Ironic effects of political ideology and increased risk-taking in Ohio drivers during COVID-19 shutdown

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Abstract

Introduction. In March, Ohio, along with many other states, enacted a stay-at home order in to limit the spread of COVID-19. As a result, lower traffic should have reduced crashes. However, increased speeding and alcohol consumption may have increased serious crashes. We investigated whether crash rates declined in Ohio during the stay-at-home order and explore possible reasons for the decrease, such as reduced travel in compliance with the stay-at-home order, speeding, alcohol, and drug use. In addition, ideological differences have emerged in terms of COVID-19 that could also influence staying at home; we further examined whether support for President Trump would relate to stay-at-home compliance and crashes.

Method. We compiled a set of publicly available crash data and cellphone mobility data over a 22-week period from March-August 2020, controlling for crash rates from the previous five years. Crash data included severity of the crash and whether the crash was speeding-, alcohol-, or drug-related.

Results. Total and minor crashes fell as people stayed home, but serious crashes did not. Percentage of alcohol-related crashes increased, and percentage of speed-related crashes was higher in areas with lower travel. This may explain why rates of serious crashes did not fall. Support for President Trump predicted greater of crashes (of all types) through travel as a mediator, even while controlling for county-level income, rurality, and Appalachian region. This mediated effect was even greater during the weeks of the stay-at-home order.

Conclusions. The shutdown had the counterintuitive effect of reducing total and less crashes while having no noticeable effect on serious ones. Instead, and perhaps tellingly, it had the effect of increasing the proportion of alcohol related crashes. In addition, responses to COVID-19 were divided by political ideology, including greater travel and thus lower compliance with stay-at-home orders in areas with greater support for President Trump.

Practical Applications. Results suggest that stay-at-home orders in response to COVID-19 may have had indirect benefits to traffic crashes, but reduced compliance in Republican areas limited those benefits. Researchers should study the effects of political ideology on responses to public health or safety communications.

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 in early 2020 [1] that markedly reduced traffic [2]. This gave researchers the opportunity to examine the effect of a drastic reduction in traffic on crashes. The strong link between increased traffic and crashes [3-4] suggests that this reduced traffic should have resulted in reduced crashes and fatalities. In one of the first places hit by the pandemic, New York City, the higher unemployment rates predicted fewer people involved in crashes [5].

However, this expected benefit in reduction in traffic deaths did not materialize. A report by NHTSA found that despite a 13.2% decline in miles driven, deaths increased by 7.2% over 2019. 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 period [6]. Similarly, the North Carolina Department of Transportation shows fewer total crashes during their shutdown but no decline in fatal crashes [7], and the same was found in Connecticut [8]. It should be the case that if this decline was due to reduced traffic, we will find a link between greater travel after the issuance of stay-at-home orders and crash rates, although the reduction was not expected for more serious crashes, based on these earlier analyses.

Hypothesis 1: Percent of people staying home would be associated with lower crash rates, particularly minor crashes.

It appears that those drivers who remained on the roads post-shutdown engaged in more reckless driving, such as extreme speeds [9], which resulted in some states (e.g., Minnesota) experiencing an increase in crashes and fatalities despite the reduction in traffic. Indeed, more recent research found that seeing fewer fellow drivers than normal may have reduced the perceived risk of speeding and made the task of driving more "boring" without higher speeds. [10]. While speeding is one reason for the lack of a reduction in crashes, there are others.

During March and April, Americans consumed more alcohol [11-12]. This is not surprising given that the use of alcohol and drugs to relieve mental health symptoms is common [13-14], and large numbers of Americans experienced increased anxiety and depressive symptoms, particularly in areas that have been impacted more [15,16]. 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 [17-19]. Drug use, especially marijuana, has also been linked to worse driving outcomes [20-21]. Thus, even as traffic decreased, increased substance use may have contributed to more serious crashes. However, this possibility has not yet been confirmed, so we tested the hypothesis that:

Hypothesis 2: Speeding-related, alcohol-related, and drug-related crashes would make up a larger proportion of total crashes in March and April.

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 [22] and moral values [23]. 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 [24,25]. The loyalty to authority figures in particular may be responsible for the outsized effect that President Trump's statements in 2020 had on perceptions of COVID-19 among Republicans.

With respect to COVID-19, Republicans perceive less risk due to COVID-19 and were more likely to believe that the pandemic is a hoax [26], and approval of President Trump drove the relationship between ideology and risk perceptions [27]. Support for and compliance with distancing behaviors to stop the spread of the virus were also strongly divided along party lines, with Democrats indicating greater support for distancing measures and complying with them at greater rates than Republicans [28]. Political differences also extended into driving behavior: Controlling for population density, areas that voted for President Trump in 2016 engaged in less physical distancing [29] and greater mobility [30]. These studies suggest that responses to COVID-19 related 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 spread, the lack of compliance with necessary safety precautions put Republican areas at increased risk for COVID-19 and threatened to erode the potential benefit of lowered traffic. Thus, we expected to find that:

Hypothesis 3: Support for President Trump would predict lower stay-at-home compliance, which would in turn predict higher crash rates.

Method

In the current study, we chiefly study crash rates by severity and travel frequency from cellphone data. The latter was used to estimate compliance with the stay-at-home order in March and April. Like other states, Ohio’s traffic declined during its shutdown [31,32], and speeding increased during this time in at least part of Ohio [33]. 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 [34]. 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 22 weeks of data from March 3rd to August 2nd. Percent of residents travelling, support for President Trump and covariates (i.e., median income, rurality, and Appalachian region, see Supplement 1) were available by county, so data were aggregated by county by week.

