The Effect of Open Access to Marijuana on Driving-Related Fatalities

Jacob Horstmann, Justin Ravago, Eden Schow, Kyler Zarate
10 December 2022

Research Question and Data

Driving under the influence of marijuana impairs a driver's reflexes and endangers lives. When legalizing or decriminalizing recreational and medical marijuana in the United States, each state risks the possibility that people will drive under the influence. Furthermore, people that drive under the influence may access marijuana despite their state's policies. Does legalization or decriminalization of marijuana increase highway fatalities? By comparing states with different policies about the legalization of marijuana, we can understand the relationship between state policy and highway fatalities, and seek to determine if pro-marijuana legislation poses a threat to public safety.

Our analysis used an event study model covering all fifty states in the United States from 1994 to 2020 to determine if there is a causal effect between marijuana legalization and an increase in traffic fatalities. To do this, we created a data set consisting of traffic data from the Insurance Institute for Highway Safety (IIHS) and US Department of Transportation. These organizations work together to compile yearly traffic-related data by state. From this data, we created regression models based on the separate legalizations of recreational and medical marijuana. Because states vary in when they passed different marijuana-related laws, we used an event study to account for these differences. To offset other intrinsic, demographic differences between the states, our model includes variables such as population, GDP, and alcohol-related deaths as controls. To strengthen our analysis, we used state and year fixed effects to help control for other factors that contribute to accidents.

Empirical Design

Our empirical design is an event study model using panel data covering all fifty states in the United States from 1994 to 2020. Our model is as follows:

$$Fatalities_{st} = \sum_{\tau} \beta_{\tau} \mathbf{1}(t - E_s = \tau) + \gamma_s + \theta_t + X_{st} + \epsilon_{st}$$

In this model, $Fatalities_{st}$ is the outcome given a specific state and year. τ indicates the event time. β_{τ} is the effect of legalization on fatalities in a given event time. The variable and subscript 't' is the calendar year. E_s is the first calendar year of marijuana legalization in that state, γ_s is our state fixed effects, θ_t is our year fixed effects, and ϵ_{st} is our error term. X_{st} is a vector containing all other controls.

In order for our experiment to produce a causal estimation, we had to provide evidence for the common trends assumption. This means that our event time estimators should not be statistically significant before τ_0 (year of legislation implementation). This would imply that our control group is a good counterfactual for the treatment.

Important events for this study include recreational marijuana legalization and medical marijuana legalization. The control group are those states which have not yet implemented the legalization policy of marijuana, or decriminalized its use. From our outputs in Table 1, we were able to see the trends in the control are a good counterfactual for the treatment since all the estimators before τ_0 are statistically insignificant.

Identifying and addressing omitted variable bias is important. These variables include age, state funding for road repairs, alcohol-related accidents, recklessness, and population density, all of which are inherently state-variant. For example, the minimum age to get a driver's license is 15 years old in Colorado, but 16 years old in Utah. Younger and immature drivers on the road could have an effect on highway fatalities. The states' funding regarding road repairs may differ, with factors such as neglected roads, constant construction, confusing signage, and/or poorly lit areas. The presence of alcohol is both a leading cause of accidents and commonly used in conjunction with marijuana. While the metropolitan areas are similar, the state-wide difference in population densities could also be significant. For example, the population of a given state may be as small as Wyoming with only 600 thousand or as large as California with nearly 40 million.

