Inadequate Safe Truck Parking: Impacts on Pandemic Response Supply Routing and Delivery

S. Hernandez, Ph.D.[1]; and B. Velasquez[2]

[1]Dept. of Civil Engineering, Oregon State Univ., Corvallis, OR.
Email: sal.hernandez@oregonstate.edu
[2]Dept. of Civil Engineering, Oregon State Univ., Corvallis, OR.
Email: velasqub@oregonstate.edu

ABSTRACT

Inadequate truck parking along major US highways, a national crisis, worsens road safety and leads to hours of service (HOS) violations due to trucks parking in unauthorized areas. This study, focusing on challenges during pandemics and similar disruptions, used a survey revealing 85% of truck drivers struggled to find parking during the pandemic. Employing a random-parameters bivariate ordered probit model (RPBOPM), the study identified factors affecting parking availability and HOS compliance both before and during pandemic events. These findings highlight the severity of the truck parking issue and provide a basis for developing targeted programs and policies to alleviate these challenges, particularly during critical times like pandemics, thus enhancing overall highway safety.

1. INTRODUCTION

The COVID-19 pandemic not only intensified the long-standing issue of inadequate truck parking on America's major highways, affecting all states and regions, but also led to severe shortages of essential goods like non-perishable foods, cleaning products, and medical supplies (Boggs et al. 2019; Bunn et al. 2019; FHWA Freight Management and Operations 2020; FHWA Office of Operations 2020; Hernández and Anderson 2017; Mahmud et al. 2020; McNally 2021). This surge in consumer demand strained supply chains and increased the demand for truck parking services, exacerbating the already critical nationwide shortage of truck parking spaces. Recognizing this, the Federal Highway Administration (FHWA), Federal Motor Carrier Safety Administration (FMCSA), and various state Departments of Transportation (DOTs) implemented measures to aid motor carriers and truck drivers. The FMCSA issued a National Emergency Declaration, allowing vehicles delivering essential goods to bypass regulations such as the mandatory 30-minute break and the standard 34-hour restart, with continual updates to meet the evolving needs of essential services. Additionally, DOTs eased truck size and weight limits for larger shipments during the health crisis, and the FHWA permitted food trucks to operate at rest areas, providing crucial support to truck drivers and travelers, highlighting the need for immediate solutions to the truck parking deficit.

In 2019, the Federal Highway Administration (FHWA) and the National Coalition on Truck Parking identified approximately 313,000 truck parking spaces in the United States, with a 6% increase in public and an 11% increase in private parking facilities from 2014 to 2019, including 40,000 at public rest stops and 273,000 at private truck stops (FHWA Office of Operations 2020). However, state Departments of Transportation (DOTs) struggled with developing new public parking facilities, facing challenges in planning, funding, and provisioning. This was exacerbated by a significant ratio of truck drivers to parking spaces, as reported by the American Trucking Associations (ATA), which found that 98% of drivers struggled to find adequate parking, spending an average of 56 minutes daily in their search and suffering an approximate annual wage loss of $5,500, or a 12% reduction in earnings. Furthermore, 58% of drivers often resorted to unauthorized parking spots (McNally 2021). The COVID-19 pandemic intensified these issues, with increased demand for essential goods delivery and pandemic-related restrictions like shelter-in-place orders, further straining the already limited parking availability and underscoring the urgent need for solutions to the truck parking crisis in the United States.

In terms of related research, the American Transportation Research Institute (ATRI) and the Owner-Operator Independent Drivers Association (OOIDA) Foundation, conducted a critical examination of the operational disruptions faced by the trucking industry during the onset of the COVID-19 pandemic. In the early onset of the pandemic, ATRI monitored truck activity in several states from February to April 2020, finding an initial surge in truck movements due to increased demand for essentials (American Transportation Research Institute 2020). This spike, however, was followed by a decline in April as economic activities slowed due to the pandemic. Later both ATRI and OOIDA designed a survey to further understand changes in trucking operations, encompassing delivery, travel times, detention, and parking (The American Transportation Research Institute and The OOIDA Foundation 2020). Results from over 5,100 respondents painted a mixed picture: nearly half reported lower freight volumes, while others saw no change or increases. The pandemic notably shifted operations towards local trucking, with short trips doubling and detention times lengthening for some. Traffic congestion eased considerably, but parking remained a challenge, with nearly half of the drivers finding it more difficult, though a similar proportion reported no change. Overall, the survey highlighted the significant yet diverse impacts of COVID-19 on the trucking sector. This research highlights the diverse and substantial impacts of the pandemic on trucking operations, and the industry's resilience and adaptability in the face of global pandemic.

