# Recreational Marijuana Dispensaries and Fatal Car Crashes

Theodore L. Caputi

MIT Labor Lunch https://www.theodorecaputi.com/files/marijuana-crashes.pdf

October 2022

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Marijuana and Fatal Car Crashes

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# Questions for You!

- Are there any other interesting questions that could be answered?
- What could make these results more robust / is there anything that calls the validity of these findings into question?
- Do you have a good angle for framing this paper? Recommendations on placement?

#### Overview

#### Introduction

#### 2 Data



#### 4 Results

- 5 Robustness to Alternatives
- 6 Two Further Questions

#### Conclusion

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# Introduction

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### Motivation

- Automobile crashes are a major public health priority
  - Automobile crashes are a leading cause of death for Americans ages 1-54
  - 38,000+ deaths in 2020 alone
  - Estimated annual economic cost of motor vehicle crashes: \$242 billion
  - A major contributing cause of fatal crashes is driving under the influence of drugs/alcohol (over 50%) (NHTSA, 2021)
- State marijuana legalization is one of the most major changes in public health policy over the past 20 years
  - Proponents argue: increased tax revenue, decreased criminal justice waste, less substitution to more dangerous drugs
  - Opponents argue: marijuana addictive and harmful to health, increased societal costs, increased use of complement drugs

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#### At the Intersection



- Marijuana legalization could theoretically increase or decrease automobile crashes
  - Increase: Experimental evidence shows marijuana use impairs driving ability; people could complement marijuana with alcohol/other drugs
  - Decrease: People could substitute away from alcohol/other drugs

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#### **Preview of Findings**

• The effect of recreational marijuana on fatal car crashes is a policy-relevant, empirical question!

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#### **Preview of Findings**

- The effect of recreational marijuana on fatal car crashes is a policy-relevant, empirical question!
- I find recreational marijuana dispensaries increase fatal car crashes by around 5.7%
  - Event study provides evidence against selection of dispensaries into areas with increasing car crashes
  - Evidence that effect not due to increased commercialization at time of dispensary opening
  - (Provisional) insights into sales trade-off and complementarity with alcohol

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### Comparisons to Other Interventions

- Minimum legal drinking age of 21 reduced youth traffic fatalities by 9-11% (Dee, 1999)
- Texting bans temporarily decreased fatal car accidents by 4% (Abouk and Adams, 2013)
- Mandatory seat belt laws reduced deaths from car crashes by 8% (Carpenter and Stehr, 2008)
- Increase of 10% in beer taxes reduces motor vehicle fatalities among drivers aged 15-24 by 1.3% (Morrisey and Grabowski, 2011)

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### Existing Literature

- Past studies have found small or negligible effects of recreational marijuana laws (RMLs) on traffic crashes (Aydelotte et al., 2017, 2019; Santaella-Tenorio et al., 2020; Hansen et al., 2020; Gunadi, 2022)
- However, past studies suffered from several limitations:
  - $\bullet\,$  Limited in geographic or temporal scope  $\implies\,$  underpowered
  - Subject to state-level confounding
  - Few studies look at most relevent treatment: *dispensaries* (Ellis et al., 2019; Gunadi, 2022)

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# Contribution

- Focus on effect of *local dispensaries* instead of *state laws*, significantly improving power and reducing aggregation bias
- Coverage of five states with operational recreational marijuana dispensaries: CA (2018), CO (2014), MA (2018), OR (2016), and WA (2014)
- Account for state-level confounding with state-by-time fixed effects
- ⇒ Differences-in-differences at the zip code X month level:
  - D = 1 if active dispensary license in zip code X month
  - D = 0 if no active dispensary

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#### Data

#### Fatal Accident Data

- Fatal Accident Reporting System (FARS): Census of all fatal car accidents in all 50 US states
  - Motor vehicle traveling on a trafficway customarily open to the public
  - Resulted in death of a motorist or non-motorist within 30 days of the crash
- Collected by National Highway Traffic Safety Administration
- Latitude and longitude of crashes consistently reported since 2001

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#### Dispensary and Covariate Data

- Construct dispensary licensure dataset using FOIA requests from five states: CA, CO, MA, OR, and WA
- $\bullet\,$  First dispensary opened in January 2014  $\rightarrow\,$  Use sample period of 2005-2019
- Zip code characteristics from Decennial Census (2000, 2010), 5-Year American Community Survey (2011-2019), and Zip Code Business Patterns (2005-2019)
  - Linear interpolation at annual level for missing years
- County-level unemployment data from Bureau of Labor Statistics
- Aggregate everything to the zip code X month level

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# Summary Statistics at Zip Code-Month Level (N=606,504)

