Investigating the Impact of COVID-19 on Traffic Safety: From "Lockdown" to the "New Normal"

Yaobang Gong, Ph.D.
Postdoctoral Research Associate
Department of Civil and Environmental Engineering
University of Utah, Salt Lake City, UT, U.S., 84112
Email: yaobang.gong@utah.edu

Pan Lu, Ph.D.
Associate Professor
Upper Great Plains Transportation Institute
North Dakota State University, Fargo, ND, U.S., 58108
Email: pan.lu@ndsu.edu

Xianfeng (Terry) Yang, Ph.D.
Assistant Professor
Department of Civil and Environmental Engineering
University of Maryland, College Park, MD, U.S., 20742
Email: xtyang@umd.edu

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ABSTRACT

COVID-19 pandemic has placed pronounced and prolonged impacts on traffic safety. Many studies found the crash frequency reduced but the severity level increased during the earlier "Lockdown" period. However, there is a lack of studies investigating the pandemic's impact on traffic safety during the later stage of the pandemic. Therefore, this study employs statistical methods to investigate whether the impact of COVID-19 on traffic safety differs during the different stages. Pairwise t-tests were conducted to compare the crash frequency and crash severity levels before, during the earlier stage, and the later stage of the pandemic. Negative binomial models and binary logit models were utilized to study the effects of the pandemic on the crash frequency and severity respectively while accounting for the exposure, environmental and human factors. The results show that the crash frequency is significantly less than that of the pre-pandemic during the whole course of the pandemic. However, it significantly increases during the later stage due to the relaxed restrictions and possibly drivers' behavioral changes. Crash severity levels increased during the earlier pandemic due to the prevalence of risky driving behavior and increased presence of commercial vehicles, but it reduced to a level comparable to the pre-pandemic later. Statistical models show that the impacts of the pandemic on drivers' behavior are decaying, leading to the insignificance of all pandemic quantifiers during the later stage of the pandemic when accounting for the exposure, weather, and economic factors.

Keywords: COVID-19, Traffic Safety, Crash Frequency, Crash Severity

INTRODUCTION

Since March of 2020, the global COVID-19 pandemic has placed pronounced and prolonged impacts on various aspects of society. As of 26 July 2022, across the world, more than 568.7 million people have been infected with COVID-19 and more than 6.3 million people have died from the disease (*1*). In addition to the loss of life and illness, the pandemic has resulted in a great impact on traffic safety. Many studies found that during the earlier stage of the pandemic, especially when "*lockdown*" measures were implemented to control the spread of the disease, the crash frequency dropped significantly (*2–9*), mostly due to the reduced traffic volume. Moreover, higher rates of severe crashes were also observed during the earlier pandemic (*2*, *7–10*), mainly owing to the prevalence of risky driving behavior including driving under the influence of alcohol or drugs, speeding, distracted driving, and not using the seat belt.

The restrictions in the U.S. gradually relaxed due to the reduced COVID-19 cases and the rollout of the vaccines in early 2021, resulting in a recovery of mobility to the level comparable to the pre-pandemic during the year 2021 (*11*, *12*). Although the outbreak related to the Omicron variant briefly stagnated the process, policymakers, public health professionals, and most of the general public all learned from the outbreak that "living with COVID-19" may be inevitable (*13–15*). A "*New Normal*" is inches away. As government policies, public perceptions, and even the virus itself changed dramatically during the later stage of the pandemic, factors contributing to the crash frequency and crash severity, such as traffic volume and drivers' behavior, are likely to change as well. However, there are few studies focusing on traffic safety in the U.S. during the later pandemic. A preliminary study (*16*) from National Highway Traffic Safety Administration shows that the increase in severe injury rates has continued, but the analysis was only conducted for the first half of 2021. Therefore, there is a critical research need of studying the impact of COVID-19 on traffic safety in the later state of the pandemic to assist the decision-making of transportation agencies such as state DOTs on safety improvements and get prepared for the "*New Normal*".

To fill the research gap, this study will take the State of Utah as an example to investigate the impact of COVID-19 on both crash frequency and severity during the whole course of the pandemic. Specifically, the study aims to answer the question "What are the differences of the impact between the earlier and the later stages of the COVID-19 pandemic?". Comparisons will be conducted to verify whether there exist statistically significant differences in terms of crash frequency and severity levels. Several statistical models will also be estimated to investigate the effect of the pandemic while accounting for other confounding factors.

METHODOLODY

Study Area and Data

The study selects the most populous metropolitan county, namely Salt Lake County, in the State of Utah as the study area (Figure 1). Five datasets are used in the county-wide study: 1) crash data from January 2019 to April 2020; 2) factors related to the pandemic; 3) Vehicle Miles Traveled (VMT) of freeways within the county; 4) weather conditions; 5) macroscopic economic conditions.

