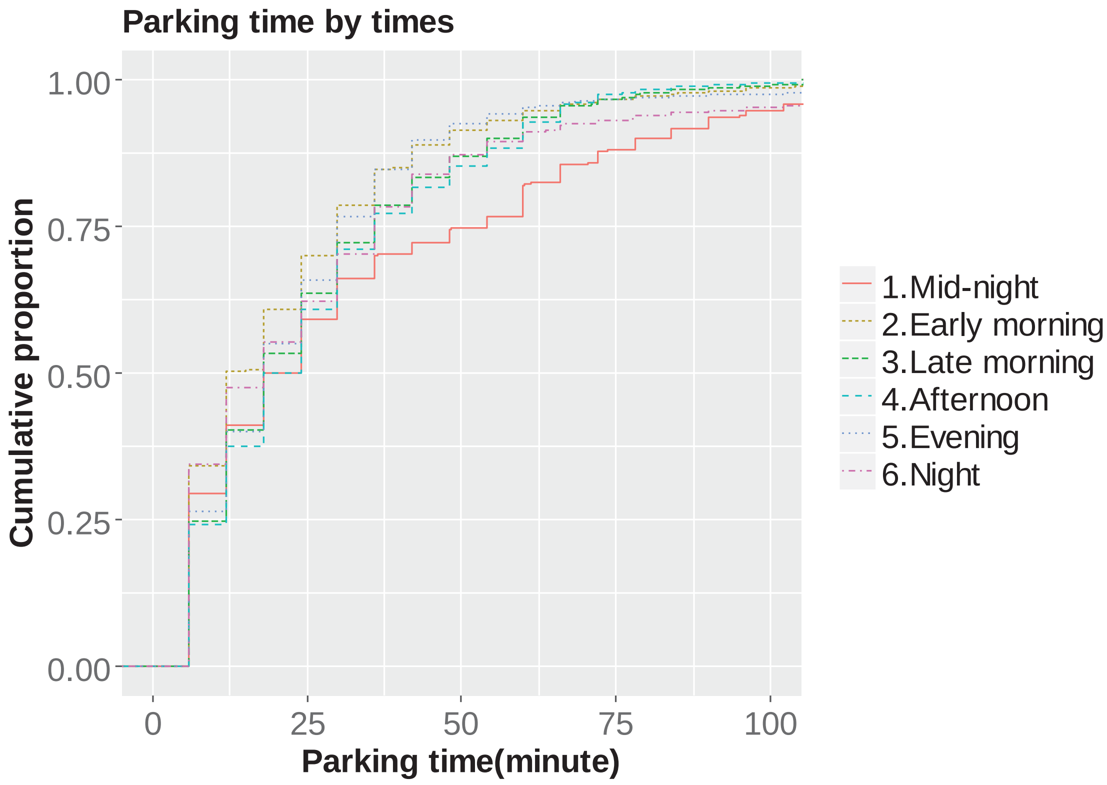
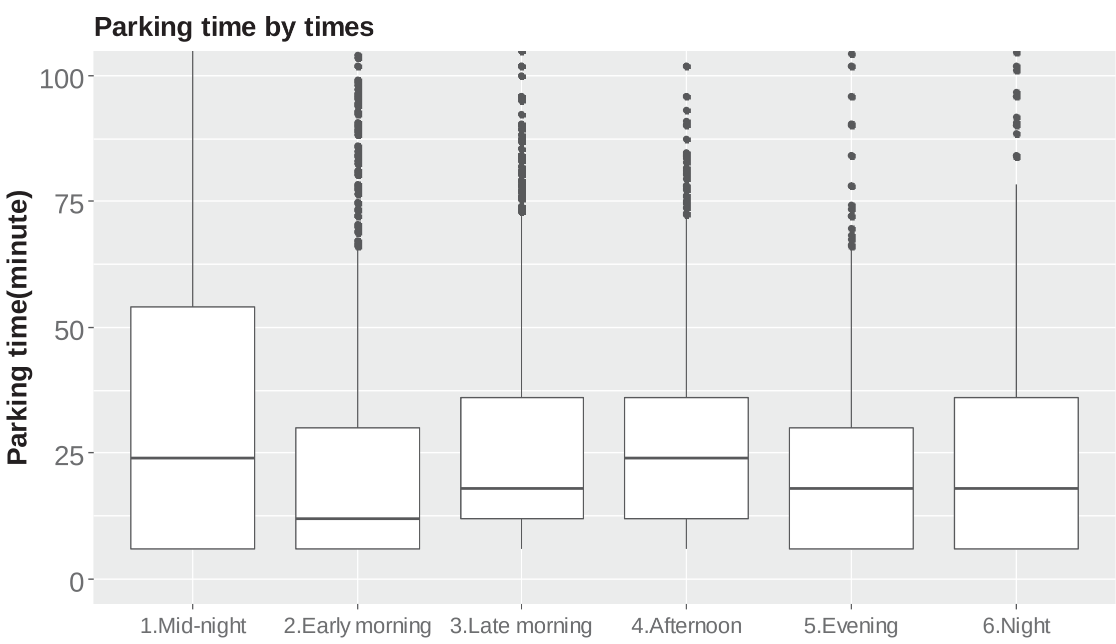


