Multi-State Assessment of Roadway Travel, Social Separation, and COVID-19 Cases

Scott Parr[1], *Brian Wolshon[2], Pamela Murray-Tuite[3], and Tim Lomax[4]
*corresponding author

[1] Department of Civil Engineering, Embry Riddle Aeronautical University, Email: parrs1@erau.edu

[2]Gulf Coast Research Center for Evacuation and Transportation Resiliency, Department of Civil and Environmental Engineering, Louisiana State University, Email: brian@rsip.lsu.edu

[3] AMASCE, Department of Civil Engineering, Clemson University, Email: pmmurra@clemson.edu

[4]Texas A&M Transportation Institute, Texas A&M University, Email: t-lomax@tamu.edu

ABSTRACT

This research was undertaken to comparatively assess the unprecedented travel and activity conditions related to the onset of COVID-19 in the US in the first half of 2020. In the work, roadway travel volumes were used to relate government directives for social separation and the progression of COVID-19 cases in ten diversely populated and located states. Among the key contributions of the research were its illustration of the amounts and time scales of public response to public closures across the country and the general finding that overall, governmental directives, as reflected through rapid traffic decreases, likely served their purpose. Another key finding was that by June 1st, no state returned to routine levels of travel. Combined, the results of this study illustrate the results of governmental actions with respect to the course of the virus, including how varied timings of responses reflected outcomes based on the levels of threat and characteristics of individual locations. It is expected that this paper will be of use to practitioners, governmental, and researchers to assess and develop plans for future similar major events and emergencies.

KEY WORDS

COVID-19, coronavirus, travel behavior, traffic, quarantine, social distancing, global, pandemic

INTRODUCTION

The 2020 global coronavirus infectious disease (COVID-19) pandemic brought historically unprecedented levels of global social and economic disruption. Concerns over the effects of the virus and the limited capability to treat it, coupled with its rapid spread and unknown mechanism of transmission during its onset, prompted public officials throughout the world to issue directives to limit person-to-person contact. Interestingly however, governmental action to slow the spread of the virus varied widely from country to country. In the United States (US), where governmental authority is distributed between federal, state, and local bodies and population density varies widely, restrictions were also varied in terms of the timing, type, and level of limitations that were placed on citizens.

During the early stages of the virus in the US, state-level governmental directives most commonly began with Declarations of Emergency. While the effect of these actions on influencing or restricting personal movement and interaction is unknown, they gave states a legal basis upon which to make and enforce restrictions to protect the public. With these declarations, authorities were able to impose limitations on public activities and prohibit large gatherings of people. In most states, restrictions started with school closures and "stay-at-home" requests, progressed to limits on non-essential businesses like gyms and bars, then ultimately lead to the cancellation of sporting events and concerts and closure of theme parks and movie theaters.

While there is little doubt that assessments of the complex and significant impacts of the COVID-19 pandemic will go on for years to come, there is also a need for rapid and immediate assessment of efforts and outcomes as they continue to evolve. One of the most critical of these is the need to assess public acknowledgement and adherence to governmental calls to isolate and separate from one another and determine their relationship to COVID-19 case rates. Given the near-infinite potential for person-to-person interaction and the virtual impossibility to comprehensively monitor the movement of individuals, it can be difficult to make community-wide assessments of social activity, interaction, and quantify the temporal and spatial response of the public to governmentally mandated limitations. Contact-tracing is a widely used (Dhillon and Srikrishna 2018) and effective method to assess personal interaction and virus transmission in epidemics and health emergencies. However, this method was not viable during the onset of COVID-19 in the US because of the large percentage of asymptomatic cases and the limited ability to get timely test results (Kretzschmar et al. 2020). Another metric that has been applied to assess behavioral response during COVID-19 was public travel (e.g., Parr et al. 2020).

Because it is so ubiquitous, travel, particularly vehicular roadway travel, can be used to show movement and activity across wide geographic areas and over long time durations. A recent study by Parr et al. (2020) found that traffic volume data collected in the State of Florida during the onset period of the COVID-19 pandemic provided a reliable, low-cost, comprehensive, consistent, and readily available source of data that shows levels of public activity. While most traffic volume data sources do not disaggregate the activities of individual travelers and cannot describe travel purpose, such data can be used as a surrogate representation of the level of public movement and the general level of interaction at aggregate levels. Traffic volume data is also valuable because it reflects location-specific conditions over time and by roadway class. In most states, traffic volume is recorded continuously by networks of automated collectors on representative freeway and arterial roads throughout urban, suburban, and rural regions. This also gives it consistency across states.

In the research described in this paper, traffic volume was used to show the effects of government-mandated social distancing directives and the progression of COVID-19 cases. Cases were selected as the health metric over hospitalizations and deaths because the cases are more directly related to travel and exposure. Hospitalizations and deaths occur with variable timeframes and depend on complex individual health factors and healthcare system differences. This work is unique and useful because it examines behavioral responses and COVID-19 infections during the onset, low point, and initial activity recovery periods. The paper also demonstrates the impact of travel on COVID-19 infections in terms of declines and increases as restrictions were implemented and then eased across ten states. The states in the study were selected to reflect varying populations, governmental reactions, numbers of COVID-19 cases, and even political orientation, as responses tended to be influenced by political leaning of the governmental authority.

The paper includes four primary sections that highlight and summarize the primary components of the study. The first is a brief review of related efforts and reports to examine the travel and health outcomes of governmental restrictions during the onset of the COVID-19 in the United States. This is followed by a description of the data and methods of the research. This section includes a description of state traffic count data collection systems and national COVID-19 databases and how their output was used for this study. This is followed by a presentation and discussion of the analytical testing of the data and the findings that were gathered from it. Finally, the paper concludes with a discussion of what these data and results may be suggesting, especially in terms of policy guidance - both existing and future - and the public response to government guidance and recommendations.

BACKGROUND AND PRIOR ANALYSES

Crowding has negative impacts on health outcomes with respect to viruses. For instance, crowded neighborhoods were correlated with influenza-associated hospitalizations for children. Such hospitalizations were at least twice as likely in areas with higher levels of household crowding (more than one occupant per room) than in low crowding areas (Yousey-Hindes and Hadler 2011). While households' ability to control crowding in their residences is limited, social contact outside the home is influenced by strategies such as social distancing. The degree to which the public avoids gathering in public areas may be influenced by culture (Huynh 2020), although cultural heterogeneity exists within countries. Gender may also play a role, as survey results found that males were less likely to alter their travel patterns in response to possibly spreading influenza (Hotle et al. 2020). During a pandemic, social distancing's benefits include reducing the spread of a disease, delaying and reducing the size of the peak, and spreading cases over time, thus reducing the burden on the health care system (Fong et al. 2020). School closures can help reduce social contacts and are part of many countries' pandemic plans (Sadique et al. 2008). School closures can reduce transmission of viruses, such as influenza (Stevenson et al. 2009). However, once schools reopen, disease transmission tends to increase (Jackson et al. 2013). For COVID-19, the loosening of broader restrictions may similarly be associated with a rise in cases.

The impact of COVID-19 on general mobility has been remarkable in terms of its speed and extent. A survey conducted in the Netherlands found that 80 percent of respondents reduced their outdoor activity with overall trip reductions of 55 percent (de Hass et al. 2020). Further survey results from Australia discovered household trips reduced by over 50 percent across all modes and the proportion of transit trips decreased from a pre-lockdown level of 14 percent to just 7 percent (Beck 2020). A study of roadway detectors in Florida found that vehicle volumes across the state had dropped by 47.5 percent (Parr et al. 2020). Work has also attempted to correlate mobility habits and the proliferation of COVID-19. In Italy, the number of daily new COVID-19 cases was related to trips performed three weeks earlier (Carteni et al. 2020) and another study found that mobility reductions had a significant impact on reducing COVID-19 cases in the United Kingdom (Hadjidemetriou et al. 2020).

Air travel has been similarly impacted, with 98 percent of passenger revenues experiencing severe restrictions (Suau-Sanchez et al. 2020). An analysis of prior events affecting air transport suggested unemployment in the airline workforce could range between seven and thirteen percent (Sobieralski 2020). Forecasting models suggested that reductions in air travel could reduce global gross-domestic product by nearly two percent (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 (Mikolaou and Loukas 2020; Nakamura and Shunsuke 2020). Further investigations into cruise ship travel sought to understand the relationship between passenger landings and COVID-19 outbreaks (Ito et al. 2020).

Despite significant traffic decreases during the pandemic, there has been increasing speculation that once societal interactions return to pre-pandemic levels, roadway traffic volumes might increase significantly (Sung and Monschauer 2020). This idea is based on theories that suggest a general avoidance of shared modes of transportation (De Vos 2020). Shared-use mobility modes (e.g. bus, subway, taxis, mobile phone-based apps, shared bicycles etc.) experienced significant drops in ridership during the pandemic onset period (Hendrickson and Rilett 2020; Teixeira and Lopes 2020). Further studies have investigated the role of transportation modes in the spread of COVID-19 (Zhang et al. 2020). Tirachini and Cats (2020) suggested several factors may contribute to high-risk public transit including confined spaces, high occupancy infected workers, and multiple surfaces that easily transfer germs. Avoidance of public transit is likely to be most apparent during the highest demand periods (weekday commuter travel) when transit utilization typically peaks.