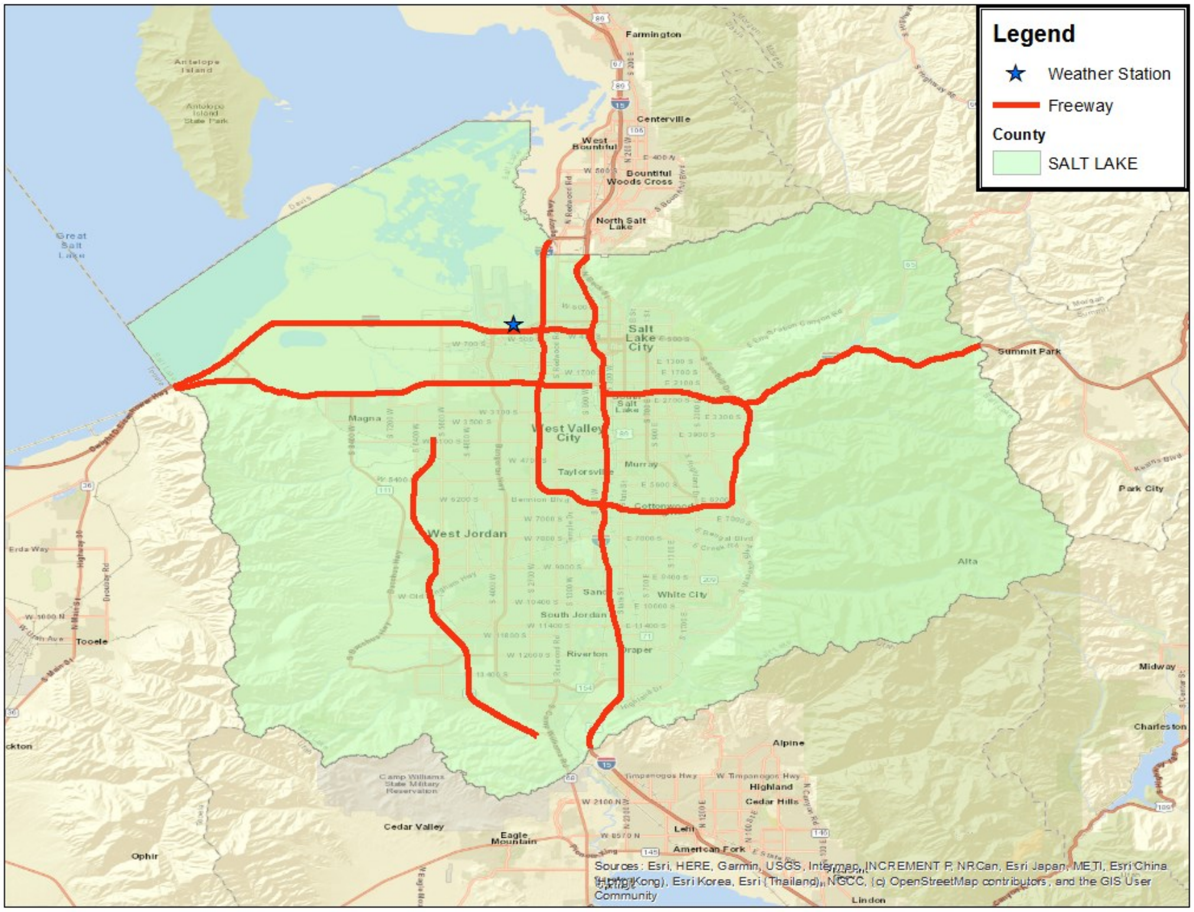

Figure 1 Freeways and the Weather Station in the Salt Lake County of the State of Utah

Detailed crash data were collected from the Numeric system of the Utah Department of Transportation (UDOT), including crash time, location, injury severity, manner of collision, vehicles' characteristics, characteristics of people involved, and environmental conditions. Since the most important crash contributing factor, i.e., the exposure measure (such as VMT and traffic volume), is only available in detail for freeways during the whole study period, this study will only focus on crashes that occurred on the freeways. County-wide daily number of crashes is used as the dependent variable of the crash frequency analysis. As for the crash severity analysis, crashes were classified into two classes: 1) with injury (KAB) and 2) without injury (CO), and the class acts as the dependent variable of the crash severity analysis. Several variables describing the crash's characteristics that are possibly related to the injury severity, such as whether a driver was driving under the influence (DUI), whether a driver was unrestrained (not wearing the seat belt), whether a driver was distracted, etc., were selected for the modeling. Further data cleaning was conducted for injury severity analysis to exclude crash records with missing or unknown values of these variables of interest.

Several factors related to the COVID pandemic are collected as explanatory variables. The number of daily new COVID-19 confirmed cases, percentage of hospitalized cases, and deaths among the new confirmed cases were collected from the Utah Department of Health (*17*). The number of confirmed cases is used by many existing studies to quantify the severity of the pandemic. And those indicating the severity of diseases that caused by the virus (deaths, hospitalizations) are used to provide additional information. Noted that using the absolute numbers of deaths and hospitalizations may raise collinearity issues since they are highly correlated with the number of cases, the rates are utilized instea. Pandemic-related policies (*17*) were also reviewed. Two binary indicators, namely whether there were "lockdown" policies restricting travel directly and whether there were mask mandates that potentially influence people's willingness to travel, were then summarized. When a certain policy is effective on a specific day, the indicator was set to 1; otherwise, it was set to 0.

County-wide VMT of all freeways is used to quantify vehicular traffic. The VMT data was collected from the UDOT Performance Measurement System (PeMS) (*18*) during the study period. Weather conditions such as daily average temperature and total precipitation were collected from the nearest airport weather station (Figure 1) through the National Oceanic and Atmospheric Administration (*19*). The economy may have various impacts on traffic safety (*20*), and the pandemic has imposed great challenges on the economy. Therefore, an economic indicator, the daily news sentiment index, is employed to show the macroscopic economic trends. The daily news sentiment index proposed by the Federal Reserve Bank of San Francisco (*21*) is a measure of economic sentiment based on a lexical analysis of economics-related news articles from 24 major newspapers in the US. The developers of the index created a sentiment scoring model based on publicly available lexicons with a news-specific lexicon constructed by the developers. Then the scores of individual articles are aggregated into a daily time-series measure of news sentiment which is statistically adjusted to account for changes in the composition of the sample across newspapers. Then the index is constructed as a trailing weighted average of time series, with weights that decline geometrically with the length of time since article publication. The index provides information regarding economic downturns and overall sentiment in the public eye.

Two dummy variables were created to help the comparisons before and during the pandemic as well as the earlier and later stages of the pandemic. The first variable is a binary variable indicating the existence of the pandemic. The cut-off date is March 12th, 2020, which is when the first COVID-19 case was confirmed in the State of Utah. If a crash occurred before March 12th, 2020, the value of the dummy variable was assigned to be 1, otherwise, it was assigned to be 0. The other variable is a trinary variable indicating the progression of the pandemic. Besides March 12th, 2020, the other cut-off date is April 10th, 2021, when the state-wide mask mandate expired. The date was selected due to several reasons. First, it marks the end of the outbreak mainly related to the Alpha variant. Second, new state-wide travel restrictions and mask mandates were never issued after that date, which could indicate the policies of the State government have changed. Thirdly, covid vaccines were widely available and the public started to be fully vaccinated after the date. Thus, the risk perception toward COVID-19 may be changed. If a crash occurred before March 12th, 2020, the value of the dummy variable was assigned to be 1; if a crash occurred from March 12th, 2020 to April 10th, 2021, which is defined as the earlier stage of the pandemic, the value was assigned to be 1, otherwise, it was assigned to be 2.

There were 17,038 crashes during the whole study period. 7,295 crashes occurred before the pandemic, and 9,743 crashes occurred during the pandemic. Out of the 9,743 crashes, 4,078 occurred during the earlier stage of the pandemic, and 5,449 occurred during the later stage. Please refer to Table 1 and Table 4 for other descriptive statistics.

