Effect of political ideology, stay-at-home rates, and increased risk taking in Ohio drivers during COVID-19 shutdown

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Abstract

In response to COVID-19, Ohio, along with many other states, enacted a stay-at-home order in March to limit the spread of the pandemic. Crashes appear to have fallen as people stayed home, but fatal crashes did not. We investigated whether increases in speeding, alcohol use, or drug use could have taken place to offset the reduction in traffic. In addition, we examined whether support for President Trump would relate to both stay-at-home compliance and rates of crashes. Stay-at-home compliance predicted lower overall crash rate, particularly for less severe crashes, but not for fatal crashes. We did not find evidence that speeding or drug-related crashes increased during the stay-at-home order, but percentage of speed-related crashes was higher in areas with greater stay-at-home compliance. Alcohol-related crashes were involved in a greater proportion of crashes during the shutdown, and as they are more severe, may explain why fatal crashes did not fall. Support for President Trump was related to lower stay-at-home compliance and increased percentage of alcohol-related crashes controlling for median income, rurality, and Appalachian region. The combination of rejection of recommendations from public health officials and increased rates of alcohol-related crashes may put a particular burden on Republicans.

Keywords: Motor vehicle crashes; alcohol use, drug use, speeding, COVID-19, social distancing, political ideology

INTRODUCTION

Effects of COVID-19 shutdown on traffic and crashes

To limit the spread of COVID-19, most US states enacted stay-at-home orders [1] that markedly reduced traffic [2]. This has given researchers the opportunity to examine the effect of a drastic reduction in traffic on crashes. The link between increased traffic (e.g., on holidays) and increased crashes [3-4], suggests that this reduced traffic should have resulted in reduced crashes and fatalities.

However, this expected benefit in reduction in traffic deaths did not materialize. Analyses conducted by the National Police Foundation report decreased crashes in Florida, Iowa, Ohio, Massachusetts, and Missouri in the months of March and April but also find increases in the fatality of those crashes during the same time period [5]. Similarly, the North Carolina Department of Transportation shows fewer total crashes during their shutdown but no decline in fatal crashes [6]. It appears that drivers remaining on the roads have engaged in more reckless driving, such as extreme speeds [7], which has resulted in some states (e.g., Minnesota) experiencing an increase in crashes and fatalities despite the reduction in traffic.

While speeding is one reason for the lack of a reduction in crashes, there are others. During March and April, Americans consumed more alcohol [8-9]. This is not surprising given that the use of alcohol and drugs to relieve mental health symptoms is fairly common [10-11], and large numbers of Americans are experiencing increased anxiety and depressive symptoms, particularly in areas that have been impacted more [12,13]. It seems very likely that consumption of other mind-altering substances, like marijuana and opioids, could have increased as well. There is an abundance of evidence that alcohol has deleterious effects on driving, even at very low levels [14-15]. Drug use, especially marijuana, has also been linked to worse driving outcomes [16-18]. Thus, even as traffic decreased, increased substance use may have contributed to more serious crashes. However, this possibility has not yet been confirmed.

Politically divided response to COVID-19

The response to COVID-19 in the United States has been starkly divided along ideological groups. Political ideology is an important part of identity and encompasses broad worldviews that inform more basic motivations [19] and moral values [20]. While liberals tend to prefer less social hierarchy and are excited by new experiences, conservatives tend to value loyalty to their ingroups and authority figures and prefer stable, familiar experiences [21,22]. The loyalty to authority figures in particular is likely responsible for the outsize effect that President Trump's statements have had on perceptions of COVID-19 among Republicans.

With respect to COVID-19, Republicans perceive less risk due to COVID-19 and are more likely to believe that the pandemic is a hoax [23], and approval of President Trump drives the relationship between ideology and risk perceptions [24]. Support for and compliance with distancing behaviors are also strongly divided along party lines, with Democrats indicating greater support for distancing measures and complying with them at greater rates than Republicans [25]. These studies suggest that responses to COVID-19 relate to political party per se, rather than confounding factors such as population density (as more dense areas are both more liberal and have been more impacted by COVID-19). As COVID-19 spreads, the lack of compliance with necessary safety precautions puts Republican areas at increased risk for COVID-19, but could also erode the potential benefit of lowered traffic. Areas with less support for President Trump may enjoy greater compliance with stay-at-home orders and lower crash rates relative to areas that support President Trump more.

