Megaregional Traffic Impact of COVID-19 Pandemic: Analysis of Activity Restriction

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February 2024

A publication of the USDOT Tier 1 Center:
Cooperative Mobility for Competitive Megaregions
At The University of Texas at Austin

Technical Report Documentation Page

1. Report No. CM2-63	2. Government Accession No.	3. Recipient's Catalog No. ORCID: 0000-0002-1703-2995
4. Title and Subtitle Megaregional Traffic Impact of COVID-19 Pandemic: Analysis of Activity Restriction		5. Report Date February 2024 6. Performing Organization Code
7. Author(s) Brian Wolshon		8. Performing Organization Report No. CM2-63
9. Performing Organization Name and Address The University of Texas at Austin School of Architecture 310 Inner Campus Drive, B7500 Austin, TX 78712 Louisiana State University Department of Civil and Environmental Engineering 3255 Patrick F. Taylor Hall Baton Rouge, LA 70803		10. Work Unit No. (TRAIS) 11. Contract or Grant No. USDOT 69A3551747135
12. Sponsoring Agency Name and Address U.S. Department of Transportation Federal Transit Administration Office of the Assistant Secretary for Research and Technology, UTC Program 1200 New Jersey Avenue, SE Washington, DC 20590		13. Type of Report and Period Covered Technical Report conducted September 2021 – November 2022 14. Sponsoring Agency Code
15. Supplementary Notes Project performed under a grant from the U.S. Department of Transportation's University Transportation Center's Program.		
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ORCID: 0000-0002-1703-2995</td></tr>
<tr><td colspan="6">during the COVID-19 pandemic is critical in preserving the continuity of service and preventing supply shortages in the event of future outbreaks.</td></tr>
<tr><td colspan="4">17. Key Words
COVID-19, Travel restrictions, Commodity carriers/trucking, surface transportation, pandemic response</td><td colspan="2">18. Distribution Statement
No restrictions.</td></tr>
<tr><td>19. Security Classif. (of report)
Unclassified</td><td colspan="2">20. Security Classif. (of this page)
Unclassified</td><td colspan="2">21. No. of pages
10</td><td>22. Price</td></tr>
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Truck Traffic during COVID-19 Restrictions

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Abstract: The global COVID-19 pandemic had an unprecedented impact on transportation worldwide. Significant decreases in transportation across all modes were evident and sustained as governments worldwide implemented various countrywide closures and quarantine restrictions to slow the spread of the virus. This paper quantifies and assesses daily vehicle counts by Federal Highway Administration (FHWA) vehicle classifications during the COVID-19 pandemic in New York and Florida throughout 2020. The study found that during March and April of 2020, traffic among all investigated FHWA categories was significantly reduced in both Florida and New York. However, commodity carriers in both states were able to recover faster and remained more consistent than passenger vehicles. This pattern was also observed in both urban and rural communities in Florida. The findings of this work demonstrate how commodity carrier movements, assessed through FHWA vehicle category counts, were less impacted by the governmental restrictions during the pandemic than passenger transportation. While overall traffic volume dropped by more than half in most places at the height of the pandemic, larger commodity-carrying vehicles remained nearly unchanged from the prior year by June of 2020. This was likely because of the critical need to maintain trucking movements to sustain populations. Understanding how truck traffic and freight movements more broadly were impacted during the COVID-19 pandemic is critical in preserving the continuity of service and preventing supply shortages in the event of future outbreaks. **DOI: 10.1061/JTEPBS.TEENG-7271.** *© 2024 American Society of Civil Engineers.*

Author keywords: COVID-19; Travel restrictions; Commodity carriers/trucking; Surface transportation; Pandemic response.

Introduction

In March 2020, the World Health Organization declared the coronavirus disease 2019, abbreviated as COVID-19, a global pandemic (Deb et al. 2020). In the United States, a public health emergency was announced in January 2020, eventually leading to a national emergency declaration on March 13, 2020 (Aubrey 2020; Liptak 2020). As the spread rate of COVID-19 increased, several methods were implemented to slow virus transmission. The most common were social distancing, face masks, self-isolation, limits on the number of people in indoor environments, and work-from-home options. Ultimately, the most restrictive measure was near-total population lockdowns. The response to the COVID-19 pandemic also brought radical changes to transportation, as the need for personal movement was drastically reduced. This research sought to quantify and understand this change by first observing and then comparing the volume counts of different vehicle categories in Florida and New York during the pandemic. Data came from permanent detector stations managed by the State Departments of Transportation (DOT) in both locations and were compared using paired t-tests and percent change to reveal differences between the classification categories.

Not surprisingly, both Florida and New York were impacted by the COVID-19 pandemic in terms of public health and traffic volume. COVID-19 cases initially surged in New York during March and April of 2020, while an initial surge was seen in Florida in July and August. Ultimately, COVID-19 infections in 2020 peaked in both states in late December with a 7-day average of approximately 14,000 to 15,000 cases (Johns Hopkins Coronavirus Resource Center 2020). Pandemic-related business closures and social distancing requirements reduced demand for both travel and some, but not all, commodities. Significant demand increases were seen for many goods, particularly cleaning and hygiene products. These shifts in demand altered not only what goods were being consumed and their amounts but also the timing, mode, and location of their delivery. These trends yield valuable insights to help us better understand how freight transportation was impacted during the COVID-19 pandemic. Furthermore, they underscore the criticality of preserving continuity of service to prevent supply shortages in potential future outbreaks and disruptive events.

Vehicle categories are defined by the Federal Highway Administration (FHWA) to describe vehicle configuration and size. This paper describes traffic trends among the five most prevalent FHWA vehicle types throughout the COVID-19 pandemic in Florida and New York. Specifically, this paper investigated:

- How commodity carriers were impacted (percent change in traffic, year over year) by the pandemic, and how this compared to passenger vehicles?
- When did changes to the travel patterns of various vehicle categories significantly deviate from prior year levels and when did travel return (timing of traffic deviations)?

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Note. This manuscript was submitted on December 31, 2021; approved on December 5, 2023; published online on February 23, 2024. Discussion period open until July 23, 2024; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering, Part A: Systems***, © ASCE, ISSN 2473-2907.

- What differences persisted between urban and rural areas in Florida (percent change in traffic and timing of traffic deviations)?
- What differences persisted between Florida and New York (percent change in traffic and timing of traffic deviations)?

Volume data from all 13 FHWA categories were initially considered. However, this research focused on the five most pervasive categories. The inclusion criteria was that each category must represent at least one percent of the total annual traffic volume. Inclusion criteria were that each category must represent at least one percent of the total annual traffic volume. This was done to ensure that excessively rare vehicle categories did not impact the study findings. The five selected categories cumulatively account for over 95% of the total traffic volume in both Florida and New York.

This paper is divided into four sections. The first outlines the findings of prior studies on the impacts and changes to transportation use during the pandemic. The second describes the methodology used to analyze the detector data obtained from the Florida and New York DOTs. From this, the results of the comparative analyses are presented in the third section. Then, the overall conclusions from this research and avenues for future work are used to close the discussion in the final section of the paper.

Background and Prior Analysis

Social distancing's intended benefits include reducing the spread of disease, delaying and reducing the size of the peak, and spreading cases over time, thus reducing the burden on the healthcare system (Fong et al. 2020). The degree to which the public avoids gathering in public areas may be influenced by culture (Huynh 2020). As part of many countries' pandemic plans, school closures can aid in reducing social contact (Sadique et al. 2008). However, the reopening of schools often leads to an increase in disease transmission (Jackson et al. 2013). Similarly, the relaxation of broader restrictions for COVID-19 may be linked with an upsurge in cases.