Crash Frequency Modeling: Negative Binomial Model

The study employs the widely used negative binomial (NB) model to model the impact of COVID-19 on county-wide crash frequency (*22*). A NB modal can be specified as follows:

$$\lambda_i = \exp(\boldsymbol{\beta X_i} + \varepsilon_i) \tag{1}$$

$$P(y_i) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i + 1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_i}{\frac{1}{\alpha} + \lambda_i}\right)^{y_i} \tag{2}$$

where $P(y_i)$ is the probability of entity i having y_i crashes in a given time period and $\Gamma(\cdot)$ is the gamma function; λ_i is the Poisson parameter which is the expected number of crashes in the given time period; $\boldsymbol{X_i}$ is a set of explanatory variables; $\boldsymbol{\beta}$ is the corresponding coefficient set; ε_i is the error term and $\exp(\varepsilon_i)$ is gamma-distributed with mean 1 and variance α; the corresponding all factors at the timestamp $t + 1$

although we are only interested in the VMT, and n is the length of historical time series which is a tunable factor. Akaike Information Criterion (AIC) and Pseudo-R^2 are used as the goodness-of-fit measures.

Crash Severity Modeling: Binary Logit Model

As stated earlier, the severity of each crash is classified into two levels. Therefore, a binary logic modal is used to investigate the probability of a crash leading to injuries (positive outcome) against no injury (negative outcome) (*23*). A negative binomial modal can be specified as follows:

$$g(x) = \boldsymbol{\beta X_i} \tag{3}$$

$$\pi(x) = \frac{\exp(g(x))}{1 + \exp(g(x)} \tag{4}$$

where $\boldsymbol{X_i}$ is a set of explanatory variables; $\boldsymbol{\beta}$ is the corresponding coefficient set; $g(x)$ is a latent variable; and $\pi(x)$ is the conditional probability of the positive outcome, i.e., a crash leads to injuries. Akaike Information Criterion (AIC) and Pseudo-R^2 are also used as the goodness-of-fit measures.

Comparison: Welch's T-Test & Holm–Bonferroni Method

Comparisons will be conducted to: firstly, study whether there exist differences before and during the pandemic as well as at the earlier and later stages of the pandemic in terms of crash frequency and severity; secondly, investigate the possible reasons by comparing specific explanatory variables in the statistical models to see whether they are statistically different. When the only single comparison between two groups is needed, Welch's t-test (*24*) is employed since two groups may have unequal sizes and/or possibly unequal variances. Welch's t-test defines the statistic t by:

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_1}}} \tag{5}$$

where $\overline{x_i}$, s_i, N_i are the sample mean, standard deviation, and size of sample i. The degree of the freedom df associated is calculated as follows:

$$df \approx \frac{\left(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}\right)^2}{\frac{s_1^4}{N_1^2(N_1 - 1)} + \frac{s_2^4}{N_2^2(N_2 - 1)}} \tag{6}$$

When multiple comparisons are conducted simultaneously, pairwise t-tests are employed. To control the possible family-wise error rate, p-values are adjusted by Holm–Bonferroni method(*25*). The Holm-Bonferroni method firstly sorts m p-values of the pairwise t-tests into order lowest-to-highest $p_1, \dots, p_m$, and their corresponding null hypotheses $H_1, \dots, H_m$. Starting from p_1, at step k, test whether $p_k < \frac{\alpha}{m+1-k}$. If so, reject H_k and continue to test the larger p-values. This ensures that the family-wise error rate is less than the preset significant level α. It should be noted that although this method could control the family-wise error rate, it could sacrifice statistical power.

RESULTS AND DISCUSSION

Impact of COVID Pandemic on Crash Frequency

Table 1 shows the descriptive statistics of the variables during different time periods and the results of t-tests, while Figure 2 shows the number of crashes with the progression of the pandemic (Noted that although the statistical modeling uses daily data, weekly data is employed here for better illustration). Although the crash frequency is significantly less than that of pre-pandemic during the whole course of the pandemic, it varied significantly between the earlier and later stages. During the earlier stage of the pandemic, the number of crashes dropped dramatically when the lockdown was in place. Once the travel restrictions were relaxed, the crash frequency gradually increased but it remained low compared to the pre-pandemic period. However, at the later stage of the pandemic, the crash frequency gradually increased back to a level that is slightly less but comparable to the pre-pandemic. Another outbreak related to the omicron variant briefly reduced the crash frequency and it is increasing back to the previous level.

