Initial impact of COVID-19's stay-at-home order on motor vehicle traffic and crash patterns in Connecticut: an interrupted time series analysis

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ABSTRACT

Introduction Understanding how the COVID-19 pandemic has impacted our health and safety is imperative. This study sought to examine the impact of COVID-19's stay-at-home order on daily vehicle miles travelled (VMT) and MVCs in Connecticut.

Methods Using an interrupted time series design, we analysed daily VMT and MVCs stratified by crash severity and number of vehicles involved from 1 January to 30 April 2017, 2018, 2019 and 2020. MVC data were collected from the Connecticut Crash Data Repository; daily VMT estimates were obtained from StreetLight Insight's database. We used segmented Poisson regression models, controlling for daily temperature and daily precipitation.

Results The mean daily VMT significantly decreased 43% in the post stay-at-home period in 2020. While the mean daily counts of crashes decreased in 2020 after the stay-at-home order was enacted, several types of crash rates increased after accounting for the VMT reductions. Single vehicle crash rates significantly increased 2.29 times, and specifically single vehicle fatal crash rates significantly increased 4.10 times when comparing the pre-stay-at-home and post-stay-at-home periods.

Discussion Despite a decrease in the number of MVCs and VMT, the crash rate of single vehicles increased post stay-at-home order enactment in Connecticut after accounting for reductions in VMT.

INTRODUCTION

SARS-CoV-2, else the 2019 novel coronavirus (COVID-19), has swept across the globe with unparalleled destruction.[1] COVID-19 has resulted in unprecedented policies to promote 'social distancing' behaviours,[2] including those aimed at stopping the flow of intrastate and interstate travel to reduce disease transmission, referred to as stay-at-home or shelter-in-place orders.[3] These orders, which largely discourage non-essential travel, were issued in 42 states over a period of time between March and April of 2020.[3] Connecticut's governor issued a stay-at-home order effective 23 March 2020.[4] Early reports suggest that stay-at-home orders have changed traffic patterns within the USA as well as reduced MVCs in California.[5 6]

A current report issued by the Road Ecology Center at the University of California Davis states that vehicle miles travelled (VMT) decreased between 61% and 90% throughout the USA following the implementation of state-based stay-at-home orders.[5] Other reports from the Road Ecology Center noted that the number of traffic crashes reduced significantly when comparing the pre-stay-at-home with post-stay-at-home period in California. Analysis of traffic patterns and COVID-19 cases has identified that reductions in VMT has negatively correlated with COVID-19 cases and deaths across the USA.[6]

Recent news media suggest that Connecticut police have seen an increase in drivers speeding during the pandemic, suggesting more risky driving has been occurring.[7] Other news reports suggest lower police presence in Connecticut and throughout the USA, which could be influencing illegal driving behaviour.[8 9]

Understanding COVID-19's causal impact on daily traffic patterns and MVCs is imperative as we seek to mitigate the negative health effects of both the current and future pandemic waves and similar future disease outbreaks. As such, we sought to examine the causal impact of COVID-19 and its associated stay-at-home order on traffic patterns and MVCs within the State of Connecticut.

METHODS

We used an interrupted time series design to compare daily VMT and MVCs in Connecticut before and during the COVID-19 stay-at-home order, effected 23 March 2020.[10 11]

Data

We collected daily MVC counts in Connecticut between 1 January and 30 April in 2017, 2018, 2019 and 2020. We accessed these counts via the online publicly available Connecticut Crash Data Repository (CTCDR), maintained by the University of Connecticut and Connecticut Department of Transportation.[12] The CTCDR provides detailed information regarding the severity of crashes and other variables to understand MVC circumstances. Crash severity is broken into three categories: fatal crashes, injury crashes or non-injury crashes (property damage only). Crash severity is derived from the most severe injury to any one person in the crash and is meant to simplify the use of the crash data records.[13] Fatal crashes include one or more individuals within the crash event suffering a

fatal injury within 30 days of the MVC. We stratified our MVC outcomes by crash severity, into four categories: (1) overall crashes, (2) any injury crashes, (3) non-injury crashes and (4) fatal crashes. Within each category, we further stratified our outcomes by the number of vehicles involved in the crash (either a single vehicle or multiple vehicle crash).

To address possible changes in VMT associated with COVID-19's stay-at-home order, we accessed StreetLight's Insight database to create estimates of total daily VMT during our study periods.[14] StreetLight's Insight database uses billions of anonymous location records from smartphones and other driving devices to transform data points into traffic patterns using proprietary algorithms.[14 15] Data are updated bimonthly and validated and calibrated using thousands of permanent traffic counters throughout the USA.[16] StreetLight's Insight database estimates the number of departure and return trips and the average length of each trip type per day. Estimates of total daily VMT are then calculated by adding the product of the estimated number of departure trips by the average departure trip length in miles to the product of the number of return trips by the average return trip length in miles for each day between 1 January and 30 April in 2017, 2018, 2019 and 2020. Previous reports examining the impact of COVID-19 on traffic patterns have relied on Streetlight Insight for daily estimates of VMT.[5]

We included a measure of average daily precipitation for Connecticut to control for possible seasonal weather conditions that could have impacted VMT and crashes. We also included a measure of average daily maximum temperature as previous research indicated that high temperature days can potentially lower measures of social distancing during COVID-19.[17 18] We accessed these variables using the National Climatic Data Center's Climate Data Online database.[19] The data are publicly available through request and provide daily weather estimates from up to 150 different weather stations located in Connecticut. We collapsed recorded maximum temperature and precipitation into daily state averages from all available Connecticut weather stations for all study years.

Analysis

We provided a descriptive analysis within 2020. We provided mean daily counts and total counts for all MVC outcome models within 2020 for the pre-stay-at-home and post-stay-at-home periods. We tested for whether mean daily counts were statistically significantly different across time periods and calculated the per cent change in total counts and mean daily counts. All statistical tests for independence were calculated using two-sided t-tests.

We evaluated whether post-stay-at-home time trends in daily VMT and MVC differed significantly from pre-stay-at-home time trends using a segmented Poisson regression analysis.[10 11] For each of the 12 MVC outcomes, we specified the following model:

$$Y_t = \beta_0 + \beta_1 T + \beta_2 I_t + \beta_3 \left(T*I\right)_t + X_t + \text{Log}\left(\text{Daily VMT}\right)$$

where, Y_t equals the 12 MVC outcomes in daily counts; T equals time; I equals a dummy variable indicating the pre-stay-at-home period (coded=0) or the post-stay-at-home period (coded=1); T*I equals an interaction term between time and stay-at-home dummy variable; X equals covariates of average daily precipitation and average daily maximum temperature, population offset equal to the log transformation of daily VMT and with a log link function. Time, average daily precipitation and average daily maximum temperature were modelled as continuous variables. β_2, or the stay-at-home order dummy variable, represents the step change estimate, or the incidence rate ratio (IRR), of MVCs, comparing the pre-stay-at-home to post-stay-at-home order. β_3, or the interaction between time and the stay-at-home dummy variable, represents the slope change in MVC incidence following COVID-19's stay-at-home order. For all models, we specified robust SEs, or Huber-White (Robust) Sandwich Estimators, to account for possible variance heteroskedasticity producing more conservative estimates of model SEs.[20]

We assessed the impact of COVID-19's stay-at-home order in two ways. First, we assessed the *within year* change associated with the stay-at-home order in the years 2017, 2018, 2019, and 2020. This analysis provided the change in expected MVC rates associated with the stay-at-home order during the 2020 COVID-19 outbreak and also provided placebo years to test whether similar reductions in MVC rates existed in past years. In this analysis, MVC outcomes were treated separately for each year, providing 48 separate models (12 each in 2017, 2018, 2019 and 2020). We additionally conducted a sensitivity analysis wherein we modelled the impact of the stay-at-home order to begin 16 March, a week prior to its enactment.