Current study

In the current study, we examined Ohio crash rates and compliance with the stay-at-home order in March and April. Like other states, Ohio's traffic also declined during its shutdown [26,27], and speeding increased during this time in at least part of Ohio [28]. On March 23, a stay-at-home order went into effect ordering Ohioans to stay at home unless they were engaged in an essential activity [29]. We expected that:

Hypothesis 1: More people would stay at home in mid-March and April, as had been observed in other states and data sets [1-2, 26-27, 29].

We also expected to find a reduction in crashes in response to the order, but we also divided the crashes by severity to determine whether less-serious injury crashes, crashes in which someone was killed or seriously injured (KSI), or property-damage-only (PDO) crashes declined. KSI crashes were not expected to decline, consistent with other analyses [5,6], perhaps due to increased reckless behavior [7-9, 28]. We also wanted to rule out the possibility that the decline in crashes was really a decline in the reporting of crashes, perhaps due to people being hesitant to call officers if they had violated the stay-at-home order or officers only responding on scene to more serious accidents. However, if minor-injury crashes also decreased, it would suggest that the decline reflected actual rates of crashes rather than simply reporting. Thus, we tested:

Hypothesis 2: Crash rates would decline during March and April, but this would be limited to PDO and minor-injury crashes, and not KSI crashes.

Furthermore, we expected to find that stay-at-home compliance directly related to these crash rates, which would be consistent with studies linking volume of traffic and crashes [3,4]:

Hypothesis 3: Greater percent of people staying home would be associated with lower crash rates.

Because of the increased speeding and consumption of alcohol during the pandemic [7-9, 28], we also expected that:

Hypothesis 4: Speeding-related, alcohol-related, and drug-related crashes would make up a larger proportion of total crashes in March and April.

Ohio tends to be a battle ground state. In 2016, over 5 million Ohioans (71% of registered voters) voted in the Presidential election, and 51% of them voted for President Trump. Counties ranged from 31 to 81% voting in favor of President Trump [31]. Ideology, and support for President Trump in particular has been linked to lower risk perceptions and protective behaviors [23-25], so we expected that:

Hypothesis 5: Support for President Trump would predict lower stay-at-home compliance.

Finally, because of the effect of compliance on crash rates, we predicted that:

Hypothesis 6: Support for President Trump would be associated with higher crash rates, due to the lower stay-at-home compliance.

In addition, we examined whether the proportions of crashes might be related to three other variables related to the impact of COVID-19. The first is rurality. Urban areas support President Trump less, have more cases than rural areas, and more ability to stay closer to home than people in rural areas, so we expected rural areas to stay home less. In addition, crashes in rural counties will be further from hospitals on average than crashes in urban centers, which could make fatalities more likely. Second, we examined income. Income may mitigate the impact of COVID-19 on economic and health outcomes, so we expected that income might reduce the proportion of drug- and alcohol-related crashes. Finally, we included Appalachian region. Thirty-two of Ohio's eighty-eight counties are considered part of Appalachia by the Appalachian Regional Commission [32]. Counties in Appalachian Ohio tend to have lower income, higher poverty, and lower educational attainment [33]. Appalachian Ohio has worse health outcomes than non-Appalachian Ohio, including higher rates of drug use, but less excessive drinking [34]. Because of the possibility of greater economic and health impacts on Appalachia in particular, we thought that alcohol and drug-related crashes may be disproportionately high for that region. Including these variables was also important to help us distinguish between the effects of support for President Trump versus potential confounds, such as county level of objective COVID-19 risk and impact.

METHOD

Scope of data

Because of variation over the course of a week (e.g., more traffic on weekdays), and the availability of data (e.g., cellphone mobility data were collapsed by week [30]), analyses were conducted on 10 weeks of data from March 2nd – May 10th

Week 1: Mar 2 – Mar 8

Week 2: Mar 9 – Mar 15

Week 3: Mar 16 – Mar 22

Week 4: Mar 23 – Mar 29

Week 5: Mar 30 – Apr 5

Week 6: Apr 6 – Apr 12

Week 7: Apr 13 – Apr 19

Week 8: Apr 20 – Apr 26

Week 9: Apr 27 – May 3

Week 10: May 4 – May 10

Additionally, percent of residents staying at home, median income, population, percent rural, and percent voting for Trump were available by county, so data were aggregated by county by week.