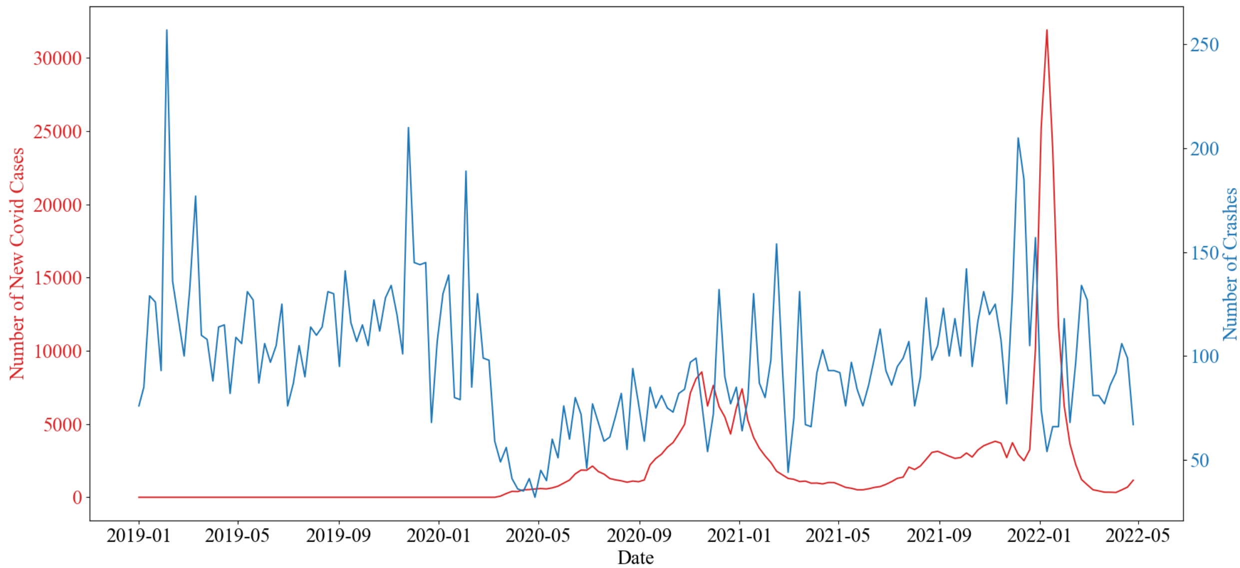

Figure 2 Weekly Number of Crashes versus Number of New COVID Cases

Three different NB models were estimated to investigate the effects of the pandemic while accounting for the impact of other compounding factors. The first model uses the binary dummy variable indicating the existence of the pandemic as the only variable quantifying the effect of the pandemic; the second model uses the trinary dummy variable indicating the progression of the pandemic as the only pandemic-related variable; and the third model employs multiple pandemic-relate variables. The modeling results are shown in Table 2. Noted that the Variance Inflation Factor (VIF) of every variable in three models was checked to avoid the collinearity issue. All VIFs are less than 5, which indicates that collinearity issue should not be concerned (*26*).

TABLE 1 Descriptive Statistics and Results of T-Tests for Crash Frequency Analysis

Variable	Covid		Descriptive Statistics		T-Test		
			Mean	S.D.	Pair	T Value[#]	P Value
Number of Crashes	Before		16.7317	11.2001	**Before-During****	**6.8847**	**<0.0001**
	During	Total	12.5071	8.3181	**Before-Earlier****	N/A	**<0.0001**
		Earlier	10.4506	7.1871	**Before-Later****		**0.0027**
		Later	14.6224	8.8637	**Earlier-Later****		**<0.0001**
Non-Covid-Related Variables							
Ln (VMT) (The unit of VMT is mile)	Before		16.0869	0.1951	**Before-During****	**7.8779**	**<0.0001**
	During	Total	15.9944	0.1983	**Before-Earlier****	N/A	**<0.0001**
		Earlier	15.9316	0.2046	**Before-Later***		**0.0287**
		Later	16.0591	0.1690	**Earlier-Later****		**<0.0001**
Average Temperature (°F)	Before		50.6353	18.7123	**Before-During****	**-4.0272**	**0.0001**
	During	Total	55.1887	19.2418	**Before-Earlier****	N/A	**0.0029**
		Earlier	54.8456	19.1433	**Before-Later****		**0.0008**
		Later	55.5417	19.3612	Earlier-Later		0.6141
Total Precipitation (inch)	Before		0.0536	0.1314	**Before-During****	**3.0762**	**0.0022**
	During	Total	0.0311	0.1044	**Before-Earlier****	N/A	**0.0006**
		Earlier	0.0252	0.0852	Before-Later		0.1240
		Later	0.0372	0.1208	Earlier-Later		0.1240
News Sentiment Index	Before		-0.0501	0.1300	**Before-During****	**25.0062**	**<0.0001**
	During	Total	-0.1533	0.2312	**Before-Earlier****	N/A	**<0.0001**
		Earlier	-0.2951	0.2348	**Before-Later****		**<0.0001**
		Later	0.0076	0.0993	**Earlier-Later****		**<0.0001**
Covid-Related Explanatory Variables							
Numerical Variable	During Covid		Descriptive Statistics		T-Test		
			Mean	S.D.	Pair	T Value	P Value
Number of New Covid Cases	Earlier		368.1722	349.3825	**Earlier-Later****	**-3.0318**	**0.0026**
	Later		517.8047	903.7283			
Hospitalization Rate (%)	Earlier		5.6673	3.6075	Earlier-Later	0.5392	0.5899
	Later		5.5262	3.6960			
Death Rate (%)	Earlier		0.1804	0.6748	**Earlier-Later***	**2.0541**	**0.0403**
	Later		0.1014	0.3524			
Categorial Variables	During Covid		Descriptive Statistics		T-Test		
			Count	%	Pair	T Value	P Value
Lockdown: Yes	Earlier		52	13.1646	N/A		
Mask Mandate: Yes	Earlier		387	72.6582	**Earlier-Later****	**22.4098**	**<0.0001**
	Later		42	10.9375			

* Statistically significant at 0.05 level.
** Statistically significant at 0.01 level.
[#] The t values of pairwise t-tests may be misleading since the p values were adjusted. Therefore, they were omitted.

TABLE 2 Estimates of Crash Frequency Models

Variable	Estimates	Std. Error	Z Value	P Value
With Only Binary Covid Indicator				
(Intercept)**	**-17.7847**	**1.3316**	**-13.3558**	**<0.0001**
Ln (VMT)**	**1.2911**	**0.0832**	**15.5043**	**<0.0001**
Average Temperature**	**-0.0055**	**0.0008**	**-6.6046**	**<0.0001**
Total Precipitation**	**1.7313**	**0.1185**	**14.6048**	**<0.0001**
News Sentiment Index**	**0.3401**	**0.0807**	**4.2140**	**<0.0001**
During Covid: Yes**	**-0.0963**	**0.0319**	**-3.0177**	**0.0026**
Observations	1215			
AIC	7904			
Pseudo-R^2	0.488			
With Only Trinary Covid Indicator				
(Intercept)	-17.2481	1.3440	-12.8333	**<0.0001**
Ln (VMT)**	**1.2583**	**0.0840**	**14.9806**	**<0.0001**
Average Temperature**	**-0.0058**	**0.0008**	**-6.8705**	**<0.0001**
Total Precipitation**	**1.7184**	**0.1183**	**14.5289**	**<0.0001**
News Sentiment Index*	**0.2201**	**0.0966**	**2.2768**	**0.0228**
During Covid Earlier Stage: Yes**	**-0.1607**	**0.0435**	**-3.6967**	**0.0002**
During Covid Later Stage: Yes	-0.0592	0.0359	-1.6491	0.0991
Observations	1215			
AIC	7901			
Pseudo-R^2	0.492			
With Covid Quantifier				
(Intercept)*	**-16.0617**	**1.3544**	**-11.8593**	**<0.0001**
Ln (VMT)**	**1.1855**	**0.0846**	**14.0051**	**<0.0001**
Average Temperature*	**-0.0060**	**0.0009**	**-6.8318**	**0.0427**
Total Precipitation**	**1.6716**	**0.1175**	**14.2246**	**<0.0001**
News Sentiment Index	0.1731	0.0885	1.9571	0.0503
Number of New Covid Cases	-0.00003	<0.0001	-0.9350	0.3498
Hospitalization Rate*	**-0.0096**	**0.0042**	**-2.2871**	**0.0222**
Death Rate	0.0582	0.0354	1.6471	0.0995
Lockdown: Yes**	**-0.4523**	**0.0991**	**-4.5658**	**<0.0001**
Mask Mandate: Yes*	**-0.1025**	**0.0406**	**-2.5237**	**0.0116**
Observations	1215			
AIC	7884			
Pseudo-R^2	0.510			

* Statistically significant at 0.05 level.
** Statistically significant at 0.01 level.