With the expansion of technology into all aspects of travel planning and transportation, there are many sources of regular information on traffic volume and congestion. For several private companies, the interest in COVID-19 pandemic conditions has created another business opportunity within their primary markets. Vehicle traffic volume, travel speeds, truck data and, in some cases bicycle and pedestrian data, have been tracked at a variety of geographic and temporal scales. In most cases, the data are baselined against the period immediately before the pandemic, despite the seasonal traffic differences that would be involved with using January/February as a benchmark. Google, with their Global Mobility Data (2020), Unacast (2020), INRIX (2020), StreetLight (2020) and the Center for Advanced Transportation Technology (CATT) Laboratory at the University of Maryland (2020) are detailed vehicle travel information sources with a variety of free and pay-for-data services.

Each of these platforms uses a combination of anonymized cell phones and connected vehicles to provide information on estimated trip types and a variety of US geographies including states and counties. What distinguishes them from one another are the available data, the possible products, and the effort required by the user to analyze the data. Google and the CATT Lab, for example, have publicly available information about broad travel trends, as well as a variety of trip purpose, day-of the week, and geographic comparison tools. MS2's Traffic Count Database System (2020), on the other hand, uses data derived by communicating with state DOT automated traffic volume counting devices to provide traffic count data for passenger vehicles and trucks. This device-based permanent counter network allows comparisons across many years of consistent data collection. SafeGraph (2020) has a service that provides pedestrian activity data using opt-in anonymized mobile devices to study usage patterns for a variety of location types including restaurants, retail shops, supermarkets, movie theaters, airports and other industries. Their collection methods are also similar across 2019 and 2020, allowing year-over-year comparisons.

DATA AND METHODS

The data and methods used in this study build from related work conducted during the initial appearance of COVID-19 in Florida (Parr et al 2020). As such, it includes both virus-related health statistics reported to public health agencies and traffic volume data collected by state DOTs. By the late spring of 2020, COVID-19 had been diagnosed in every state of the US. From a public health standpoint, the manner and variation of where, when, and how the virus was occurring and spreading was of primary interest. While the virus was overwhelming health care systems in some states and, more specifically some metropolitan regions (like New York), it was having comparatively far less impact in others (like Montana). Clearly, one explanation for these differences was the high amount and density of the population in these areas. However, factors like the amount of interaction between people, levels of mobility, and the availability of testing were likely also contributing to these differences.

A sample set of ten states were selected to comparatively assess the range of conditions and COVID-19 cases. While the inclusion of all 50 states would have been ideal to comprehensively illustrate and discuss every case, limitations in data availability and quality; its timeliness and spatial extent; and its ability to "representatively" reflect conditions, made it impractical. Although, nearly all the states were in the eastern half of the country, they reflect diversity among relevant characteristics in the study. Table 1 lists the states and summarizes key population, mobility and broad political orientation characteristics to illustrate the studied states diversity.

Table 1. Characteristics of State Study Pool

State	Population[a]	Population Density (people/mi^2)[b]	Largest Transit Trips per Capita of Urbanized Areas in the State[c]	Governor's Political Party[d]	State Senate Majority[d]
Florida	21,477,737	401	53.3	Republican	Republican
Illinois	12,671,821	228	75.1	Democratic	Democratic
Indiana	6,732,219	188	35.7 (excluding Chicago metro area)	Republican	Republican
Massachusetts	6,892,503	884	93.1	Republican	Democratic
Michigan	9,986,857	177	42.2	Democratic	Republican
Montana	1,068,778	7	15.6	Democratic	Republican
New Hampshire	1,359,711	152	5.2 (excluding Boston metro area)	Republican	Democratic
New York	19,453,561	413	223.4	Democratic	Democratic
Ohio	11,689,100	286	26.4	Republican	Republican
Vermont	623,989	68	23.5	Republican	Democratic

[a]Estimate by US Census (2019); [b] Statista (2020); [c] US Department of Transportation (2015); [d] Kaiser Family Foundation (2020)

Traffic Data and Statistics

As part of the National Highway Performance Monitoring System (HPMS), the Federal Highway Administration (FHWA) mandates state departments of transportation to submit annual traffic statistics (FHWA 2014). State transportation agencies build, operate, and maintain permanent traffic monitoring stations to collect, among other measures, traffic count information. Referred to as continuous count stations, these traffic count detectors report hourly traffic counts continuously throughout the year, year-over-year, to meet the federal requirements outlined by the HPMS. The states analyzed in this study have made their traffic count data publicly available through their websites (NY), through data requests (FL), or have permitted Modern Traffic Analytics (a third party vendor) to share HPMS data, publicly online (IL, IN, MA, MI, MT, NH, OH, VT).

The analysis of traffic patterns was completed by comparing daily traffic totals for each day from continuous count stations located in the ten states. Traffic counts from 2020 for each station were compared to base year levels for similar days in 2019 using a paired t-test. Traffic counts were aggregated for each 24-hour period and no distinction was made between vehicle types. The detectors were located on major highways and arterials in a mix of urban and rural locations throughout each state. The comparison dates were March 1 to May 31, 2020 and March 3 to June 2, 2019, with matched days of the week. For example, a paired t-test was used to investigate if the daily traffic measured by 137 detectors in the state of New York from Friday, May 29, 2020 was significantly different from the daily traffic measured, at these same 137 detectors, on Friday, May 31, 2019. The null hypothesis was that no difference in traffic occurred between these two dates. The alternative hypothesis was that traffic between these dates were not equal.

A common error found in the data was missing data and/or stations reporting zero values. The zero values were due to road closures because of incidents, scheduled maintenance work, and malfunctioning roadway sensors. Sensors with missing information were removed from consideration for that day, but were included in the analysis when volume data was available. The daily number of observations therefore varied, depending on which stations within the state had paired data between years. The median, minimum, maximum, and standard deviation of the number of observations used in the paired t-test analysis, for each state, was provided in the figures shown in the *Findings* section (lower right-side corner of each figure). Statistically significant changes based on the results of a paired two-sided t-test rejection of the null hypotheses of equal means at a significance level 0.05 were noted, along with days for which t-testing failed to reject the null hypotheses (suggesting traffic on the 2019 and 2020 days may have been similar).

Health Data and Statistics

The coronavirus health-related data for the ten study states was obtained from the daily updates from Johns Hopkins University (Dong et al. 2020). This dataset provided the number of reported cases and deaths by US state (and other parts of the world). This dataset was selected for several reasons including: its scope, widespread use, and update regularity. The range of dates used for this study were January 22, 2020 (the earliest dataset available from this data source) to June 14, 2020 (two weeks after the last traffic observation). In the graphs presented later in this paper, daily COVID-19 cases are shown as seven day moving-averages to remove the day-to-day testing and reporting variations. The COVID-19 data in the analyses has also been temporally offset from the traffic data by two weeks (that is, the COVID-19 case data is reported for the date two weeks prior to its posting). This was done to associate the extent of COVID-19 cases with the traffic conditions during the time when virus infections occurred. The Centers for Disease Control and Prevention (CDC) recommend this period to account for viral incubation and testing time (CDC 2020). The authors recognize that there are many other exposure opportunities that are not associated with vehicular travel (e.g., spread within a household).

The raw data provided the cumulative number of reported cases. The daily number of reported cases was obtained by taking the difference between two consecutive days. A few data inconsistencies were identified. For example, in the New Hampshire dataset, two days showed a decline in the cumulative values of more than 50 cases (April 2 and 14). Examination of the county-level data revealed some difficulties with Hillsborough County in Florida. On April 2, this county was missing but was present on adjacent days. On April 14, this County's report was lower than on the adjacent days. For both anomalies, the reports for this county were linearly interpolated from the adjacent days and then added to the sum of the other counties to produce the state total.

Beginning of Pandemic Cases

The first three COVID-19 cases in the ten study states occurred well in advance of the other cases, and before the infection was a significant public concern. Table 2 lists the dates of the first three COVID-19 cases in each state. The distribution of the first infection dates are fairly broad. The two Illinois cases were a wife who had traveled to Wuhan, China and her husband (Ellwood

2020); the early Massachusetts case was a student who also traveled to Wuhan (Burke 2020). The third case dates are more indicative of the beginning of sustained cases in each state. The third case occurred across a narrower 15-day range between February 29 and March 14.

Table 2. First Three Confirmed COVID-19 Infection Dates in Each State

State	First COVID-19 Case Date	Second COVID-19 Case Date	Third COVID-19 Case Date
Florida	2-Mar	2-Mar	3-Mar
Illinois	24-Jan	30-Jan	29-Feb
Indiana	6-Mar	8-Mar	9-Mar
Massachusetts	1-Feb	3-Mar	6-Mar
Michigan	11-Mar	11-Mar	13-Mar
Montana	11-Mar	14-Mar	14-Mar
New Hampshire	2-Mar	3-Mar	8-Mar
New York	2-Mar	3-Mar	4-Mar
Ohio	10-Mar	10-Mar	10-Mar
Vermont	8-Mar	12-Mar	14-Mar

Governmental Directive Dates

The dates of the State of Emergency (SOE) declarations, statewide closures of schools (Sch. Closed) and restaurants (Rst. Closed) and reopening phases (Phase 1, Phase 2, and Phase 3 Reopen) are shown in Table 3. Governmental directives, closures, and re-openings were collected from state official websites, executive orders, and print news articles covering gubernatorial press conferences.