Sources of data

Crash data

We obtained crash data from the Ohio Department of Public Safety portal [35] and aggregated the data by week and by county. Data included information about the severity of crashes and whether they involved several factors, such as speeding, drug use, and alcohol use. Because counties with lower population would experience lower absolute numbers of crashes, we calculated the rates of crashes per ten thousand population using U.S. Census Data [36]. Some counties did not experience any crashes in a week, with the highest rate being nearly 7 crashes per ten thousand population in a given week ($M=2.45$, $SD=1.15$). Around 75% of the crashes were PDO and <1% were KSI crashes. We utilized both number of crashes per week and percent of crashes per week due to speeding (range= 0 – 100%, $M=14.81$, $SD=13.22$), alcohol (range= 0 – 100%, $M=5.64$, $SD=8.41$), and drugs (range= 0 – 100%, $M=3.09$, $SD=7.03$).

Stay-at-home compliance

To estimate compliance with the stay-at-home order, we utilized a publicly available dataset from Cuebiq [30]. Cuebiq uses cellphone mobility data to estimate percentage of a county staying home during a week. Aggregated mobility data is provided by Cuebiq, a location intelligence and measurement platform. Through its Data for Good program, Cuebiq provides access to aggregated mobility data for academic research and humanitarian initiatives. This first-party data is collected from anonymized users who have opted-in to provide access to their location data anonymously, through a GDPR-compliant framework. It is then aggregated to the county level to provide insights on changes in human mobility over time. We verified that these data were correlated with a data set of traffic data obtained from the Ohio Department of Transportation Office, Technical Services, Traffic Monitoring Section. However, because several counties were not included in the traffic monitoring data, we used the Cuebiq data in order to utilize data for all Ohio counties. Compliance was a proportion ranging from 0-1 (range= 0.31 – 0.53, $M=0.35$ (0.08), with greater numbers indicating greater compliance.

Support for President Trump

Support for President Trump was the percent of voters in a county who voted for Trump in the 2016 Presidential election [31]. The data are publicly available and were accessed from the Ohio Secretary of State website. Support was a proportion ranging from 0-1, with greater numbers indicating greater support (range = 0.31 – 0.81, $M=0.65$, $SD=0.11$).

County rurality

County rurality was the proportion of the population living in rural areas as of the 2010 Census [31]. The rurality could range from 0 to 1, with greater numbers indicating more rural residents (range=0.01 – 1.00, $M=0.48$, $SD=0.25$).

Median income

Median household income was in 2018 inflation-adjusted dollars and was obtained from the U.S. Census data portal [36]. Incomes ranged from \$36,894 to \$104,322 ($M=\$53,751$, $SD=\$10,585$). To make the coefficients easier to interpret, we converted raw income to income in tens of thousands (i.e., by dividing by 10,000).

Appalachian county

Thirty-two of Ohio's eighty-eight counties are considered part of Appalachia by the Appalachian Regional Commission [32]. These counties were coded as a 1; non-Appalachian counties were coded as 0. This allowed region to be analogous to the other county-level variables, as the proportion of Appalachian county residents living in Appalachia is 1.

Analysis strategy

We conducted analyses on overall crash rates and crash rates by severity. Then, to see if certain types of crashes increased, we conducted parallel sets of analyses on the percentage of weekly crashes related to speeding, alcohol, drugs, and motorcycle.

We started with mixed models to test for linear and curvilinear effects of week. The analyses used to determine the effect of support for President Trump, stay-at-home compliance, rurality, income, and Appalachian region were conducted using generalized estimating equations (GEE) with identity link functions and week and stay-at-home compliance entered as within-subjects variables. Nonsignificant effects were removed one at a time. Because we were treating counties as observations with 10 repeated measures, we estimated our power based on RMANOVA with one group and 10 measurements, a correlation of .5 among measures, .95 power, and .05 alpha. To a within-group effect (e.g., of week) of size = .25, we would need a sample of 29 and for .15 effect size, we would need sample = 62. For between-factors effects (e.g., support for President Trump), we required $N = 24$ for .25 effect size and 60 for a .15 effect size. Thus, we concluded we would have sufficient power for our analyses.