We further assessed the impact of CT's stay-at-home order by comparing the *between year* crash rates during the post-stay-at-home period. This analysis provided evidence as to whether MVC rates seen in 2020 during the post-stay-at-home period were unique compared with previous years during the same time frame. In this analysis, we expressed time as consecutive integers representing the number of days from the first day of the year, starting with 1, or 1 January in each year, and ending with 120, or 30 April in each year (29 February 2020 was excluded to maintain commonality in number of days). The model then excluded integers 1–81, or 1 January to 22 March, to compare the similar time range of post-stay-at-home order between years. The model excluded the interaction term between time and the presence of the stay-at-home order as it is all during the post-stay-at-home period. For each outcome, we created a dichotomous indicator variable where 2017, 2018 and 2019 were equal to '0', and 2020 was equal to '1', which compared crash rates during the post-stay-at-home period in 2020 to the average crash rates from 2017, 2018 and 2019 during the same time period.

All analyses were conducted in Stata, V.15.0.[21] No patients or members of the public were involved in the design and conduct of this research.

RESULTS

The impact of COVID-19's stay-at-home order on VMT was significant. Figure 1 displays daily VMT represented as 3-day moving averages, from 1 January to 30 April for all years considered. The years 2017, 2018, 2019 and 2020 had similar daily VMT during the pre-stay-at-home period of time, from 1 January to 22 March. During the post-stay-at-home order period, VMT for years 2017, 2018 and 2019 continued on a slightly upward trajectory, while the VMT for 2020 drastically dropped off, and settled on a new slope. In 2020, average daily VMT changes from 18.05 per 10 million VMT to 10.23 per 10 million VMT (p value <0.001), a 43% decrease (table 1).

Within 2020, there were significant reductions in the number of total crashes and the average number of daily crashes from the pre-stay-at-home to post-stay-at-home order periods (table 1); the average number of daily crashes was around 54.9% lower in the post-stay-at-home period (115.6) than the pre-stay-at-home period (256.4). However, different trends were present among different crash types. For injury and non-injury crashes, there were significant differences in both total crashes and average

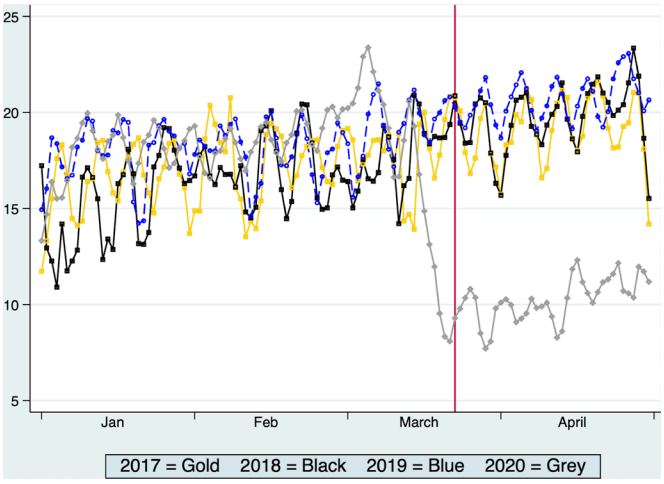

Figure 1 Daily vehicle miles travelled estimates per 100 million in Connecticut, January–April 2017–2020.

daily crashes between the pre-stay-at-home and post-stay-at-home periods. Fatal crashes, however, did not change significantly, despite a significant decrease in VMT.

Table 2 presents the *within* year comparison of the impact of the stay-at-home order associated with the COVID-19 pandemic using 2020 as actual data and 2017, 2018 and 2019 as comparison years, wherein they were treated as if a stay-at-home order was issued on 23 March 2017, 2018 and 2019. Within 2020, there were no changes in the incidence rates of all type crashes, any injury crashes and non-injury crashes from the pre-stay-at-home to post-stay-at-home period. However, crash rates for all crash types involving single vehicles increased 2.29 times (95% CI 1.32 to 3.99), any injury single vehicle crash rate increased 1.76 times (95% CI 1.11 to 2.79) and non-injury single vehicle crash rate increased 2.55 times (95% CI 1.38 to 4.69). Crash rates for all crash types involving multiple vehicles decreased significantly, except for fatal crashes. The expected rates of fatal single vehicle crashes increased 4.10 times (95% CI 1.06 to 15.86). The expected rates of all type, any injury and non-injury multiple vehicle crashes all significantly declined around 20% in the post-stay-at-home period. Slope changes in the post-stay-at-home period were non-significant. Online supplemental figures S1–S12 provide images of the within year differences for each of the 12 MVC outcomes.

We observed different patterns between the pre-stay-at-home and post-stay-at-home periods of the comparison years; in 2019, only one outcome decreased in the post-stay-at-home period. Non-injury multiple vehicle crash incidence decreased 29% (IRR=0.71, 95% CI 0.51 to 0.99); no outcomes changed in the post-stay-at-home period in 2018; and all type and non-injury multiple vehicle crash rates decreased in 2017 in the post-stay-at-home period. Notably, unlike 2020, neither 2017, 2018 or 2019 had significant increases in any crash rates.

Sensitivity analysis of impact of stay-at-home order on MVC in 2020 (online supplemental table 1) indicates that the impact of the gubernatorial order may have started ahead of its effective date. The 1 week lead model showed similar patterns of significant impact across outcomes except for single vehicle fatal crashes. Importantly, almost all significant effect size in the sensitivity analysis were smaller than the *within year* analysis, indicating that the stay-at-home order likely exacerbated existing MVC patterns.

Table 3 provides between year comparisons of the post-stay-at-home period crash rates associated with COVID-19 in 2020 compared with the average crash rates from 2017, 2018 and 2019. Crash rates in 2020 were significantly different than the average of the previous 3 years for almost all outcomes. In 2020, compared with the average of the previous 3 years, there were significantly lower all type crash rates for all outcomes except fatal crashes, significantly lower multiple vehicle crash rates for all outcomes except for fatal crashes and significantly greater single vehicle crash incidence for all outcomes. Single vehicle fatal crash rates were 2.35 times greater than expected comparing 2020 with the average of 2017, 2018 and 2019 during the post-stay-at-home time period.