Table 3. Key COVID-Related Closing and Opening Dates

State	State of Emergency	Schools Closed	Restaurants Closed	Phase 1 Opening	Phase 2 Opening
Florida	9-Mar	13-Mar	20-Mar	18-May	5-June
Illinois	9-Mar	13-Mar	17-Mar	1-May	29-May
Indiana	6-Mar	19-Mar	16-Mar	4-May	22-May
Massachusetts	10-Mar	17-Mar	17-Mar	18-May	8-June
Michigan	10-Mar	16-Mar	16-Mar	7-May	26-May
Montana	12-Mar	16-Mar	21-Mar	27-April	1-June
New Hampshire	13-Mar	16-Mar	16-Mar	18-May	15-June
New York	7-Mar	16-Mar	17-Mar	8-June	19-June
Ohio	9-Mar	16-Mar	16-Mar	12-May	22-June
Vermont	13-Mar	18-Mar	17-Mar	17-April	22-May

Beyond the Study Period

In terms of the study duration and its end date, it should be noted that the course of the pandemic was clearly not over by June 1, 2020. Health data in early June began to show that the spread of COVID-19 had not subsided as hoped. In fact, by June and July, COVID-19 deaths, hospitalizations, and infections had begun to increase. In some places, like the State of Florida, numbers had increased quite significantly as the phased re-opening of major gathering places continued, tourism returned, and traffic volume neared prior-year levels. In fact, statistics in Florida showed that daily COVID-19-related fatalities in mid-July were double those of the peaks of April and May. How the virus will continue to evolve and affect highway, air, rail, public transit etc. modes throughout 2020 and in the years that follow will be studied for some time. However, given the criticality of initial viral onset periods, the focus of this paper, was on the initial wave of the pandemic in the US.

FINDINGS

The traffic volume and virus trends during the onset of the pandemic in the US were analyzed both on individual, state-by-state bases as well as in-total and by like-combinations of metrics. Results are also discussed and presented mathematically, statistically, graphically, and tabularly. The graphical comparisons, presented in Figures 1 through 10 and discussed in the following section, illustrate overall trends and comparative levels of impact within and across states. They simultaneously illustrate all three key parameters in the study; changing traffic volumes, governmental directives, and COVID-19 diagnoses.

State Graphical Summary

The traffic volume trend lines in Figures 1 through 10 represent the percentage change observed between 2020 and the corresponding 2019 day-of-week dates (that is, the second Mondays of March were compared to each other). Statistically significant decreases in traffic between the years, using paired t-testing (significance level 0.05), are noted with asterisks. The amount of change in traffic from 2019, is also represented relative to a “0% Change in Vehicles” and has been further emphasized in the figures with gradient shading; the darker the shading the greater the difference. Days for which t-testing failed to reject the null hypotheses (suggesting traffic on these days may have been similar) are indicated with a circle. The median (*Med*), minimum

(*Min*), maximum (*Max*), and standard deviation (*StDev*) for the number of observations (Obs.) (i.e. traffic detectors) is provided in the lower right corner of each state graph. Finally, dark gray dots are used to represent daily COVID-19 diagnoses per million in population in each state. These cases are represented in the figures as seven-day moving-averages and, as previously described, are temporally offset by two weeks to account for the viral incubation and testing time. This period was selected to associate the case data with the traffic situations, during the time of virus contraction (CDC 2020).