	After Dispensary		Before Dispensary		Never Dispensary	
	Mean	SD	Mean	SD	Mean	SD
Fatal Crashes	0.15	0.41	0.14	0.40	0.11	0.36
Dispensary Open	1.00	0.00	0.00	0.00	0.00	0.00
Population	24825.07	17634.16	25 020.63	18216.50	15 424.27	18 330.67
Population Per Sq. Mi.	3352.80	5572.57	3739.52	6069.87	2202.87	4455.63
Land Area in Sq. Mi.	104.81	188.30	91.09	171.58	94.46	197.22
Share Male	0.50	0.03	0.50	0.03	0.50	0.05
Share Aged 21-39	0.27	0.09	0.27	0.08	0.22	0.09
Median Age	39.53	7.22	38.48	6.99	41.54	8.72
Median Household Income (2010 Dollars)	55 263.01	18715.16	52 492.94	17 440.84	60 824.58	26734.07
Avg. Household Size	2.52	0.45	2.57	0.51	2.66	0.56
No. Employees	10490.01	12324.10	9714.59	11 551.62	5368.48	9444.95
No. Establishments	732.82	594.78	686.28	579.39	362.24	491.62
County Unemployment	4.30	1.44	7.35	2.95	7.06	3.36
Year	2017.54	1.43	2010.70	3.70	2012.00	4.32

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#### Distribution of Fatal Car Crashes by Year



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# Methods

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#### Preferred Specification

• Two-way fixed effects, staggered treatment design model, estimated using Poisson regression equation:

 $log(E[Y_{zst}]) = \gamma 1(\text{Dispensary Open})_{zt} + X_{zt}\beta + \alpha_z + \alpha_{st} + \epsilon_{zst}$ 

- Outcomes Y<sub>zst</sub>: fatal crashes, automobile deaths, nighttime deaths, etc.
- Confounders X<sub>zt</sub>: population per square mile, log(total population), log(median household income), median age, share male, share between age 21 and 39, average household size, number of employees, number of business establishments
- $\alpha_z, \alpha_{st}$ : Zip code and state  $\times$  time fixed effects

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#### $\mathsf{State} \times \mathsf{Time} \; \mathsf{Fixed} \; \mathsf{Effects}$

- State-level policies could confound the relationship between dispensaries and car crashes
  - Marijuana policies (e.g., decriminalization, medical marijuana laws)
  - Drug-related policies (e.g., blood alcohol laws)
  - Healthcare policies (e.g., Medicaid expansion, substance use treatment)
  - Traffic policies (e.g., increased traffic enforcement)
- Controlling for these individually leaves analysis subject to omitted variables bias
- State × Time FE ⇒ Compares zip codes within states ⇒ Rules out *all* state-level confounding

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#### Concerns about Heterogeneous Treatment Effects

- Many have pointed out that TWFE can assign negative weights to comparisons (Roth et al., 2022) in the presence of heterogeneous treatment effects, particularly when:
  - Large share of groups are treated
  - Groups are treated for many periods
- Negative weights can lead to estimates outside of convex set of group-specific estimates
- No negative weights (De Chaisemartin and d'Haultfoeuille, 2020) in my main specification (using linear model)

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# Additional Considerations (1/2)

- Licenses vs. Dispensaries: Licenses with no dispensary (or vice versa)
  - Measurement error would attenuate results
- State-Level Effect: Policy could affect stigma across states
  - My approach nets out state-level effects
  - Would attenuate results, assuming stigma and dispensary effects are in the same direction
  - Results speak more directly to decision to open dispensary

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# Additional Considerations (2/2)

#### Some controls could be "bad controls"

- Would probably attenuate results
- Try with and without

• Spillovers: Dispensary opening in one zip code could affect another

- Would attenuate results in main specification, as long as neighboring zip codes experience same effect as treated zip codes
- Average zip code over 90 square miles land area
- Show results using distance to a dispensary

# Additional Considerations (2/2)

#### Some controls could be "bad controls"

- Would probably attenuate results
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• Spillovers: Dispensary opening in one zip code could affect another

- Would attenuate results in main specification, as long as neighboring zip codes experience same effect as treated zip codes
- Average zip code over 90 square miles land area
- Show results using distance to a dispensary
- Could consider these results conservative/lower bound

#### Distance Model for Spillovers

 Two-way fixed effects, staggered treatment design model, estimated using Poisson regression equation:

 $log(E[Y_{zst}]) = \gamma \text{Distance to Dispensary}_{zt} + X_{zt}\beta + \alpha_z + \alpha_{st} + \epsilon_{zst}$ 