According to Table 2, the exposure measure VMT is significantly and positively related to the crash frequency, which is expected. Precipitation is significantly positively related to the crash frequency since precipitation may lead to adverse road surface conditions and low visibility (*27*), and thus increase the crash risk. Although the effect is relatively low, the daily average temperature is negatively related to the crash frequency. A possible reason is that during the wintertime when the temperature is low, precipitation is likely to be in the form of snow, which leads to an even higher risk (*27*). The aforementioned variables are statistically significant in all three models. The economic indicator, the news sentiment index, is significant in the first two models and is almost significant (p-value = 0.0503) in the third model. Crash frequency reduces when there is an economy downturn, which has been observed during previous recessions (*20*).

As for the pandemic-related parameters, in the first model, the COVID dummy variable is statistically significant with a negative coefficient, meaning that crash frequency reduced during the pandemic while accounting for other confounding factors. However, the second model reveals that crash frequency reduction is only statistically significant during the earlier stage of the pandemic but not during the later stage of the pandemic.

The results of the third model reveal some possible reasons for the difference. The hospitalization rate is significantly negatively related to crash frequency while the number of new covid cases is insignificant. A possible explanation is that the public perception of the pandemic may be mainly affected by the probability of getting a severe disease rather than getting infected but free of any symptoms. Therefore, the hospitalization rate, which is related to severe diseases, may better quantify the public perception. Both pandemic-related policies are found significantly negatively related to crash frequency, while lockdown has a stronger impact. According to Table 1, although there is no statistically significant difference in hospitalization rate, the lockdown policy was only in place during the earlier pandemic and the number of days when wearing masks is mandated is significantly higher during the earlier pandemic. The differences in policies contribute to the different crash frequencies between earlier and later stages of the pandemic. Hospitalization rate and pandemic-related policies may be related to human factors that are not explicitly modeled. Firstly, they may impact the risk perception of the public, which in turn impacts their travel and driving behaviors. Secondly, government policies directly alter travel behaviors. In addition to the lockdown orders that directly restrict traveling, the so-called "social distancing" policies encourage remote working during the earlier pandemic and working from home is negatively related to the crash frequency (*28*).

Admittedly, the pandemic may also indirectly impact the crash frequency by influencing other factors, as suggested by the earlier research. Significant higher VMT and better economy could also be the contributing factors to the higher crash frequency during the later stage compared to the earlier stage of the pandemic.

Impact of COVID Pandemic on Crash Severity

Table 4 shows the descriptive statistics and the results of t-tests, while Figure 3 shows the percentage of injury crashes ("Injury Rate") with the progression of the pandemic. Different from the crash frequency, the crash severity increased significantly during the earlier stage of the pandemic, but it generally reduced to a level comparable to the pre-pandemic during the later stage. The results of the t-tests confirm the statistical (in)significance.

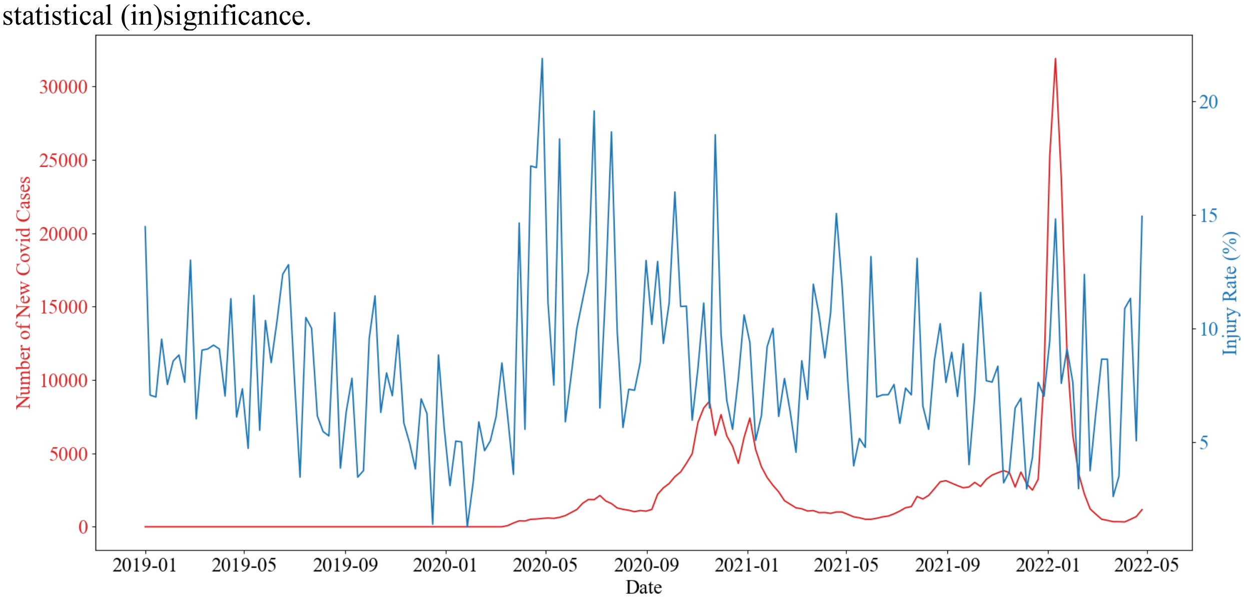

Figure 3 Weekly Average Injury Rate versus Number of New COVID Cases

Similar to the settings of the crash frequency analysis, three different logit models were estimated to investigate effects on crash severity. The modeling results are shown in Table 4. VIFs were also checked to clear the concern of the collinearity issue.

