Psychedelics

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The Impact of Psychedelic Reforms on Crime Rates in California: A Quasi-Experimental Approach

Background & Motivation

- Longstanding interest in determinants of crime
- Drug policy is a major area of criminology and public policy
- Marijuana legalization widely studied
- **Gap:** Minimal research on psychedelic decriminalization

Legal Landscape of Psychedelics (Nationwide)

- 2019: Denver decriminalizes psilocybin
- 2020: Oregon passes Measure 109 for supervised psilocybin therapy
- 2022: Colorado approves Prop 122 for Natural Medicine Access Program
- Local reforms: Cities in CA, MA, MI deprioritize enforcement
- *(Sources: Siegel, 2023; Kilmer, 2024)*

California's Legislative Efforts

- **SB 519 (2021):** Proposed decriminalization, reduced to a study
- **SB 58 (2022–23):** Passed both chambers, vetoed by Governor Newsom
- **SB 803 and SB 1012:** Failed attempts at regulated therapy framework
- Local actions: Oakland, Santa Cruz, San Francisco lead city-level reforms

Research Opportunity

- California's lack of state reform = natural comparison between cities
- Local deprioritization provides quasi-experimental conditions
- Unique chance to analyze policy effects on crime trends

Research Question & Contribution

Research Question:

- How has local psychedelic decriminalization impacted violent and property crime rates in California cities?

Historical Context of Psychedelic Research

- 1950s: Initial studies on psychedelics, especially for alcoholism treatment
- 1970: Schedule I classification → federal restrictions halt research
- Concord Prison Experiment (1965): Psilocybin used with incarcerated individuals to reduce recidivism
- Follow-up (Doblin, 1998): No significant long-term impact due to lack of reentry support

Modern Research on Psychedelics & Crime

- Neitzke-Spruill (2023): Qualitative analysis of psilocybin experiences in CPE. Concluded that psilocybin experiences facilitated:
  - Key themes: introspection, cognitive shifts, emotional reconnection
  - "Crystallization of discontent" $\rightarrow$ re-evaluation of criminal identity
  - Desistance linked to internal transformation + need for social integration (important to curb crime).

Quantitative Evidence from Community Corrections

- Hendricks et al. (2014): Longitudinal study of 25,622 substance-involved offenders under community corrections supervision:
  - Hallucinogen use disorder $\rightarrow$ 40% **reduction** in supervision failure risk
  - Compared to cannabis, cocaine, alcohol, opioid users (higher failure risk)
  - Controlled for sociodemographic and criminal history variables
- Psychedelics facilitate psychological transformation.

Psychedelics and Psychological Transformation

- Psychedelic-assisted psychotherapy shows long-term psychological benefits
- **Griffiths et al. (2006, 2008, 2011):**
  - Mystical / transformative experiences $\rightarrow$ sustained improvements in mood, behavior
- Growing rationale for linking these psychological effects to crime-related outcomes

Relevance to Policy Reform

- Modern research supports potential for psychedelics in reducing criminal behavior
- Builds theoretical foundation to explore policy impact on:
  - Property crime
  - Violent crime
- Sets up justification for this study's empirical approach

What Are Psychedelics?

- Psychoactive substances with entheogenic properties
- Induce mystical or spiritual experiences
- Examples:
  - Psilocybin (mushrooms)
  - DMT (ayahuasca)
  - Mescaline (cacti)
  - Ibogaine (iboga)
- Over 180 mushroom species contain psilocybin or psilocin
- Psilocybin $\rightarrow$ metabolized into psilocin $\rightarrow$ psychoactive effects

Major Psychedelics in Focus (Plant-based)

Ayahuasca (DMT + MAO inhibitors):

- Brew from Psychotria viridis shrub (DMT) and Banisteriopsis caapi vine (MAO)
- DMT is orally active due to MAO inhibitors
- Produces intense, often spiritual experiences

Mescaline-containing cacti:

- Peyote, San Pedro, Peruvian Torch, Bolivian Torch
- Used in spiritual/ceremonial traditions

Ibogaine (from iboga root):

- Native to Central Africa
- Studied for potential in addiction treatment

Federal Legal Status

- Psychedelics = Schedule I under Controlled Substances Act (1970)
- Schedule I = no accepted medical use + high abuse potential
- Most arrests happen at state / local level
- Exceptions:
  - Clinical trials
  - Expanded Access (e.g., MDMA)
  - Religious exemptions (e.g., peyote, ayahuasca)

Clinical Trials

- VISIONS Act (2023): restricts federal interference in state psilocybin programs
- NDAA 2024: funds psychedelic PTSD/TBI clinical research for service members
- FDA Breakthrough Therapy designation → psilocybin formulation
- NIDA (2024): funds ibogaine analog research for opioid use disorder

Access Pathways for Patients (Outside Clinical Trials)

Expanded Access Program (FDA):

- For life-threatening conditions with no alternatives
- Requires IRB + physician + manufacturer approval
- As of 2024, only MDMA accessed this way

Right to Try Act (2018):

- Allows investigational drugs without FDA review
- DEA still restricts Schedule I substances
- Bills introduced to expand Right to Try for psychedelics (not passed)