The impact of COVID-19 on general mobility has been staggering. A survey conducted in the Netherlands found that 80% of respondents reduced their outdoor activities and the number of trips taken reduced by 55% (de Haas et al. 2020). Further survey results from Australia discovered household trips reduced by over 50% across all modes (Beck and Hensher 2020). A study of roadway detectors in Florida found that vehicle volumes across the state had dropped by 47.5% in the first half of 2020, compared to 2019 (Parr et al. 2020). In Italy, the number of daily new COVID-19 cases was related to trips performed three weeks earlier (Cartenì et al. 2020), and another study in the United Kingdom found that mobility reductions had a significant impact on reducing COVID-19 (Hadjidemetriou et al. 2020).

Public transport and other shared mobility modes faced significant challenges during the pandemic. Prior research in this area has compiled best practices implemented by public agencies for social distancing on various public transportation modes in the US (Tirachini and Cats 2020). An investigation into subway ridership and bike-sharing usage in New York City, NY, found subway trips decreased by 90%, and bike-share trips were reduced by 71%. The research by Teixeira and Lopes (2020) also found that bike-share trips were longer during the pandemic, possibly indicating a mode shift from transit. Another study suggested that biking and walking increased during the pandemic and concluded by providing design specifications for adequate social distancing on bike and pedestrian facilities (Donné 2020). Zhang et al. (2020) investigated the role of transportation modes in the spread of COVID-19. Investigations into cruise ship travel sought to understand the relationship between passenger landings and COVID-19 outbreaks (Ito et al. 2020).

Air travel has been significantly impacted during the first year of the pandemic. Suau-Sanchez et al. (2020) found a 98% reduction in airline revenues resulting from various travel restrictions. An analysis of prior events affecting air transport suggests unemployment in the airline workforce could range between 7% and 13% (Sobieralski 2020). Forecasting models suggest that these reductions in air travel could reduce global gross-domestic products by nearly 2% (Iacus et al. 2020). Another avenue of research into air travel has sought to identify critical airports for controlling the global spread of COVID-19 (Nikolaou and Dimitriou 2020; Nakamura and Managi 2020).

Freight transportation, global supply chains, and the overall movement of goods have experienced significant changes during the pandemic. Research efforts by Ivanov (2020) sought to identify the risk associated with the global pandemic and more specifically how these risks impact the supply of healthcare goods (Govindan et al. 2020). In Germany, road tonnage shipments of dry products typically associated with retail increased significantly during the lockdown (Loske 2020). In Italy's Veneto region, maritime transport was reduced by 69% (Depellegrin et al. 2020). Simulation analysis has shown that policy changes could have a positive impact on freight delivery while still supporting social distancing (Choi 2020). Research into the freight labor force found that COVID-19 has exacerbated existing job-related stressors for truck drivers and introduced new stressors. Potentially having adverse effects on health and safety (Lemke et al. 2020).

A gap in the existing literature exists, as no peer-reviewed studies have investigated the differential impacts on vehicle categories within the highway transportation system. The international literature provides seemingly conflicting assessments of freight movements. In Germany, road tonnage shipments increased (Loske 2020), but in Italy maritime transport, a major contributor to roadway tonnage decreased (Depellegrin et al. 2020). This apparent contradictions suggest further analysis is needed to assess conditions in the United States. Parr et al. (2021) examined total volume changes on roads in 10 states within the US but did not separate out vehicles by category. Separating the vehicles by category allows for the examination of differences between commercial travel and personal travel. If the increase in online shopping persists (Nguyen et al. 2020; Ali 2020; Bhatti et al.2020; Roggeveen and Sethuraman 2020; Koch et al. 2020), then increases in goods movement during the pandemic may be somewhat indicative of future demand.

Data and Methods

Broadly, the data and methods were divided into two primary tasks, data collection and management, and statistical analysis. Both research tasks used the data collected from continuous-count-station detectors placed in $N = 268$ locations in Florida and $N = 102$ locations in New York state. Both Florida and New York install and maintain arrays of detectors to monitor and archive traffic data. Detectors are located to ensure statewide coverage and are diversified in different road types, from urban roads to interstate freeways. The methodology used in this study followed a similar approach utilized in prior studies (Parr et al. 2021; Hadjidemetriou et al. 2020). Data collection and management compared traffic counts by FHWA category classifications, between years for matched days of the week. For example, the total number of vehicles passing over Florida's continuous count stations on the first Monday in March of 2020 was compared with the same count station totals, for the first Monday in March of 2019. This data was presented cumulatively for each day by FHWA classification, showing percent changes between years. This approach allows for a broader understanding of the magnitude of travel pattern changes. This analysis assisted in answering the research questions by analyzing the relative changes in vehicle volume, between years. Next, paired t-tests were conducted to compare traffic counts at individual stations for similar days between 2019 and 2020, with each vehicle category. A paired t-test was selected for the analysis because traffic volumes were being measured at the same location, on similar days in 2019 and 2020. The paired t-test investigated if the distribution of differences between these paired volumes was significantly different than zero. Conversely, an unpaired test and its assumption of independence between the two samples would not have been appropriate. This analysis establishes a timeline of when changes in traffic were significant, by vehicle category and investigates the research questions with regard to onset, recovery, and shows travel trends and patterns, over time. Furthermore, the difference in volumes (percentage change) between 2019 and 2020 can help further identify the onset and recovery periods of each vehicle category.

Data Collection and Management

State departments of transportation are required to submit annual traffic statistics to FHWA as part of the Highway Performance Monitoring System (HPMS) (Shekhar et al. 2012). States are responsible for constructing and maintaining an array of traffic sensors to fulfill this federal requirement. One tool to accomplish this is the deployment of continuous count stations that are distributed accordingly in each area and ensure adequate coverage of the transportation network for each state, in order to have an accurate representation of traffic conditions. Hourly traffic counts are collected from the same location, 24 h a day, seven days a week, year after year. State departments of transportation provided these public records upon request. Traffic data files contain the date, time, detector id, direction, and total volume for each of the 13 FHWA vehicle categories (USDOT 2016):

- Category 1–Motorcycles
- Category 2–Passenger Cars
- Category 3–Four tire, single unit (vans)
- Category 4–Buses
- Category 5–Two axles, six tires, single unit
- Category 6–Three axles, single unit
- Category 7–Four or more axles, single unit
- Category 8–Four or less axles, single trailer
- Category 9–Five axles, tractor semitrailer
- Category 10–Six or more axles, single trailer
- Category 11–Five or less axles, multitrailer
- Category 12–Six axles, multitrailer
- Category 13–Seven or more axles, multitrailer

Data for the period January to December 2019 were compared with data from January to December 2020. Data reliability was ensured by filtering all the provided data for errors. A common error, for instance was very high or low traffic counts or prolonged (several hours/days/weeks) where a counter recorded zero traffic. Erroneous count stations were reviewed and eliminated from consideration. This resulted in a final tally of 268 count stations in Florida and 102 in New York. Traffic volume counts create repeated patterns with a frequency of seven days and support the decision to match the years by day-of-week instead of calendar day (Parr et al. 2020). From the 13 categories count stations can distinguish, five categories constituted over 95% of traffic in both Florida and New York. Therefore, the decision was made to move forward with the investigation of these five categories and exclude lower-frequency vehicle categories which could have biased the results. The categories representing personal travel were Category 2 (passenger cars) and Category 3 (four tire, single unit vans), while representing heavier, commodity carrier vehicles were Category 5 (two axles, six tire, single unit), Category 8 (Four axels, single trailer), and Category 9 (five axels, single trailer). All the data were organized in manageable databases with the use of Python 3.7. The research analyzed the data to understand the changes in traffic patterns during four critical stages in Florida:

- State of Emergency (SOE) which started March 9th, 2020 including mandating the use of face masks in public spaces and indoor settings. Implementing social distancing measures in public places, including businesses and transportation systems. Ordering the closure of nonessential businesses and services. Prohibiting large gatherings and events to prevent the spread of the virus. Enforcing quarantine and isolation measures for individuals who have been exposed to or diagnosed with COVID-19. Allocating resources and funding for healthcare facilities to manage the influx of patients. Providing financial assistance and support to individuals and businesses affected by the pandemic. Facilitating the distribution of vaccines and other essential medical supplies
- Phase I reopening (Phase I) which started May 18th, essential businesses, such as grocery stores, pharmacies, and healthcare facilities, outdoor recreational areas, parks, and beaches with strict adherence to social distancing protocols, emphasis on remote work and telecommuting for nonessential workers where possible.
- Phase II reopening (Phase II) which started June 5th, bars, movie theaters, and entertainment venues, personal care businesses, such as salons and barbershops, restrictions on outdoor gatherings and events
- Phase III reopening (Phase III) which started September 25th (Cutway 2020) reopen bars, businesses, and restaurants at 100%.

In New York:

- SOE stage started on March 7th 2020 including all the aforementioned in Florida state.
- Phase I reopening on June 8th, construction, manufacturing, agriculture, forestry, fishing, and select retail that can offer curbside pickup.
- Phase II on June 22nd, outdoor dining at restaurants, hair salons and barber shops, offices, real estate firms, in-store retail, vehicle sales, retail rental, repair services, cleaning services, and commercial building management.
- Phase III on July 6th, indoor dining at restaurants and bars at 50% capacity (excluding New York City) and personal care services.
- Phase IV reopening on July 20th outdoor activities at 33% capacity (outdoor zoos, botanical gardens, nature parks, historical sites, outdoor museums, etc.); low-risk indoor activities at 25% capacity outside of New York City (malls, indoor museums, historical sites, art galleries, aquariums, etc.).

All information concerning the number of COVID-19 cases per day were based on the information provided by the Johns Hopkins, Coronavirus Resource Center (Johns Hopkins Coronavirus Resource Center 2020).

Statistical Analysis

The changes in the general traffic patterns between 2019 and 2020 were significant and lasted several months. The statistical analysis conducted for this research was used to identify when these travel patterns began and subsequently ended, for five pervasive FHWA vehicle categories. To evaluate the changes in the traffic volumes before and during the COVID-19 pandemic, the paired two-tailed t-test was applied to the two databases (Florida and New York) comparing 2019 and 2020. The results of this test identify on what days traffic changes between years were statistically significant and on what days these differences were attributable to random fluctuations. This was done by vehicle category, within each state, for every day between March and December. The null hypothesis was that the mean of the paired differences between 2019 and 2020 daily traffic counts of a given FHWA category were equal to zero. The alternative hypothesis was that the mean of the paired differences was not equal to zero. The paired, two-tailed t-test utilized a 95% confidence interval and an alpha value of 0.05. The normal distribution of a similar data set was examined and identified by O'Leary et al. (2022). The two-tailed paired t-test was calculated based on Eq. (1) (Walpole et al. 2006).

$$t_{c,d} = \frac{\frac{\sum_{i=1}^{N}(X_{i,c,d}^{2020} - X_{i,c,b}^{2019})}{N} - \mu_o}{s_D/\sqrt{N}} \tag{1}$$

where $t_{c,d}$ is the t-statistic for vehicle category c for day d in 2020; $x_{i,c,d}^{2020}$ is the daily traffic total for category c, at location i, on day d in 2020; $x_{i,c,b}^{2019}$ is daily traffic total for category c, at location i, on day b in 2019; i is an individual continuous count detector; c is the FHWA vehicle category (2, 3, 5, 8, or 9); d is the analysis day in 2020; b is the corresponding day for d, in 2019 (matched by day of week); N is the number of paired observations and is equal to the total number of detector locations i; s_D is the standard deviation of the differences between each pair; and μ_0 is zero.

For the state of Florida, the equation was applied to both rural and urban levels, as the data set was thoroughly investigated at these specific levels of analysis as well. Furthermore, the relative percentage change was calculated to describe the difference between the two years; it also can be used to compare the patterns of different categories with each other. The relative change was calculated with the use of Eq. (2) (Bennett and Briggs 2005)

$$R_{c,m}(x_{c,m,}^{2020}, x_{c,m}^{2019}) = \frac{\sum_{I=1}^{N}(X_{i,c,m}^{2020}) - \sum_{I=1}^{I=N}(X_{i,c,m}^{2019})}{\sum_{I=1}^{N}(X_{i,c,m}^{2019})} \tag{2}$$

where R is the percent change between years for FHWA vehicle category c, during month m; $x_{i,c,m}^{2020}$ is the monthly traffic total for category c, at location i, over month m, in 2020; $x_{i,c,b}^{2019}$ is the monthly traffic total for category c, at location i, over month m, in 2019; m is the month in 2020 corresponding to 2019; c is FHWA vehicle category (2, 3, 5, 8, or 9); i is an individual continuous count detector; and N is the number of paired observations and is equal to the total number of detector locations i.

Findings

The results are presented in a series of five figures. The first two figures show on what days traffic volumes were significantly different between years, i.e., the paired t-test conducted on these days rejected the null hypothesis of equal means. The significant days are represented with a horizontal bar, on those that the difference was not significant the bar is missing for the specific category. The x-axis represents the time period from the State of Emergency (SOE) until the end of the year. On the first y-axis (left side), the various vehicle categories are displayed based on the FHWA grouping. On the second y-axis (right side), the number of COVID-19 cases is presented. This is first shown for Florida for both urban and rural data collection sensors and then for New York state as a whole. These figures provide quantifiable evidence establishing a timeline for when various vehicle categories significantly deviated from prior year levels and when travel returned. Furthermore, these figures are used to analyze differences in travel pattern timing between urban and rural areas in Florida as well as to compare onset and recovery times in Florida and New York State. The last three figures show the percent change in traffic between years for urban sites in Florida, rural sites in Florida, and New York State. These last three figures allow for a comparison in percent volume change, year-over-year by vehicle category.

Statistical Analysis

Fig. 1 presents the daily t-test results for urban and rural areas for five vehicle categories in the state of Florida. The figure indicates that vehicle travel patterns varied by category during the pandemic. The passenger car and van vehicle types, Categories 2 and 3, performed similarly to each other, as did the commodity carrier types, Categories 5, 8, and 9. For both urban and rural areas, Category 2 is depicted by a continuous line, illustrating the variation in the daily vehicle count, which remained notably distinct for 2020 compared to 2019 subsequent to the State of Emergency (SOE) declaration. The percentage difference exceeds 10% for the majority of the months, with a peak of 51% for this specific category (see Tables 1 and 2). Category 3 vehicles were notably affected during the State of Emergency (SOE), particularly in Phase I, and further during the two peaks of daily COVID-19 cases in July and December, with impacts ranging from over 6% to as high as 35%.