Figure 6: Average parking time by SA/PA



(a) Cumulative proportion of parking time by periods



(b) Boxplots of parking time separated in terms of periods

Figure 7: Features of parking time by periods

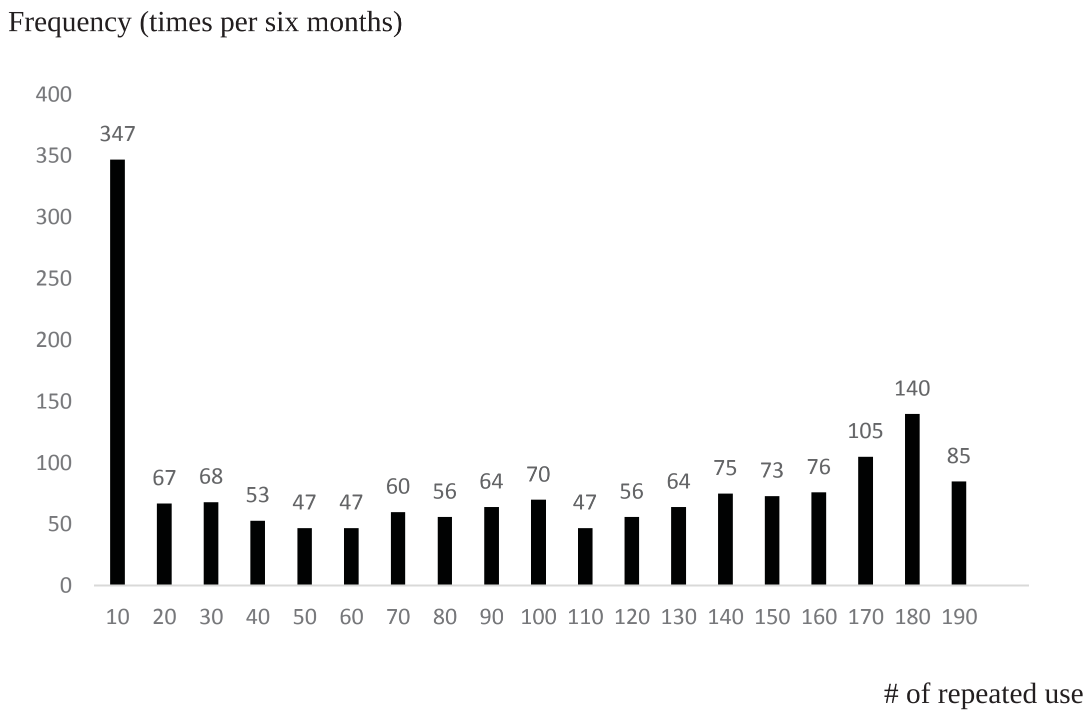
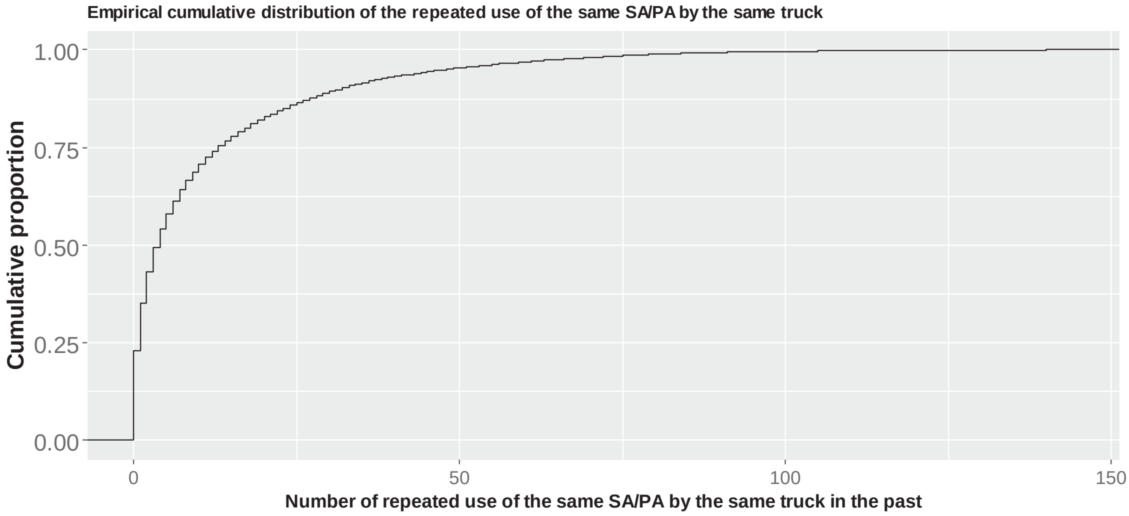
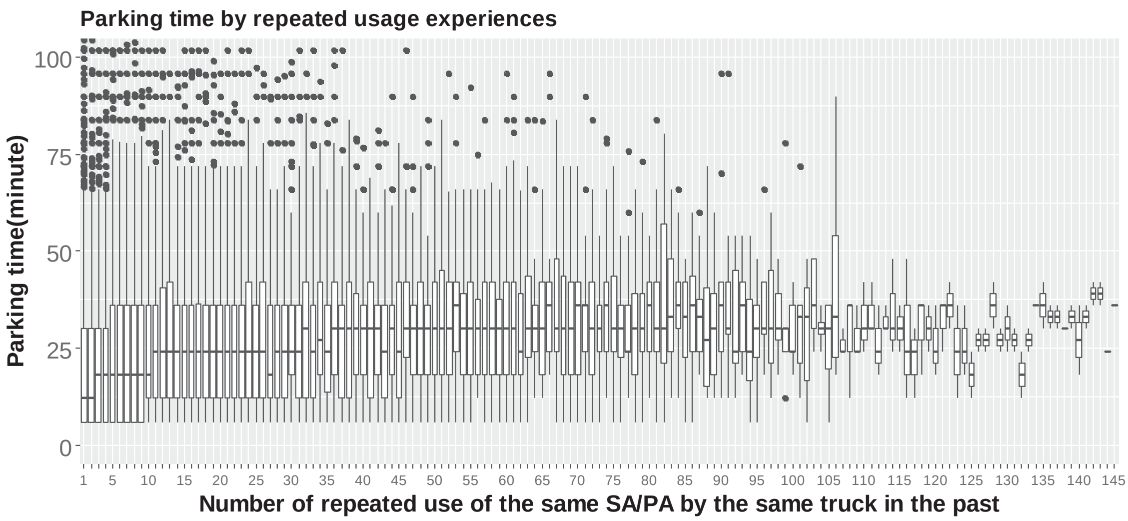


Figure 8: Frequency distribution of repeated use by the same truck



(a) Cumulative distribution of repeated use of the same SA/PA by the same truck in the past



(b) Boxplots of parking time separated by repeated use of the same SA/PA by the same truck in the past

Figure 9: Features of repeated use of the same SA/PA by the same truck in the past