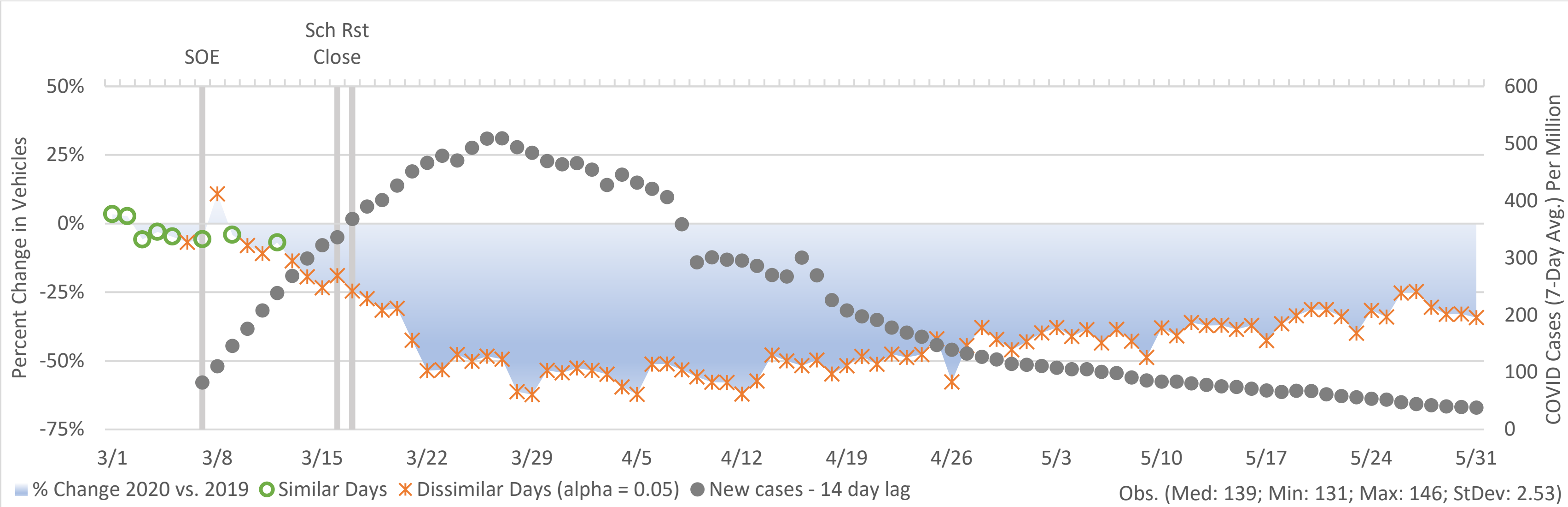

Figure 1: New York (State) Daily Traffic, New COVID Cases, and Directives

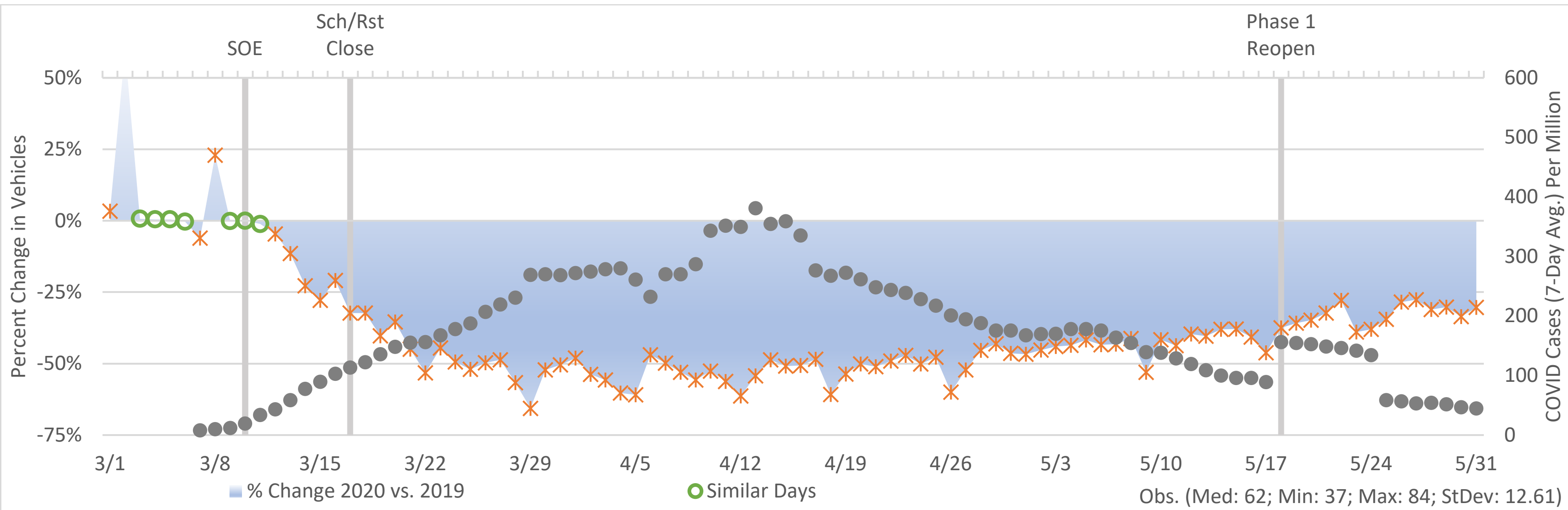

Figure 2: Massachusetts Daily Traffic, New COVID Cases, and Directives

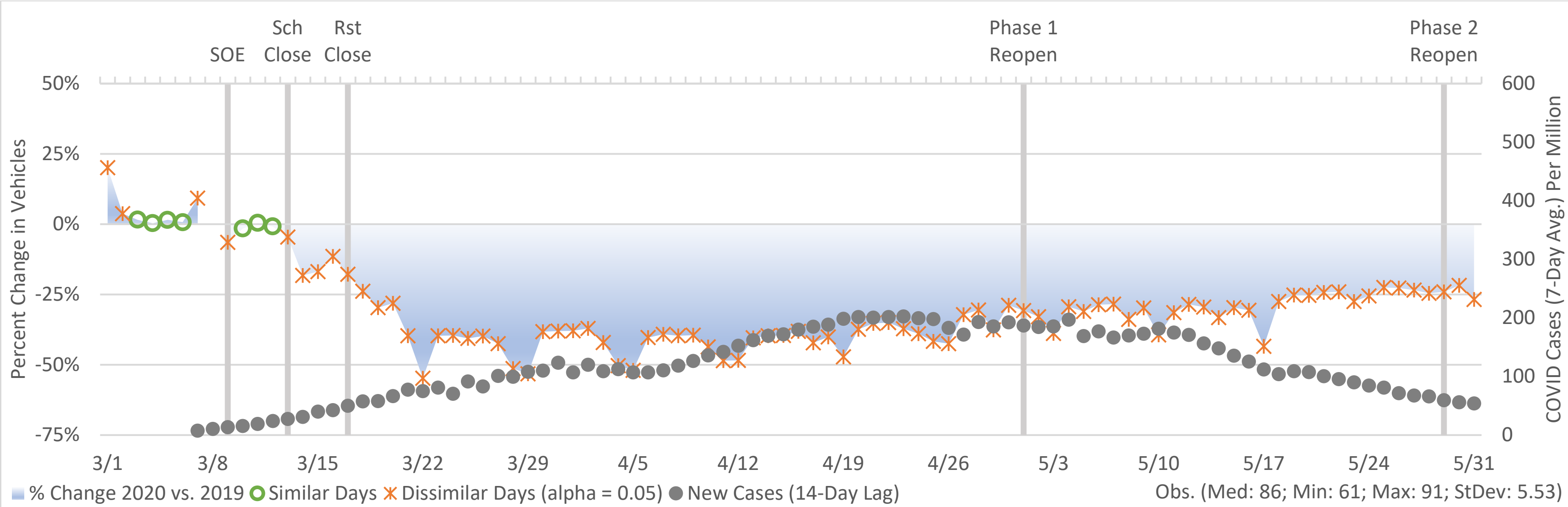

Figure 3: Illinois Daily Traffic, New COVID Cases, and Directives

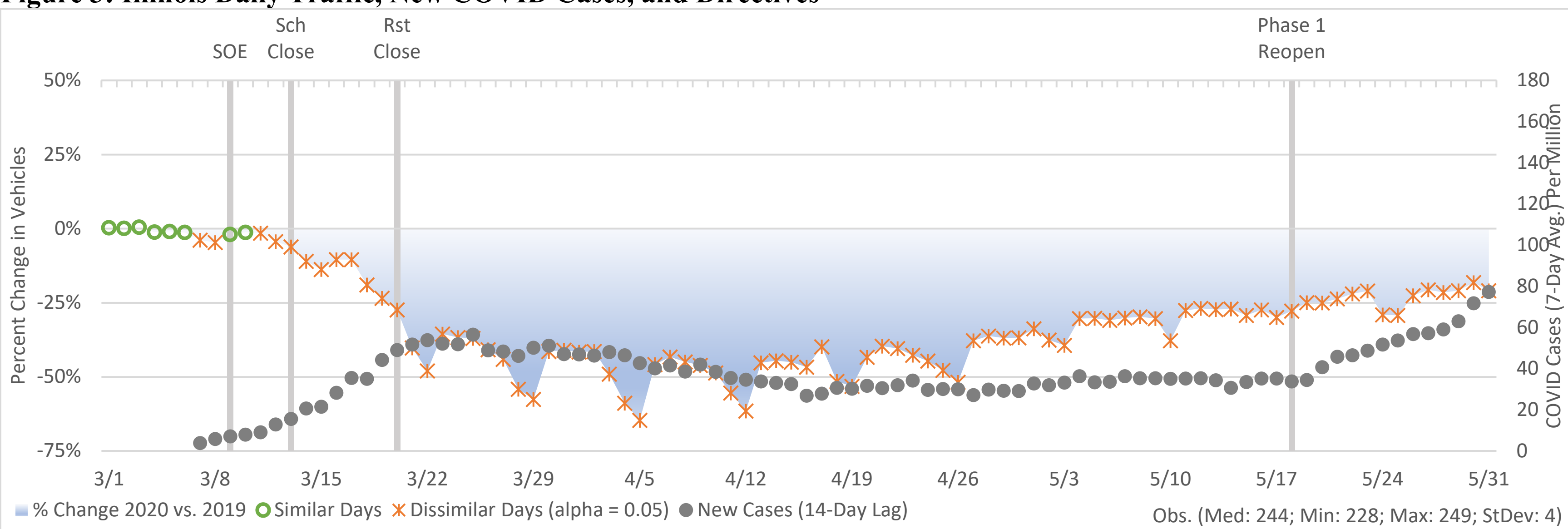

Figure 4: Florida Daily Traffic, New COVID Cases, and Directives

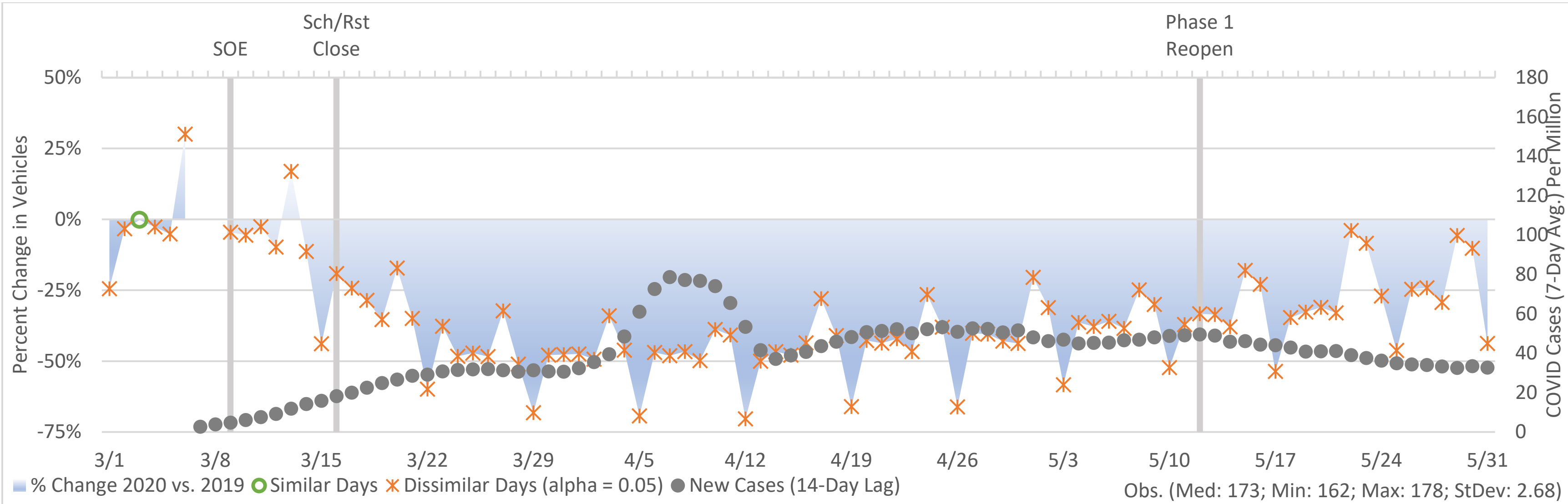

Figure 5: Ohio Daily Traffic, New COVID Cases, and Directives

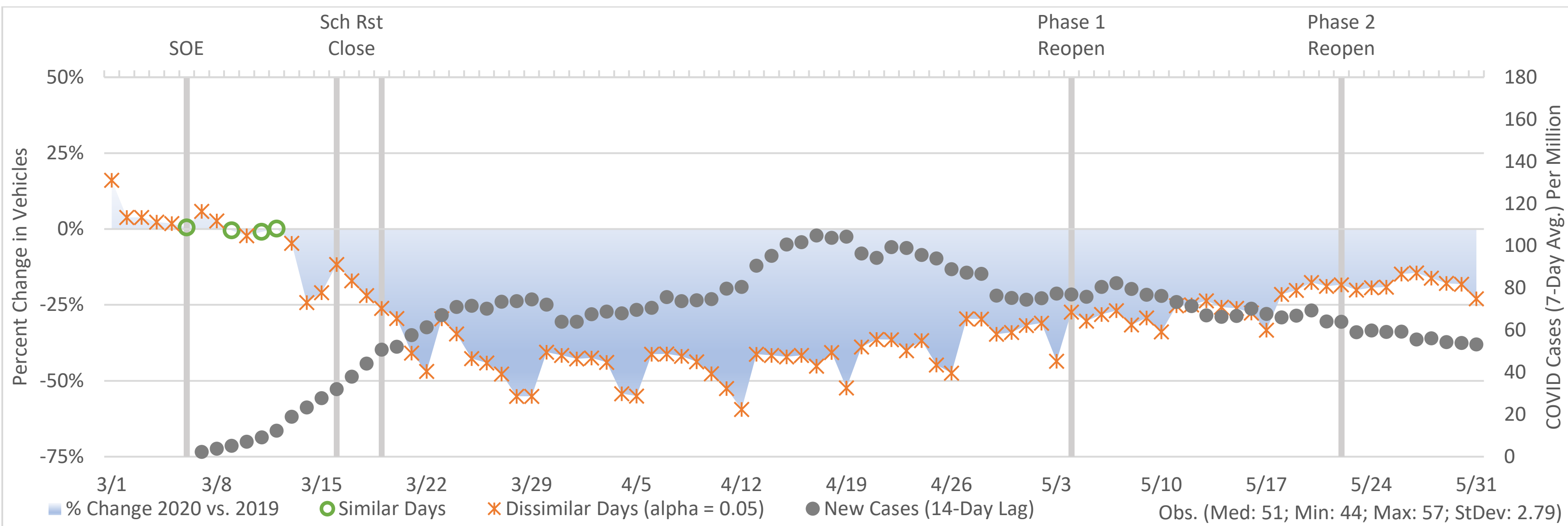

Figure 6: Indiana Daily Traffic, New COVID Cases, and Directives

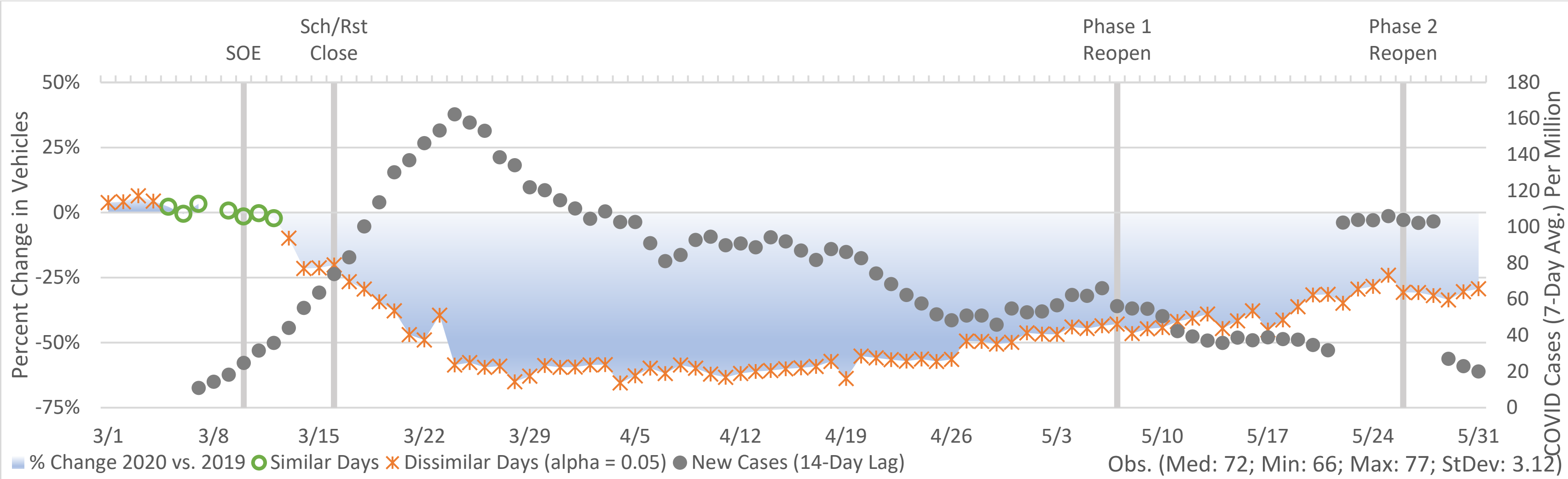

Figure 7: Michigan Daily Traffic, New COVID Cases, and Directives

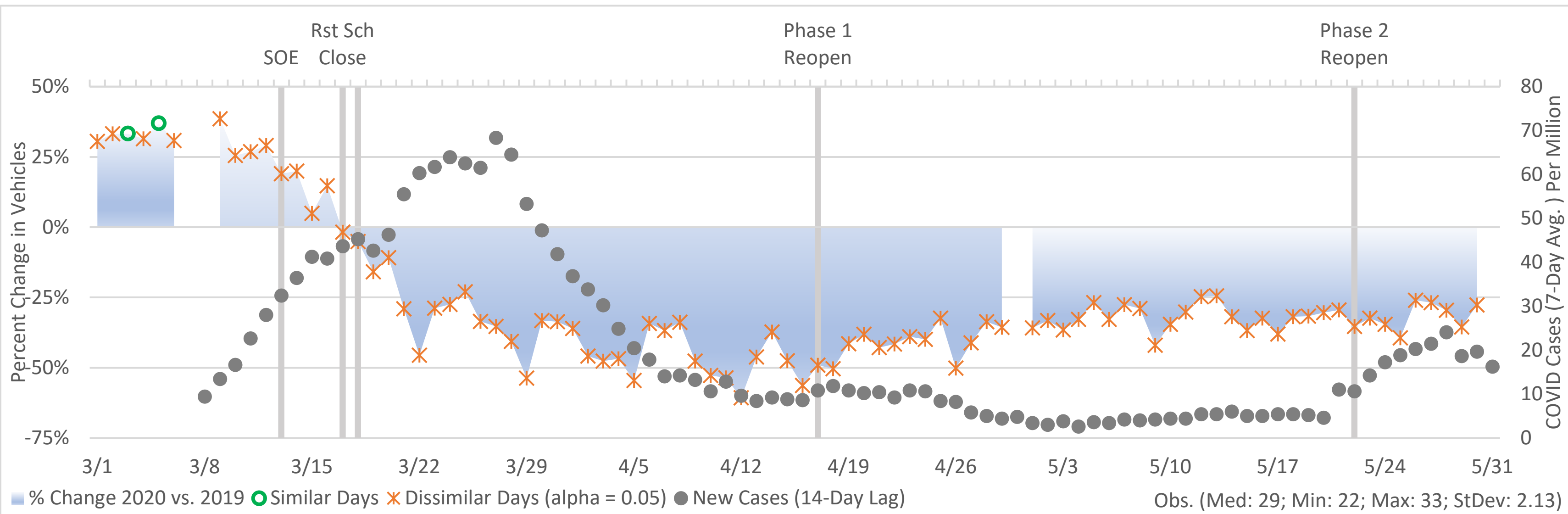

Figure 8: Vermont: Daily Traffic, New COVID Cases, and Directives

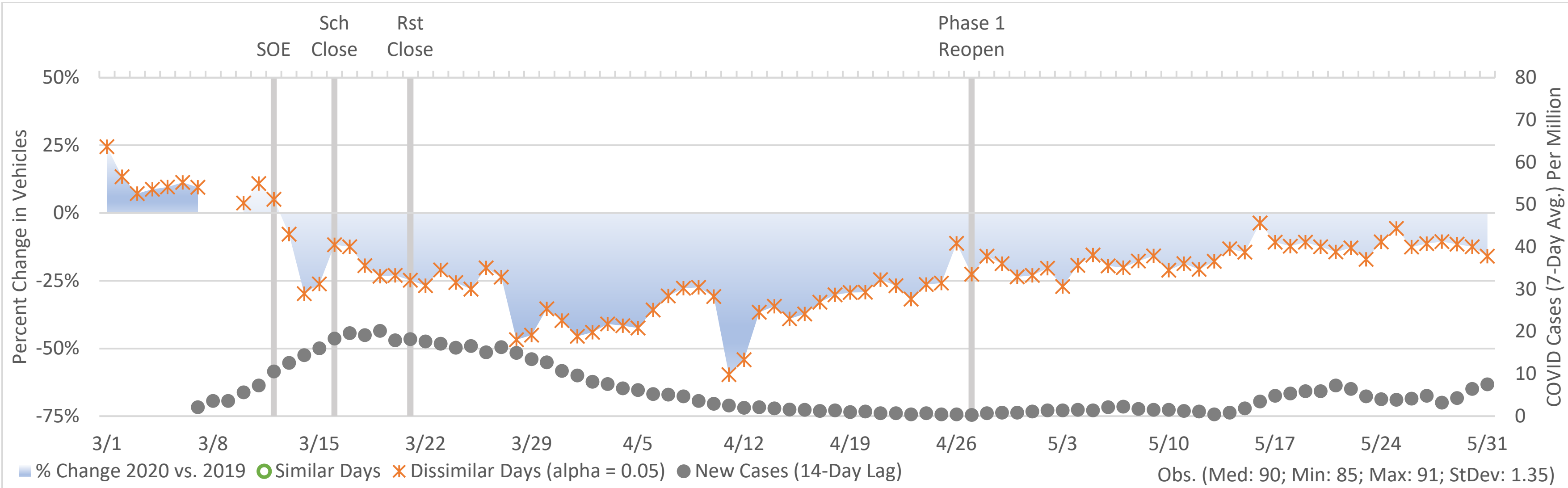

Figure 9: Montana Daily Traffic, New COVID Cases, and Directives

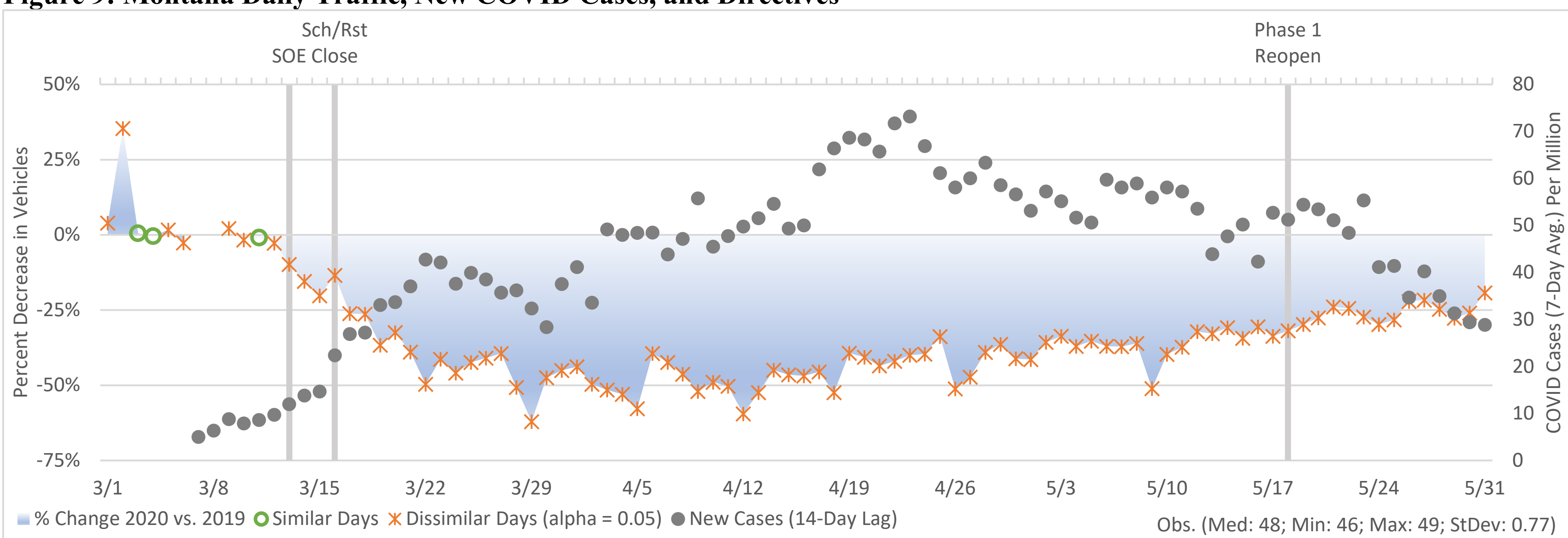

Figure 10: New Hampshire Daily Traffic, New COVID Cases, and Directives

As the figures show, the traffic volume data in every state followed a similar general pattern, with a sharp initial decline, some period at a low level relative to the same dates in 2019, and then a gradual increase back toward 2019 levels. Also clear was that the vast number of days in all the states had significantly lower year-to-year traffic differences, especially after the first week of March. The peak in COVID-19 diagnoses, shown as a seven-day rolling average of new cases, varied across a broad range of periods (Table 4). The states in Table 4 are organized by the number of days to reach the initial COVID-19 case peak; the period is labeled from "Early" in the COVID case increase period to "Late" in the COVID case increase period.

Table 4. Initial Peak of COVID-19 Case Growth

State	Third COVID-19 Case	7-day Moving Avg Peak	Days Between	Peaking Pattern	Peak of Cases Per Million Population
Montana	14-Mar	19-Mar	5	Early	20
Michigan	13-Mar	24-Mar	11	Early	170
Vermont	14-Mar	27-Mar	13	Early	70
Florida	3-Mar	25-Mar	22	Middle	80
New York	4-Mar	27-Mar	23	Middle	500
Ohio	10-Mar	7-Apr	28	Middle	80
Massachusetts	6-Mar	13-Apr	38	Late	400
Indiana	9-Mar	17-Apr	39	Late	110
Illinois	29-Feb	13-Apr	44	Late	220
New Hampshire	8-Mar	23-Apr	46	Late	70

To examine the initial onset period more closely, Table 5 shows the initial date in each state on which 2020 traffic volume was statistically different from 2019. All fell within the same narrow 12-day window from March 6 to 17. The third diagnosed COVID-19 case benchmark (in all states this was the beginning of a sustained case increase), the difference between that case and the first significant traffic decline ranges from negative one day in Ohio to 9 days later in Illinois.

Table 5. Initial Onset Period – State COVID-19 Case and Traffic Volume Changes

State	Third COVID Case	First Traffic Decrease	Days to Change
Ohio	10-Mar	9-Mar	-1
Michigan	13-Mar	13-Mar	0
Montana	14-Mar	14-Mar	0
Massachusetts	6-Mar	7-Mar	1
Indiana	9-Mar	10-Mar	1
New York	4-Mar	6-Mar	2
Vermont	14-Mar	17-Mar	3
Florida	3-Mar	7-Mar	4
New Hampshire	8-Mar	12-Mar	4
Illinois	29-Feb	9-Mar	9