Crash data

We obtained crash data for 2015 through 2020 from the Ohio Department of Public Safety portal [35]. The averages from those five years before 2020 were then retained and controlled for as a covariate in each analysis involving crash rates, so that we could be more confident our results were not simply due to natural variation. (See Supplement 2.) Crashes were classified by severity into five categories which we reduce to three for simplicity of analysis. The crash types were property damage only (PDO), "minor injury," "possible injury," "serious-injury-suspected," and "fatal." For simplicity in our analysis, "fatal" and "serious-injury-suspected" were combined into "killed or seriously injured" (KSI). "Minor injury" and "possible injury" were combined into "injury." Most (71.3%) of the crashes were PDO, 25.2% were Injury, and the remaining 3.4% were KSI crashes.

Data also 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 over 9 crashes per ten thousand population (M=3.94, SD=1.18 in 2020). We also analyzed number of crashes per week and percent of crashes per week due to speeding, alcohol, and drugs. For each week in our analysis, we were thus able to analyze the proportion of each crash type from all years in every county.

Travel

To estimate movement, we utilized a publicly available cellphone mobility dataset from Cuebiq [37], 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 traffic dataset obtained from the Ohio Department of Transportation Office, Technical Services, Traffic Monitoring Section. However, because several counties were not included in the state's traffic monitoring data, we used the Cuebiq data to utilize data for all Ohio counties. Travel was a percentage ranging from 0-1 (range=46.7% - 83.5%, M=69.9% (7.86%)).

Shutdown

To determine the effect of stay-at-home order in particular, we coded each week as either shutdown=1, for weeks during Ohio's stay-at-home order, or shutdown=0 for weeks before and after the order. The stay-at-home order, ran from March 23rd through April 30th, falls within weeks 4 through 8 in our analysis.

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 [38]. 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 [39]. 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 [40]. These counties were coded as a 1; non-Appalachian counties were coded as 0. This allowed region to be analogous to the other county characteristic variables, as the proportion of Appalachian county residents living in Appalachia is 1.

Analysis strategy

Using IBM SPSS [41], we first analyze the rate of travel, and by extension, degree of compliance with the stay-at-home order while it was in effect. Next, 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, and drugs.

To test for linear and curvilinear effects of week and shutdown on the dependent variables just mentioned, we conducted generalized estimating equations (GEE) for each outcome (i.e., travel and crash rates). This approach allowed us to estimate average responses across counties, controlling for within-county correlations and analyzing all available data. We also chose GEE because it is robust to misspecification of the correlation model (e.g., Ballinger, 2004; Hardin & Hilbe, 2012; Liang & Zeger, 1986). When crash rates were an outcome, we controlled for corresponding crash averages from the previous five years. In a separate set of analyses, we added county characteristic predictors of support for President Trump, travel, rurality, income, and Appalachian region. In these additional analyses for crash rates, we also included the travel rate as a covariate.

Because we were treating counties as N=88 observations with 22 repeated measures, we estimated our power using G*Power [42] based on RMANOVA with one group and 22 measurements, a correlation of .5 among measures, .95 power, and .05 alpha. To detect 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 [43] within each week. The indirect effect of support for President Trump on crash rates was estimated using bootstrapping with 5,000 resamples. We controlled for the same covariates (i.e., 5-year average, rurality, income, and Appalachian region).

Results

Interactive Figures on Tableau

In addition to the forgoing, each of the Hypotheses is supported by a Dashboard available at https://public.tableau.com/app/profile/mason.shihab/viz/IronicEffects/OhioCrashesReport.

Tests of Hypothesis 1: Percent of people staying home would be associated with lower crash rates, particularly minor crashes.

Travel and Compliance with stay-at-home order

Percent of people travelling was strongly affected by week and the stay-at-home order (**Figure 1**). Travel was much lower while the order was active, b(se)= −11.06 (0.19), Wald $\chi^2(1)$=3,400.81, $p<.001$. In addition, the percentage of people travelling decreased slightly over the 22 weeks, b(se) = −1.04 (.04), Wald $\chi^2(1)$=562.92, $p<.001$, and there was a curvilinear effect of week such that travelling hit a low point in late March but then increased for the remainder of the weeks we examined, b(se) = 0.06 (0.002), Wald $\chi^2(1)$=908.93, $p<.001$. In addition to the effects of week and shutdown, county characteristics also predicted rate of travel

As expected, percent of people travelling was greater for counties with more Trump voters, b(se) = 13.35 (1.63), Wald $\chi^2(1)$=66.76, $p<.001$. Counties with higher median incomes had lower rates of travel, b(se) = −0.87 (0.14), Wald $\chi^2(1)$=40.11 $p<.001$. Appalachian region and rurality did not predict travelling after accounting for the other predictors. The linear and curvilinear effects of week, as well as the effect of shutdown, were unchanged after adding in these county characteristics covariates to the model, suggesting independence from them.