Significant drops in traffic of more than 20% were observed for all vehicle categories during the SOE and throughout the analysis period. However, as demonstrated later in this paper, the changes in travel patterns differed between the larger and smaller vehicle categories. In general, rejections of the null hypothesis observed in Figs. 1 and 2 for Category 2 and 3 vehicles, were likely driven by reductions in 2020 traffic levels. While the same is true for Categories 5, 8, and 9 during the initial onset of the pandemic, observations taken later in the year show the significant changes observed in Figs. 1 and 2 likely correspond to significant increases in traffic up to 15% for these larger vehicle categories, later shown in Figs. 3–5. Phase 2 and Phase 3, Category 5 vehicles (two axles, six tires) and Category 8 vehicles (four axles, trailer) in urban areas exhibited a marginal deviation of merely 5% from their In contrast, Category 9 vehicles (five axles, semitrailer) in urban areas of Florida exhibited the least impact among all vehicle types examined in this study. Their percentage difference was at a maximum of 10% throughout the entire period, with the mean value of differences averaging around 3%. During the SOE, significant differences more than 5% in Category 9 traffic were observed. However, these tended to be intermittent and predominately occurred in rural areas. Urban areas, by contrast, saw few days of dissimilar traffic between years, and these generally occurred near typical holiday travel periods; the first weeks of July and September (Independence Day and Labor Day) where holiday travel varies by day-of-week or prevailing weather conditions.

The results of the statistical analysis for New York are presented, statewide, in Fig. 2. The small number of active detectors ($N = 102$) prevented an accurate investigation into urban and rural distinctions. Again, the analysis suggests that Categories 2 and 3 (four-tire, single-unit vans similarly responded to the pandemic, as did Categories 5, 8, and 9. Similarly to traffic trends in Florida, the 2020 vehicle counts in Categories 2 and 3 significantly differed up to 50% from those in 2019 for most of the study period, with the exception of October and early November (see Table 3). The analysis suggests that Category 5 (two axel, six tire) vehicles were only marginally impacted, with these disruptions predominately occurring in April, June, and July with up to 34.2% reduction. Category 8 (four axels, trailer) and 9 (five axels, semitrailer) vehicles appear to have reacted to the pandemic similarly; both

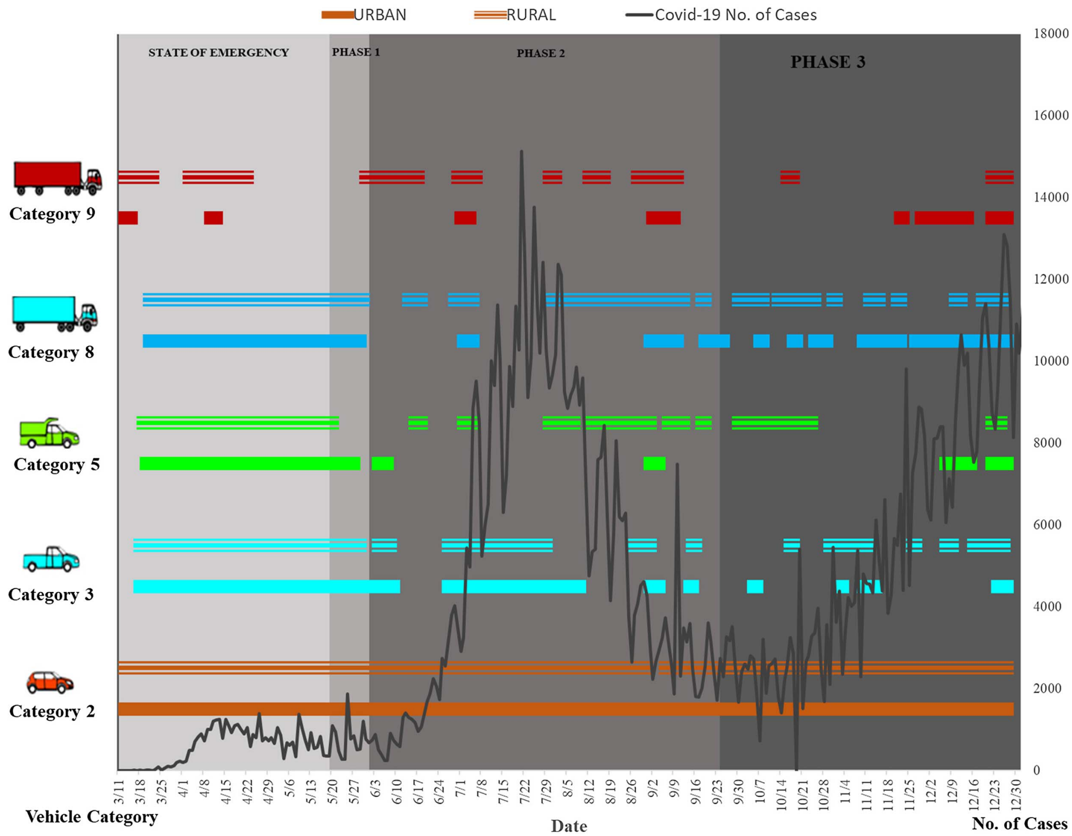

Fig. 1. Days with significant changes between 2019 and 2020 for each vehicle category in Florida. (Icons © FHWA 2014.)

Table 1. Florida urban traffic volume per month in 2019 and 2020

Florida urban count stations monthly total (vehicles 10^6)										
	Cat. 2 (passenger cars)		Cat. 3 (vans)		Cat. 5 (two axel, six tires)		Cat. 8 (four axel trailer)		Cat. 9 (five axel semitrailer)	
Month	2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
March	103.8	78.8 (−24.1%)	30.3	25.9 (−14.7%)	3.9	3.6 (−9%)	1.5	1.3 (−10%)	3.4	3.5 (5.4%)
April	100.6	48.9 (−51.4%)	29.3	19 (−35.2%)	3.8	3 (−22.1%)	1.5	1.1 (−24%)	3.3	3.1 (−5%)
May	102.7	68.5 (−33.3%)	29.6	24.3 (−18%)	3.7	3.4 (−9.7%)	1.4	1.4 (−6.2%)	3.3	3.3 (1.1%)
June	97.3	78.6 (−19.2%)	29.2	27.2 (−6.8%)	3.7	3.7 (−1.1%)	1.4	1.5 (2.8%)	3.3	3.4 (2.1%)
July	100.3	79.4 (−20.9%)	30.0	27.5 (−8.2%)	3.8	3.8 (0%)	1.5	1.5 (4.1%)	3.3	3.4 (5.3%)
August	96.4	80.3 (−16.7%)	28.5	26.9 (−5.6%)	3.6	3.7 (2.9%)	1.3	1.4 (8.3%)	3.2	3.2 (2.7%)
September	90.4	79.9 (−11.5%)	27.0	27 (0.1%)	3.5	3.8 (9%)	1.2	1.4 (14.7%)	3.1	3.4 (8.4%)
October	98.3	84.7 (−13.8%)	29.8	28.5 (−4.4%)	3.9	3.9 (1.9%)	1.4	1.4 (5.2%)	3.4	3.5 (2.7%)
November	96.1	81.2 (−15.5%)	28.6	26.9 (−6%)	3.6	3.7 (3.2%)	1.3	1.3 (5.4%)	3.2	3.4 (3.8%)
December	92.3	81.5 (−11.7%)	27.2	27 (−0.9%)	3.3	3.7 (10.4%)	1.1	1.3 (15.2%)	3.0	3.4 (11.6%)

experiencing times of significant decreases and increases, throughout the analysis period from −36.8% up to 66.9%.

Percent Change in Volume

Further analysis was conducted on the number of vehicles based on the monthly percentage change between 2020 and 2019. Monthly traffic totals were calculated for 2019 and 2020, for each category of vehicle. The analysis investigated the percent changes in these volumes between years for urban regions in Florida (Table 1), rural regions in Florida (Table 2), and New York State (Table 3). Positive changes show that traffic increased in 2020, while negative values show that traffic decreased in 2020.