Therefore, this study extends existing research into truck parking by exploring factors that impact a driver's compliance with hours-of-service (HOS) regulations, with a particular focus on pandemics or similar widespread disruptions. Given the strict HOS rules that dictate driving hours and rest periods, drivers are forced to plan to meet these requirements and maintain job performance. The study aims to deepen understanding of the relationship between the availability of safe and adequate truck parking and adherence to HOS regulations. It includes an analysis of a stated-preference survey from the COVID-19 pandemic period and employs a random-parameters bivariate ordered probit model (RPBOPM) to investigate the parking challenges drivers face, a first. Applications of the random-parameter bivariate ordered probit models in transportation are not new (Chen et al. 2019b; Mannering et al. 2016), however it provides a mechanism to better understand the diverse responses collected from individuals during various stages of the pandemic. Additionally, the study seeks to identify factors that contribute to these challenges both prior to and during the pandemic. Identifying these factors will shed light on the parking shortage in the US and help develop programs or policy initiatives to support truck drivers in need.

2. EMPIRICAL SETTING

This study utilized a stated preference survey targeting truck drivers across the nation, conducted during the COVID-19 pandemic. The survey aimed to gauge truck drivers' perspectives on operational changes before and amid the pandemic and to identify factors influencing their ability to find safe and adequate parking while complying with hours-of-service (HOS) regulations. Conducted from May 25th to June 1st, 2020, the survey was facilitated by the University of Arkansas and distributed via Qualtrics, an online survey platform, to large truck operators (Hernandez et al. 2020). Participation was voluntary, with eligibility criteria including being at least 18 years old, holding a Commercial Driver's License (CDL), having over a year of experience in operating a commercial motor vehicle, and active driving during the pandemic. Out of the respondents, 521 truck drivers met these criteria and completed the survey.

The survey comprised of 67 questions, divided into nine sections: socioeconomic background, business details, driver demographics, driving characteristics, safety perceptions, time-of-day operations, management of driving, and truck configuration. To comprehensively assess drivers' opinions on the changes pre-and-during the pandemic, Likert scale questions were utilized. Notably, the proportion of drivers who never faced parking issues was double during the pandemic compared to before.

Both Tables 1 and 2 summarize key characteristics and behaviors of truck drivers before and during the COVID-19 pandemic, established through the truck driver survey. Before the pandemic, a majority of drivers were aged between 30 and 49 (57%), and a significant proportion (79%) received hazard pay. Most drivers had more than a year of experience, with only 4% being less experienced. During the pandemic, 66% of the drivers were male.

3. METHODOLOGY

In undertaking the diverse responses collected from individuals during various stages of the pandemic, this study proposes the use of a bivariate random parameter ordered probit model. This advanced econometric model is essentially a hierarchical system composed of two interconnected equations, designed to simultaneously analyze the relationship between two distinct yet related response variables. Utilizing this model facilitates a more nuanced understanding of the dynamics at play, allowing for the identification of significant factors that influence parking availability. Moreover, it enables the quantification of the impact these factors have on the frequency with which drivers encounter a lack of parking—a critical part in addressing this issue in the trucking industry (Xiao et al. 2021).