- Advantages:
  - Account for spillovers across zip codes
- Disadvantages:
  - Don't have data on all dispensaries nationwide
  - Before 2014, there were no dispensaries; I cap distance at 50 miles
  - Interpretation less straightforward

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# Results

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Results

# Main Results (Poisson)

Dependent Variables: Model:	(1)	Fatal C (2)	rashes (3)	(4)	Deaths (5)
Dispensary Open	0.0800*** (0.0203)	0.0551** (0.0228)	0.0562** (0.0228)	0.0572** (0.0228)	0.0526** (0.0239)
<i>Controls</i> Demographic Controls Business Controls	No No	No No	Yes No	Yes Yes	Yes Yes
<i>Fixed-effects</i> Zip Code Month (180) Month-State (900)	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Fit statistics # Zip Code Observations Squared Correlation Pseudo R <sup>2</sup> BIC Dependent variable mean	3,476 625,680 0.12801 0.15154 446,757.3 0.11557	3,476 625,680 0.13040 0.15397 455,226.8 0.11557	3,375 606,504 0.12842 0.14749 452,096.9 0.11880	3,375 606,504 0.12844 0.14749 452,121.6 0.11880	3,375 606,504 0.11834 0.15014 484,028.6 0.12958

Clustered (ZIP) standard-errors in parentheses Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

#### OLS Main Results

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### Distance Results (Poisson)

Dependent Variables: Model:	(1)	Fatal (2)	Crashes (3)	(4)	Deaths (5)
Distance to Dispensary (10mi)	-0.0172*** (0.0043)	-0.0238 <sup>***</sup> (0.0077)	-0.0243 <sup>***</sup> (0.0077)	-0.0253 <sup>***</sup> (0.0077)	-0.0226*** (0.0082)
<i>Controls</i> Demographic Controls Business Controls	No No	No No	Yes No	Yes Yes	Yes Yes
Fixed-effects Zip Code Month (180) Month-State (900)	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Fit statistics # Zip Code Observations Squared Correlation Pseudo R <sup>2</sup> BIC Dependent variable mean	3,476 625,680 0.12801 0.15154 446,755.4 0.11557	3,476 625,680 0.13041 0.15398 455,222.5 0.11557	3,375 606,504 0.12843 0.14750 452,092.6 0.11880	3,375 606,504 0.12846 0.14750 452,116.8 0.11880	3,375 606,504 0.11835 0.15015 484,024.5 0.12958

Clustered (ZIP) standard-errors in parentheses Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

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#### Robustness to Alternatives

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# Alternative Hypotheses

- I argue that this effect is due to increased impairment (either marijuana impairment or marijuana + other drug impairment)
- Need to rule out alternative explanations that the increase in crashes is due to an increase in traffic
  - Marijuana dispensaries open in more commercial areas with increasing traffic/accidents
  - Marijuana dispensaries open at the time of new development, which may increase traffic/accidents

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# Explanation 1: Selection

• Marijuana dispensaries not randomly assigned  $\implies$  Check for parallel pre-trends



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# Explanation 2: Commercialization

- Areas with increased development may be more likely to open a marijuana dispensary and to have increased traffic deaths
- Robustness Checks:
  - Inclusion of demographic and business controls (already shown)
  - Placebo analysis for another business that might also open at the time of new development
  - Decompose effect by first and subsequent dispensary openings, as subsequent dispensary openings cater to existing customers
  - Decompose effect by time of day, i.e., after dispensaries close

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# Retail Pharmacy Placebo (Excluding MA)

Dependent Variables:	Fatal Crashes	Deaths	Daytime Crashes	Nighttime Crashes
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>	-0.0072	0.0138	-0.0388	0.0364
Pharmacy Open	(0.0290)	(0.0295)	(0.0440)	(0.0389)
<i>Fixed-effects</i> Zip Code (2,890) Month-State (720)	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Fit statistics Observations Squared Correlation Pseudo R <sup>2</sup> BIC Dependent variable mean	519,204 0.12953 0.14442 407,615.0 0.12922	519,204 0.11858 0.14658 437,637.2 0.14124	519,204 0.05249 0.11061 259,797.4 0.05854	519,204 0.08519 0.15193 275,581.4 0.06863

Clustered (Zip Code) standard-errors in parentheses Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

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#### First and Subsequent Dispensary