Another interesting general traffic volume trend in Figures 1 through 10 was that traffic conditions demonstrated periodic patterns of change relative to 2019 levels, particularly weekly Monday-to-Monday stepped increases. While all days of the week in 2020 were less than the corresponding 2019 days, weekend traffic decreases (Sundays in particular) were more pronounced across most states during the analysis period. This is likely because weekend discretionary travel was impacted most acutely by the closure orders. A similarly notable trend in the graphs is the inverse relationship between traffic volume and COVID-19 infections. Not surprisingly, closures of business and cancellation of activities with high person-to-person interaction led to decreases in both traffic volume and rates of COVID-19 spread. Reduction in spread rates were not instantaneous, however. Even taking the two-week time adjustment into account, it was non-uniformly related across the sample states. This further suggests that other mechanisms of virus spread, aside from interactions reflected through travel, also accounted for initial infection increases.

State-Specific Trends

Montana data, shown in Figure 9, illustrates the conditions of a low population density, largely rural state. Traffic in early-March 2020 across Montana was actually significantly higher than 2019 then declined steadily through mid-March. COVID-19 cases in the state peaked in mid-to-late March, declining to fewer than ten daily new cases throughout the remainder of the study period. These low case numbers were sustained after the late-April Phase 1 reopening even as traffic volume recovered – ultimately returning to within about 15 percent below prior year levels.

Michigan's trend data (Figure 7), shows that the first significant traffic volume decline occurred after the state of emergency declaration. This was after COVID-19 cases had already begun a steep increase. The traffic trough and virus case peak both happened in the last week of March. Interestingly, while COVID-19 cases began to decline after the peak, traffic volume slowly increased, remaining 50 percent lower than 2019 through late-April. During May, cases generally continued to decline, but traffic increased. Ultimately, traffic remained 25 percent below 2019 levels by the end of the study period.

Vermont, another relatively low population state, experienced the clearest offset relationship between traffic volume and COVID-19 infections. As shown in Figure 8, new cases decreased with traffic volumes after an initial peak. Obviously, this was the intended relationship and the purpose for limiting personal interaction. Similar to Montana, Vermont's 2020 traffic volume was also higher than 2019 prior to the closures of schools and restaurants. Later, traffic volume dropped rapidly and significantly while COVID-19 infections grew rapidly and significantly through the remainder of March. Ultimately, as also shown in Table 4, infections peaked at a level near the peaks of Florida and Ohio when adjusted for population. While traffic volume in Vermont stayed low throughout March, April, and May, COVID-19 cases did as well; even through their mid-April Phase 1 opening – one of the earliest of any state. Traffic volume in Vermont continued to stay around 25 percent below 2019 levels even after the Phase 2 opening in late May. COVID-19 infections in the state, however, began a near-immediate surge after the easing of restrictions without a clear link to traffic and travel trends. However, this "surge" represented only about 20 reported cases per million people per day.

As shown in Figure 4, Florida maintained a relatively constant rate of infection, comparatively speaking, during most of the analysis period. Alarming from a health outcome standpoint, however, was that COVID-19 diagnoses in Florida began to grow in late-May as traffic steadily trended closer to 2019 levels. Positive diagnoses accelerated sharply after the Phase 1 re-opening and as traffic volumes continued the several-week trend of steady increase.