The bivariate random-parameter ordered probit model assumes that two ordered dependent variables, y_j (j = 1 before pandemic, 2 during pandemic) result from a joint decision-making process. These decisions are influenced by the individual characteristics unique to each probit equation, and there is a correlation between the errors of the two equations. Consequently, the model can be characterized as follows (Xiao et al. 2021):

$$y_{i,j=1} = k,\ \ if\ \mu_{j=1,k-1} < y^*_{i,j=1} < \mu_{j=1,k} \tag{1}$$

$$y_{i,j=2} = 1,\ \ if\ \mu_{j=2,l-1} < y^*_{i,j=2} < \mu_{j=2,l}$$

where $\mu_{j,k-1}, \mu_{j=1,k}, \mu_{j,l-1}, \mu_{j,l}$ are thresholds or cut-off values used to determine the reported frequency lack of parking caused HOS adherence problems before and during the pandemic, their values are relative to their corresponding influencing factors in driver i. Additionally, k (k = 0, 1, 2,..., K) and l (l = 0, 1, 2,..., L) represent ordinal categories of the frequency lack of parking caused HOS adherence problems reported by each driver. $y^*_{i,j=1}$ and $y^*_{i,j=2}$ serve as thresholds for the conditions and can be calculated using real data as follows:

$$y^*_{i,j=1} = \beta'_1 X_{i,j=1} + \varepsilon_{i,j=1} \tag{2}$$

$$y^*_{i,j=2} = \beta'_2 X_{i,j=2} + \varepsilon_{i,j=2}$$

where $y^*_{i,j=1}$ represents latent, unobserved variables denoting a boundary for choosing one alternative to the other, in which *i = 1,...n*, is the number of observations; $X_{i,j}$ represents individual specific covariates; β_j denotes the regression coefficients, and $\varepsilon_{i,j}$ represents the random components in the errors that are attempted to be captured by the unobserved factors associated with two involved parties, which are assumed to be exogenous and follow a bivariate normal distribution as follows (Chen et al. 2019a):

$$\begin{pmatrix} \varepsilon_{i,j=1} \\ \varepsilon_{i,j=2} \end{pmatrix} \sim \mathrm{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{3}$$

where ρ is the estimated correlation parameter between $\varepsilon_{i,j=1}$ and $\varepsilon_{i,j=2}$. If significant, provides evidence that the bivariate approach is appropriate. Therefore, $y^*_{i1}$and y^*_{i2} denote the frequency in lack of parking causing HOS adherence problems for drivers before and during the pandemic, respectively, and x_{i1} and x_{i2} include various influencing factors, such as socioeconomic, business, and driver characteristics captured in the survey.

The observed ordered dependent variable follows the rule by the following equation:

$$y_{ij} = \begin{cases} 0\ if\ y^*_{ij} = Never \\ 1\ if\ y^*_{ij} = Sometimes \\ 2\ if\ y^*_{ij} = About\ half\ the\ time \\ 3\ if\ y^*_{ij} = Most\ of\ the\ time \\ 4\ if\ y^*_{ij} = Always \end{cases} \tag{4}$$

While bivariate ordered probit can address the problem of factors correlation between the two conditions, this method assumes the parameters β'_1, β'_2 to have a certain value neglecting the effect of unobserved heterogeneity of observations. The random-parameter approach is designed to manage unobserved heterogeneity by permitting parameters to differ among observations. Consequently, the random parameters in a bivariate ordered probit model are established by configuring the following settings:

$$\beta'_i = \beta + \gamma_i \tag{5}$$

where β'_i is the vector of specific parameters and is estimated by the maximum likelihood method with Halton draws; $\gamma_i$is the randomly distributed term which is normally distributed with a zero mean value and variance σ^2.

4. ESTIMATED RESULTS AND DISCUSSION

To determine the significant factors affecting a driver's ability to locate adequate and safe parking during pandemics or comparable system disruptions, a bivariate random parameter ordered probit model was estimated. This model estimated the probabilities of five distinct outcomes—never, sometimes, about half the time, most of the time, always—across 28 variables that were found to be statistically significant at the 10% level (See Tables 2 and 3).