Fig. 3 (corresponding to Table 1) shows the percent traffic change in the urban regions of Florida. March, April, and May show the most drastic decreases in travel, compared to 2019 across all vehicle categories. The figure suggests that the impact of the pandemic on traffic is likely related to category/size. The data suggests that larger vehicles experienced a relatively smaller percentage reduction in traffic volume during the SOE. By June, Category 5, 8, and 9 vehicles approached and surpassed their 2019 levels. By the Phase 2 reopening, it appears that Category 2 and 3 traffic had become fairly stable. Between June and December, Category 2 vehicles were reduced between 20% to 11% and Category 3 vehicles reductions ranged from 8% to 0%. Meanwhile, Category 5, 8, and 9 vehicle traffic showed steady increases between

Table 2. Florida rural traffic volume per month in 2019 and 2020

	Florida rural count stations monthly total (vehicles 10^6)									
	Cat. 2 (passenger cars)		Cat. 3 (vans)		Cat. 5 (two axel, six tires)		Cat. 8 (four axel trailer)		Cat. 9 (five axel semitrailer)	
Month	2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
March	24.5	18.7 (−23.6%)	9.3	8 (−14%)	1.3	1.2 (−8.8%)	0.8	0.8 (−8.6%)	2.8	2.9 (2.5%)
April	22.8	10.7 (−52.9%)	8.7	5.7 (−35.2%)	1.3	1 (−21.8%)	0.8	0.6 (−29.8%)	2.8	2.6 (−6.5%)
May	23.1	17 (−26.8%)	8.7	7.8 (−11.2%)	1.3	1.2 (−6.4%)	0.8	0.7 (−8.2%)	2.7	2.7 (−0.7%)
June	21.6	18.8 (−12.8%)	8.7	8.4 (−2.9%)	1.2	1.3 (1.9%)	0.7	0.8 (1.6%)	2.7	2.7 (1.5%)
July	22.8	18.8 (−17.4%)	9.1	8.5 (−6.2%)	1.2	1.3 (4.5%)	0.7	0.8 (6.7%)	2.6	2.7 (6.3%)
August	20.6	18.3 (−11.2%)	8.2	8.2 (0.4%)	1.2	1.3 (7.7%)	0.7	0.7 (12.4%)	2.5	2.7 (8.3%)
September	19.2	18 (−6.4%)	7.9	8.1 (2.3%)	1.2	1.3 (7.5%)	0.6	0.7 (12.1%)	2.5	2.6 (3.8%)
October	21.6	19.9 (−8%)	8.9	8.9 (0%)	1.3	1.4 (5.5%)	0.7	0.8 (9%)	2.9	2.9 (−0.1%)
November	22.4	19.2 (−14.3%)	8.9	8.4 (−6.3%)	1.2	1.3 (2.5%)	0.7	0.7 (3.3%)	2.7	2.5 (−5.3%)
December	22.1	18.9 (−14.7%)	8.7	8.2 (−6%)	1.1	1.2 (5.6%)	0.6	0.6 (8.3%)	2.5	2.5 (−0.7%)

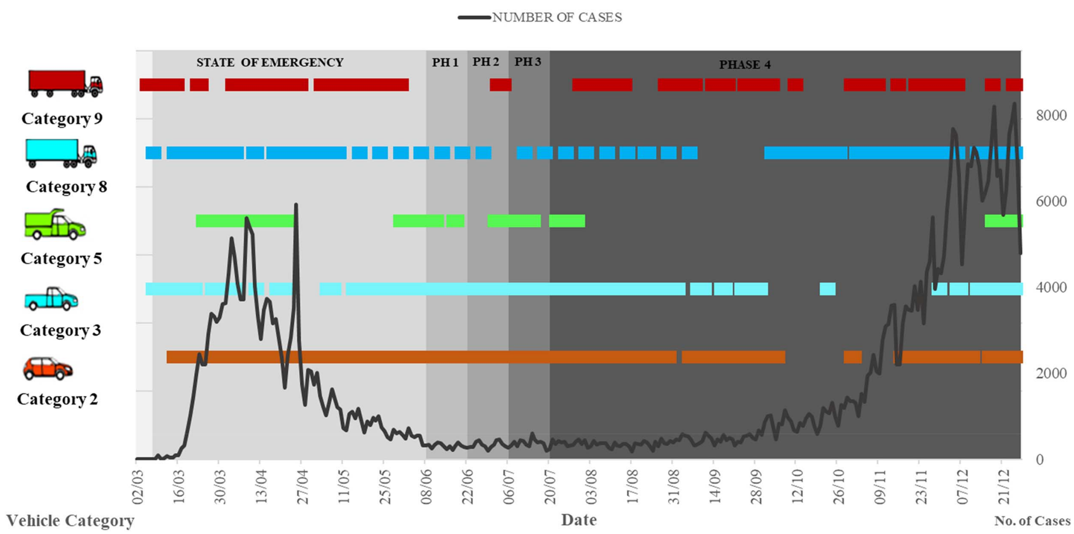

Fig. 2. Days with significant changes between 2019 and 2020 for each vehicle category in New York. (Icons © FHWA 2014.)

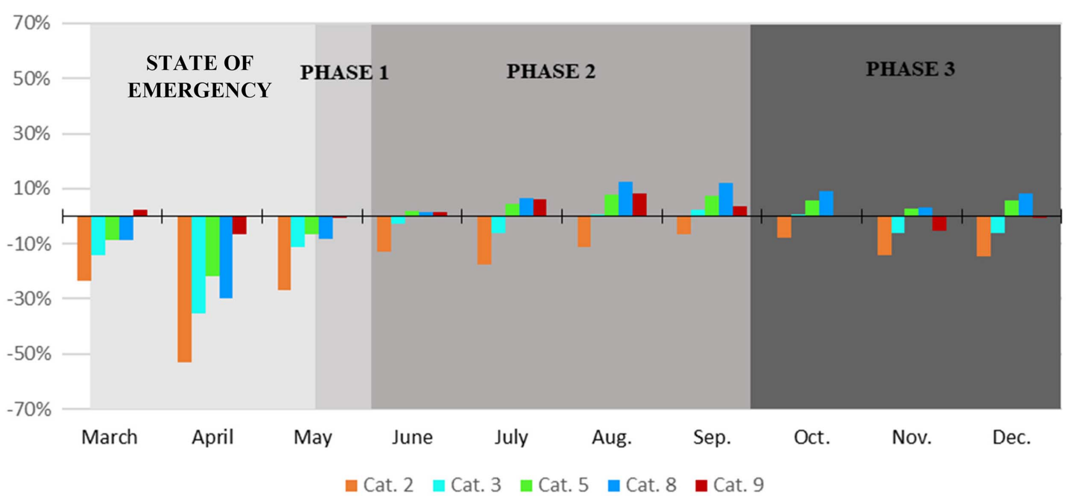

Fig. 3. Monthly traffic changes on Florida urban roadways.

May and September. October and November saw these volumes fall, comparatively, however, they remained above 2019 levels. December also saw heavy volumes of these vehicles. With the exception of April, monthly totals for Category 9 vehicles did not drop below their 2019 levels within the urban regions of Florida.