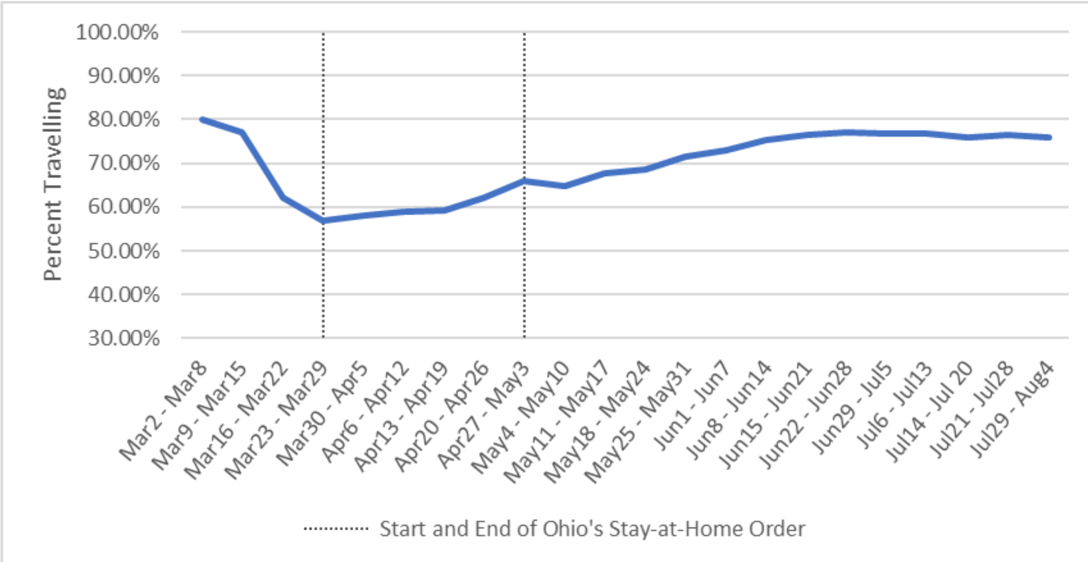

Figure 1. Percent of Ohioans staying home by week, adjusted for population.

Crash rates

Total Crashes

As expected, we found that the rate of crashes was lower during the shutdown period, b(se)= −0.89 (0.06), Wald $\chi^2(1)=198.37$, $p<.001$ (**Figure 2**). There was also a curvilinear effect of week, b(se) = 0.003 (0.001), Wald $\chi^2(20.40)$, $p<.001$, such that crash rates fell during the first weeks of March but began to increase again throughout April. The linear effect of week was not significant, b(se)=−0.03 (0.01), Wald χ^2 (1)=3.48, p=.062. The effect of previous 5-year crash rate was significant, b(se)=0.66 (0.05), Wald $\chi^2(1)=162.57$, $p<.001$. When the county characteristic variables were added, the linear effect of week became significant, b(se)=0.05 (0.02), Wald $\chi^2(1)=9.42$, p=.002 (likely capturing remaining, unaccounted for, effects once travel was retained in the model). However, the effect of shutdown ($p>.10$) and the curvilinear effect of week ($p>.05$) were reduced to non-significance. Instead, there was an effect of traveling such that counties with more people travelling had more crashes, b(se)=0.07 (0.01), Wald

$\chi^2(1)=122.40$, $p<.001$. None of the other county characteristic covariates had significant effects.

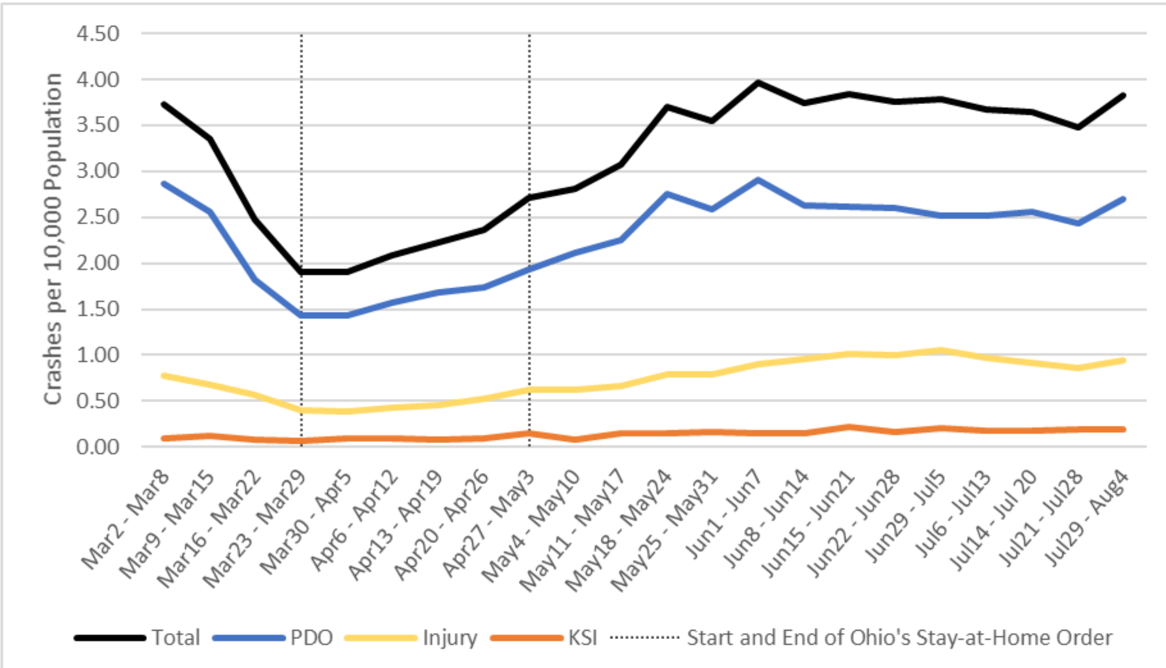

Figure 2. Crash rates in Ohio per week from March to August, adjusted for population.