Table 1. Summary Statistics of Model Parameters (Before)

Variable **Before Pandemic**	**Frequency**	**Percentage**
Socioeconomic Characteristics		
Driver age (1 if between 30 and 49, 0 otherwise)	295	57%
Compensation (1 if received hazard pay, 0 otherwise)	411	79%
Driver experience (1 if less than one year, 0 otherwise)	23	4%
Business Characteristics		
Trips conducted (1 if completed fewer number of trips during pandemic than before, 0 otherwise)	163	31%
Driver Characteristics		
Participation in team driving (1 if never, 0 otherwise)	87	17%
Participation in team driving (1 if sometimes, 0 otherwise)	178	34%
Participation in team driving (1 if about half the time, 0 otherwise)	135	26%
Participation in team driving (1 if most of the time, 0 otherwise)	69	13%
Time of Day Operations		
Most difficult time of day to locate safe truck parking (1 if early morning, 0 otherwise)	132	25%
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	184	35%
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	132	25%
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	78	15%
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	21	4%
Service disruptions encountered at public truck stops (1 if fuel services, 0 otherwise)	124	24%
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	125	24%
Service disruptions encountered at public truck stops (1 if restrooms, 0 otherwise)	130	25%
Driving Management		
Real time parking availability tools used (1 if communications with other drivers, 0 otherwise)	196	38%
Real time parking availability tools used (1 if none, 0 otherwise)	40	8%
Drive while tired (1 if rarely, 0 otherwise)	96	19%
Drive while tired (1 if never, 0 otherwise)	35	7%
Driver’s most commonly driven truck configuration (1 if single unit truck, 0 otherwise)	203	39%

Table 2. Summary Statistics of Model Parameters (During)

Variable During Pandemic	Frequency	Percentage
Socioeconomic Characteristics		
Driver gender (1 if male, 0 otherwise)	343	66%
Driver Characteristics		
Participation in team driving (1 if sometimes, 0 otherwise)	121	23%
Participation in team driving (1 if never, 0 otherwise)	82	16%
Time of Day Operations		
Normal driving start time (1 if mid-day, 0 otherwise)	121	23%
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	120	23%
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	125	24%
Service disruptions encountered at public truck stops (1 if take out and/or drive thru food services, 0 otherwise)	128	25%
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	117	23%
Service disruptions encountered at private truck stops (1 if showers, 0 otherwise)	136	26%
Service disruptions encountered at private truck stops (1 if truck wash stations, 0 otherwise)	91	18%
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	69	13%
Driving Management		
Drive while tired (1 if very often, 0 otherwise)	78	15%
Real time parking availability tools used (1 if websites, 0 otherwise)	196	38%
Real time parking availability tools used (1 if none, 0 otherwise)	40	8%

The overall model fit was tested by using the chi-square distribution and Akaike information criterion (AIC), which are calculated using equations (6) and (7) below, where the likelihood ratio tests are conducted to statistically assess if these models on the frequency of lack of parking are significantly different across the fixed-parameter model and the random-parameter model:

$$X^2 = 2\left[LL\ (\beta_{random}) - \ LL\ \left(\beta_{fixed}\right)\right], \tag{6}$$

$$AIC = 2k - 2\ln(L) \tag{7}$$

where $\mathrm{LL}(\beta_{random})$ is the log-likelihood at convergence of the random-parameter ordered probit model and the $LL\ \left(\beta_{fixed}\right)$ is the log-likelihood at convergence of the fixed parameter ordered probit model. The likelihood ratio is chi-square distributed with degrees of freedom equal to the number of estimated random parameters. K is the number of parameters of the model. The smaller the AIC and the higher the chi-square values, the better the model fits the data.

Table 3 presents the results of the random parameters bivariate ordered probit models. The finding of normally distributed random parameters in both models explicitly demonstrates the existence of heterogeneity in the effects of influencing factors. The following subsections describe the changes in the trucking industry found to be most influential on the frequency of lack of parking causing HOS adherence problems. The marginal effects that were used to assess the effect of the estimated parameters in the models are shown in Tables 4 and 5, respectively.