Table 1 Total counts and mean daily counts of MVCs, comparing pre-stay-at-home to post-stay-at-home order stratified by crash type and number of vehicles, 2020

	2020						
	Pre-stay-at-home		Post-stay-at-home				Difference, mean daily counts
Outcome models	Total counts	Mean daily counts	Total counts	Mean daily counts	Per cent change, total counts	Per cent change, mean daily counts	P value
All type crashes	21 026	256.4	4509	115.61	−78	−54.9	**<0.000**
Single	3866	47.1	1400	35.89	−63	−23.9	**0.013**
Multiple	17 160	209.2	3109	79.7	−81	−61.9	**<0.000**
Any injury crash	4859	59.2	1108	28.4	−77	−52	**<0.000**
Single	1172	14.2	397	10.1	−66	−28.8	**<0.000**
Multiple	3687	44.9	711	18.2	−80	−59.5	**<0.000**
Non-injury crash	16 120	196.5	3380	86.6	−79	−55.9	**<0.000**
Single	2666	32.5	990	25.3	−62	−21.9	0.056
Multiple	13 454	164.07	2390	61.2	−82	−62.6	**<0.000**
Fatal crash	47	0.573	21	0.538	−55	−6.1	0.801
Single	28	0.341	13	0.333	−54	−2.4	0.942
Multiple	19	0.231	8	0.205	−57	−11.5	0.756
Vehicle miles travelled	–	18.01	–	10.23	–	−43	**<0.000**

T-test for statistical independence used for p values. Preperiod from 1 January to 22 March; postperiod from 23 March to 23 April 30. Vehicle miles travelled presented per 100 million VMT. Single refers to single vehicle crash; multiple refers to MVC.
Bold Values note statistical significance <=0.05.

Table 2 Impact of COVID-19 on MVCs stratified by number of vehicles included in crash, comparison within years 2018–2020

	2020			2019			2018			2017		
Outcome models	Step change IRR	Slope change	P value	Step change IRR	Slope change	P value	Step change IRR	Slope change	P value	Step change IRR	Slope change	P value
All type crashes	1.08 (0.84 to 1.41)	0.99 (0.99 to 1.00)	0.52	0.91 (0.81 to 1.03)	1.00 (0.99 to 1.00)	0.148	1.06 (0.86 to 1.29)	1.01 (1.00 to 1.02)	0.56	0.87 (0.74 to 1.02)	1.01 (1.00 to 1.02)	0.09
Single	**2.29** (**1.32 to 3.99**)	0.98 (0.97 to 1,00)	<0.01	0.77 (0.60 to 0.88)	0.99 (0.99 to 1.00)	0.08	0.87 (0.54 to 1.34)	1.01 (1.00 to 1.02)	0.55	1.01 (0.71 to 1.44)	1.02 (1.01 to 1.04)	0.95
Multiple	**0.83** (**0.71 to 0.95**)	1.00 (0.99 to 1.01)	0.01	0.95 (0.84 to 1.07)	1.00 (0.99 to 1.00)	0.43	1.11 (0.92 to 1.32)	1.00 (1.00 to 1.01)	0.25	**0.84** (**0.73 to 0.97**	1.00 (1.00 to 1.02)	0.01
Any injury crash	1.03 (0.79 to 1.35)	0.99 (0.98 to 1.00)	0.79	0.98 (0.86 to 1.11)	1.00 (0.99 to 1.00)	0.78	1.00 (0.83 to 1.22)	1.00 (1.00 to 1.01)	0.93	0.92 (0.78 to 1.07)	1.00 (0.99 to 1.01)	0.29
Single	**1.76** (**1.11 to 2.79**)	0.98 (0.98 to 1.00)	0.02	0.95 (0.72 to 1.25)	0.99 (0.99 to 1.00)	0.74	0.81 (0.61 to 1.07)	1.01 (1.00 to 1.02)	0.14	1.13 (0.83 to 1.55)	1.01 (0.99 to 1.02)	0.42
Multiple	**0.79** (**0.63 to 0.98**)	1.00 (0.99 to 1.01)	**0.04**	0.98 (0.85 to 1.14)	1.00 (0.99 to 1.01)	0.87	1.08 (0.87 to 1.32)	1.00 (0.99 to 1.01)	0.50	0.86 (0.74 to 1.01)	1.00 (0.99 to 1.01)	0.07
Non-injury crash	1.10 (0.84 to 1.43)	0.99 (0.98 to 1.00)	0.47	0.89 (0.79 to 1.01)	1.00 (0.99 to 1.00)	0.09	1.07 (0.86 to 1.33)	1.00 (1.00 to 1.01)	0.49	0.85 (0.72 to 1.01)	1.01 (1.00 to 1.02)	0.08
Single	**2.55** (**1.38 to 4.69**)	0.98 (0.96 to 1.00)	<0.01	**0.71** (**0.51 to 0.99**)	0.99 (0.97 to 1.00)	0.04	0.89 (0.50 to 1.57)	1.01 (0.99 to 1.02)	0.69	0.96 (0.64 to 1.44)	1.02 (1.01 to 1.04)	0.86
Multiple	**0.84** (**0.72 to 0.97**)	1.00 (0.99 to 1.00)	0.01	0.94 (0.82 to 1.06)	1.00 (0.99 to 1.00)	0.34	1.12 (0.93 to 1.34)	1.00 (1.00 to 1.01)	0.22	**0.83** (**0.72 to 0.97**)	1.00 (1.00 to 1.01)	0.02
Fatal crash	2.17 (0.68 to 6.89)	1.01 (0.97 to 1.04)	**0.18**	0.93 (0.29 to 2.93)	0.99 (0.95 to 1.04)	0.91	0.79 (0.26 to 2.41)	1.03 (0.99 to 1.06)	0.69	1.37 (0.50 to 3.77)	1.00 (0.60 to 1.04)	0.53
Single	**4.10** (**1.06 to 15.86**)	1.01 (0.96 to 1.06)	**0.04**	0.73 (0.16 to 3.32)	0.99 (0.93 to 1.05)	0.68	1.28 (0.27 to 6.08)	1.03 (0.98 to 1.08)	0.75	1.67 (0.38 to 7.42)	0.99 (0.94 to 1.05)	0.49
Multiple	0.84 (0.11 to 6.02)	1.01 (0.95 to 1.08)	0.86	1.22 (0.18 to 7.96)	1.00 (0.93 to 1.08)	0.83	0.52 (0.12 to 2.25)	1.02 (0.97 to 1.07)	0.38	1.10 (0.27 to 4.37)	1.00 (0.95 to 1.06)	0.887

Model specified a Poisson distribution of the outcome with a log transformed VMT as population offset. Robust SEs were specified for a more conservative estimate of coefficients. Models include linear time, average daily precipitation and average daily highest recorded temperature. Years 2019 and 2018 are provided as comparison for 2020 and are thus comparison units of measure. Post-stay-at-home period is 23 March–30 April.
Bold Values note statistical significance <=0.05.
IRR, incidence rate ratio; VMT, vehicle miles travelled.