Additionally, we conducted mediational analyses to determine whether support for President Trump indirectly predicted increased crash rates via lowered stay-home compliance. We conducted mediation analyses using PROCESS within each week. The indirect effect of support for President Trump on crash rates was estimated using bootstrapping with 10,000 resamples.

RESULTS

Compliance with stay-at-home order

Percent of people staying at home was strongly affected by week (**Figure 1**). The percentage of people staying at home increased over the ten weeks, $b(se) = 12.10 (0.20)$, $p < .001$, and there was a curvilinear effect of week such that staying home peaked in late March and fell for the remainder of the weeks we examined, $b(se) = -0.85 (0.02)$, $p < .001$. In addition to the effect of week, county characteristics also predicted likelihood of staying home. As expected, percent of people staying home was lower for more rural (vs. urban) counties, $b(se) = -0.03 (0.01)$, $p = .007$ and counties with more Trump voters, $b(se) = -0.13 (0.02)$, $p < .001$. Counties with higher median incomes were more likely to stay home, $b(se) = 0.01 (0.002)$, $p < .001$. Appalachian region was not retained as a predictor ($p > .90$).

Figure 1. Percent of Ohioans staying home by county by week in March and April, adjusted for population. The start of the stay-at-home order, March 23, is indicated by a black line.

Overall crash rate

As expected, we found that crashes fell during the first weeks of March but began to increase again throughout April (**Figure 2**). Both a linear effect of week, $b(\text{se}) = -0.93 (0.06)$, $p < .001$ and a curvilinear effect of week, $b(\text{se}) = 0.06 (0.005)$, $p < .001$ were significant. GEE showed that in addition to the effect of week, counties with a lower proportion of people staying at home had more crashes, $b(\text{se}) = -11.56 (2.33)$, $p < .001$, and more rural counties had a lower rate of crashes, $b(\text{se}) = -1.38 (0.42)$, $p = .001$. Support for President Trump, median income, and Appalachian region were not retained in the final model.

Figure 2. Overall crash rate in Ohio per week in March and April, adjusted for population. The start of the stay-at-home order, March 23, is indicated by a black line.

Exploratory mediation analysis

Our expectation that support for President Trump would lead to greater crashes (due to lack of compliance) was not supported in our overall analyses on crash rates. However, the strong effect of stay-

at-home compliance could have reduced any effect of ideology to non-significance, as would be the case if the effect of ideology was fully mediated by stay-at home compliance. We also controlled for the rurality of the county, as it was a significant predictor of crash rates.

In the first week of March, support for President Trump did not relate to compliance with the stay-at-home order, but every week after that (see **Table 1**), increased support for President Trump was associated with lower compliance with the stay-at-home order. Rurality had parallel independent effects on staying at home in Week 2 through Week 9. Crash rates were not consistently predicted by either support for President Trump or rurality, but in Weeks 3-10, greater compliance with the stay-at-home order predicted lower crash rates, and there were significant indirect effects of support for President Trump on crash rates through compliance with the stay-at-home order.

Table 1. Mediation analysis for ideology, stay-at-home compliance, and crashes per 10,000 population by week. Results for direct effects are reported as unstandardized betas with standard errors in parentheses; results for indirect effects are reported as 95% confidence intervals. * $p < .05$ ** $p < .01$