Crashes by Severity

The effects of shutdown and week on crashes was stronger for property-damage-only (PDO) crashes than the other types. This effect is visible on **Figure 2**. For both PDO and injury crashes, like the total crash rate, we notice a significant curvilinear effect such that crashes first fell in late March and then resumed pre-pandemic levels by mid-June, even when controlling for the average crash rates from the past five years (**Table 1**). For KSI crashes, we did not observe a linear or curvilinear effect of week but did still find a reduction during the shutdown weeks, b(se)= −0.03 (0.01), Wald $\chi^2(1)=7.42$, $p=.006$.

	PDO	Injury	KSI
Week (linear)	−0.02 (0.01)	<0.001 (.001)	0.004 (0.003)
Week (curvilinear)	0.002 (.001) **	0.001 (<.001) **	<0.001 (<0.001)
Shutdown	-0.65 (.05) ***	-0.24 (.02) ***	-0.03 (0.01) **
Previous 5 year	0.62 (.047) ***	-0.44 (.06) ***	0.15 (0.046) **

Table 1. Effects of week (linear and curvilinear) and shutdown. Parameter estimates (B) with standard errors in parentheses are reported. *p<.05 **p<.01 ***p<.001

Of important note, the effect of Shutdown is significant for all three crash types but with a noticeable decline in effect size with increasing severity. However, when our county characteristic variables are added into the models, the effects of shutdown for all three crash types becomes insignificant. This result, which can be seen in **Table 2**, suggests that the shutdown is being mediated by those county characteristic variables and crash rates, likely travel in particular. The travel rate's effect size and significance levels appear to closely mimic the effect of Shutdown in the sparser model.

	PDO	Injury	KSI
Week (linear)	0.03 (.01) **	0.02 (0.01)***	0.007 (0.003)*
Week (curvilinear)	-0.001 (0.001)*	-0.001 (0.003)*	<0.001 (<0.001)
Shutdown	-0.1 (0.07)	-0.03 (0.03)	-0.001 (0.01)
Previous 5 year	0.57 (0.05)***	0.37 (0.06)***	0.07 (0.05)
Travel	0.05 (0.005)***	0.02 (0.002)***	0.003 (0.001)**
Median Income	-0.04 (0.03)	-0.02 (0.01)	-0.004 (0.004)
Trump Support	-0.39 (0.43)	-0.88 (0.28)**	-0.16 (0.06)*
Rural	-0.002 (0.003)	0.01 (0.01)	0.13 (0.03)***
Appalachian	-0.11 (0.09)	-0.04 (0.04)	-0.01 (0.01)

Table 2. Effects of week (linear and curvilinear) and shutdown, controlling for additional variables. Parameter estimates (B) with standard errors in parentheses are reported. *p<.05 **p<.01 ***p<.001

With these more complete analyses, we support for Hypothesis 1, that the proportion of people travelling would predict lower crash rates, and that this influence would be more pronounced for crashes with lower severity.

First, in addition to the effects of week on PDO crashes, counties with greater travel had higher rates of PDO crashes, b(se) = .05 (0.005), p<.001. Appalachian region, support for President Trump, rurality, and income did not have significant effects (p's>.1). Analyses of minor injury crashes also supported Hypothesis 1. Independent of the effect of week, counties with more travel also had greater rates of injury crashes b(se)= 0.02 (0.002), $p<.001$, as did those with lower support for President Trump, b(se)= −.88 (0.28), p=.001. Income level, Appalachian region, and rurality did not predict minor/possible injury crash rates (p's>.15). Finally, the rate of KSI crashes adjusted for population was also greater for counties with more travel, b(se) = 0.003 (0.001), p=.006, rural counties b(se) = 0.13 (0.03), $p<.001$, and those with less support for President Trump b(se) = -0.16(0.06), p=.016. Income level and Appalachian region did not predict KSI crashes (p's>.50). Regarding Hypothesis 1, it can be seen from the forgoing that travel had a stronger impact on less severe crashes. This is also verified by checking Dashboard 1 in the Supplemental Dashboards, where a strong connection between Travel and less serious crashes can be observed.

Tests of Hypothesis 2: greater proportion of speeding-, alcohol-, and drug-related crashes

Like before, we ran tested models which only tested the linear and curvilinear effects of week, as well as shutdown, before rerunning those models with the county characteristic covariates added. We found partial support for Hypothesis 2, as there was a significant increase in alcohol-related crashes during the shutdown. More details for each crash type that we studied are below, and the full results are available at **Table 3** and **Table 4**.

Speeding-related crashes

Neither week nor shutdown predicted greater number of speed-related crashes (p's>.20). Instead, counties with greater travel had a *lower* percentage of speed-related crashes, b(se)= -0.26 (0.07), Wald $\chi^2(1)=13.15$, $p<.001$. Speed-related crashes were also higher for Appalachian counties, b(se) = 3.80 (1.16), Wald $\chi^2(1)=10.73$, p=.001, and more rural counties b(se)=6.27(2.68), Wald $\chi^2(1)=5.49$, p=.019. Support for President Trump and income were not significant predictors (p's>.30).

Alcohol-related crashes

In lone support of Hypothesis 2, Alcohol-related crashes were higher during the shutdown weeks, b(se)=1.30 (0.53), Wald $\chi^2(1)=5.97$, p=.015. Even when the county characteristic covariates were added, the effect of shutdown remained significant b(se)=1.60 (0.71), Wald $\chi^2(1)=5.04$, p=.025. No other effects emerged for this crash type. The significant effect of Shutdown on Alcohol crashes can be seen on **Figure 3** below. It can also be seen on Dashboard 2 of the Supplemental Dashboards. There, we also point out a connection to KSI crashes that may help explain the lack of a dip in that crash rate seen in the prior section.