Table 3 Differences in MVCs stratified by number of vehicles included in crash during post-stay-at-home order, comparisons between 2020 and average of 2019, 2018 and 2017

	Post-stay-at-home order-2020 compared with average of 2019, 2018 and 2017		
Outcome models	**Incidence rate ratio (IRR)**	**95% CI**	**P value**
All type crashes	**0.80**	(0.73 to 0.88)	<0.00
Single	**1.47**	(1.20 to 1.82)	0.00
Multiple	**0.66**	(0.62 to 0.71)	0.00
Any injury crash	**0.83**	(0.74 to 0.91)	0.00
Single	**1.34**	(1.13 to 1.59)	0.00
Multiple	**0.68**	(0.61 to 0.75)	0.00
Non-injury crash	**0.79**	(0.72 to 0.87)	0.00
Single	**1.52**	(1.20 to 1.92)	0.00
Multiple	**0.66**	(0.61 to 0.70)	0.00
Fatal crash	1.66	(0.97 to 2.84)	0.06
Single	**2.35**	(1.19 to 4.64)	0.01
Multiple	1.08	(0.68 to 2.42)	0.84

Model specified a Poisson distribution of the outcome with a log transformed VMT as population offset. Robust SEs were specified for a more conservative estimate of coefficients. Model includes linear time, average daily precipitation and average daily highest recorded temperature. Comparison during post-stay-at-home order (order effective in Connecticut on 23 March 2020). VMT, vehicle miles travelled.
Bold Values note statistical significance <=0.05.

DISCUSSION

This examination provides evidence of the impact of the COVID-19 stay-at-home order on MVCs in Connecticut. It is the first such examination that has included daily counts and a daily measure of crash exposure risk, in the form of daily VMT, which is essential for understanding the true change in MVCs associated with COVID-19. Our descriptive analysis found similar reductions in VMT and the number of MVC compared with previous reports on the impact of stay-at-home orders.[5 6] However, after accounting for crash exposure risk, we identified that single vehicle crashes and fatal crashes saw greater rates in the post-stay-at-home period while multiple vehicle crashes saw lower rates.

The impact of the COVID-19 stay-at-home order on MVCs in Connecticut was heterogeneous across crash types. The expected rates of single vehicle crashes—whether they be injurious, non-injurious or fatal—increased, while the expected rates of injurious and non-injurious multiple vehicle crashes decreased. Notably, the rate of single vehicle, fatal crashes increased 4.10 times in the stay-at-home time period in 2020. The same time periods in 2017, 2018 and 2019 did not have similar increases.

Media reports suggest a decrease in traffic volume accompanied by an increase in the proportion of drivers speeding on the roads in Connecticut when comparing the pre-stay-at-home to post-stay-at-home periods.[7] We hypothesise that the increase in single vehicle crashes is due in part to increased driving speed associated with decreased traffic volume and reduced police presence.[8 9] In addition, our hypothesis is supported by existing empirical research on the perceptual and cognitive processes implicated in motor vehicle operation,[22 23] which suggests that decreased traffic volume is likely to result in increased speeding,[24] and potentially other risky driving behaviours. Multiple vehicle crashes may have decreased as a function of less vehicles operating on roadways; this is logical as the overall, injurious, non-injurious and fatal crash rates did not significantly change in the post-stay-at-home period. This implies that the types of crashes were altered by the traffic circumstances, as the overall crash rates were not significantly different.

Notably, we tested to see if crash rates seen from 23 March to 30 April 2020 were significantly different from previous years during the same time (table 3). Results indicate that the increases in single vehicle crashes and the reductions in multiple vehicle crashes seen in 2020 are likely wholly due to COVID-19, as 2020 crash rates were significantly different than the average of the previous 3 years. This suggests that the effects produced by the stay-at-home order on crash rates in 2020 (table 2) was likely solely due to changes in traffic circumstances associated with the gubernatorial policy.

The findings presented here are likely generalisable to states that experienced similar changes in VMT and traffic circumstances associated with stay-at-home orders. As previous reports noted that VMT decreased in the initial weeks of stay-at-home orders throughout the USA,[5] there is reason to suspect similar changes in crash rates were seen in other states.

Future research on the impact of COVID-19 should attempt to elucidate why single vehicle crashes increased during the post-stay-at-home period and multiple vehicle crashes reduced. Researchers should attempt to understand how low traffic volume conditions affected drivers' visual information, perceptions of speed and safety and appropriateness of driving behaviour, all likely explanations of why the impact of COVID-19 on MVC was heterogenous by crash types. It is known that traffic calming measures lead to speed reductions[25] and examining how these strategies could be temporarily implemented in similar emergencies could lead to a reduction in crashes. To better prepare for additional COVID-19 waves where stay-at-home orders may again be necessary, as well as future epidemics, it is imperative to understand the behavioural aspects of why some types of vehicle crashes increased and why others did not in order to prevent traffic crashes and deaths. Additionally, future research should examine medium and long-term VMT and MVC trends related to stay-at-home orders to fully understand their ramifications.

Limitations

Our research is not without limitations. There is a low probability that we have misspecified our MVC outcome models. The CTCDR uses law enforcement officer reports to categorise MVCs by severity, and all officers in the state are trained on proper data collection techniques and provided additional

training when necessary. Additionally, if anecdotal reports of lowered police presence are correct, it is possible that our MVC outcomes are under-reported, as the lowered presence could correspond to less reported crashes. The use of StreetLight Insight data to provide estimates of VMT is relatively new and as such potentially serves as a source of bias. Despite its proprietary uses, there is limited peer-reviewed literature that uses StreetLight Insight data to measure traffic patterns.[26] However, reports that have examined the impact of COVID-19 on vehicle traffic cite StreetLight data as their source of daily VMT estimates.[5]

Conclusion

COVID-19's impact on the world, and on the USA, has been devastating. It is a public health crisis unlike any other, and the true negative population health ramifications will continue to be discovered for years to come. Evidence presented here suggests that despite drops in the total counts and mean daily counts of crashes during the post-stay-at-home period in Connecticut, there were significant increases in single vehicle crashes and fatal crashes after accounting for changes in VMT as well as weather conditions.

What is already known on the subject

- ► During state-issued stay-at-home periods associated with the SARS-CoV-2 (COVID-19) pandemic, motor vehicle traffic reduced significantly within the USA.

What this study adds

- ► This study accounts for daily MVCs as well as daily estimates of vehicle miles travelled allowing for an estimation of crash rates in the State of Connecticut.
- ► Despite reductions in motor vehicle traffic, the incidence rate of single vehicle crashes increased nearly twofold (incidence rate ratio=1.96; 95% CI 1.47 to 2.62) comparing the pre-stay-at-home to-post-stay-at-home order in Connecticut.

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Contributors All authors conceived of the study. MLD, AT and MEA coordinated data acquisition. MLD designed the study's statistical approach and performed the data analysis. MLD, AT, MEA, AW, KB and CG contributed to an initial manuscript draft. All authors provided substantive feedback on all manuscript drafts. GL provided senior author leadership in study design and statistical decision making.

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Patient consent for publication Not required.

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Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data may be obtained from a third party and are not publicly available. MVC data from the Connecticut Transportation Safety Research Center are publicly available (https://www.ctcrash.uconn.edu). Data pertaining to estimated daily vehicle miles traveled were accessed through the company StreetLight Data under a licensed agreement and are not available upon request per agreement.