	Direct effect of Trump support on compliance	Direct effect of rurality on compliance	Direct effect of compliance on crash rate	Direct effect of Trump support on crash rate	Direct effect of rurality on crash rate	Indirect effect of ideology on crash rate with 95% CI
Mar 2 – Mar 8	–0.03 (0.02)	0.01 (0.01)	–4.55 (8.07)	–0.32 (1.63)	–1.80 (0.70)*	0.13 (–0.33, 1.76)
Mar 9 – Mar 15	–0.05 (0.02)**	0.01 (0.01)	–10.16 (8.37)	–1.69 (1.58)	–1.00 (0.66)	0.50 (–0.08, 1.74)
Mar 16 – Mar 22	–0.10 (0.03)**	–0.04 (0.01)**	–15.30 (5.64)**	–0.88 (1.67)	–1.18 (0.71)	1.59 (0.38, 3.53)
Mar 23 – Mar 29	–0.08 (0.04)**	–0.08 (0.02)**	–12.11 (3.51)**	–1.19 (1.18)	–0.81 (0.56)	1.00 (0.38, 1.99)
Mar 30 – Apr 5	–0.10 (0.03)**	–0.08 (0.01)**	–10.48 (4.04)*	–0.82 (1.30)	–1.06 (0.63)	1.00 (0.41, 1.93)
Apr 6 – Apr 12	–0.12 (0.03)**	–0.07 (0.01)**	–11.78 (3.98)**	–0.78 (1.30)	–1.33 (0.60)*	1.32 (0.54, 2.57)
Apr 13 – Apr 19	–0.11 (0.04)**	–0.08 (0.02)**	–11.39 (3.60)**	–3.52 (1.23)**	–0.28 (0.57)	1.23 (0.52, 2.22)
Apr 20 – Apr 26	–0.13 (0.03)**	–0.07 (0.01)**	–14.65 (4.80)**	–2.41 (1.55)	–0.58 (0.70)	1.85 (0.69, 3.48)
Apr 27 – May 3	–0.13 (0.03)**	–0.05 (0.01)**	–15.99 (5.46)**	–4.48 (1.78)*	–0.13 (0.76)	2.12 (0.85, 4.09)
May 4 – May 10	–0.11 (0.03)**	–0.06 (0.01)**	–16.88 (6.67)*	–1.54 (1.82)	–1.54 (0.81)	1.82 (0.34, 3.59)

Crashes by severity

The decline in crashes was due primarily to a decline in property-damage-only (PDO) crashes (**Figure 3**). Both a linear decrease, $b(se) = -0.71 (0.05)$, $p < .001$, and a curvilinear effect, $b(se) = 0.05 (0.004)$, $p < .001$, were observed for PDO crashes. Crashes in which an injury was either possible or minor showed the same pattern and were combined into a category for ease of presentation. For these minor injury crashes, both the linear decrease, $b(se) = -0.21 (0.02)$, $p < .001$, and curvilinear pattern, $b(se) = 0.01 (0.002)$, $p < .001$ were smaller than the effect found for PDO crashes. For crashes in which someone was killed or seriously injured (KSI), rates did not change over time, either analyzed as individual categories or combined (p 's $> .50$).

The rate of KSI crashes adjusted for population was very slightly greater for more rural counties, $b(se) = 0.02 (0.004)$, $p = .001$. The effects of stay-at-home compliance and support for President Trump were also very small and did not reach significance, $b(se) = -0.01 (0.01)$, $p = .052$ and $b(se) = -0.02 (0.01)$, $p = .053$, respectively. Income level and Appalachian region did not predict KSI crashes (p 's $> .60$).

Independent of the effect of week, counties with lower rates of minor or possible injury crashes had greater stay-at-home compliance, $b(se) = -3.18 (0.64)$, $p < .001$, and lower support for President

Trump, $b(se) = -1.10 (0.22)$, $p < .001$. Income level, Appalachian region, and rurality did not predict minor/possible injury crash rates ($p's > .20$).

In addition to the effects of week on PDO crashes, counties with lower rates of PDO crashes had higher stay-at-home compliance, $b(se) = -9.33 (1.74)$, $p < .001$, and rurality, $b(se) = -1.23 (0.29)$, $p < .001$. Appalachian region, support for President Trump, and income were not retained as predictors ($p's > .20$).

Figure 3. Crashes per 10,000 population by severity. For ease of presentation, fatal and serious-injury suspected were combined into “killed or seriously injured” (KSI). Minor injury or possible injury were combined into “injury.” PDO = Property damage only. The start of the stay-at-home order is indicated by the black line.