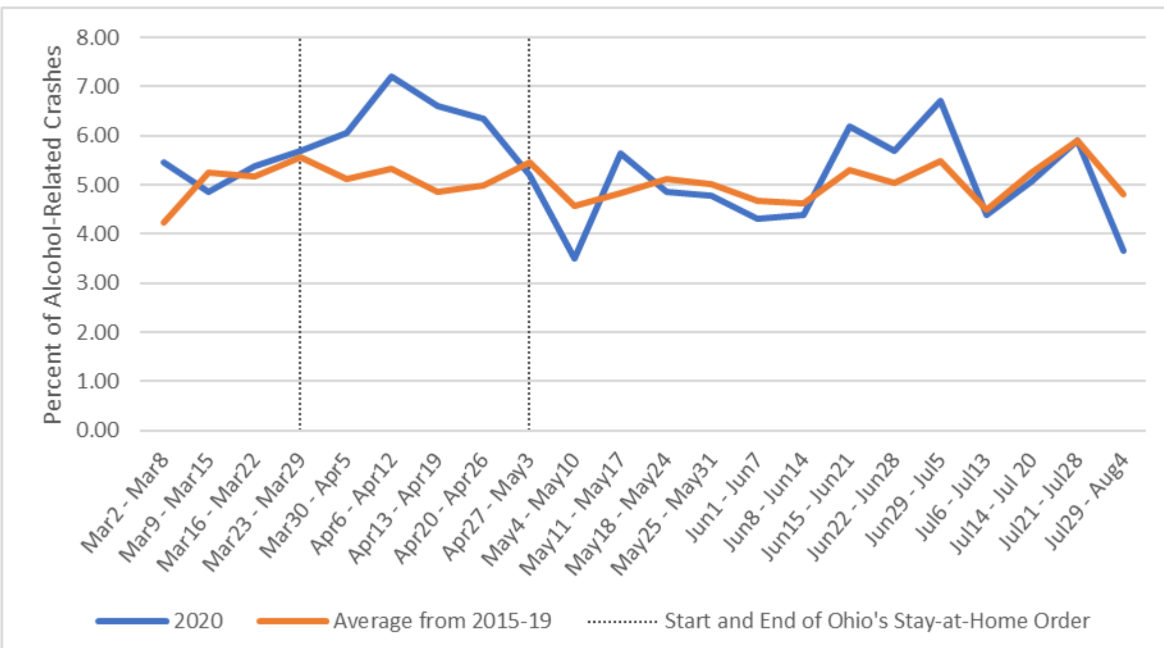

Figure 2. Proportion of Alcohol-Related Crashes both from 2020 and the average of the years 2015 through 2019.

Drug-related crashes

The proportion of drug-related crashes remained stable over the weeks we examined (all effects of shutdown and week p>.30). Instead, Appalachian counties had higher percentages of drug-related crashes, b(se)=1.36 (0.43), Wald χ^2 (1)=10.15, p=.001 (All other predictors had p >.40).

	Speed		Alcohol		Drug	
Week (linear)	0.18	(0.17)	-0.002	(0.09)	-.1	(0.1)
Week (curvilinear)	-0.004	(0.007)	<.001	(0.004)	.002	(0.004)
Shutdown	0.9	(0.82)	1.3	(0.53)*	-.3	(0.32)
Previous 5 year	0.46	(0.07)***	0.16	(0.08)*	.06	(0.08)

Table 3. Effects of week (linear and curvilinear) and shutdown. Parameter estimates (B) with standard errors in parentheses are reported. *p<.05 **p<.01 ***p<.001

	Speed		Alcohol		Drug	
Week (linear)	-0.12	(0.19)	0.02	(0.11)	-0.08	(0.09)
Week (curvilinear)	0.01	(0.009)	-0.001	(0.005)	0.001	(0.004)
Shutdown	-2	(1.15)	1.59	(0.71)*	-0.1	(0.32)
Median Income	.005	(0.39)	0.09	(0.15)	0.07	(0.13)
Trump Support	-5.5	(5.69)	2.7	(2.6)	1.26	(1.68)
Rural	6.27	(2.68)*	0.002	(0.01)	-0.71	(0.91)
Appalachian	3.8	(1.16)**	0.42	(0.5)	1.36	(0.42)**
Previous 5 year	0.31	(0.088)***	0.14	(0.07)	-0.01	(0.09)
Travel	-0.26	(0.07)***	0.03	(0.03)	0.02	(0.03)

Table 4. Effects of week (linear and curvilinear) and shutdown, controlling for additional variables. Parameter estimates (B) with standard errors in parentheses are reported. *p<.05 **p<.01 ***p<.001

Test of Hypothesis 3: Indirect effect of support for President Trump on crash rates

Our expectation that support for President Trump would lead to greater crashes (due to lack of stay-at-home compliance) was not directly supported in our analyses on overall crash rates. However, the effect of suppressed travel could have prevented this result if the effect of ideology was fully mediated by said travel. Furthermore, we suspected the influence of Trump support on Travel may be greater during Shutdown weeks, as adherence the Shutdown may have depended in part on ideology. We tested this potential relationship using the below relationship with a moderated mediation model (**Figure 3**).