Table 3. Results of Random-Parameter Bivariate Ordered Probit Models

Variable	**Mean**	**t-Stat**
Before Pandemic		
Constant	2.067	8.39
Driver age (1 if between 30 and 49, 0 otherwise)	0.179	1.78
Compensation (1 if received hazard pay, 0 otherwise)	0.438	3.5
Driver experience (1 if less than one year, 0 otherwise)	-0.458	-1.95
Trips conducted (1 if completed fewer number of trips during pandemic than before, 0 otherwise)	-0.275	-2.63
Participation in team driving (1 if never, 0 otherwise)	-1.07	-4.76
Most difficult time of day to locate safe truck parking (1 if early morning, 0 otherwise)	0.371	3.21
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	0.329	3.03
Participation in team driving (1 if sometimes, 0 otherwise)	-0.742	-3.76
Participation in team driving (1 if most of the time, 0 otherwise)	-0.541	-2.42
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	-0.646	-3.15
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	-0.353	-2.63
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	-0.91	3.39
Service disruptions encountered at public truck stops (1 if fuel services, 0 otherwise)	0.332	-2.51
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	0.261	-3.49
Service disruptions encountered at public truck stops (1 if restrooms, 0 otherwise)	-0.277	2.95
Real time parking availability tools used (1 if communications with other drivers, 0 otherwise)	0.243	-2.29
Real time parking availability tools used (1 if none, 0 otherwise)	-0.532	-2.66
Drive while tired (1 if rarely, 0 otherwise)	-0.375	-2.84
Drive while tired (1 if never, 0 otherwise)	-0.899	-4.53
Driver’s most commonly driven truck configuration (1 if single unit truck, 0 otherwise)	0.219	2.15
mu1	1.105	16.98
mu2	2.043	32.76
mu3	2.996	37.05
During Pandemic Model		
Constant	1.666	8.09
Driver gender (1 if male, 0 otherwise)	0.366	2.33
Participation in team driving (1 if sometimes, 0 otherwise)	-0.563	-3.53
Participation in team driving (1 if never, 0 otherwise)	-1.034	-4.66
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	0.551	3.54

Drive while tired (1 if very often, 0 otherwise)	0.521	2.8
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	0.378	2.24
Service disruptions encountered at public truck stops (1 if take out and/or drive thru food services, 0 otherwise)	0.296	1.94
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	-0.384	-2.35
Service disruptions encountered at private truck stops (1 if showers, 0 otherwise)	-0.286	-1.9
Service disruptions encountered at private truck stops (1 if truck wash stations, 0 otherwise)	0.318	1.92
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	-0.878	-4.07
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	1.446	1.98
Real time parking availability tools used (1 if websites, 0 otherwise)	0.373	2.46
Real time parking availability tools used (1 if none, 0 otherwise)	-0.951	-2.23
Normal driving start time (1 if mid-day, 0 otherwise)	0.293	1.78
mu1	0.989	9.91
mu2	1.909	21.51
mu3	2.891	26.72
rhow (correlation parameter)	0.475	5.42
No. of Observations	521	
Log likelihood at convergence	-580.69	
Log likelihood at zero	-608.99	
McFadden Rho-squared	0.05	

Table 4. Estimated Marginal Effects for Ordered Probit Model of Before Model

Variable	Never	Sometimes	About half the time	Most of the time	Always
Driver age (1 if between 30 and 49, 0 otherwise)	-0.0016	0.0000	-0.0060	-0.0062	0.0000
Compensation (1 if received hazard pay, 0 otherwise)	-0.0048	0.0000	-0.0195	-0.0217	0.0000
Driver experience (1 if less than one year, 0 otherwise)	0.0085	0.0000	0.0348	0.0404	0.0000
Trips conducted (1 if completed fewer number of trips during pandemic than before, 0 otherwise)	-0.0004	0.0000	-0.0014	-0.0015	0.0000
Participation in team driving (1 if never, 0 otherwise)	0.0077	0.0000	0.0305	0.0361	0.0000
Most difficult time of day to locate safe truck parking (1 if early morning, 0 otherwise)	-0.0009	0.0000	-0.0034	-0.0036	0.0000
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	-0.0023	0.0000	-0.0082	-0.0083	0.0000
Participation in team driving (1 if sometimes, 0 otherwise)	0.0099	0.0000	0.0418	0.0490	0.0000
Participation in team driving (1 if most of the time, 0 otherwise)	0.0084	0.0000	0.0326	0.0379	0.0000
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	-0.0036	0.0000	-0.0134	-0.0134	0.0000
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	0.0060	0.0000	0.0265	0.0290	0.0000

Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	-0.0055	0.0000	-0.0171	-0.0158	0.0000
Service disruptions encountered at public truck stops (1 if fuel services, 0 otherwise)	-0.0041	0.0000	-0.0134	-0.0132	0.0000
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	-0.0016	0.0000	-0.0058	-0.0059	0.0000
Service disruptions encountered at public truck stops (1 if restrooms, 0 otherwise)	0.0030	0.0000	0.0115	0.0120	0.0000
Real time parking availability tools used (1 if communications with other drivers, 0 otherwise)	0.0019	0.0000	0.0072	0.0075	0.0000
Real time parking availability tools used (1 if none, 0 otherwise)	0.0538	0.0000	0.1361	0.1017	0.0000
Drive while tired (1 if rarely, 0 otherwise)	0.0050	0.0000	0.0210	0.0232	-0.3038
Drive while tired (1 if never, 0 otherwise)	0.0238	0.0000	0.0862	0.1254	0.0000
Driver’s most commonly driven truck configuration (1 if single unit truck, 0 otherwise)	-0.0035	0.0000	-0.0126	-0.0122	0.0000

Table 5. Estimated Marginal Effects for Ordered Probit Model of During Model

Variable	Never	Sometimes	About half the time	Most of the time	Always
Driver gender (1 if male, 0 otherwise)	-0.0025	0.0000	-0.0040	-0.0007	0.1102
Participation in team driving (1 if sometimes, 0 otherwise)	0.0037	0.0000	0.0054	0.0010	-0.1593
Participation in team driving (1 if never, 0 otherwise)	0.0075	0.0000	0.0119	0.0016	-0.2989
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	-0.0032	0.0000	-0.0066	-0.0021	0.1555
Drive while tired (1 if very often, 0 otherwise)	-0.0023	0.0000	-0.0047	-0.0014	0.1141
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	-0.0033	0.0000	-0.0063	-0.0019	0.1531
Service disruptions encountered at public truck stops (1 if take out and/or drive thru food services, 0 otherwise)	-0.0025	0.0000	-0.0047	-0.0013	0.1146
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	0.0022	0.0000	0.0036	0.0006	-0.0953
Service disruptions encountered at private truck stops (1 if showers, 0 otherwise)	0.0026	0.0000	0.0044	0.0010	-0.1132
Service disruptions encountered at private truck stops (1 if truck wash stations, 0 otherwise)	-0.0020	0.0000	-0.0038	-0.0011	0.0922
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	0.0060	0.0000	0.0093	0.0008	-0.2286
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	-0.0061	0.0000	-0.0168	-0.0104	0.3566
Real time parking availability tools used (1 if websites, 0 otherwise)	-0.0017	0.0000	-0.0032	-0.0009	0.0782
Real time parking availability tools used (1 if none, 0 otherwise)	0.0538	0.0000	0.1361	0.1017	-0.3038
Normal driving start time (1 if mid-day, 0 otherwise)	-0.0023	0.0000	-0.0046	-0.0015	0.1093

4.1 Socioeconomic Characteristics

Table 4 shows that before the pandemic, young drivers aged 30-49, who constitute 56.6% of surveyed drivers and align with the national median age of 46, experienced more frequent HOS adherence issues due to parking shortages. In contrast, drivers with less than a year of experience faced fewer such issues, possibly due to their use of real-time parking tools and decision-making regarding parking locations. Drivers receiving hazard pay, often involved in emergency relief, also faced more parking challenges before the pandemic, likely linked to decreased freight movement in various industries and reduced demand from businesses that slowed or shut down production. The Bureau of Labor Statistics reported a loss of 140,000 truck driver jobs by December 2020. Additionally, traffic congestion significantly decreased, with 87% of respondents in an ATRI and OOIDA survey reporting shorter congestion times. Post-pandemic, a higher proportion of male drivers, about two-thirds of those surveyed, reported increased difficulties in finding adequate parking. (Cheeseman Day and Hait 2019; U.S. Bureau of Labor Statistics 2020; The American Transportation Research Institute and The OOIDA Foundation 2020).