In New York, the first significant drop in traffic occurred on March 6, 2020 but statewide traffic did not have a sustained significant statewide traffic decrease until a week later, just before the closure of schools, as shown in Figure 1. By the time restaurants closed on March 17, traffic had decreased by 25 percent. Ultimately, traffic in the state decreased by 62 percent and by Sunday May 31, the last day of observation, traffic was still 32 percent below 2019 levels. New York's COVID-19 rate increased more significantly than any other state in March and April despite notable reductions in vehicular traffic. The high case rate has been associated with New York City's high population and its high transit ridership (about 50 percent of all trips are made by bus or train (Berggren 2020)) suggesting that road traffic reductions only accounted for a portion of the travel declines. Another source has been theorized to be the internationally-transient nature of the City. Similar to cities like London, Hong Kong, and Dubai, New York is a crossroads for international travelers. It is likely that the city was one of the primary gateways for the entry of the virus into the US. However, it is also notable that after about six weeks of traffic reductions, the rate of new reported cases of COVID-19 dropped to half of the peak level.

Ohio's COVID-19 and traffic trends are both unique within the ten analyzed states. Figure 5 shows a varying traffic volume pattern throughout the period, even by day of the week. The "saw tooth" volume trendline is the result of pronounced peaking on Fridays and Saturdays then significant decreases on Sundays throughout the pandemic. While late week traffic peaks with weekend declines is typical in urbanized areas with heavy commuter travel, the trends in Figure 5 are not "volume," they are the "volume differences" between 2020 and 2019. Thus, the data suggest that traffic in Ohio was less impacted on Fridays and Saturdays during the pandemic than other states, while Sunday reductions in traffic were comparatively more severe.

The large decreases in Ohio's Sunday traffic (70 percent of 2019 levels) were the largest amount of traffic decline in the study sample and had the longest sustained duration (of any day of the week) at its low (29 days) from late-March to late-April (Figure 6). Also notable was the fact the Friday traffic volumes were so consistently and unusually high that by the end of the study period, they were nearly back to 2019 levels. From a health-outcomes perspective, Ohio faired about in the middle of the sample of states. The state COVID-19 cases peaked at around 80 cases per million people in early April, then generally remained steady through late April and early May. Cases declined during May after the Phase 1 re-opening while traffic volumes increased.

Both Illinois and Massachusetts showed interesting connections between traffic and the course of the virus as shown in Figures 2 and 3. The first reported case of COVID-19 in Illinois and Massachusetts were January 24th and February 2, 2020, respectively; several weeks prior to any other state in the sample. Traffic decreases reached their maximums in both states somewhat earlier than other states, then both reached their peak COVID-19 diagnoses rates later than the other states. This relationship points to the desired connection between lowered travel and COVID-19 case "curve flattening." Interestingly, however, by the end of the study period both states remained among the slowest in volume returns to 2019 levels. Massachusetts also had one of the higher overall rates of COVID-19 fatalities in the sample (see Table 4), while Illinois was on the lower end.