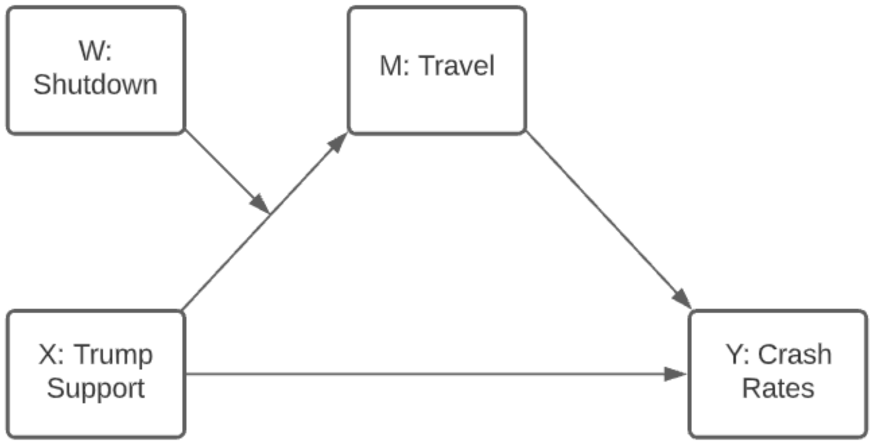

Figure 4. Hypothesized Moderated Mediation Model

For all crashes, the confidence interval for the index of moderated mediation of shutdown did not contain zero (95%CI:0.53, 1.09), indicating that the difference in conditional effects before vs. during shutdown was meaningful. In addition, the confidence interval for weeks before and after the shutdown also did not contain zero (95%CI:0.61, 1.24), indicating that support for Trump influences greater crashes through the mediator of travel, perhaps due to Trump supporters living away from cities and needing their own cars at higher rate. Nevertheless, this relationship strengthened during the shutdown (95%CI:1.45, 2.00). This held for all the three crash types in our analysis.

The shutdown had a more modest effect on the trump-travel-crash relation when only including specific types of crashes, but with decreasing effect sizes with more serious crashes. This algins with decreasing effects of travel by increasing severity seen in GEE tests of Hypothesis 1. The crash type with the strongest effect was PDO (95%CI:0.37, 0.75). Injury was next at (95%CI:0.16, 0.33), and the weakest was KSI, at (95%CI:0.03, 0.06). As none of the indirect confidence intervals contained 0, Hypothesis 3 received strong support. See Supplement 3 for more moderated mediation statistics. For each analysis, we controlled for the county characteristic variables (Rural, Appalachian, and Income), as well as the corresponding average crash rate from 2015 through 2019, retaining them as covariates in the models.

Lastly, Dashboard 3 in the Supplemental Dashboards shows the connection between crash rates and Trump support during the Shutdown (weeks 4 through 8). On the left map, we can see a connection between crash rates and county ideology that is greater during the Shutdown (seen by the contrast in circle size by color). On the right map, one can see the effect of key variables on all counties over time. The default view is Week 5 for both maps because we find the most noticeable example of the relationship hypothesized in Figure 4 during that week. The default variable on the right map is set to Travel to get a complete view of this relationship.

Discussion

From the large decline in travel, we can deduce that Ohioans largely complied with the stay-at-home order, with the lowest travel in its first week. Interestingly, travel had already begun to trend down before the order, perhaps due to school closings and changes to work arrangements. Looking at **Figure 1** and **Figure 2,** Ohio's crash rates did decline briefly in April and March, closely mirroring the reduction in travel, but only for less serious crashes, not involving fatal or serious injuries. These results are consistent with our expectations based on analyses conducted on overall and fatal crashes [6-8]. They are also consistent with our analyses supporting Hypothesis 1 that show a reduction in travel predicted lower crash rates (to a stronger degree with decreasing crash severity).

Travel had a greater effect on the total crash rate than it did on the rate of any single crash type (using our three-tiered approach). Thus, when travel fell during the shutdown, the overall crash rate saw a greater decline than that of PDO, Injury, or KSI crashes. This reduction was primarily driven by PDO and Injury crashes, which could be due to the relative rarity of severe crashes, even aggregated to the county level. Most counties have two or fewer severe crashes per week, so it may be difficult to detect a difference in serious crashes, given their infrequency. In addition, we did find an effect of rurality predicting more KSI crashes, perhaps due to greater distance from hospitals. For the more frequent and minor types of crashes, the reduction in travel had a stronger association with crash rate reduction (likely through the stay-at-home order), supporting Hypothesis 1.

Hypothesis 2 was supported only for alcohol-related crashes, not for speeding or drug-related crashes. It is unclear why speed-related crashes did not increase during the shutdown, given the reports of greater speeding [33]. Data recently provided by the Ohio Department of transportation shows that the percent of drivers going over 85 mph on freeways increased by 50% from the start of the pandemic to July 2020, only recently returning to pre-pandemic levels the following April (Supplement 4). However, a slow increase in crashes late into the summer and delayed return to normal would not have been detected by the analyses we performed.

Another possibility is that speeding may not have increased enough to impact crashes or that only some areas observed increased speeding, such as those that had less travel or those that were more rural. Indeed, both rurality and fewer people traveling predicted greater speed-related crashes, and ODOT data further suggests that increased speeding was limited to rural areas (Supplement 4). It could be that in those counties, people were taking advantage of empty roads with disastrous results, as some have speculated [9]. This possibility may also explain why travel has the weakest relationship with serious crashes; while these counties may have had fewer crashes overall, the drivers remaining on the road could have been driving more dangerously and thus getting into more serious crashes. Lastly, Appalachian counties also 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.

Alcohol, but not drugs, was a factor in a greater percentage of crashes during the shutdown. While there is evidence that alcohol consumption has increased in response to COVID-19 [8-9], the effect of COVID-19 on sales of other drugs are unknown. Although the self-medication hypothesis [13] would predict that drug consumption also increased, this may not actually be the case. The stay-at-home order may have made it more difficult to obtain illegal drugs or prompted users of legal, but mind-altering, drugs to stay home. Alcohol use is more common [14], so it may have been easier to detect an effect of alcohol-related crashes increasing than drug-related crashes. Alcohol-related crashes (like speeding-related crashes) tend to be more severe [18], so this may explain why the reduction in traffic during the COVID-19 shutdown did not translate into lower fatalities.