4.2 Business Characteristics

Concerning business characteristics, the only significant factor identified was the reduced number of trips taken during the pandemic compared to before. Consequently, drivers who took fewer trips experienced fewer instances of parking shortages leading to HOS adherence issues.

4.3 Driver Characteristics

Negative coefficient values indicate that team driving before and during the pandemic led to a decrease in parking-related HOS adherence issues. Tables 5 and 6 show that before the pandemic, drivers who never engaged in team driving had a lower likelihood (probability 0.0077) of experiencing HOS issues. However, during the pandemic, these drivers were more likely (probability 0.0075) to avoid HOS issues, while those who sometimes participated in team driving faced the highest risk of problems (probability 0.0037). Team drivers who stayed together during the pandemic, likely part of the same social bubble or family, were more efficient at finding adequate parking.

4.4 Time of Day Operations

Time-of-day factors significantly influenced the frequency of parking shortages causing HOS adherence issues both before and during the pandemic. Mondays were found particularly challenging for finding parking (increased). Attempting to park on Mondays reduced the likelihood of avoiding HOS problems by 0.0032 in both periods. Moreover, a shift in drivers' normal start times to mid-day during the pandemic, with 34% fewer starting in the morning and increases of 50% and 140% for mid-day and afternoon starts respectively, also affected parking availability. This shift likely relates to decreased passenger traffic and changes in delivery schedules for essential goods, as indicated by the ATRI and OOIDA survey findings.

Facility closures significantly impacted parking issues. Closed private truck stops or those with limited amenities reduced parking challenges before and during the pandemic. During the pandemic, shower access at private facilities decreased HOS issues, whereas truck wash stations increased them, influenced by the popularity of stops with certain amenities. Conversely, restrooms at public facilities decreased parking issues before the pandemic, but fuel services and vending machine access increased them. During the pandemic, vending machine and food service availability continued to exacerbate parking challenges.

4.5 Driving Management

In terms of driving management, using websites as real-time truck parking availability tools did not effectively reduce HOS regulation adherence problems due to parking shortages. Before the pandemic, website use slightly decreased the likelihood of avoiding HOS issues (probability of 0.0017), while not using these tools significantly increased the probability of never experiencing HOS issues (probability of 0.0538), a trend consistent during the pandemic. Additionally, communicating with other drivers was unreliable for finding parking before the pandemic, leading to more HOS issues.

Fatigued driving also impacted parking-related HOS problems. Before the pandemic, rarely or never driving while tired helped nearly all respondents avoid difficulties in finding parking. However, during the pandemic, frequently driving tired increased the challenges in adhering to HOS regulations.

4.6 Truck Configuration

Before the pandemic, truck configuration characteristics emerged as a significant factor, with single unit trucks more likely to face HOS adherence problems due to parking shortages. Although 39% of surveyed drivers operated single unit trucks, they represent 77.6% of all registered trucks nationally. This higher occurrence of issues among single unit trucks aligns with the American Trucking Associations (ATA) survey findings, which reported more than 11 truck drivers for every parking space and 98% of drivers facing difficulties in finding safe parking. Additionally, nearly half of the drivers in this survey admitted to willingness to park illegally, highlighting the severe impact of the national truck parking shortage. (Bureau of Transportation Statistics 2019). (McNally 2021)

5. CONCLUSION

This study sheds light on the pandemic's impact and the truck parking shortage. It used a random parameters bivariate ordered probit model to analyze how lack of parking affects HOS adherence issues, revealing a correlation in unobserved factors before and during the pandemic. The findings highlight the pandemic's adverse effects on trucking industry characteristics and service availability at rest stops. Disruptions in amenities like vending machines, takeout services, and truck wash stations have led to increased parking and HOS compliance challenges for drivers. The importance of rest stop services, including restrooms, fuel, and showers, emerged as critical for drivers seeking parking. Additionally, the study found that fatigued driving and driving during mid-day or on Mondays heightened parking-related HOS issues. This research offers valuable insights for policy formulation and management regarding HOS regulations, truck parking, and road safety, addressing the national parking shortage. Future studies should focus on modeling based on facility type and geographic region, aiding state agencies, planners, and engineers in crafting effective policies for resilient supply chains and infrastructure.

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