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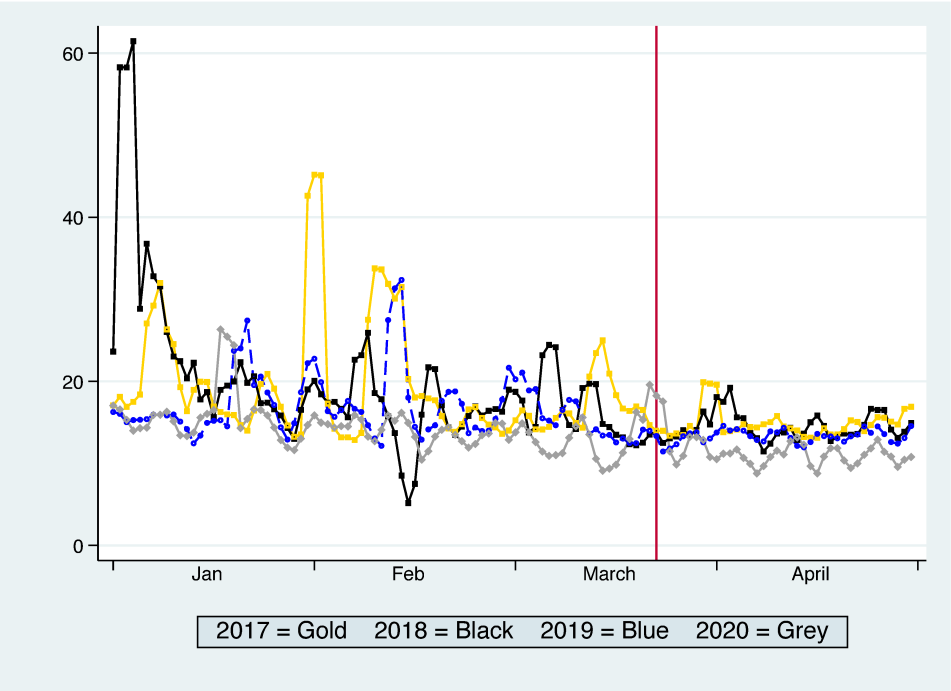
Supplemental Material

Table S1. Impact of COVID-19 on Motor Vehicle Crashes Stratified by Number of Vehicles Included in Crash, Sensitivity Analysis for Stay-at-Home order in 2020

Outcome Models	Incidence Rate Ratio (IRR)	95% Confidence Interval (CI)	P-value
All Type Crashes	1.04	(0.86, 1.26)	0.64
Single Vehicle	**2.09**	(1.41, 3.09)	<0.01
Multiple Vehicle	**0.84**	(0.72, 0.97)	0.02
Any Injury Crash	1.00	(0.81, 1.25)	0.95
Single Vehicle	**1.66**	(1.16, 2.36)	<0.01
Multiple Vehicle	**0.81**	(0.66, 0.98)	0.03
Non-Injury Crash	1.05	(0.87, 1.27)	0.55
Single Vehicle	**2.32**	(1.50, 3.58)	<0.01
Multiple Vehicle	**0.85**	(0.73, 0.99)	0.03
Fatal Crash	1.28	(0.46, 3.52)	0.62
Single Vehicle	1.79	(0.50, 6.34)	0.37
Multiple Vehicle	0.78	(0.16, 3.79	0.76

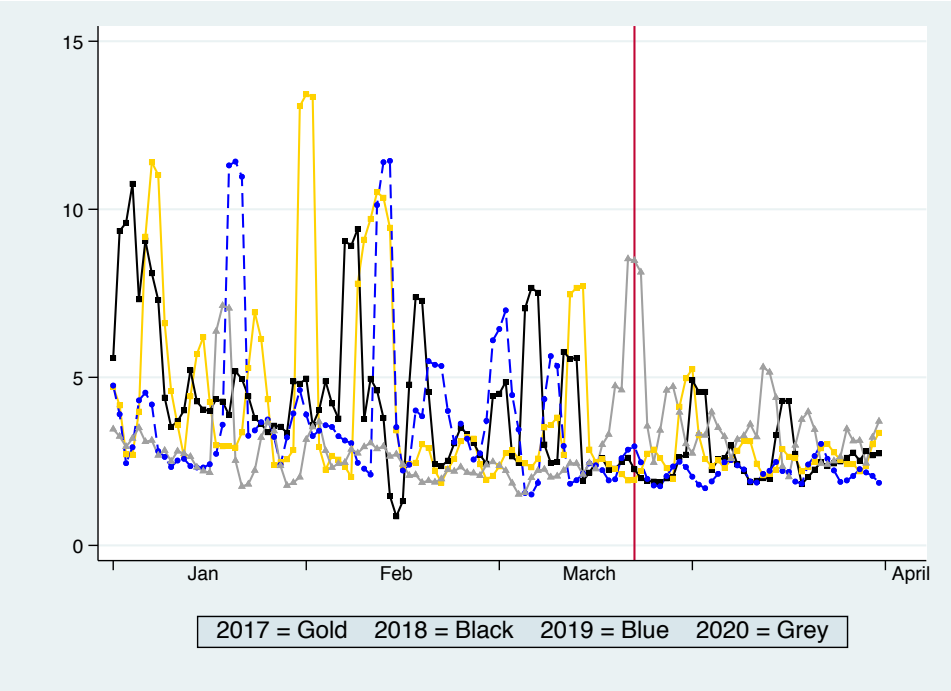
Model specified a Poisson distribution of the outcome with a log transformed VMT as population offset. Robust standard errors were specified for a more conservative estimate of coefficients. Model includes linear time, average daily precipitation and average daily highest recorded temperature. Model only includes data from 2020. Stay-at-home order starts on March 16th instead of the actual date March 23rd to test impact.

Figure S1. Daily Rates of All Type Crashes per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



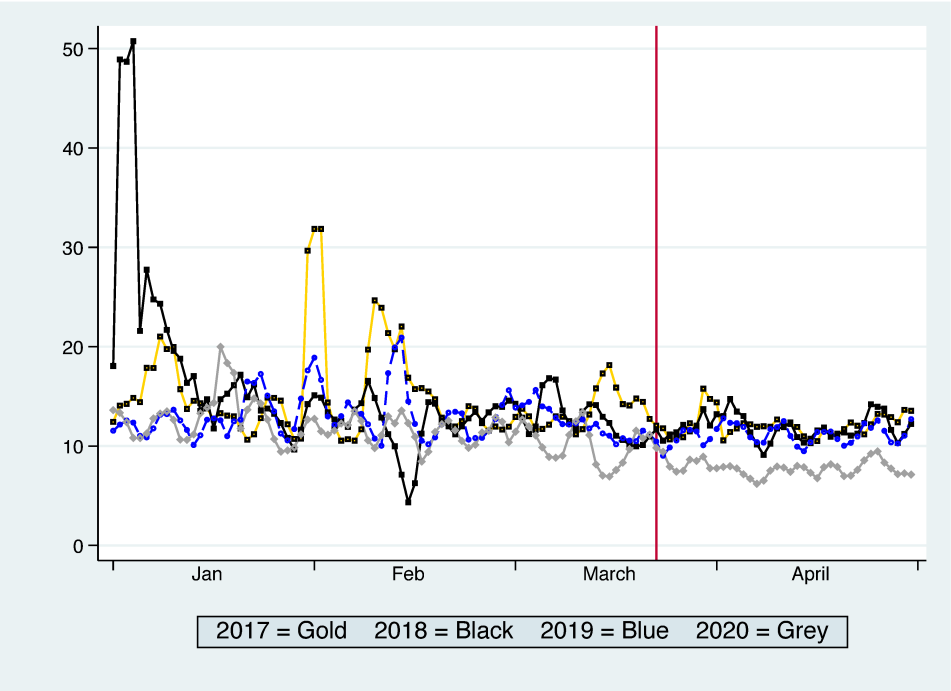
*Three-day Moving Average

Figure S2. Daily Rates of All Type Crashes, Single Vehicle per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