Dependent Variable: Model:	(1)	Fatal Crashes (2)	(3)
Variables First Dispensary	0.0680***		0.0836***
6	(0.0225)		(0.0281)
Subsequent Dispensary		0.0340	-0.0296
		(0.0203)	(0.0555)
Fixed-effects			
Zip Code (3,375)	Yes	Yes	Yes
Month-State (900)	Yes	Yes	Yes
Fit statistics			
Observations	606,504	606,504	606,504
Squared Correlation	0.12845	0.12843	0.12844
Pseudo R <sup>2</sup>	0.14750	0.14748	0.14750
BIC	452,118.8	452,126.6	452,131.4
Dependent variable mean	0.11880	0.11880	0.11880

Clustered (Zip Code) standard-errors in parentheses Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

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# Crash Timing



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#### Two Further Questions

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# Connection to Marijuana Sales

- How much marijuana is associated with one additional fatal car crash?
- Only have dispensary-level monthly sales data for Washington
- Rough approximation from two-sample IV
  - Outcome: Fatal car crashes
  - Treatment: Marijuana Sales
  - Instrument: Active Dispensary License in Zip Code-Month
  - First stage estimated in entire sample, reduced form estimated in Washington
  - Control for business and demographic covariates, as well as state-by-month and zip code FE

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#### Marijuana Sales Results

#### • One fatal car crash per \$23 million of marijuana sales

- For reference, approx. one fatal car crash per \$20 million of alcohol sales in US (11,000 crashes / \$220B sales)
- Major caveat: Estimate based on sales per treated zip code in Washington, but could be *very different* in other states
  - In 2019, Washington marijuana sales per capita was approx. \$150
  - Other states range from around \$60 (Massachusetts) to around \$250 (Colorado)
- Nonetheless, comforting that a reasonable amount of marijuana (order of millions of dollars) required for an additional fatal car crash

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# Connection to Drunk Driving

- How much of the observed increase in fatal car crashes is due to increased alcohol-impaired driving?
- Data to explore this question is limited:
  - Not clear in the data who is at fault or whether alcohol was the cause of the accident
  - Lots of missing data in all states
- Judgement calls
  - Define "alcohol-involved" as car crashes where officer **reported** alcohol involvement for at least one driver
  - $\bullet\,$  Exclude MA because <25% of crashes had non-missing data for any driver

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# Drunk Driving Results (Excluding MA)

Dependent Variable:	Alcohol-Involved Crash			
Model:	(1) Deiesen	(2)		
	Poisson	UL3		
Variables				
Dispensary Open	0.1014**	0.0032**		
	(0.0468)	(0.0014)		
Fixed-effects				
Zip Code (2,890)	Yes	Yes		
Month-State (720)	Yes	Yes		
Fit statistics				
Observations	519,204	519,204		
Squared Correlation	0.04090	0.03845		
Pseudo R <sup>2</sup>	0.12550	-0.05914		
BIC	168,292.6	-316,888.4		
Dependent variable mean	0.02916	0.02916		

Clustered (Zip Code) standard-errors in parentheses Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

• Around 23% (= 0.0032/0.0142) of the effect due to increase in alcohol-involved crashes

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# Conclusion

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# Conclusion

- Using a differences-in-differences approach, I find evidence that marijuana dispensaries increase fatal car crashes by around 5.7%
- Conservative estimate due to spillovers to neighboring zip codes (distance estimate around 8.5%)
- I provide evidence that the effect is due to increased impairment, ruling out alternative explanations such as:
  - Selection of dispensaries into areas with increasing crashes
  - Increased commercialization confounding results
  - Increased crash-prone drivers
- More provisional findings:
  - One fatal car crash per \$24 million of marijuana sales
  - About a quarter of the effect due to increase in alcohol-involved accidents

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### Back to: Questions for You!

- Are there any other interesting questions that could be answered?
- What could make these results more robust / is there anything that calls the validity of these findings into question?
- Do you have a good angle for framing this paper? Recommendations on placement?

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# Thank You! Questions/Comments: tcaputi@gmail.com

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# Related Outcomes (OLS)

Dependent Variables:	Fatal Crashes	Deaths	Daytime Crashes	Nighttime Crashes
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>	0.0138***	0.0135 <sup>***</sup>	0.0029	0.0105***
Dispensary Open	(0.0033)	(0.0037)	(0.0021)	(0.0026)
<i>Fixed-effects</i> Zip Code (3,375) Month-State (900)	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Fit statistics Observations R <sup>2</sup> Within R <sup>2</sup> Dependent variable mean	606,504 0.12489 0.00023 0.11880	606,504 0.11482 0.00024 0.12958	$\begin{array}{c} 606,504 \\ 0.04976 \\ 8.25 \times 10^{-5} \\ 0.05387 \end{array}$	606,504 0.08063 0.00014 0.06308

Clustered (Zip Code) standard-errors in parentheses Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

Poisson Related Outcomes

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