TABLE 3 Estimates of Injury Severity Models

Variable	Estimates	Std. Error	Z Value	P Value
With Only Binary Covid Indicator				
(Intercept)**	**-6.0506**	**0.8037**	**-7.5281**	**<0.0001**
Average Speed**	**0.0478**	**0.0124**	**3.8641**	**0.0001**
News Sentiment Index**	**-0.4651**	**0.1686**	**-2.7592**	**0.0058**
During Covid: Yes	0.0167	0.0649	0.2571	0.7971
Manner of Collision: Angle**	**1.5957**	**0.0988**	**16.1581**	**<0.0001**
Manner of Collision: Head On**	**1.2698**	**0.3093**	**4.1048**	**<0.0001**
Manner of Collision: Single Vehicle	0.0333	0.0790	0.4211	0.6737
Manner of Collision: Parked Vehicle	0.3612	0.4359	0.8286	0.4073
Manner of Collision: Rear to Rear	-10.4520	199.9340	-0.0523	0.9583
Manner of Collision: Rear to Side	0.8267	1.0608	0.7794	0.4357
Manner of Collision: Sideswipe Opposite Direction	0.6165	0.5663	1.0886	0.2763
Manner of Collision: Sideswipe Same Direction**	**-0.6126**	**0.1023**	**-5.9898**	**<0.0001**
Daylight Condition*	**-0.1422**	**0.0684**	**-2.0786**	**0.0376**
Commercial Vehicle Involved*	**0.2264**	**0.0976**	**2.3186**	**0.0204**
Distracted Driving Involved**	**0.5667**	**0.1085**	**5.2216**	**<0.0001**
Drowsy Driving Involved**	**0.8825**	**0.1667**	**5.2953**	**<0.0001**
DUI Involved**	**1.1576**	**0.1128**	**10.2596**	**<0.0001**
Motorcycle Involved**	**2.6213**	**0.1971**	**13.2969**	**<0.0001**
Older Driver Involved**	**0.4439**	**0.0958**	**4.6360**	**<0.0001**
Overturn or Rollover Involved**	**1.6735**	**0.1113**	**15.0337**	**<0.0001**
Unrestrained Involved**	**1.7572**	**0.1356**	**12.9624**	**<0.0001**
Wrong Way Driving Involved*	**0.8962**	**0.4124**	**2.1780**	**0.0294**
Observations	16748			
AIC	8015			
Pseudo-R^2	0.128			
With Only Trinary Covid Indicator				
(Intercept)**	**-6.1078**	**0.8196**	**-7.4524**	**<0.0001**
Average Speed**	**0.0487**	**0.0126**	**3.8613**	**0.0001**
News Sentiment Index*	**-0.5049**	**0.1985**	**-2.5437**	**0.0110**
During Covid Earlier Stage: Yes	-0.0067	0.0894	-0.0747	0.9404
During Covid Later Stage: Yes	0.0302	0.0738	0.4092	0.6824
Manner of Collision: Angle**	**1.5981**	**0.0989**	**16.1504**	**<0.0001**
Manner of Collision: Head On**	**1.2720**	**0.3096**	**4.1085**	**<0.0001**
Manner of Collision: Single Vehicle	0.0348	0.0791	0.4398	0.6601
Manner of Collision: Parked Vehicle	0.3628	0.4362	0.8317	0.4056
Manner of Collision: Rear to Rear	-10.4402	199.8936	-0.0522	0.9583
Manner of Collision: Rear to Side	0.8308	1.0609	0.7832	0.4335
Manner of Collision: Sideswipe Opposite Direction	0.6220	0.5660	1.0990	0.2718
Manner of Collision: Sideswipe Same Direction**	**-0.6116**	**0.1023**	**-5.9782**	**<0.0001**
Daylight Condition*	**-0.1422**	**0.0684**	**-2.0786**	**0.0360**
Commercial Vehicle Involved*	**0.2263**	**0.0976**	**2.3184**	**0.0204**
Distracted Driving Involved**	**0.5668**	**0.1085**	**5.2225**	**<0.0001**
Drowsy Driving Involved**	**0.8816**	**0.1667**	**5.2893**	**<0.0001**
DUI Involved**	**1.1572**	**0.1128**	**10.2553**	**<0.0001**
Motorcycle Involved**	**2.6188**	**0.1972**	**13.2766**	**<0.0001**

Variable	Estimates	Std. Error	Z Value	P Value
Older Driver Involved**	**0.4435**	**0.0958**	**4.6312**	**<0.0001**
Overturn or Rollover Involved**	**1.6732**	**0.1113**	**15.0313**	**<0.0001**
Unrestrained Involved**	**1.7564**	**0.1356**	**12.9530**	**<0.0001**
Wrong Way Driving Involved*	**0.8954**	**0.4127**	**2.1697**	**0.0300**
Observations	16748			
AIC	8017			
Pseudo-R^2	0.128			
With Covid Quantifier				
(Intercept)	**-6.0821**	**0.8160**	**-7.4539**	**<0.0001**
Average Speed**	**0.0484**	**0.0126**	**3.8513**	**0.0001**
News Sentiment Index**	**-0.5067**	**0.0183**	**-2.7654**	**0.0057**
Number of New Covid Cases	<0.0001	<0.0001	0.3076	0.7584
Hospitalization Rate	-0.0016	0.0091	-0.1714	0.8639
Death Rate	-0.0297	0.0858	-0.3466	0.7289
Lockdown: Yes	-0.0863	0.2313	-0.3730	0.7091
Mask Mandate: Yes	-0.0090	0.0864	0.1046	0.9167
Manner of Collision: Angle**	**1.5962**	**0.0989**	**16.1463**	**<0.0001**
Manner of Collision: Head On**	**1.2664**	**0.3094**	**4.0932**	**<0.0001**
Manner of Collision: Single Vehicle	0.0354	0.0790	0.4474	0.6546
Manner of Collision: Parked Vehicle	0.3598	0.4360	0.8254	0.4092
Manner of Collision: Rear to Rear	-10.4576	19.9863	-0.0523	0.9583
Manner of Collision: Rear to Side	0.8260	1.0608	0.7787	0.4362
Manner of Collision: Sideswipe Opposite Direction	0.6147	0.5667	1.0846	0.2781
Manner of Collision: Sideswipe Same Direction**	**-0.6119**	**0.1023**	**-5.9789**	**<0.0001**
Daylight Condition*	**-0.1409**	**0.0686**	**-2.0536**	**0.0400**
Commercial Vehicle Involved*	**0.2265**	**0.0977**	**2.3186**	**0.0204**
Distracted Driving Involved**	**0.5660**	**0.1085**	**5.2166**	**<0.0001**
Drowsy Driving Involved**	**0.8832**	**0.1669**	**5.2905**	**<0.0001**
DUI Involved**	**1.1594**	**0.1128**	**10.2752**	**<0.0001**
Motorcycle Involved**	**2.6212**	**0.1971**	**13.2980**	**<0.0001**
Older Driver Involved**	**0.4435**	**0.0958**	**4.6301**	**<0.0001**
Overturn or Rollover Involved**	**1.6722**	**0.1113**	**15.0249**	**<0.0001**
Unrestrained Involved**	**1.7583**	**0.1356**	**12.9685**	**<0.0001**
Wrong Way Driving Involved*	**0.8964**	**0.4131**	**2.1699**	**0.0300**
Observations	16748			
AIC	8023			
Pseudo-R^2	0.128			

* Statistically significant at 0.05 level.
** Statistically significant at 0.01 level.