Exploratory mediation analysis on accidents by severity

As with the overall crash rate, we conducted additional mediational analyses on crashes divided by severity. For KSI crashes, there were no direct or indirect effects of support for President Trump or compliance with the stay-at-home order on the weekly rate of crashes. For minor injury accidents, the stronger effects of compliance on the crash rate were the week prior to the stay at home order and the first four weeks of the order. During those weeks, counties with higher support for President Trump were indirectly more likely to have increased crashes, due to the lower proportion of the population staying home (Table 2). Given the huge proportion of crashes that PDO crashes contribute to the overall crash rate, it is not surprising that the results for PDO crashes were nearly identical to the overall crash rate; in Weeks 3-10, greater compliance with the stay-at-home order predicted lower crash rates, and there were significant indirect effects of support for President Trump on crash rates through compliance with the stay-at-home order. (Table 3).

Table 2. Mediation analysis for ideology, stay-at-home compliance, and minor injury crashes per 10,000 population by week. Results for direct effects are reported as unstandardized betas with standard errors in parentheses; results for indirect effects are reported as 95% confidence intervals. * $p < .05$ ** $p < .01$

	Direct effect of Trump support on compliance	Direct effect of rurality on compliance	Direct effect of compliance on crash rate	Direct effect of Trump support on crash rate	Direct effect of rurality on crash rate	Indirect effect of ideology on crash rate with 95% CI
Mar 2 – Mar 8	–0.03 (0.02)	0.01 (0.01)	–0.97 (2.91)	–0.89 (0.59)	–0.14 (0.25)	0.03 (–0.16, 0.57)
Mar 9 – Mar 15	–0.05 (0.02)*	0.01 (0.01)	1.05 (3.27)	–1.55 (0.62)*	0.01 (0.26)	–0.05 (–0.40, 0.18)

Mar 16 –	–0.10 (0.03)**	–0.04 (0.01)**	–4.75 (2.31)*	–0.72 (0.69)	–0.14 (0.29)	0.49 (0.08, 1.19)
Mar 22						
Mar 23 –	–0.08 (0.04)*	–0.08 (0.02)**	–2.36 (1.28)	–0.78 (0.43)	0.03 (0.21)	0.19 (0.01, 0.51)
Mar 29						
Mar 30 –	–0.10 (0.03)**	–0.08 (0.01)**	–2.83 (1.62)	–1.2 (0.52)*	0.04 (0.25)	0.27 (0.03, 0.65)
Apr 5						
Apr 6 –	–0.12 (0.03)**	–0.07 (0.01)**	–4.51 (1.33)	0.73 (0.44)	–0.48 (0.2)	0.52 (0.26, 0.87)
Apr 12						
Apr 13 –	–0.11 (0.04)**	–0.08 (0.02)**	–4.40 (1.36)	–1.50 (0.46)	0.08 (0.22)	0.48 (0.19, .91)
Apr 19						
Apr 20 –	–0.13 (0.03)**	–0.07 (0.01)**	–3.12 (1.91)	–1.35 (0.61)*	0.13 (0.28)	0.39 (–0.04, 0.93)
Apr 26						
Apr 27 –	–0.13 (0.03)**	–0.05 (0.01)**	–0.64 (1.92)	–1.55 (0.63)	0.56 (0.27)*	0.08 (–0.34, 0.53)
May 3						
May 4 –	–0.11 (0.03)**	–0.06 (0.01)**	–1.81 (2.37)	–0.73 (0.65)	0.14 (0.29)	0.19 (–0.41, 0.75)
May 10						

Table 3. Mediation analysis for ideology, stay-at-home compliance, and PDO crashes per 10,000 population by week. Results for direct effects are reported as unstandardized betas with standard errors in parentheses; results for indirect effects are reported as 95% confidence intervals. * $p < .05$ ** $p < .01$