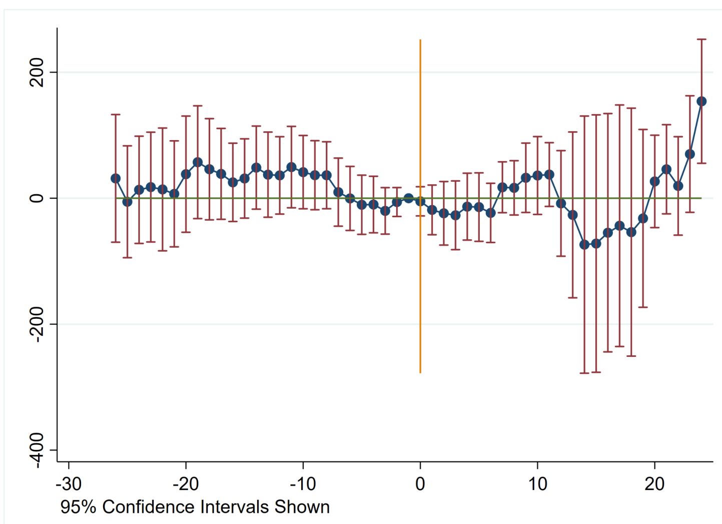
We think all these factors affect lawmakers' decisions on whether they choose to legalize marijuana and traffic fatalities. For example, a state with high vehicle accidents/fatalities due to other factors might choose to not legalize marijuana in an attempt to keep those already high rates from rising further. The omitted variables accounted for in our model are state population, alcohol related fatalities per state, and state GDP. However, due to the design of event-study models including state and year fixed effects, omitted variables are not likely to have any significant impact on coefficient estimates.

We tested the vulnerability to omitted variable bias in our model. In Table 1, we can see how the outputs change when we add controls. Columns 2-4 and 6-8 show outputs adding in population, alcohol-related fatalities, and state GDP controls, respectively. We can then compare the results in those columns to those without controls (columns 1 for medical and 5 for recreational). This shows us that there is very little change in both magnitude and statistical significance when we add controls. This effect provides evidence that we have both a good counterfactual and little vulnerability to omitted variable bias.

Results

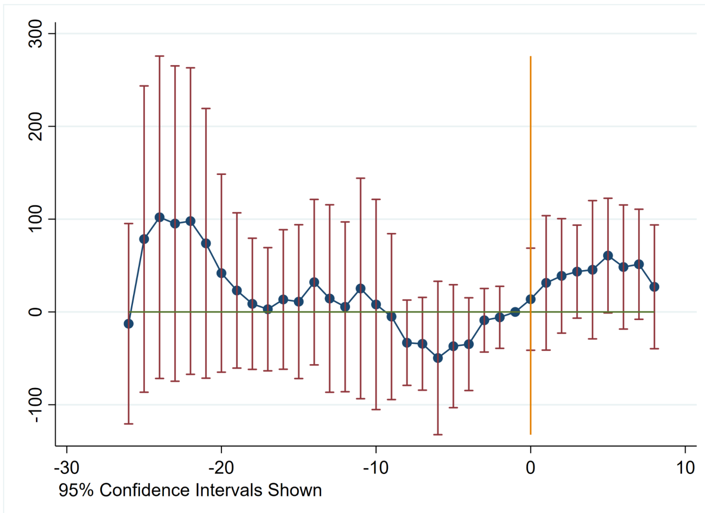
From the regression outputs in the table below, we were able to see that implementing marijuana-friendly legislation had no statistically significant effect on total roadway fatalities. However, there is a statistically significant effect approximately twenty-four years after, where we see an increase of about 150 fatalities (Table 1). In terms of the whole nation, this is not an economically significant effect. This is because not many states have had legalized marijuana long enough to be included in the treated group towards the end of the study. Because this estimate is only based on about five treated states, it is unlikely there is any real effect. Adding balance to the model in the future could controle for this.

Legalizing Medical Marijuana has Insignificant Effects on Traffic Fatalities



From this graph depicting the event study, we can see that the legalization of medical marijuana has very little effect on the trends in traffic fatalities. The coefficients we generated from 1994 to 2020 stay close to our x-axis, with the confidence intervals never ranging above or below zero. It is not until over two decades later that the confidence interval range does not include zero. We can see that graphically, we have a good counterfactual in the coefficients before $\tau = 0$.