Religious Exemptions & Legal Precedents

- 1994: Peyote use legalized for Native American rituals
- DEA allows religious groups to apply for exemptions
- Key rulings:
  - *Gonzales v. O Centro Espirita* (2006)
  - *Church of the Holy Light of the Queen v. Mukasey* (2009)
- Permit DMT use in religious ceremonies

California's Psychedelic Laws

- CA Health and Safety Code classifies most psychedelics as Schedule I
- Examples:
  - Psilocybin: §11054(d)(18)
  - DMT: §11054(d)(10)
  - Mescaline: §11054(d)(14)
- Penalties for cultivation, distribution, or manufacturing
- §11150 allows reclassification if federally approved

Local Reform in California

- Statewide reform efforts stalled in legislature
- Cities like Oakland, Santa Cruz, SF passed local decriminalization
- Grassroots org: **Decriminalize Nature**
  - Advocates for access to entheogens
  - Supports *gift/grow/gather* model without limits
- Reflects growing municipal push against prohibition

Treated vs. Never-Treated Cities

Table: **Comparison of Treated and Never-Treated Cities**

Treatment Cohort	**Original Data**	**Data Sample**	**Full Data**
Never Treated	888	297	284
Oakland (2019-6)	1	1	1
Santa Cruz (2020-1)	1	1	1
Arcata (2021-10)	1	1	1
San Francisco (2022-9)	1	1	1
Berkeley (2023-7)	1	1	1
Eureka (2023-10)	1	0	0
Total cities	894	302	289

Notes:

Original Data: All agencies reporting in UCR from CA DOJ.
Data Sample: Cleaned dataset (excludes overlaps, missing/negative entries).
Full Data: Crime-per-capita dataset with controls added.

Rollout of Psychedelic Reforms

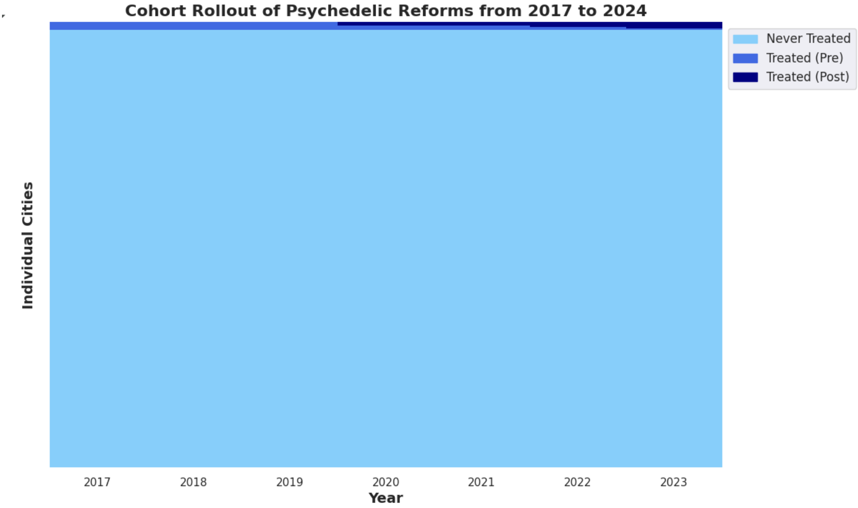


Figure: **Rollout of Psychedelic Reforms in California Cities**

Crime Data Overview

- Source: Monthly city-level UCR data (2017–2023)
- Provided by CA DOJ Criminal Justice Statistics Center (CJSC)
- Based on FBI's Uniform Crime Reporting (UCR) system
- Includes 8 Part I offenses:
  - **Violent crime:** homicide, rape, robbery, aggravated assault
  - **Property crime:** burglary, larceny-theft, motor vehicle theft
  - Arson treated separately

Crime Classification and UCR Rules

- UCR uses a **hierarchy rule** (only most serious offense counted)
- Exceptions: arson, auto theft, trafficking, justifiable homicide
- Violent crime counts = number of victims
- Property crime counts = number of incidents
- Some undercounting may occur in multi-offense cases

Limitations of County-Level Data

- County-level UCR data is unreliable:
  - Inconsistent reporting from LEAs
  - FBI imputations distort trends (Maltz & Targonski, 2002)
- Data was designed for *aggregation*, not local analysis
- Non-reporting agencies can skew county crime totals
- **This study uses only city-level UCR data**

City-Level Data Processing

- Overlapping jurisdiction resolved via UCR reporting rules:
  - City LEAs take precedence over county/state LEAs
- Excluded:
  - County agencies (e.g. CHP, BART Police)
  - Jurisdictions with no consistent yearly reporting
- Zero-population areas (universities, hospitals) reassigned to cities
- Population data from Census $\rightarrow$ crime rates per 100,000 calculated

Summary Statistics Overview

- 289 cities (after merging and cleaning CA DOJ data)
- 5 cities treated, 1 excluded (Eureka) due to missing data
- Crime Variables: 8 UCR Part 1 crimes + aggregates
- Means $>$ medians $\rightarrow$ right-skewed distribution
- Crime variables will be log-transformed to reduce skewness
- Large standard deviations $\rightarrow$ substantial variation across cities