Political ideology, as indicated by a county's level of support for President Trump, was indirectly associated with more crashes via greater travel, and thus lower stay-at-home compliance, even during weeks outside of the shutdown. As expected, and supporting Hypothesis 3, the extent to which a county's residents had voted for President Trump was related to the extent they travelled, over and above an effect of rurality, which is consistent with travel due to political noncompliance with the order rather than due to necessity. (For instance, 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, but this was not consistent across all crash types. In contrast, we find a robust effect in the opposite direction when looking deeper at indirect effects through travel, and during the shutdown weeks in particular. This indirect effect was stronger for less serious crashes. This is something we see many times over, and we hypothesize it is because PDO crashes are more likely to be due simply to increased travel than are the more serious types. Additional risk factors like Speeding or Alcohol use can result in more severe collision outcomes.

Interestingly, support President Trump was strongly correlated with Rurality (.74), which itself had strong positive effects on both KSI and speed-related crashes. While Trump support may not have had these direct effects, future mediational analyses between analyses and crash rates may also find rurality as a mediator between ideology and crash rates. (Trump and Rural had similar correlations to most crash rates, except for speed, alcohol, and KSI). There may be interesting mediational effects of income to be found as well, as this was correlated with lower rates of all severities of crashes and negatively correlated with Trump support.

For both the rate of total crashes and all four sub-types, the effects of week remained even after controlling for travel and county characteristic variables (as well as the average rate of similar crashes over the prior five years), which suggests that additional factors contributed to the lowered crash rate. Lack of reporting may be one factor, but there may be others. Our findings are limited in generalizability due to our use of a convenient data set of Ohio crashes, but future research could examine whether similar effects are observed in other states. Ohio is a good test state due to its large population and diversity in terms of our variables of interest and covariates. For example, in 2016, over 5 million Ohioans (71% of registered voters) voted in the Presidential election, and 51% of them voted for President Trump [31]. In addition, the mean rurality of Ohio counties is 48% [39].

Practical applications

Our analysis presented a strong case for the existence of a political difference in response to significant public safety measures, which has been noted elsewhere [26-30]. However, our results reveal several novel ironic consequences for the shutdown order on lower traffic accidents. While the shutdown kept people off the road, it was also associated with greater alcohol-related crashes and speed-related crashes, which tend to be more serious (Supplement 5) [17-18]. Thus, most of the benefit for reduced traffic on crashes were for less-serious crashes. This benefit was only temporary, as it was likely due to time-limited travel restrictions. However, the ironic consequences may outlast and outweigh these benefits, as relative increases in the rates of serious crashes, fatalities, and speeding violations remained, even as travel returned to normal [44].

Researchers should continue to examine the relationship between political ideology and decisions in response to government policy and the consumption of information. Although we focused on traffic here, there may be other indirect consequences, such as increased rates of other alcohol-related injuries. The National Institute of Health found that alcohol consumption was elevated from the beginning of the pandemic to at least February 2021 [45], to the point of greater health risk [46]. This, combined with our results, should also direct researchers to research the effect of these elevated figures beyond traffic accidents.

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Supplemental materials for

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

Supplement 1: Covariates

In addition to support for President Trump and percent of Ohioans travelling, 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 are 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 [40].

Counties in Appalachian Ohio tend to have lower income, higher poverty, and lower educational attainment [36]. Appalachian Ohio has worse health outcomes than non-Appalachian Ohio, including higher rates of drug use, but less excessive drinking [39]. 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.

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Supplement 2: Controlling for the effect of crash rates from 2015 through 2019

Road travel varies throughout the year, as do crash rates. To help rule out the possibility that our results were swayed by natural changes in crash rates instead of the unique conditions we study, we gathered crash data from 2015 through 2019 and compared them with crashes from 2020. Specifically, we retained and controlled for the average from those years as a covariate in each analysis involving crash rates, for each type of crash. Other studies found that 2020 crashes differed significantly from this average [48]. We obtained this data for the previous five years from the same publicly available source that provided us the data for 2020, maintained by the Ohio Department of Transportation.

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Supplement 3. Moderated Mediation Statistics