Legalizing Recreational Marijuana has Insignificant Effects on Traffic Fatalities



Our model of the effects of legalizing recreational marijuana follows a similar pattern as medical. This graph depicts our findings on the effect of the legalization of recreational marijuana on the trends in traffic fatalities. These coefficients tend to be positive more often than negative, however the confidence intervals remain in range of our x-axis of zero. While the confidence intervals stay in range of zero in the pretreatment years, we can see that there is a lot of variation around the coefficients and the confidence intervals are large. This could be due to many states legalizing medical marijuana before recreational. There are no coefficients that diverge from the rest, meaning that the effect that the legalization of recreational marijuana had on traffic fatalities was minimal.

Conclusion

Our initial question asked if policies restricting access to medical or recreational marijuana directly causes an increase in traffic fatalities. By using an event study model, we were able to capture this causal estimate, as well as control for external factors appropriately, and satisfy the common trends assumption. While we discovered that there are increases in traffic fatalities, it is not economically significant. Citizens and policymakers should not worry about the effect that marijuana legalization has on traffic fatalities. Since we started to see an increasing effect on fatalities after legalizing medical marijuana toward the end of the available data, we will be able to study the effects more with time and with balanced models. In the future, it would be beneficial to look at how other drug-related policies like laws affecting opioid prescription affect traffic fatalities.

Table 1 - Outputs of our models and controls used.

	Medical Legalization				Recreational Legalization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Without Other Controls	Pop. Controls	Alc. Related Fatalities Controls	State GDP Controls	Without Other Controls	Pop. Controls	Alc. Related Fatalities Controls	State GDP Controls
τ = -26	31.48	30.25			-12.67	-12.82		
	(51.73)	(51.83)			(55.07)	(54.83)		
τ = -25	-5.641	-10.83			78.54	85.87		
	(45.31)	(45.40)			(84.22)	(83.59)		
τ = -24	13.36	13.13			102.0	103.0		
	(43.46)	(43.20)			(88.65)	(89.30)		
τ = -23	17.68	20.32			95.25	95.07		
	(44.47)	(43.58)			(86.69)	(86.39)		
τ = -22	13.94	13.16			97.94	100.0		
	(49.75)	(50.12)			(84.26)	(84.62)		
τ = -21	6.921	3.976	3.651	4.320	73.94	76.56	-6.711	-4.712
	(42.92)	(43.47)	(26.24)	(25.78)	(74.14)	(74.10)	(22.00)	(23.97)
τ = -20	38.18	36.85	34.00	34.61	41.81	42.54	-7.517	-5.687
	(47.06)	(47.55)	(25.78)	(25.40)	(54.43)	(54.40)	(23.11)	(24.40)
τ = -19	57.18	57.59	29.20	28.32	23.14	24.98	14.31	15.64
	(45.68)	(45.88)	(25.80)	(26.30)	(42.68)	(43.58)	(24.53)	(25.34)
τ = -18	46.03	46.78	-2.703	-3.372	8.782	9.388	43.10	44.39
	(41.01)	(40.63)	(22.93)	(22.61)	(36.06)	(36.29)	(26.92)	(27.59)
τ = -17	38.62	37.84	8.136	7.850	2.942	3.160	5.449	6.691
	(36.82)	(37.04)	(24.86)	(24.82)	(33.87)	(34.17)	(19.31)	(20.27)
τ = -16	25.21	25.27	0.867	0.453	13.45	15.65	28.11	29.35
	(31.73)	(31.76)	(23.43)	(23.43)	(38.35)	(38.82)	(21.91)	(22.74)
τ = -15	31.34	31.58	14.01	13.72	11.09	14.98	12.37	13.51