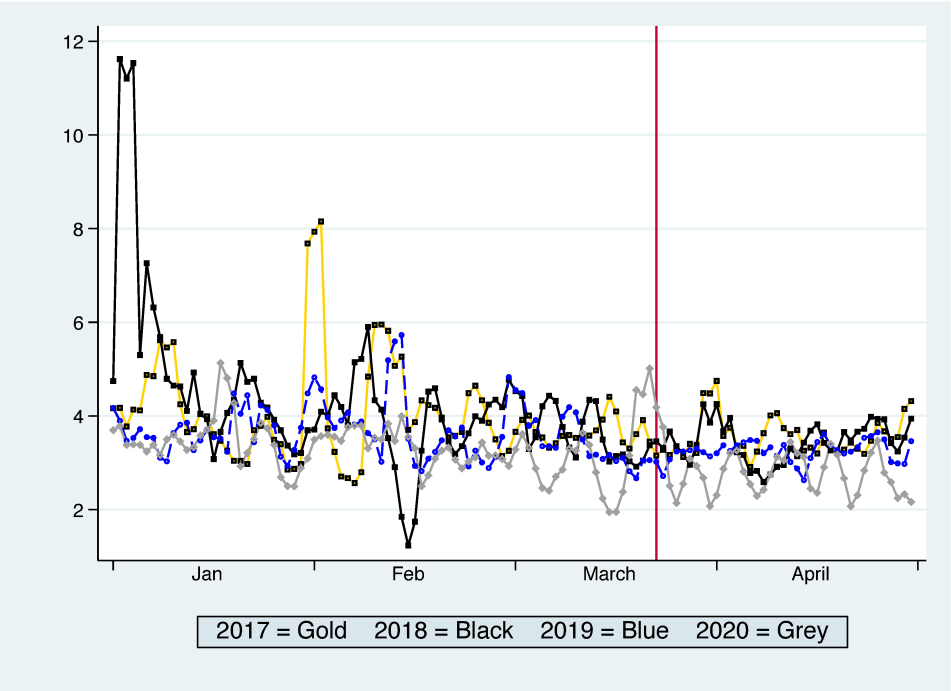
*Three-day Moving Average

Figure S3, Daily Rates of All Type Crashes, Multiple Car per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



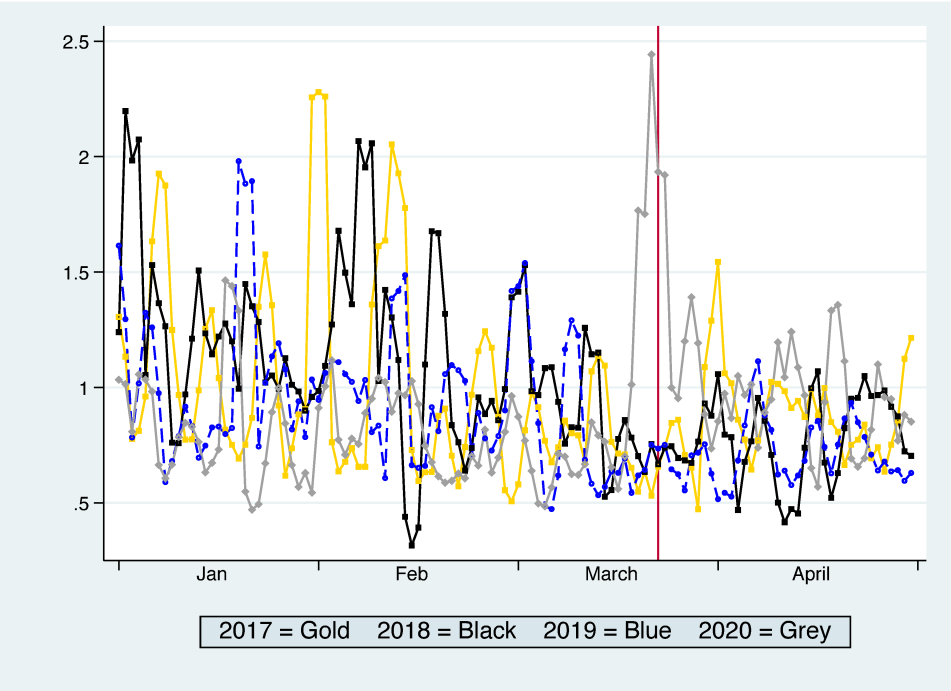
*Three-day Moving Average

Figure S4, Daily Rates of Any Injury Crashes per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



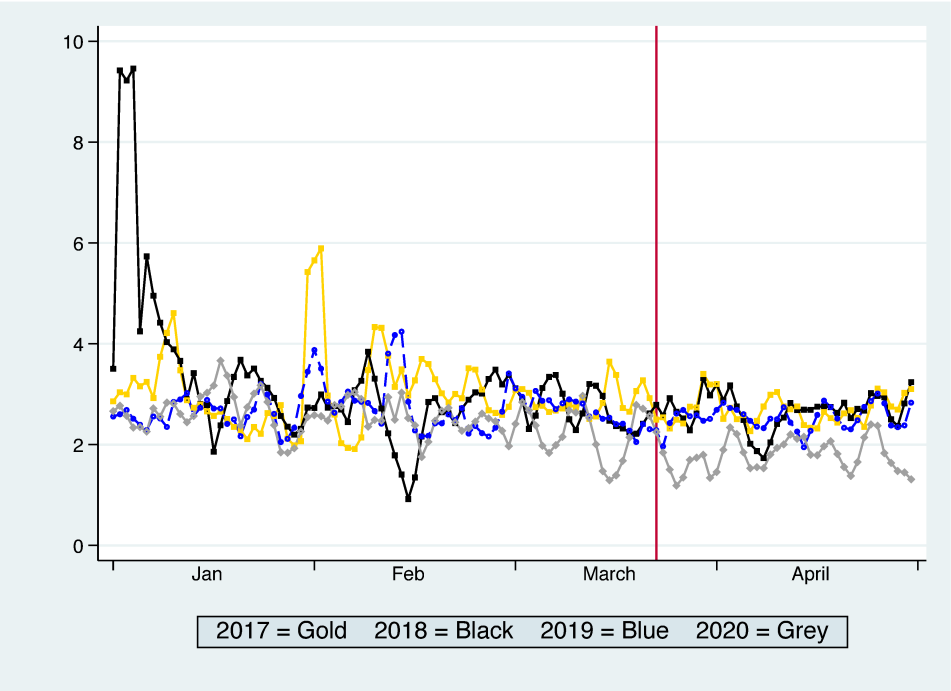
*Three-day Moving Average

Figure S5, Daily Rates of Any Injury Crashes, Single Vehicle per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