	Direct effect of Trump support on compliance	Direct effect of rurality on compliance	Direct effect of compliance on crash rate	Direct effect of Trump support on crash rate	Direct effect of rurality on crash rate	Indirect effect of ideology on crash rate with 95% CI
Mar 2 –	–0.03 (0.02)	0.01 (0.01)	–3.18 (6.93)	0.91 (1.4)	–1.88 (0.6)**	0.09 (–0.29, 1.29)
Mar 8						
Mar 9 –	–0.05 (0.02)*	0.01 (0.01)	–8.43 (6.98)	0.17 (1.32)	–1.24 (0.55)*	0.42 (–0.11, 1.48)
Mar 15						
Mar 16 –	–0.10 (0.03)**	–0.04 (0.01)**	–11.22 (4.21)**	–0.08 (1.25)	–1.23 (0.53)*	1.17 (0.24, 2.65)
Mar 22						
Mar 23 –	–0.08 (0.04)*	–0.08 (0.02)**	–9.81 (3.29)**	–0.53 (1.11)	–0.84 (0.53)	0.81 (0.27, 1.74)
Mar 29						
Mar 30 –	–0.10 (0.03)**	–0.08 (0.01)**	–7.21 (2.97)*	0.70 (0.96)	–1.31 (0.46)**	0.69 (0.24, 1.37)
Apr 5						
Apr 6 –	–0.12 (0.03)**	–0.07 (0.01)**	–7.51 (3.41)*	–0.27 (1.11)	–0.87 (0.51)	0.87 (0.23, 1.8)
Apr 12						
Apr 13 –	–0.11 (0.04)**	–0.08 (0.02)**	–6.87 (2.98)*	–1.72 (1.01)	–0.54 (0.47)	0.74 (0.21, 1.47)
Apr 19						
Apr 20 –	–0.13 (0.03)**	–0.07 (0.01)**	–10.08 (3.66)**	–0.75 (1.18)	–0.75 (0.53)	1.27 (0.45, 2.35)
Apr 26						
Apr 27 –	–0.13 (0.03)**	–0.05 (0.01)**	–15.35 (4.59)**	–2.50 (1.50)	–1.03 (0.64)	2.03 (0.86, 3.86)
May 3						
May 4 –	–0.11 (0.03)**	–0.06 (0.01)**	–13.29 (5.59)*	–0.60 (1.52)	–1.57 (0.68)*	1.43 (0.24, 2.84)
May 10						

Speeding-related crashes

Despite the increased speed reported in some areas of the state, overall, the percentage of speed-related crashes did not change during the shut-down, according to our analyses. Neither the linear effect, $b(se) = 0.23 (0.14)$, $p = .107$, nor curvilinear effect of week, $b(se) = -.10 (0.06)$, $p = .098$, reached significance. Interestingly, Appalachian counties and counties with greater compliance to the stay-at-home order had a greater percentage of speed-related crashes, $b(se) = 6.35 (1.60)$, $p < .001$, $b(se) = 12.41 (4.86)$, $p = .011$, respectively. Support for President Trump, income, and rurality were not significant predictors (p 's $> .20$).

Drug-related crashes

Although an increase in the rate of drug-related crashes during the shutdown would be consistent with the self-medication hypothesis [10], proportion of drug-related crashes also remained stable over the shutdown. Neither a linear nor curvilinear effect of week was found on the proportion of drug-related

crashes ($p's > .40$). The only significant predictors of a county having higher percentage of drug-related crashes was being an Appalachian county, $b(se)=2.45 (0.56)$, $p<.001$ and having a higher median income, $b(se)= 0.36 (0.17)$, $p=.033$. All other predictors were not significant ($p's > .20$).

Alcohol-related crashes

In contrast to speeding-related and drug-related crashes, it appears that alcohol was a factor in a greater proportion of crashes over the course of the shutdown, $b(se)=1.10 (0.31)$, $p<.001$, and that the rate was at its peak towards the middle of the shutdown and lower in early March and late May, $b(se)= -0.10 (0.02)$, $p<.001$. The only predictor besides week was support for President Trump. Counties with greater support for President Trump had a greater percentage of alcohol-related crashes, $b(se)= 6.49 (2.15)$, $p=.003$ (all other effects $p's > .50$).

DISCUSSION

Ohioans largely complied with the stay-at-home order, with the highest compliance in its first week. Interestingly, people had already begun to stay home before the order, perhaps due to school closings and changes to work arrangements. Ohio's crash rates did decline briefly in April and March, closely mirroring the stay-at-home compliance rates, but only for less serious crashes and crashes not involving fatal or serious injuries. These results are consistent with our expectations based on analyses conducted on overall and fatal crashes [5-6], but include new analyses showing a small decline for injury-related crashes.