As shown in Figure 6, Indiana's sustained traffic decline began on March 12 and traffic volume remained below 75 percent of 2019 volume into May. While the peak in COVID-19 cases was much later than neighboring Michigan, the number of cases per million residents was much lower. After the new case rolling average peaked in mid-April, cases declined while traffic increased.

Traffic patterns in New Hampshire were similar to neighboring Vermont, however, the infection trends were markedly different as shown in Figure 10. This could be related to the fact that Manchester, New Hampshire (population - 112,525) (Census 2019) is a more populous city than any in Vermont, but none of the cities in either state could be described as large or dense. New COVID-19 cases in New Hampshire briefly peaked in mid-to-late April at over 70 per million people, higher than even Florida during all but the end of the study period. Then, most notably, cases *dropped* markedly within the days *after* the Phase 1 opening and as traffic steadily increased.

General Trends and Observations Between Traffic Volume and Viral Progression

All states in the sample experienced a gradual increase of traffic volume toward 2019 levels in late April and May. The largest difference between the states, however, was the path of the infections over the analysis period. Table 6 summarizes the period for virus and traffic changes revealed during the time from the initial "peak" in cases to the greatest traffic decline. Montana was the only states where the time for the virus cases to peak was shorter than the time for traffic to reach its bottom point (as measured by change from 2019 levels). Figure 11 shows that for these relatively diverse ten states the more rapid the declines in traffic volume, the slower the growth in COVID-19 virus cases. The four states where it took longer than 50 days to reach the COVID-19 case peak, were also the four states with the most rapid decline to the vehicle volume "bottom." Since "flattening the curve" and delaying the peak was a primary purpose of social distancing (Fong et al. 2020), these findings suggest that overall, governmental directives, as reflected through rapid traffic decreases, served their purpose.

Table 6. Initial Peak Periods for COVID-19 Cases and Traffic Volume Decline

State	Initial Peak			
	COVID-19		Traffic Volumes	
	1st Peak Date	Days to Reach Peak	Traffic "Bottom" Date	Days to Reach "Bottom"
Montana	2-April	19	11-April	28
Michigan	9-April	27	4-April	22
Vermont	11-April	28	12-April	26
Florida	9-April	37	5-April	29
New York	11-April	38	29-March	23
Ohio	22-April	43	12-April	34
Massachusetts	28-April	53	29-March	22
Indiana	4-May 4	56	20-March	10
Illinois	5-May 5	66	22-March	13
New Hampshire	8-May 8	61	29-March	17

Days to Reach Peak – Time from third COVID case occurrence to highest rolling seven-day average cases
Days to Reach "Bottom" – Time from initial traffic decline to largest traffic volume change from 2019 to 2020.

Another primary finding was that at the conclusion of the analysis period, none of the states showed a complete return to "normal" levels and the amount of their return to routine levels varied across the sample. Table 7 shows that four states experienced renewed growth in COVID-19 cases. Three of the four states, however, were also locations where there were early initial COVID-19 case declines. Numerous factors influenced the variation in the COVID-19 and traffic volume trends, however, the intent of this paper is to explain *what* occurred rather than *why* things occurred.

Figure 11. Comparison of Days to Peak Rolling Seven-Day Average COVID Case Count and Time to The Largest Change Between 2019 and 2020 Traffic Volume

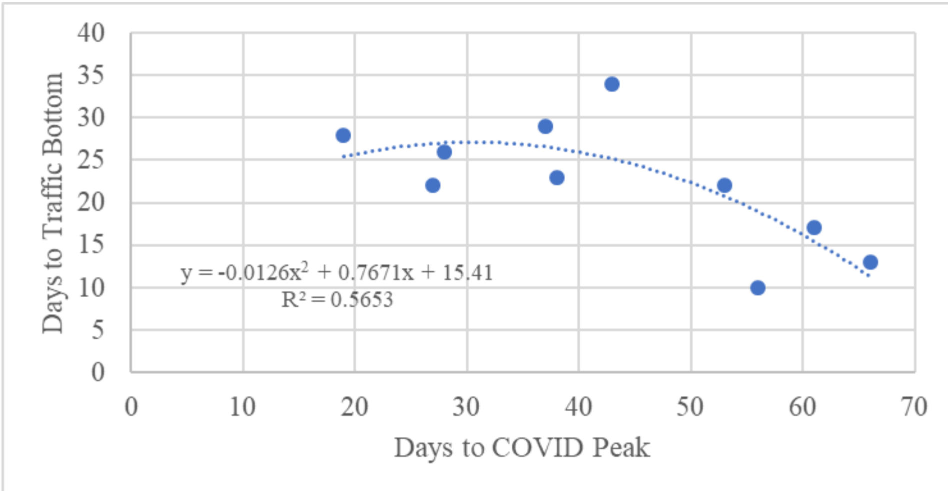

Table 7. "Progression" Summary – Return to COVID-19 Case and Traffic Volume Increases

State	COVID-19 Cases		Traffic Volume Changes	
	Second Increase	Days at "Bottom"	Start of Recovery	Days at "Bottom"
Montana	15-May	5	13-April	2
Michigan	None	NA	20-April	16
Vermont	4-June	54	4-May	22
Florida	1-June	53	13-April	8
New York	None	NA	20-April	22
Ohio	1-May	9	11-May	29
Massachusetts	None	NA	27-April	29
Indiana	None	NA	13-April	24
Illinois	None	NA	6-April	15
New Hampshire	None	NA	19-April	21

CONCLUSIONS

The findings of this research illustrate a number of key facts relative to the spread of COVID-19 during its initial onset period in the US in 2020 and its relationship to highway transportation.

While the virus will inevitably continue its spread across the world in the months and years to come, this paper provides a description of what and when governmental authorities took actions across the United States and how these actions manifested themselves in terms of roadway travel. Then, and perhaps most critically, how travel may have been related to the virus spread, particularly during its most critical initial stages. Another key contribution of this research is that it provides context on both the extent and time scale of public responses in different states and shows the varying levels of delay and/or immediacy in the COVID-19 cases that resulted from them.

While some of the findings discussed here were expected, others were somewhat-more unexpected. Among the most significant of the unexpected findings was the indication that assumptions of public behavioral response, viral spread mechanisms, and health outcomes may not be as closely linked as previously thought. The data showed a generally similar pattern of traffic decreases, then a bottom, followed by increases, across all states. Also apparent was a clear connection between the closure of schools and business and the decline in traffic. What was less clear was the connection between this decline and the timing and amount of viral spread. In fact, not only were the trends of COVID-19 infection increase and decrease markedly different from state to state, they were so even between neighboring states. This suggests that there were other personal interactions taking place, unrelated to roadway travel, that were continuing the progression of the virus.

In terms of the overall amount-of-maximum-traffic-decrease at the height of the lock down, the data suggest relative similarities of 60 to 65 percent less than 2019 levels. This amount of drop and its sustained duration across the entire United States is without equal in the past century. Even the periods of decline during World War II, the 1970s oil crisis, September 2001 terror attacks, and the economic contraction of the late 2000's saw percentage declines in the single digits (Puentes 2008 and Federal Highway Administration 2020). The data also show that, while somewhat varying on amount, there was a similar trend of traffic volume "recovery" across all states by the end of the study period. The rate of recovery has been much slower than the decline in March. By May 31st, the end of the study period, most states were in the range of about 25 to 30 percent below the 2019 traffic volumes; bounded by New Hampshire down only 16 percent and Ohio down 44 percent from prior year levels. Interestingly, these amounts did not appear to be related to population density or rates of COVID-19 infection, but more a reflection of what level of restrictions existed to create opportunities, motivation, and destinations for travel.

Combined, these results may also illustrate the need for governmental responses that are appropriate to the threat faced and the specific characteristics of the location. Clearly, the threat and outcomes faced by Montana, for example, were vastly different than those of New York. Thus, a one-size-fits-all response to these two states or across all states may not make sense within the context of actual conditions and level of risk that may exist.

It is hoped that the contributions made by this work can be used by practitioners and governmental authorities to assess and develop plans for future similar major events and emergencies as well as by researchers who will continue to assess and evaluate aspects of the COVID-19 virus and its spread throughout the country over many years to come.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge Joey Gordon of the Florida Department of Transportation for making statewide traffic count data available for this research. The authors would also like to thank Embry-Riddle Aeronautical students Tate Grant and Erika Shellenberger for their assistance in data collection and processing. The authors also recognize the United States Department of Transportation (US DOT) for their continued support of the *Gulf Coast Center for Evacuation and Transportation Resiliency* at Louisiana State University (LSU), a collaborative University Transportation Center (UTC) and a member of the *Maritime Transportation Research and Education Center* (MarTREC) at the University of Arkansas and the *Center for Cooperative Mobility for Competitive Megaregions* at the University of Texas. Partial funding for this effort was provided by National Science Foundation Award CMMI- 1822436, for which the authors are also grateful. The content of this paper is solely the responsibility of the authors and does not necessarily reflect the views of any of these sponsors.

REFERENCES

Baxter, D. H. (2001). Utilization of Florida's existing and future Intelligent Transportation Systems for enhancing statewide transportation system management during and after hurricane evacuations. In ITS America 11th Annual Meeting and Exposition, ITS: Connecting the Americas. Intelligent Transportation Society of America (ITS America).