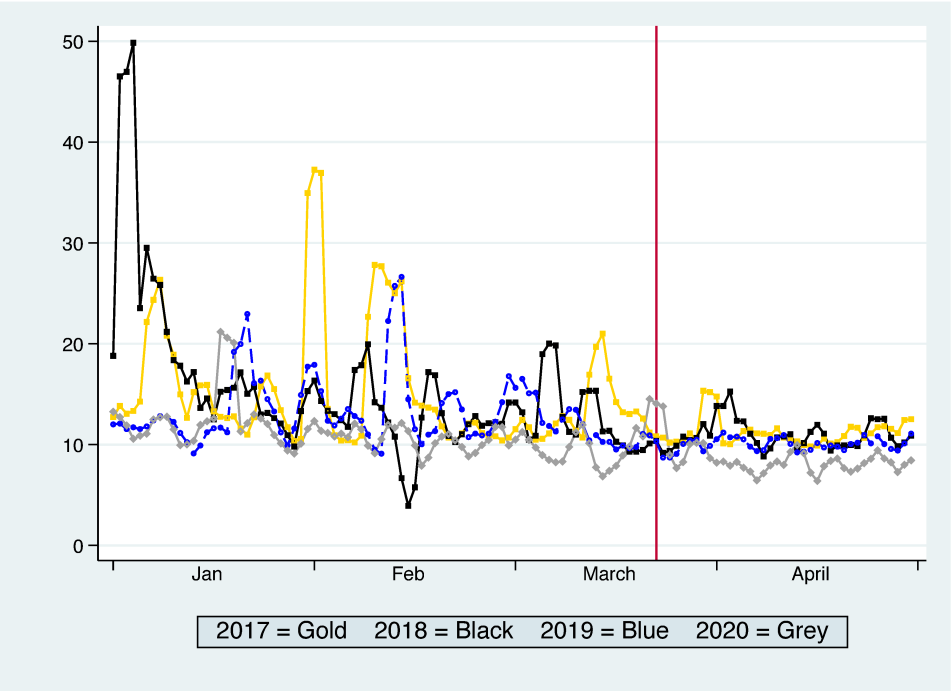
*Three-day Moving Average

Figure S6, Daily Rates of Any Injury Crashes, Multiple Vehicle per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



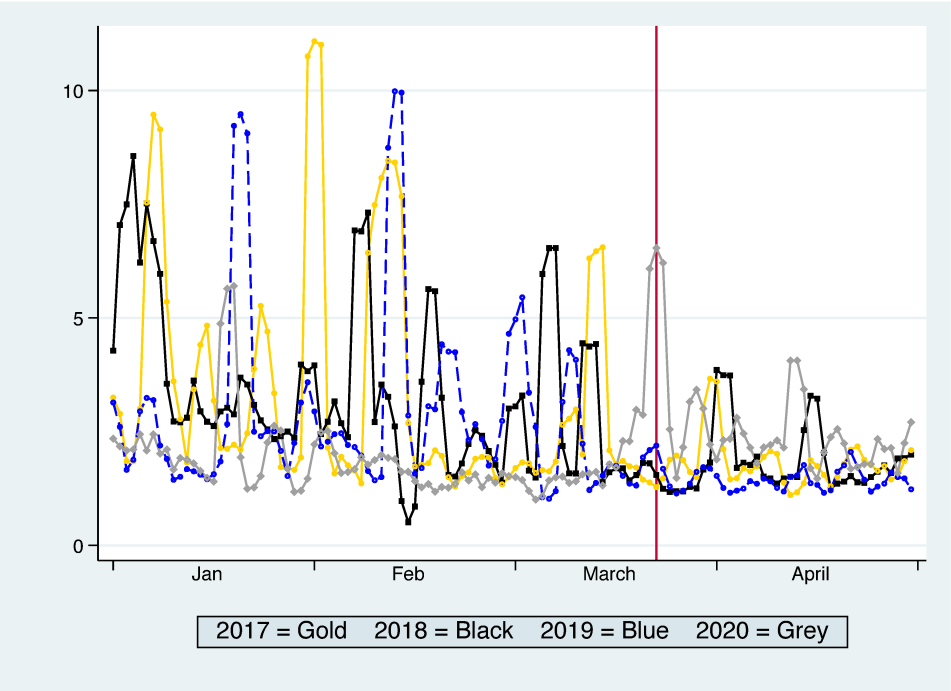
*Three-day Moving Average

Figure S7, Daily Rates of No Injury Crashes per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



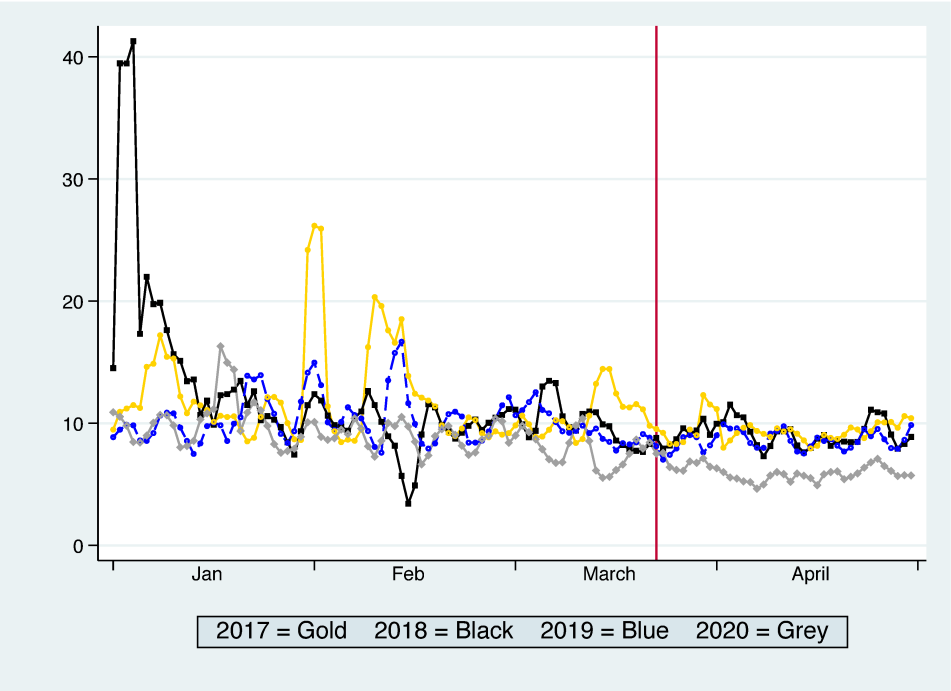
*Three-day Moving Average

Figure S8, Daily Rates of No Injury Crashes, Single Vehicle per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