Crash rate reduction was greater when stay-at-home compliance was higher for the overall crash rate, PDO crashes, and possible or minor injury crashes. However, stay-at-home compliance did not predict a decline in more serious crashes. This could be due to the relative rarity of severe crashes even aggregated to the county level. Most counties have two or fewer crashes per week, so it may be difficult to detect a difference in serious crashes given their infrequency. However, other analyses using more data (and thus higher power) also failed to detect a reduction in serious crashes [5]. For the more frequent crashes, however, it is clear that stay-at-home compliance was associated with fewer crashes.

Political ideology, as indicated by a county's level support for President Trump, was indirectly associated with more crashes via lower stay-at-home compliance beginning in mid-March, even before the stay-at-home order was enacted. As expected, the extent to which a county's residents had voted for President Trump, the less they complied with the stay-at-home order, over and above an effect of rurality, which is consistent with a lack of compliance due to lack of support for the order rather than a lack of compliance due to necessity (those in rural areas may be less able to stay home). It appears that support for Trump also had direct effects in the direction of reducing crashes, although these were not consistent across weeks when controlling for rurality. In contrast, the indirect effects of ideology on crash rate were larger and consistent throughout the study period. This indirect effect was strongest for PDO crashes. For minor injury crashes, the indirect effect only occurred during the weeks that had the highest number of people staying home. For the more serious KSI crashes, neither support for President Trump nor stay-at-home compliance predicted crashes.

For PDO crashes, effects of week remained (Wald $\chi^2(9)=23.24$, $p=.006$) even after controlling for stay-at-home compliance (and rurality), which suggests that additional factors contributed to the lowered crash rate. Lack of reporting may be one factor, but there may be others. For minor or possible injury crashes, the effect of week was not significant (Wald $\chi^2(9)=16.49$, $p=.057$) when included with stay-at-home compliance and support for President Trump, which suggests that the effect of week was mostly due to those two variables. We did not find the expected effects that stay-at-home compliance and support for President Trump significantly predicted KSI rates, but rurality did, which may be related to distance from hospitals.

It is unclear why speed-related crashes did not increase over the shutdown given the reports of greater speeding [28]. It could be that speeding did not increase enough to impact crashes or that only some areas observed increased speeding. Our analyses point to the Appalachian region and counties with greater compliance as two strong possibilities for the areas that observed increased speeding. Appalachian

counties had a greater percentage of speed-related crashes, although this could be a stable effect of having lower traffic and not due to COVID-19. Speeding-related crashes made up a greater percentage of crashes in counties that were more compliant with the stay-at-home order. It could be that in those counties, people were taking advantage of empty roads with disastrous results, as some have speculated [7]. This possibility may also explain why stay-at-home compliance was not associated with a reduction in more serious crashes, because these counties may have had fewer crashes overall, but the drivers remaining on the road were driving more dangerously and getting into more serious crashes.

Alcohol, but not drugs, was a factor in a greater percentage of crashes during the shutdown. Alcohol-related crashes (like speeding-related crashes) tend to be more severe [15], so this may explain why the reduction in traffic during the COVID-19 shutdown did not translate into lower rates of serious crashes. Because alcohol consumption has been linked to poorer mental health, this finding also suggests that counties with higher Trump support may have been experiencing poorer mental health during the shutdown.

Researchers should look for additional evidence of the disparate impact of COVID-19 on stress and mental health in Republicans. As cases spread, these counties may experience greater direct effects of COVID-19 burden from increased number of cases due to lack of compliance, but the lack of compliance also predicted greater numbers of crashes, albeit less serious ones. The combination of rejection of recommendations from public health officials and increased rates of alcohol-related crashes in particular may put a burden on areas with more Republicans. Rates of alcohol-related crashes should also continue to be monitored closely, even as states reopen and the need for distancing (hopefully) recedes. Past pandemics and other large-scale disasters have produced months of increased drinking, thus we may expect a rebound effect of traffic deaths if drinking levels remain elevated in reaction to the COVID-19 pandemic but traffic increases [38, 39].

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