Fig. 4 (corresponding to Table 2) provides the monthly traffic counts for the rural regions of Florida and follows a similar pattern to the urban areas. Comparing Figs. 3 and 4, there does not appear to be any significant distinction between the percent changes in traffic observed in urban and rural regions of the state. There do

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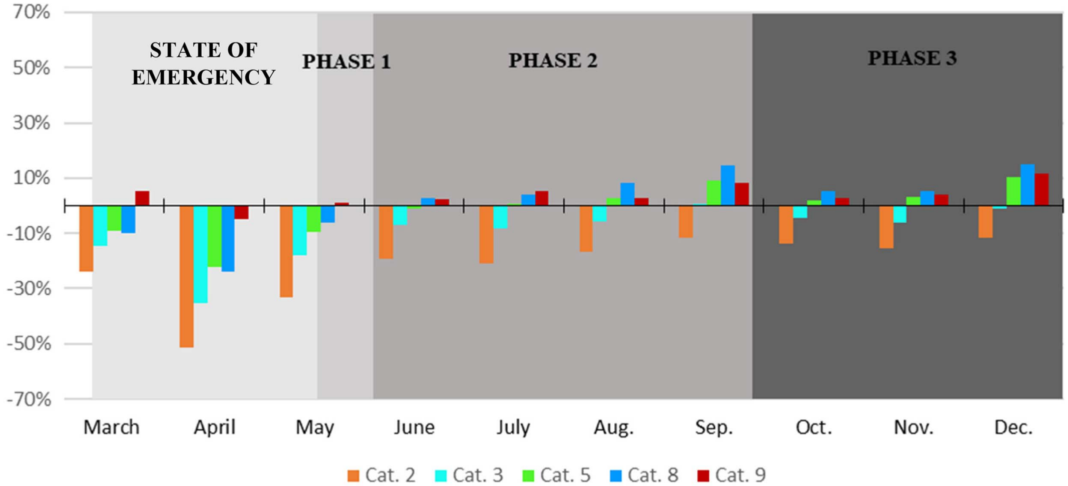

Fig. 4. Monthly traffic changes on Florida rural roadways.

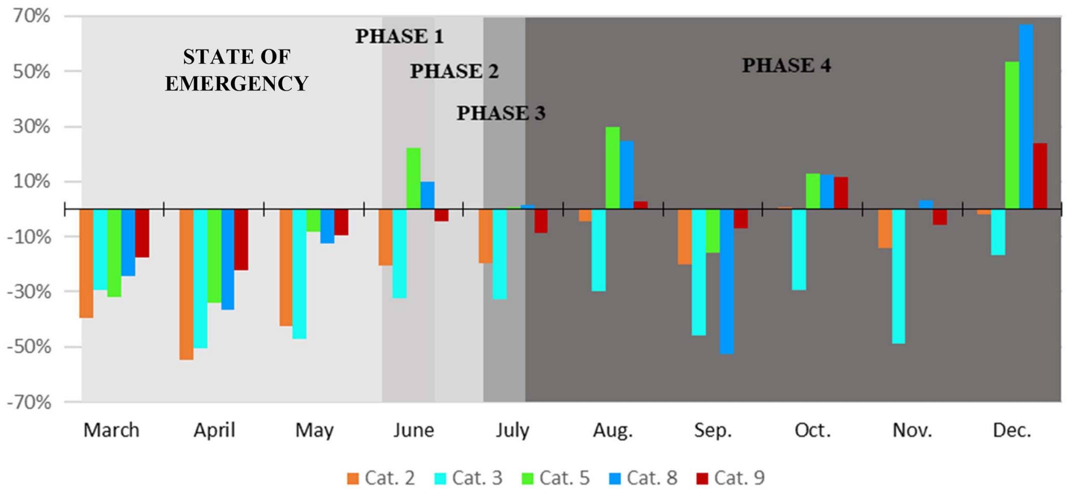

Fig. 5. Monthly traffic changes on New York roadways.

Table 3. New York total traffic volume per month in 2019 and 2020

	New York Statewide count stations monthly total (vehicles 10^6)									
	Cat. 2 (passenger cars)		Cat. 3 (vans)		Cat. 5 (two axel, six tires)		Cat. 8 (four axel trailer)		Cat. 9 (five axel semitrailer)	
Month	2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
March	21.9	13.2 (−39.8%)	5.5	3.9 (−29.5%)	0.6	0.4 (−32.1%)	0.2	0.1 (−24.3%)	1.1	0.9 (−17.7%)
April	19.7	9 (−54.6%)	5.6	2.8 (−50.4%)	0.5	0.3 (−34.2%)	0.2	0.1 (−36.8%)	1.0	0.8 (−22.3%)
May	20.4	11.7 (−42.5%)	6.5	3.4 (−47.4%)	0.4	0.4 (−8.5%)	0.2	0.2 (−12.5%)	1.0	0.9 (−9.6%)
June	23.1	18.3 (−20.7%)	6.8	4.6 (−32.2%)	0.6	0.7 (22%)	0.2	0.3 (10.1%)	1.1	1.1 (−4.4%)
July	24.1	19.3 (−19.9%)	7.1	4.8 (−32.9%)	0.6	0.6 (0.6%)	0.3	0.3 (1.5%)	1.1	1 (−8.9%)
August	22.3	21.2 (−4.6%)	6.8	4.8 (−29.9%)	0.5	0.6 (29.8%)	0.2	0.2 (24.7%)	0.9	0.9 (2.8%)
September	19.1	15.3 (−20%)	7.6	4.1 (−45.7%)	0.6	0.5 (−15.9%)	0.3	0.1 (−52.5%)	0.8	0.7 (−7%)
October	20.3	20.4 (0.1%)	7.5	5.3 (−29.3%)	0.6	0.6 (12.7%)	0.2	0.2 (12.5%)	1.0	1.1 (11.6%)
November	16.6	14.2 (−14.3%)	7.3	3.7 (−49%)	0.4	0.4 (−0.1%)	0.1	0.1 (3%)	0.8	0.7 (−5.8%)
December	15.0	14.7 (−1.8%)	4.2	3.5 (−16.8%)	0.3	0.5 (53.6%)	0.1	0.2 (66.9%)	0.7	0.9 (24%)

appear to be some discrepancies in Category 9 vehicles, with the impact of the pandemic affecting rural regions slightly more. However, these differences appear to be nominal.

Fig. 5 (corresponding to Table 3) shows the monthly percent changes in traffic on New York roadways. The figure shows drastic decreases in traffic during the months of March and April. The month of May saw increases (albeit not as high as in 2019) for vehicle Categories 5, 8, and 9. New York's phased reopening process began in June and continued throughout July. Category 2 and 3 traffic during this period was stable, with reductions of approximately 20% and 32%, respectively. Categories 5, 8, and 9 vehicles experienced a volatile return of traffic during this same period; in some cases, significantly exceeding their 2019 levels. August saw a return of traffic for all categories, with the exception of Category 3. In September, however, traffic volumes across all categories drastically reduced to levels not seen since May. October saw these volumes return. Category 2 vehicles were approximately equal to their 2019 levels, with Categories 5, 8, and 9 exceeding their 2019 benchmarks. Traffic then again dropped in November, before rebounding in December. At the year's end, Category 2 traffic remained slightly lower than the 2019 levels, while Category 5, 8, and 9 vehicles surpassed their previous year's figures by 53%, 66%, and 24%, respectively.

Discussion

Each vehicle category plays a unique role within a state's economy. It is therefore not surprising that this research found an uneven impact of the COVID-19 pandemic on vehicle categories. In terms of the onset of the pandemic, traffic dropped across all categories starting in March. However, only Categories 5, 8, and 9 were able to recover by the end of the year. Categories 2 and 3 were impacted the most by the pandemic. Among these two categories of vehicles, traffic rarely, if ever returned to 2019 levels after February. By contrast, traffic levels among larger vehicle categories began to see 2019 traffic levels as early as May, in some instances. In Florida, Category 5, 8, and 9 vehicles consistently reached or surpassed their 2019 levels beginning in June. New York saw periodic surges in traffic volume among vehicle Categories 5 and 8, which were not seen with any other vehicle type.