	(32.11)	(32.13)	(36.45)	(36.74)	(42.29)	(43.67)	(19.78)	(20.56)
τ = -14	48.61	48.87	28.16	28.09	32.09	33.07	24.35	25.33
	(33.67)	(33.69)	(25.09)	(25.09)	(45.50)	(46.11)	(18.77)	(19.34)
τ = -13	37.40	36.75	31.94	31.92	14.46	15.55	17.34	17.36
	(34.48)	(34.59)	(25.95)	(25.89)	(51.55)	(51.99)	(23.99)	(23.83)
τ = -12	36.25	35.27	28.27	28.37	5.519	6.175	12.98	13.07
	(31.36)	(31.45)	(25.75)	(25.55)	(46.69)	(46.69)	(14.17)	(13.89)
τ = -11	49.42	48.61	17.11	17.29	25.31	26.33	19.52	19.57
	(32.97)	(32.92)	(20.26)	(19.95)	(60.62)	(61.04)	(15.43)	(15.34)
τ = -10	41.38	39.95	19.00	19.21	8.063	10.26	6.096	6.097
	(29.68)	(29.47)	(17.34)	(17.14)	(57.79)	(58.60)	(14.76)	(14.52)
τ = -9	36.54	36.86	3.579	3.689	-5.030	-3.673	13.82	13.79
	(27.96)	(28.11)	(15.25)	(15.06)	(45.60)	(45.71)	(13.03)	(12.85)
τ = -8	36.46	34.27	11.01	11.14	-33.17	-29.49	11.75	11.81
	(27.14)	(27.09)	(16.45)	(16.29)	(23.45)	(24.40)	(14.01)	(13.92)
τ = -7	9.629	9.916	-6.444	-6.319	-34.31	-32.76	-3.143	-3.046
	(27.57)	(27.65)	(16.91)	(16.74)	(25.51)	(25.72)	(18.74)	(18.75)
τ = -6	-0.340	2.014	5.657	5.790	-49.62	-49.62	-7.161	-6.954
	(25.93)	(25.53)	(12.35)	(12.20)	(42.17)	(41.92)	(17.83)	(17.82)
τ = -5	-10.39	-11.59	4.206	4.418	-36.93	-36.78	12.58	12.79
	(23.98)	(24.16)	(14.39)	(14.17)	(33.80)	(33.77)	(13.91)	(13.88)
τ = -4	-10.02	-9.597	0.909	1.138	-34.73	-32.70	8.253	8.426
	(22.91)	(22.89)	(13.10)	(12.94)	(25.51)	(25.26)	(13.87)	(13.86)
τ = -3	-20.10	-22.30	1.152	1.382	-8.949	-7.666	5.750	5.753
	(18.81)	(19.27)	(8.996)	(8.825)	(17.47)	(17.74)	(12.40)	(12.37)
τ = -2	-6.046	-6.613	-2.681	-2.449	-5.801	-4.820	-3.475	-3.517
	(11.70)	(12.05)	(8.348)	(8.223)	(17.04)	(17.29)	(14.34)	(14.32)

τ = 0	-4.907	-7.697	-1.265	-1.150	13.74	13.88	0.574	0.692
	(11.83)	(11.90)	(8.000)	(8.069)	(28.07)	(28.02)	(8.259)	(8.285)
τ = 1	-18.54	-19.37	-2.978	-2.723	31.34	30.54	1.883	2.225
	(20.13)	(19.74)	(8.624)	(8.758)	(36.96)	(37.17)	(12.35)	(12.47)
τ = 2	-23.94	-25.09	-3.006	-2.770	38.87	39.80	1.978	2.507
	(25.74)	(25.87)	(10.06)	(10.22)	(31.47)	(31.98)	(11.23)	(11.17)
τ = 3	-27.11	-27.42	-5.894	-5.733	43.46*	42.07	19.87	20.56
	(27.82)	(27.81)	(13.76)	(13.91)	(25.57)	(25.64)	(26.51)	(26.66)
τ = 4	-13.37	-13.90	-12.75	-12.61	45.48	49.74	-11.03	-10.16
	(27.10)	(26.88)	(14.58)	(14.74)	(38.01)	(39.36)	(16.81)	(16.86)
τ = 5	-14.09	-16.00	-11.24	-11.03	60.76*	66.05*	-3.181	-0.719
	(27.76)	(27.64)	(13.26)	(13.34)	(31.52)	(33.70)	(21.83)	(22.44)
τ = 6	-23.29	-21.46	-19.96	-19.82	48.43	49.16	-5.406	-1.300
	(23.98)	(24.21)	(13.96)	(13.94)	(34.12)	(34.28)	(21.20)	(21.32)
τ = 7	17.35	16.37	1.197	1.382	51.40*	47.29	-17.35	-7.371
	(20.59)	(20.61)	(14.67)	(14.55)	(30.25)	(30.73)	(26.58)	(28.02)
τ = 8	16.50	17.53	-15.40	-15.12	27.08	26.82	-11.85	-1.769
	(22.00)	(22.09)	(13.90)	(13.85)	(34.02)	(33.52)	(26.96)	(29.96)
τ = 9	32.46	33.06	-12.25	-12.06				
	(28.12)	(28.29)	(14.91)	(14.83)				
τ = 10	36.06	34.77	-13.45	-13.09				
	(31.53)	(31.49)	(17.55)	(17.46)				
τ = 11	37.60	35.80	-18.02	-17.40				
	(25.82)	(25.76)	(17.32)	(17.62)				
τ = 12	-8.276	-8.147	-25.62	-24.87				
	(42.78)	(42.97)	(22.83)	(23.21)				
τ = 13	-26.52	-29.19	-45.24	-44.42				