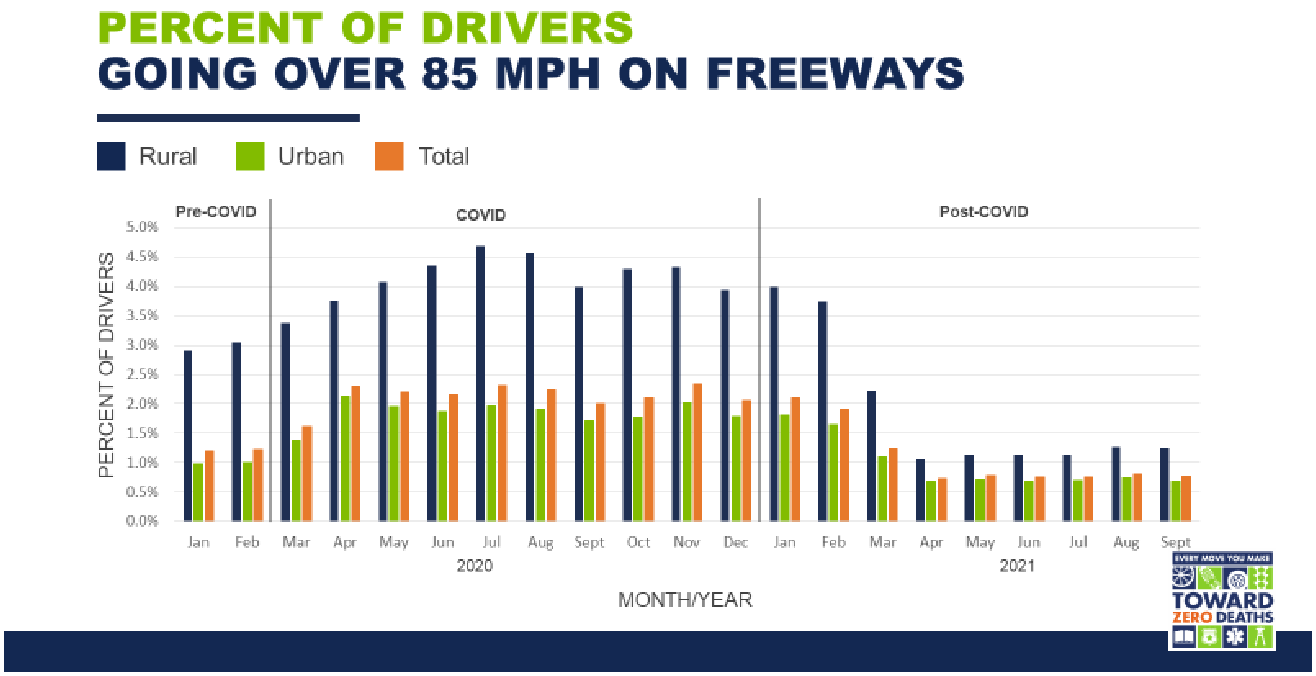
Results of Moderated Mediation Analyses. Direct, Indirect, and Moderated Effect Sizes with standard errors in parentheses are reported. *0∉[95%CI]

	KSI	Injury	PDO	*Total Crashes*
Direct Effect of Trump Support	-0.17(0.06)*	-0.91(0.14)*	-0.21(0.27)	*-1.09(0.33)**
Indirect Effect of Trump Support via Travel, Shutdown=0	0.04(0.01)*	0.28(0.05)*	0.61(0.11)*	*0.91(0.16)**
Indirect Effect of Trump Support via Travel, Shutdown=1	0.09(0.01)*	0.52(0.05)*	1.17(0.10)*	*1.72(0.14)**
Index of Moderated Mediation	**0.04(.01)***	**0.24(0.04)***	**0.56(0.10)***	***0.81(0.14)****

Results of Moderated Mediation Analyses. Direct, Indirect, and Moderated 95% Confidence Interval lower and upper bounds are reported. *0∉[95%CI]

	KSI	Injury	PDO	*Total Crashes*
Direct Effect of Trump Support	[-0.30, -0.05]*	[-1.19, -0.63]*	[-0.75, 0.32]	*[-1.74, -0.44]**
Indirect Effect of Trump Support via Travel, Shutdown=0	[0.03, 0.06]*	[0.19, 0.38]*	[0.40, 0.84]*	*[0.61, 1.24]**
Indirect Effect of Trump Support via Travel, Shutdown=1	[0.06, 0.11]*	[0.43, 0.61]*	[0.99, 1.37]*	*[1.45, 2.00]**
Index of Moderated Mediation	**[0.03, 0.06]***	**[0.16, 0.33]***	**[0.37, 0.75]***	***[0.53, 1.09]****

Supplement 4. Ohio Department of Transportation Safety Briefing on Speeding



References

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Supplement 5: Variable Correlations

	PerTrump	IncTTh	Appal	PerRural	Not@Home	AlcRate_ 2020	DrugRate_ 2020	SpeedRate_ 2020	Total_2020P erTh	PDO_2020p erTh	Injury_2020p erTh
PerTrump	1.00	-.07**	.20**	.74**	.21**	.06**	.03	.07**	-.13**	-.10**	-.16**
IncTTh	-.07**	1.00	-.52**	-.28**	-.13**	-.02	-.04	-.13**	-.10**	-.08**	-.08**
Appal	.20**	-.52**	1.00	.43**	.10**	.05*	.10**	.24**	-.11**	-.14**	-.01
PerRural	.74**	-.28**	.43**	1.00	.20**	.06**	.04	.17**	-.14**	-.16**	-.09**
Not@Home	.21**	-.13**	.10**	.20**	1.00	-.04	.01	-.02	.48**	.41**	.37**
AlcRate_2020	.06**	-.02	.05*	.06**	-.04	1.00	.24**	.12**	-.04	-.08**	.02
DrugRate_2020	.03	-.04	.10**	.04	.01	.24**	1.00	.17**	-.05*	-.09**	.01
SpeedRate_2020	.07**	-.13**	.24**	.17**	-.02	.12**	.17**	1.00	.02	-.03	.07**
Total_2020PerTh	-.13**	-.10**	-.11**	-.14**	.48**	-.04	-.05*	.02	1.00	.93**	.69**
PDO_2020perTh	-.10**	-.08**	-.14**	-.16**	.41**	-.08**	-.09**	-.03	.93**	1.00	.41**
Injury_2020perTh	-.16**	-.08**	-.01	-.09**	.37**	.02	.01	.07**	.69**	.41**	1.00
KSI_2020perTh	.06**	-.07**	.06*	.13**	.18**	.12**	.10**	.12**	.26**	.08**	.15**

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Author biographies

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Conflict of Interest

The authors declare we have no conflict of interest.