The effects of the variables related to the manner of collisions, the characteristics of vehicles involved, and the drivers' behavior are in line with previous studies (*10*, *20*, *29–31*). Speed is positively and significantly related to crash severity. Angle, head-on, overturn, and rollover crashes tend to be severer and sideswipe crashes are likely less severe. The severity of crashes that occurred during the nighttime and those with commercial vehicles and/or motorcycles involved tend to be severe. Crashes with the older driver involved are likely to be severer. Risky driving behavior, including DUI, distracted driving, drowsy driving, wrong-way driving, and unrestrained (not wearing the seat belt) could increase the crash severity. The economy is negatively related to crash severity, which is evident during the last recession.

Interestingly but not surprisingly, all pandemic-related variables are not statistically significant even at the 0.05 level in all three models. Similar results can be found in an earlier study (*10*). A plausible reason is that the impact of the pandemic can be well explained by the aforementioned variables.

Therefore, to investigate the possible contributing factors to different crash severity levels before and during the different stages of the pandemic, mean values of explanatory variables were compared. Most notably, according to the results of pairwise t-tests, drivers who are involved in crashes are likely to have risky driving behaviors, including DUI, not wearing seat belts, and driving during the nighttime, during the pandemic, especially during the earlier pandemic. The situation got improved with the progression of the pandemic. During the later pandemic, only crash with DUI involved is still higher than the pre-pandemic level but it is lower than in the earlier pandemic. There might be two possible reasons. First, during the earlier pandemic, when the public is afraid of getting infected, those who were still on the road may have higher degrees of risk acceptance. Therefore, they may have a higher probability of exhibiting risky driving behaviors. This has gradually changed with the change in the public's risk perception toward COVID-19, especially when people were getting vaccinated. When more and more people started driving again during the later pandemic, the average level of risk acceptance returned to the pre-pandemic level. Second, surveys indicate that people started, or increased substance use to cope with pandemic-related stress or emotions (*8*), which can also increase the probability of DUI, even during the later pandemic. The increased commercial vehicle-involved crashes also contribute to the increased crash severity during the pandemic. This might be due to the increased truck traffic caused by the growth of online shopping and on-demand delivery (*12*). The change of crash types exhibits mixed effects on crash severity. The percentage of head-on crashes increased, but the absolute number is too low to have a large impact on the overall crash severity level. Crashes with overturn/rollover involved increased during the earlier pandemic but dropped to the pre-pandemic level later. The percentage of less severe sideswipe crashes increased during the pandemic. This probably canceled out the effects of other factors that increase the crash severity during the later pandemic, but its effects are not strong enough to compensate for the increased crash severity during the earlier pandemic.

TABLE 4 Descriptive Statistics and Results of T-Tests for Crash Severity Analysis

Variable	Covid		Descriptive Statistics		T-Test		
			Yes	%	Pair	T Value[#]	P Value
Whether a Crash Leads to Injuries	Before		521	7.22%	**Before-During****	**-2.9360**	**0.0033**
	During	Total	804	8.44%	**Before-Earlier****	N/A	**0.0001**
		Earlier	387	9.49%	Before-Later		0.3534
		Later	417	7.65%	**Earlier-Later****		**0.0033**
Categorial Variables							
Manner of Collision: Angle	Before		352	4.87%	Before-During	-0.1120	0.9108
	During	Total	468	4.91%	Before-Earlier	N/A	0.1478
		Earlier	231	5.66%	Before-Later		0.1613
		Later	237	4.35%	**Earlier-Later***		**0.0117**
Manner of Collision: Head On	Before		46	0.64%	**Before-During***	**2.2980**	**0.0216**
	During	Total	36	0.38%	Before-Earlier	N/A	0.4559
		Earlier	19	0.47%	**Before-Later***		**0.0207**
		Later	17	0.31%	Earlier-Later		0.4559
Manner of Collision: Sideswipe Same Direction	Before		1446	20.02%	**Before-During****	**-4.7202**	**<0.0001**
	During	Total	2195	23.04%	**Before-Earlier****	N/A	**0.0001**
		Earlier	953	23.37%	**Before-Later****		**0.0004**
		Later	1242	22.79%	Earlier-Later		0.5093
Daylight Condition	Before		5238	72.54%	**Before-During***	**2.1808**	**0.0292**
	During	Total	6765	71.01%	**Before-Earlier****	N/A	**0.0006**
		Earlier	2823	69.23%	Before-Later		0.8080
		Later	3942	72.34%	**Earlier-Later****		**0.0019**
Commercial Vehicle Involved	Before		681	9.43%	**Before-During****	**-5.4457**	**<0.0001**
	During	Total	1147	12.04%	**Before-Earlier****	**N/A**	**<0.0001**
		Earlier	453	11.11%	**Before-Later****		**<0.0001**