	(67.17)	(67.47)	(33.23)	(33.63)				
τ = 14	-73.71	-75.27	-47.94	-46.99				
	(104.2)	(104.2)	(35.98)	(36.48)				
τ = 15	-72.00	-73.52	-40.15	-39.09				
	(104.3)	(104.5)	(27.80)	(28.30)				
τ = 16	-54.78	-54.46	-46.78	-45.67				
	(96.55)	(96.52)	(30.64)	(31.21)				
τ = 17	-43.68	-46.34	-52.86	-51.35				
	(97.85)	(98.48)	(36.03)	(36.74)				
τ = 18	-53.85	-57.28	-64.17	-62.46				
	(100.4)	(101.4)	(39.34)	(40.11)				
τ = 19	-32.02	-35.51	-48.29*	-46.47*				
	(72.03)	(72.88)	(25.62)	(26.36)				
τ = 20	26.67	23.28	-51.19	-49.56				
	(37.43)	(38.19)	(34.51)	(35.13)				
τ = 21	45.94	45.29	-74.81***	-74.82***				
	(36.12)	(37.57)	(27.77)	(27.55)				
τ = 22	19.51	18.74	-54.99*	-54.87*				
	(39.89)	(40.00)	(29.66)	(29.39)				
τ = 23	70.11	65.41	184.0***	183.8***				
	(47.23)	(48.58)	(27.74)	(27.43)				
τ = 24	153.9***	164.3***	-99.10**	-99.72**				
	(50.23)	(47.63)	(46.08)	(45.71)				
Constant (τ = -1)	757.5***	763.3***	233.9***	236.2***	748.4***	752.2***	232.7***	237.0***
	(15.26)	(16.46)	(44.42)	(45.49)	(24.70)	(24.16)	(39.97)	(39.46)
State & Year FE	X	X	X	X	X	X	X	X
Population FE		X	X	X		X	X	X

Alcohol-Related Fatality FE			X	X			X	X
State GDP FE				X				X
Observations	1,377	1,377	1,122	1,122	1,377	1,377	1,122	1,122
R-squared	0.984	0.984	0.995	0.995	0.984	0.984	0.995	0.995

Robust standard errors in parentheses, FE stands for Fixed Effects. Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Data Source References

“Fatalities and Fatality Rates by State, 1994 - 2020.” *FARS Encyclopedia: States - Fatalities and Fatality Rates*, National Highway Traffic Safety Administration, https://www-fars.nhtsa.dot.gov/states/statesfatalitiesfatalityrates.aspx.

Federal Reserve Economic Data, St. Louis Economic Research.

Iowa State University, Iowa Community Indicators Program.

National Conference of State Legislatures, Marijuana.

National Highway Traffic Safety Administration, Data.