Beck, Matthew J; Hensher, David A. Insights into the impact of COVID-19 on household travel and activities in Australia – The early days under restrictions. Transport Policy, Volume 96, Issue 0, 2020, pp 76-93. https://trid.trb.org/view/1719131

Berggren, C. 2020. "Top 10 Large U.S. Cities by Transit Ridership." Accessed August 4, 2020. https://www.smartcitiesdive.com/ex/sustainablecitiescollective/top-10-large-us-cities-transit-ridership/305316/

Berkoune, D., Renaud, J., Rekik, M., & Ruiz, A. (2012). Transportation in disaster response operations. Socio-Economic Planning Sciences, 46(1), 23-32.

Burke, Minyvonne. "8th coronavirus case confirmed in U.S. in Massachusetts." NBC News. February 1, 2020. https://www.nbcnews.com/news/us-news/coronavirus-case-boston-1st-massachusetts-8th-u-s-n1123096

Cartenì, Armando; Di Francesco, Luigi; Martino, Maria. How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study. Science of the Total Environment, Volume 741, Issue 0, 2020, 140489. https://trid.trb.org/view/1717215

de Haas, Mathijs; Faber, Roel; Hamersma, Marije. How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transportation Research Interdisciplinary Perspectives, Volume 6, Issue 0, 2020, 100150, https://trid.trb.org/view/1714701

De Vos, J. (2020). "The effect of COVID-19 and subsequent social distancing on travel behavior." Transportation Research Interdisciplinary Perspectives, Vol. 5.

Dhillon, R., D. Srikrishna, (2018)." When is contact tracing not enough to stop an outbreak*?"* *The Lancet - Infectious Diseases*. No. 18. pp 1302-1304.

Dong, Ensheng, Hongru Du, and Lauren Gardner. "An interactive web-based dashboard to track COVID-19 in real time." *The Lancet infectious diseases* 20, no. 5 (2020): 533-534.

Donné, Valère. Improve bicycle and pedestrian facilities for more social distancing and bicycle use. Volume 26, Issue 267, 2020, pp. 22-28. https://trid.trb.org/view/1715634

Ellwood, Patrick. “Chicago woman infects husband with coronavirus, US issues travel warning.” WGNTV. January 30, 2020. https://wgntv.com/news/chicago-woman-infects-husband-with-coronavirus-first-human-to-human-spread-in-us/

Federal Highway Administration. (2014). Highway Performance Monitoring System (HPMS). Retrieved July 13, 2020, from https://www.fhwa.dot.gov/policyinformation/hpms/hpmsprimer.cfm

Federal Highway Administration. (2020). Travel Monitoring, Traffic Volume Trends Since 1970. Retrieved July 15, 2020, from https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.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 infectious diseases 26(5): 976.

Google LLC. "Google COVID-19 Community Mobility Reports." Accessed June 12, 2020. https://www.google.com/covid19/mobility/

Hadjidemetriou, Georgios M; Sasidharan, Manu; Kouyialis, Georgia; Parlikad, Ajith K. The impact of government measures and human mobility trend on COVID-19 related deaths in the UK. Transportation Research Interdisciplinary Perspectives, Volume 6, Issue 0, 2020, 100167. https://trid.trb.org/view/1718474

Hendrickson, C. and R. Rilett (2020). “The COVID-19 Pandemic and Transportation Engineering.” Journal of Transportation Engineering, Part A: Systems, Volume 146 Issue 7 - July 2020

Hotle, Susan; Murray-Tuite, Pamela; Singh, Kunal. Influenza risk perception and travel-related health protection behavior in the US: Insights for the aftermath of the COVID-19 outbreak. Transportation Research Interdisciplinary Perspectives, Volume 5, Issue 0, 2020, 100127, https://trid.trb.org/view/1705735

Huynh, T. L. D. (2020). "Does culture matter social distancing under the COVID-19 pandemic?" Safety Science: 104872.

Iacus, Stefano Maria; Natale, Fabrizio; Santamaria, Carlos; Spyratos, Spyridon; Vespe, Michele. Estimating and Projecting Air Passenger Traffic during the COVID-19 Coronavirus Outbreak and its Socio-Economic Impact. Safety Science, Volume 129, Issue 0, 2020. https://trid.trb.org/view/1705182

INRIX, Inc. "Travel Trends (July 4-10)." Accessed July 15, 2020. https://inrix.com/covid-19-transportation-trends/

Ito, Hirohito; Hanaoka, Shinya; Kawasaki, Tomoya. The cruise industry and the COVID-19 outbreak. Transportation Research Interdisciplinary Perspectives, Volume 5, Issue 0, 2020, 100136. https://trid.trb.org/view/1709501

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.

Kaiser Family Foundation. 2020. "State Political Parties." Accessed August 4, 2020. https://www.kff.org/other/state-indicator/state-political-parties/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

Kretzschmar, M., G. Rozhnova, M. Bootsma, M. van Boven, J. van de Wijgert, and M. Bonten, (2020). "Impact of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study." The Lancet - Public Health, Vol. 5, No. 8, pp. 452-459.

Maryland Transportation Institute. "University of Maryland COVID-19 Impact Analysis Platform." University of Maryland, College Park, USA. Accessed June 4, 2020. https://data.covid.umd.edu/

MS2 LLC. "Daily Traffic Volume Trends." Accessed June 3, 2020. https://www.ms2soft.com/traffic-dashboard/

Nakamura, Hiroki; Managi, Shunsuke. Airport risk of importation and exportation of the COVID-19 pandemic. Transport Policy, Volume 96, Issue 0, 2020, pp 40-47. https://trid.trb.org/view/1719137

Nikolaou, Paraskevas; Dimitriou, Loukas. Identification of critical airports for controlling global infectious disease outbreaks: Stress-tests focusing in Europe. Journal of Air Transport Management, Volume 85, Issue 0, 2020, 101819. https://trid.trb.org/view/1697837

Parr, S., Wolshon, B., Murray-Tuite, P., Renne, J., and K. Kim, (2020). "Traffic Impacts of the COVID-19 Pandemic: Statewide Analysis of Social Separation and Activity Restriction". *ASCE Natural Hazards Review*. 21(3): 04020025

Puentes, Robert and Adie Tomer (2008). "The Road…Less Traveled: An Analysis of Vehicle Miles Traveled Trends in the U.S." Metropolitan Infrastructure Initiative at Brookings Institution. https://www.brookings.edu/wp-content/uploads/2016/06/vehicle_miles_traveled_report.pdf

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.

SafeGraph, Inc. "Data Analysis Methodology for the SafeGraph Stay-At-Home Index." Accessed June 15, 2020. https://www.safegraph.com/

Sobieralski, Joseph B. COVID-19 and airline employment: Insights from historical uncertainty shocks to the industry. Transportation Research Interdisciplinary Perspectives, Volume 5, Issue 0, 2020, 100123. https://trid.trb.org/view/1704719

Statista. 2020. "Population density in the U.S. by federal states including the District of Columbia in 2019." Accessed August 4, 2020. https://www.statista.com/statistics/183588/population-density-in-the-federal-states-of-the-us/

Stevenson, E., L. Barrios, R. Cordell, D. Delozier, S. Gorman, L. J. Koenig, E. Odom, J. Polder, J. Randolph and T. Shimabukuro (2009). "Pandemic influenza planning: addressing the needs of children." American Journal of Public Health 99(S2): S255-S260.

StreetLight Data Inc. "COVID-19 Vehicle-Miles of Travel Monitor." Accessed July 2, 2020. https://www.streetlightdata.com/VMT-monitor-by-county/

Suau-Sanchez, Pere; Voltes-Dorta, Augusto; Cugueró-Escofet, Natàlia. An early assessment of the impact of COVID-19 on air transport: Just another crisis or the end of aviation as we know it?. Journal of Transport Geography, Volume 86, Issue 0, 2020. https://trid.trb.org/view/1713333

Sung, J. and Y. Monschauer (2020). “Changes in transport behaviour during the Covid-19 crisis.” International Energy Agency Article No. 27, May 2020. [Available online at: https://www.iea.org/articles/changes-in-transport-behaviour-during-the-covid-19-crisis]

Teixeira, João Filipe; Lopes, Miguel. The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike. Transportation Research Interdisciplinary Perspectives, Volume 6, Issue 0, 2020, 100166. https://trid.trb.org/view/1721529

Tirachini, Alejandro; Cats, Oded. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. Journal of Public Transportation, Volume 22, Issue 1, 2020, 34p. https://trid.trb.org/view/1718077

Unacast. “COVID-19 Toolkit.” Accessed June 4, 2020. https://www.unacast.com/covid19/social-distancing-scoreboard

US Census. 2019. “2019 National and State Population Estimates.” Accessed August 4, 2020. https://www.census.gov/newsroom/press-kits/2019/national-state-estimates.html

US Census. 2019. “Quick Facts for Manchester city, New Hampshire”. Accessed August 4, 2020. https://www.census.gov/quickfacts/manchestercitynewhampshire

US Department of Transportation. 2015. “Transportation and Health Tool Data in Excel.” Accessed August 4, 2020. https://www.transportation.gov/mission/health/transportation-and-health-tool-data-excel

Yousey-Hindes, K. M. and J. L. Hadler (2011). "Neighborhood socioeconomic status and influenza hospitalizations among children: New Haven County, Connecticut, 2003–2010." American journal of public health 101(9): 1785-1789.

Zhang, Yahua; Zhang, Anming; Wang, Jiaoe. Exploring the roles of high-speed train, air and coach services in the spread of COVID-19 in China. Transport Policy, Volume 94, Issue 0, 2020, pp 34-42. https://trid.trb.org/view/1708959