Variable	Covid		Descriptive Statistics		T-Test		
			Yes	%	Pair	T Value#	P Value
		Later	694	12.74%	**Earlier-Later****		**<0.0001**
Distracted Driving Involved	Before		474	6.56%	**Before-During***	**2.2421**	**0.0250**
	During	Total	545	5.72%	Before-Earlier	N/A	0.2679
		Earlier	239	5.86%	Before-Later		0.0789
		Later	306	5.62%	Earlier-Later		0.6115
Drowsy Driving Involved	Before		117	1.62%	**Before-During***	**-2.1976**	**0.0280**
	During	Total	198	2.08%	Before-Earlier	N/A	0.0638
		Earlier	92	2.26%	Before-Later		0.3475
		Later	106	1.95%	Earlier-Later		0.3475
DUI Involved	Before		204	2.83%	**Before-During****	**-6.2752**	**<0.0001**
	During	Total	443	4.65%	**Before-Earlier****	N/A	**<0.0001**
		Earlier	219	5.37%	**Before-Later****		**<0.0001**
		Later	224	4.11%	**Earlier-Later****		**<0.0001**
Motorcycle Involved	Before		46	0.64%	**Before-During****	-1.9716	**0.0487**
	During	Total	86	0.90%	Before-Earlier	N/A	0.2229
		Earlier	39	0.96%	Before-Later		0.2987
		Later	47	0.86%	Earlier-Later		0.6345
Older Driver Involved	Before		691	9.57%	Before-During	0.6186	0.4978
	During	Total	890	9.34%	Before-Earlier	N/A	0.1269
		Earlier	348	8.53%	Before-Later		0.4790
		Later	542	9.95%	Earlier-Later		0.0536
Overturn/Rollover Involved	Before		211	2.92%	**Before-During***	-1.9865	**0.0470**
	During	Total	330	3.46%	**Before-Earlier****	N/A	**0.0023**
		Earlier	170	4.17%	Before-Later		0.9624
		Later	160	2.94%	**Earlier-Later****		**0.0030**
Unrestrained Involved	Before		113	1.56%	**Before-During****	**-2.8160**	**0.0049**
	During	Total	205	2.15%	**Before-Earlier***	N/A	**0.0225**
		Earlier	94	2.31%	Before-Later		0.0997
		Later	111	2.04%	Earlier-Later		0.3776
Wrong Way Driving Involved	Before		12	0.17%	Before-During	-1.8665	0.0620
	During	Total	29	0.30%	Before-Earlier	N/A	0.3770
		Earlier	12	0.29%	Before-Later		0.3100
		Later	17	0.31%	Earlier-Later		0.8760
Numerical Variables							
Variable	Covid		Descriptive Statistics#		T-Test		
			Mean	S.D.	Pair	T Value#	P Value
Average Speed (mph)	Before		65.7145	2.6788	**Before-During****	**-4.0576**	**0.0001**
	During	Total	66.2824	1.5611	**Before-Earlier****	N/A	**<0.0001**
		Earlier	66.9455	1.0452	Before-Later		0.4612
		Later	65.6002	1.7048	**Earlier-Later****		**<0.0001**
News Sentiment Index	Before		-0.0501	0.1300	**Before-During****	**25.0062**	**<0.0001**
	During	Total	-0.1533	0.2312	**Before-Earlier****	N/A	**<0.0001**
		Earlier	-0.2951	0.2348	**Before-Later****		**<0.0001**
		Later	0.0076	0.0993	**Earlier-Later****		**<0.0001**

* Statistically significant at 0.05 level.
** Statistically significant at 0.01 level.
# The t values of pairwise t-tests may be misleading since the p values were adjusted. Therefore, they were omitted.

Although forecasting the safety performance during the "New Normal" is not the main objective of this study, according to the modeling results, the overall traffic safety performance will be similar to if not better than the later pandemic. With restrictions relaxed, the traffic volume is expected to remain at the pre-pandemic level for a considerably long period. Moreover, the recent news sentiment index shows the worry about a possible economic recession. The average index for the first three weeks of July 2022 is -0.1963, which is lower than that during the later pandemic analyzed in the model. And risky driving behavior is decreasing. The possibility of an economic downturn combined with a similar traffic level may indicate the crash frequency may remain low, and the reducing risky driving behavior may indicate a low crash severity level. However, transportation agencies may still need to pay more attention to DUI-related crashes since people may still experience pandemic-related stress or emotions as the pandemic continues. Nevertheless, the truck volume may remain high because of online shopping and on-demand delivery, which could also increase the overall crash severity.

There are some limitations of this study. Firstly, due to limited data availability, the study was only conducted for freeways. Subsequent studies may assess the safety performance of arterials during the different stages of the pandemic. Secondly, due to the lack of detailed local survey data, human factors were not included in the statistical modeling of crash frequency. Further studies focusing on the relationship between human factors are crash frequency at the later pandemic are desirable. Thirdly, the pandemic may have complicated impacts on traffic beyond the VMT. For example, during the pandemic, traffic patterns changed from the typical two-peak pattern (morning peak followed by a drop and then afternoon peak) to a gradually increasing to one afternoon peak in some metropolitan areas (*32*, *33*). The authors attempted to model the change in traffic patterns by introducing speed-related factors, but the resultant models suffer from multicollinearity issues. A good future direction could be conducting real-time safety analysis (*34*) which focuses on the occurrence of each crash. It can model the impact of real-time traffic and environmental factors closely preceding the crash.

CONCLUSIONS

The global COVID-19 pandemic has placed a great impact on traffic safety across the U.S. However, there are few studies investigating the pandemic's impact on traffic safety during the later stage of the pandemic. Therefore, this study employs several statistical methods to investigate whether the impact of COVID-19 on traffic safety differs during the different stages. Freeways of Salt Lake County, Utah were selected as the study sites. Pairwise t-tests were conducted to compare the crash frequency and crash severity levels before the pandemic, during the earlier stage of the pandemic, and the later stage of the pandemic. Negative binomial models and binary logit models were utilized to study the effects of the pandemic on the crash frequency and severity respectively while accounting for the exposure, environmental and human factors. The results show that the crash frequency is significantly less than that of the pre-pandemic during the whole course of the pandemic. However, it is significantly higher during the later stage due to the relaxed restrictions and possibly drivers' behavioral changes including risk perception. When accounting for the exposure, weather, and economic factors, the pandemic-related variables still significantly affect the crash frequency during the earlier pandemic, indicating the impact of the pandemic on unobserved human factors. But the impact decayed during the later pandemic, leading to the insignificance of these variables. Crash severity levels increased during the earlier pandemic due to the prevalence of risky driving behavior and increased presence of commercial vehicles but reduced to a level comparable to the pre-pandemic later, owing to the reduction in risky driving behavior. As for the incoming "New Normal", transportation agencies may still pay attention to the impact of DUI and increased truck volume on traffic safety.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: X. Yang, P. Lu, Y. Gong; data collection: Y. Gong; analysis and interpretation of results: Y. Gong.; draft manuscript preparation: Y. Gong, X. Yang. All authors reviewed the results and approved the final version of the manuscript.

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