Both Florida and New York experienced significant declines in response to the State of Emergency, particularly for Category 2 and 3 vehicles, with the most substantial decrease reaching 54.6% in the state of New York. In Florida, Category 9 vehicles encountered the least impact, with reductions reaching up to −6.5% in terms of the percentage decrease between years, with a significant number of days exhibiting these differences. Conversely, in New York, this category experienced a more substantial reduction of up to 22.3%. Category 5 vehicles in New York were the least impacted by the pandemic (see Fig. 2). This may suggest that Category 5, and to some extent, Category 9 vehicles play different roles within the state economies. New York appears to have made a stronger initial response to the pandemic in March and April. Traffic volume decreases among all vehicle categories were more pronounced during these months in New York than in Florida. This was likely because the virus impacted New York earlier, resulting in a higher perceived risk for individuals. This would also explain why traffic began to return sooner in Florida, starting as early as May, than it did in New York. By June, Florida traffic appeared to stabilize, while New York traffic showed more volatility during the reopening. This is likely related to the reinstitution of social distancing which took place in New York after the initial Phase 1 reopening. The traffic volatility seen in New York may also represent, at least in terms of the larger vehicle categories, latent demand. During times when the New York economy was open, a surge of movement was seen.

The analysis suggests that urban and rural roadways in Florida were similarly impacted by the COVID-19 pandemic with regard to traffic volume changes (see Table 1). Figs. 3 and 4 show that the percent change in urban and rural traffic in Florida was remarkably similar. It is likely that the pandemic impacted travel demand, more or less equally among urban and rural communities. When investigating the statistical significance of travel changes between urban and rural roads, differences begin to emerge during the reopening phases. During Phases 2 and 3, Category 5, 8, and 9 vehicles in urban areas were only nominally different from their 2019 levels. However, rural areas saw more instances of the t-test rejecting the null hypothesis. This was interesting because year-over-year percent changes in volume within urban and rural areas were generally equal. The rejection of the null hypothesis in rural areas (and the failure to reject it in urban areas), was likely a function of sample variance and size. Having less variance among the constituent detectors in rural regions, likely contributed to more instances of rejection of the null hypothesis. Whereas the failure to reject the null hypothesis in urban areas, despite having overall similar percent changes in traffic, suggests that higher variance among the constituent detectors may have been present. If this is the case, it suggests that truck traffic within certain urban areas may have been concentrated, potentially at the expense of servicing others. Further analysis is needed to determine if preference was given to certain communities within urban regions for the delivery of goods during the recovery stages of the pandemic.

Conclusion

This study examined the impact of the COVID-19 pandemic and restrictions on surface transportation movements among different FHWA vehicle categories. Data was collected from over 200 continuous traffic count stations in Florida and 100 stations in New York. This research was important because it showed the change in traffic not only as aggregate fluctuations during the 2020 pandemic year, but by specific vehicle categories and across two states with different governmental policies and approaches. The results of this research provide valuable insight into what forms of travel were impacted; the extent to which they occurred; when, relative to the virus course, they occurred, and where these differences took place. Each of these on their own is a completely novel finding in the body of research that currently relates to COVID-19 and transportation.

The relative effects of the lockdown policies on commodity carriers were markedly different between the two states. Florida experienced a relative increase in truck traffic for much of 2020. However, New York experienced sporadic surges in truck traffic, far surpassing any increases seen in Florida. The volatile nature of truck travel in New York suggests a buildup of demand that was only able to be served during certain times. Although the data used in this study only shows the number of vehicles and not the content of the vehicles nor how those goods were ordered, it may be reasonable to suggest that at least a portion of increased truck travel was due to increased online shopping. Overall increases in trucking demand seen in 2020, may suggest the need for larger vehicles if these shipping trends continue into 2021 and beyond.

This study represents one of the first empirical investigations into the movement of commodity carriers during a pandemic. This research can be extended in several directions. First, the analysis period can be extended to include 2021, which allows examination of the impacts of vaccination and the degree to which personal vehicle traffic reductions persist. Second, the study can be extended to other states and countries. Finally, researchers could investigate the commodity demand changes served by vehicle Categories 5, 8, and 9 as well as the impact on global maritime transportation.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

Funding for this research was provided by the Freight Mobility Research Institute located at Florida Atlantic University, the Center for Cooperative Mobility for Competitive Megaregions at the University of Texas, and the Center for Advanced Transportation Mobility at North Carolina A&T University, all United States Department of Transportation University Transportation Centers. The authors would also like to thank Joey Gordon of the Florida Department of Transportation for his assistance in providing the data used in this research as well as, Embry-Riddle Aeronautical University Students Fanny Kristiansson and Tate Grant for their support in data collection and processing.

References

Ali, B. J. 2020. "Impact of COVID-19 on consumer buying behavior toward online shopping in Iraq." *Econ. Stud. J.* 18 (42): 267–280.

Aubrey, A. 2020. "Trump declares coronavirus a public health emergency and restricts travel from China." Accessed March 18, 2020. https://www.npr.org/sections/health-shots/2020/01/31/801686524/trump-declares-coronavirus-a-public-health-emergency-and-restricts-travel-from-c.

Beck, M. J., and D. A. Hensher. 2020. "Insights into the impact of COVID-19 on household travel and activities in Australia–The early days under restrictions." *Transp. Policy* 96: 76–93. https://doi.org/10.1016/j.tranpol.2020.07.001.

Bennett, J., and W. Briggs. 2005. *Using and understanding mathematics: A quantitative reasoning approach*. 3rd ed. Boston: Pearson.

Bhatti, A., H. Akram, H. M. Basit, A. U. Khan, S. M. Raza, and M. B. Naqvi. 2020. "E-commerce trends during COVID-19 pandemic." *Int. J. Future Gener. Commun. Networking* 13 (2): 1449–1452.

Cartenì, A., L. Di Francesco, and M. Martino. 2020. "How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study." *Sci. Total Environ.* 741: 140489. https://doi.org/10.1016/j.scitotenv.2020.140489.

Choi, T.-M. 2020. "Innovative 'bring-service-near-your-home; operations under corona-virus (COVID-19/SARS-CoV-2) outbreak: Can logistics become the Messiah?" *Transp. Res. Part E Logist. Transp. Rev.* 140: 101961. https://doi.org/10.1016/j.tre.2020.101961.

Cutway, A. 2020. "Timeline: The spread of coronavirus in Florida." Accessed December 5, 2020. https://www.clickorlando.com/news/local/2020/03/20/timeline-the-spread-of-coronavirus-in-Florida/.

Deb, S., S. Cacciola, and M. Stein. 2020. "Sports leagues bar fans and cancel games amid coronavirus outbreak." Accessed March 12, 2020. https://www.nytimes.com/2020/03/11/sports/basketball/warriors-coronavirus-fans.html.

De Haas, M., R. Faber, and M. Hamersma. 2020. "How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands." *Transp. Res. Interdiscip. Perspect.* 6: 100150. https://doi.org/10.1016/j.trip.2020.100150.

Depellegrin, D., M. Bastianini, A. Fadini, and S. Menegon. 2020. "The effects of COVID- 19 induced lockdown measures on maritime settings of a coastal region." *Sci. Total Environ.* 740: 140123. https://doi.org/10.1016/j.scitotenv.2020.140123.

Donné, V. 2020. "Improve bicycle and pedestrian facilities for more social distancing and bicycle use." *Verkeersspecialist* 26 (267): 22–28.