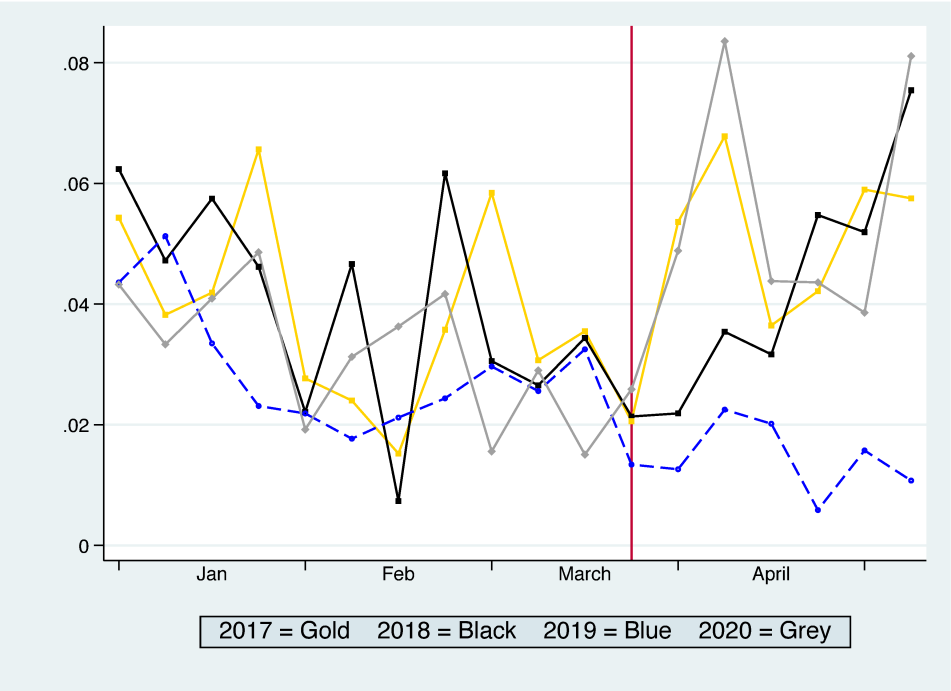
*Three-day Moving Average

Figure S9, Daily Rates of No Injury Crashes, Multiple Vehicle per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



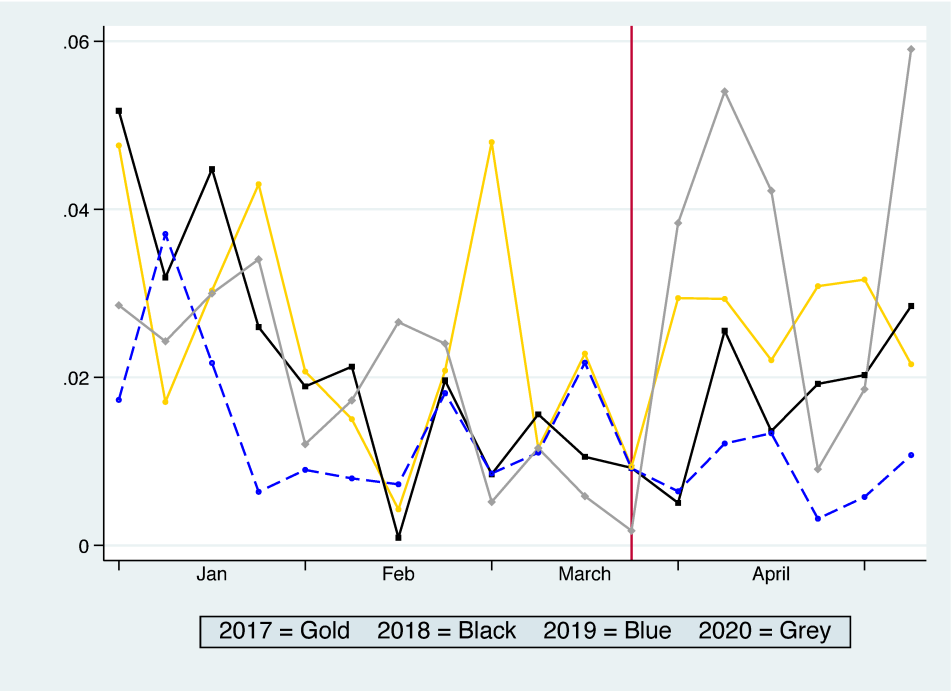
*Three-day Moving Average

Figure S10, Weekly Rates of Fatal Crashes per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



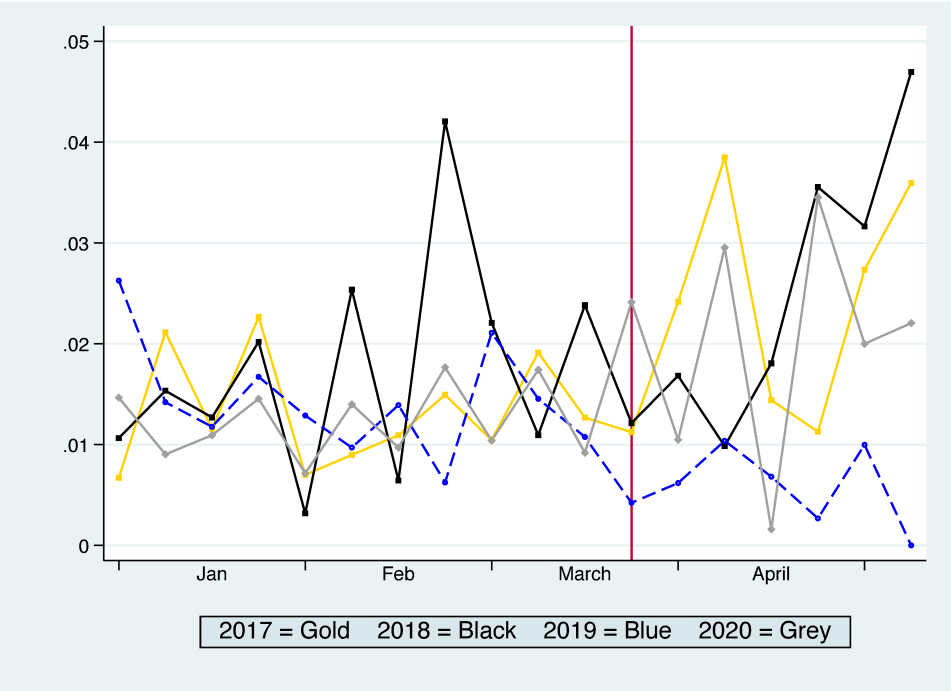
*Seven-day Moving Average

Figure S11, Weekly Rates of Fatal, Single Vehicle Crashes per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



*Seven-day Moving Average

Figure S12, Weekly Rates of Fatal, Multiple Vehicle Crashes per 10 Million Vehicle Miles Traveled in Connecticut, 2020-2017



*Seven-day Moving Average