FHWA (Federal Highway Administration). 2014. "Traffic monitoring guide. Office of highway policy information—Policy." Accessed December 5, 2020. https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_2013/vehicle-types.cfm.

Fong, M. W., H. Gao, J. Y. Wong, J. Xiao, E. Y. Shiu, S. Ryu, and B. J. Cowling. 2020. "Nonpharmaceutical measures for pandemic influenza in nonhealthcare settings—Social distancing measures." *Emerging Infect. Dis.* 26 (5): 976. https://doi.org/10.3201/eid2605.190995.

Govindan, K., H. Mina, and B. Alavi. 2020. "A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19)." *Transp. Res. Part E Logist. Transp. Rev.* 138: 101967. https://doi.org/10.1016/j.tre.2020.101967.

Hadjidemetriou, G. M., M. Sasidharan, G. Kouyialis, and A. K. Parlikad. 2020. "The impact of government measures and human mobility trend on COVID-19 related deaths in the UK." *Transp. Res. Interdiscip. Perspect.* 6: 100167. https://doi.org/10.1016/j.trip.2020.100167.

Huynh, T. L. D. 2020. "Does culture matter social distancing under the COVID-19 pandemic?" *Saf. Sci.* 130 (Oct): 104872. https://doi.org/10.1016/j.ssci.2020.104872.

Iacus, S. M., F. Natale, C. Santamaria, S. Spyratos, and M. Vespe. 2020. "Estimating and projecting air passenger traffic during the COVID-19 coronavirus outbreak and its socio-economic impact." *Saf. Sci.* 129: 104791. https://doi.org/10.1016/j.ssci.2020.104791.

Ito, H., S. Hanaoka, and T. Kawasaki. 2020. "The cruise industry and the COVID-19 outbreak." *Transp. Res. Interdiscip. Perspect.* 5: 100136. https://doi.org/10.1016/j.trip.2020.100136.

Ivanov, D. 2020. "Predicting the impacts of epidemic outbreaks on global supply chains: A simulation- based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case." *Transp. Res. Part E Logist. Transp. Rev.* 136: 101922. https://doi.org/10.1016/j.tre.2020.101922.

Jackson, C., E. Vynnycky, J. Hawker, B. Olowokure, and P. Mangtani. 2013. "School closures and influenza: Systematic review of epidemiological studies." *BMJ Open* 3 (2): e002149. https://doi.org/10.1136/bmjopen-2012-002149.

Johns Hopkins Coronavirus Resource Center. 2020. "Florida—COVID-19 overview-Johns Hopkins." Accessed December 5, 2020. https://coronavirus.jhu.edu/region/us/florida.

Koch, J., B. Frommeyer, and G. Schewe. 2020. "Online shopping motives during the COVID- 19 pandemic—Lessons from the crisis." *Sustainability* 12 (24): 10247. https://doi.org/10.3390/su122410247.

Lemke, M. K., Y. Apostolopoulos, and S. Sönmez. 2020. "Syndemic frameworks to understand the effects of COVID-19 on commercial driver stress, health, and safety." *J. Transp. Health* 18: 100877.

Liptak, K. 2020. "Trump declares national emergency—and denies responsibility for coronavirus testing failures." Accessed April 18, 2020. https://go.gale.com/ps/i.do?id=GALE%7CA617358743&sid=sitemap&v=2.1&it=r&p=EAIM&sw=w&userGroupName=anon%7Ed5045d76&aty=open-web-entry.

Loske, D. 2020. "The impact of COVID-19 on transport volume and freight capacity dynamics: An empirical analysis in German food retail logistics." *Transp. Res. Interdiscip. Perspect.* 6: 100165. https://doi.org/10.1016/j.trip.2020.100165.

Nakamura, H., and S. Managi. 2020. "Airport risk of importation and exportation of the COVID-19 pandemic." *Transp. Policy* 96: 40–47. https://doi.org/10.1016/j.tranpol.2020.06.018.

Nguyen, H. V., H. X. Tran, L. Van Huy, X. N. Nguyen, M. T. Do, and N. Nguyen. 2020. "Online book shopping in Vietnam: The impact of the COVID-19 pandemic situation." *Publ. Res. Q.* 36 (3): 437–445. https://doi.org/10.1007/s12109-020-09732-2.

Nikolaou, P., and L. Dimitriou. 2020. "Identification of critical airports for controlling global infectious disease outbreaks: Stress-tests focusing in Europe." *J. Air Transp. Manage.* 85: 101819. https://doi.org/10.1016/j.jairtraman.2020.101819.

O'Leary, H., S. Parr, and M. M. El-Sayed. 2022. "The breathing human infrastructure: Integrating air quality, traffic, and social media indicators." *Sci. Total Environ.* 827 (Apr): 154209.

Parr, S., B. Wolshon, P. Murray-Tuite, and T. Lomax. 2021. "Multistate assessment of roadway travel, social separation, and COVID-19 cases." *J. Transp. Eng. Part A Syst.* 146 (5): 04021012.

Parr, S., B. Wolshon, J. Renne, P. Murray-Tuite, and K. Kim. 2020. "Traffic impacts of the COVID- 19 pandemic: Statewide analysis of social separation and activity restriction." *Nat. Hazard. Rev.* 21 (3): 04020025. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000409.

Roggeveen, A. L., and R. Sethuraman. 2020. "How the COVID-19 pandemic may change the world of retailing." *J. Retailing* 96 (2): 169. https://doi.org/10.1016/j.jretai.2020.04.002.

Sadique, M. Z., E. J. Adams, and W. J. Edmunds. 2008. "Estimating the costs of school closure for mitigating an influenza pandemic." *BMC Public Health* 8 (1): 135. https://doi.org/10.1186/1471-2458-8-135.

Shekhar, S., K. Yang, V. M. Gunturi, L. Manikonda, D. Oliver, X. Zhou, B. George, S. Kim, J. M. Wolff, and Q. Lu. 2012. "Experiences with evacuation route planning algorithms." *Int. J. Geogr. Inf. Sci.* 26 (12): 2253–2265. https://doi.org/10.1080/13658816.2012.719624.

Sobieralski, J. B. 2020. "COVID-19 and airline employment: Insights from historical uncertainty shocks to the industry." *Transp. Res. Interdiscip. Perspect.* 5: 100123. https://doi.org/10.1016/j.trip.2020.100123.

Suau-Sanchez, P., A. Voltes-Dorta, and N. Cugueró-Escofet. 2020. "An early assessment of the impact of COVID-19 on air transport: Just another crisis or the end of aviation as we know it?" *J. Transp. Geogr.* 86: 102749. https://doi.org/10.1016/j.jtrangeo.2020.102749.

Teixeira, J. F., and M. Lopes. 2020. "The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike." *Transp. Res. Interdiscip. Perspect.* 6: 100166. https://doi.org/10.1016/j.trip.2020.100166.

Tirachini, A., and O. Cats. 2020. "COVID-19 and public transportation: Current assessment, prospects, and research needs." *J. Public Transp.* 22 (1): 34p. https://doi.org/10.5038/2375-0901.22.1.1.

USDOT. 2016. *Traffic monitoring guide*. Washington, DC: USDOT.

Walpole, R. E., R. H. Myers, S. L. Myers, and K. Ye. 2006. *Probability and statistics for engineers and scientists*. London: Pearson.

Zhang, Y., A. Zhang, and J. Wang. 2020. "Exploring the roles of high-speed train, air and coach services in the spread of COVID-19 in China." *Transp. Policy* 94: 34–42. https://doi.org/10.1016/j.tranpol.2020.05.012.

J. Transp. Eng., Part A: Systems, 2024, 150(5): 04024015