Summary Statistics Table

Table: Summary Statistics for Crime Variables (Log-transformed per capita)

Crime Variables	Treated	Never Treated	All Cities
Violent Crime Rate	4.04 (0.03)	2.95 (0.01)	2.97 (0.01)
Property Crime Rate	5.99 (0.02)	4.96 (0.01)	4.98 (0.01)
Homicide Rate	0.37 (0.02)	0.13 (0.00)	0.13 (0.00)
Forcible Rape Rate	1.60 (0.03)	0.83 (0.01)	0.84 (0.01)
Robbery Rate	2.99 (0.04)	1.48 (0.01)	1.51 (0.01)
Aggravated Assault Rate	3.34 (0.03)	2.45 (0.01)	2.46 (0.01)
Burglary Rate	3.87 (0.02)	3.05 (0.01)	3.06 (0.01)
Vehicle Theft Rate	3.97 (0.04)	2.80 (0.01)	2.82 (0.01)
Larceny-Theft Rate	5.66 (0.02)	4.51 (0.01)	4.53 (0.01)
Arson Rate	1.49 (0.03)	0.54 (0.01)	0.56 (0.01)
Violent Crime Clearance Rate	2.81 (0.03)	2.14 (0.01)	2.16 (0.01)
Property Crime Clearance Rate	3.00 (0.05)	2.53 (0.01)	2.54 (0.01)
Robbery by Firearm Rate	1.59 (0.06)	0.57 (0.01)	0.59 (0.01)
Firearm Assault Rate	1.28 (0.06)	0.73 (0.01)	0.74 (0.01)

Table: All values are per capita and log-transformed. Standard errors in parentheses.

Conditional Parallel Trends

- Treated cities weren't randomly assigned $\rightarrow$ selection bias risk
- **Conditional Parallel Trends:**
  - Assumes similar post-treatment evolution *conditional on covariates*
- Selection into treatment influenced by:
  - Socioeconomic traits, demographics, and prior crime rates

Using LASSO to Address Selection Bias

- Apply LASSO regression to pre-treatment data (pre-June 2019)
- Goal: Select the most predictive covariates for treatment adoption
- LASSO advantages:
  - Imposes sparsity $\rightarrow$ keeps only relevant variables
  - Handles high-dimensional data efficiently
- Selected covariates used to balance treated vs. control cities
- Balance check: Normalized difference (ND)

$$\text{Norm. Diff}_{\omega} = \frac{\bar{X}_{\omega,T} - \bar{X}_{\omega,C}}{\sqrt{(S^2_{\omega,T} + S^2_{\omega,C})/2}}$$

Threshold: ND > 0.25 indicates imbalance (Imbens & Rubin, 2015)

LASSO Variable Selection Table

Table: Selected Covariates from LASSO (Pre-treatment Data)

Variable	Selected
Demographics	
Foreign-Born Population	✓
Population Density	✓
Young Adults (18–24 years), Female	✓
Economic Variables	
Gini Index (Income Inequality)	✓
Median Home Value	✓
Veteran & Military	
Female – Gulf War (2001–present)	✓
Female Veterans	✓
Male – Gulf War (1990–2001)	✓
Male – Gulf War (2001–present)	✓
Male – World War II	✓

Table: All variables are per capita and log-transformed. ✓ = selected by LASSO.

Why Partially-Pooled Synthetic Control?

- Objective: Estimate effect of psychedelic decriminalization on crime
- Studied cities: Oakland, Santa Cruz, Arcata, San Francisco, Berkeley
- **Staggered treatment** $\rightarrow$ challenges:
  - Different pre/post-treatment windows
  - Varying donor pools across units
  - TWFE gives misleading results
- Solution: Use Partially-Pooled Synthetic Control Method (PPSCM) (Ben-Michael, et al. (2021))

Modeling Assumptions

- Untreated potential outcome:

$$Y_{it}^{\infty} = \lambda_i F_t + \epsilon_{it}$$

- **Assumptions:**
  - Exogeneity: $\mathbb{E}[\epsilon_{it} \mid D_i] = 0$
  - No anticipation of treatment
  - Once treated, always treated (SUTVA)
  - Fixed donor pool: only never-treated units

The Partially-Pooled SCM Estimator

- Balances:
  - Unit-specific SCM: minimizes individual imbalance
  - Pooled SCM: minimizes average imbalance across units
- Objective function:

$$\mathcal{L}(\nu) = (1-\nu)\sum_{i=1}^{N_T} d_i^2 + \nu d_{\text{pooled}}^2$$

- Hyperparameter $\nu \in [0,1]$ controls trade-off:
  - $\nu \to 0$: prioritize individual unit fit
  - $\nu \to 1$: prioritize pooled fit
- Improves stability across noisy units

Implementation Details

- Data variables: `City`, `Year`, `Month`, `Date`, `Tdate`, `Treat`, `outcomes`
- Estimator:

$$\tau_{it} = Y_{it} - \sum_{j \in \mathcal{D}} w_{ij} Y_{jt}$$

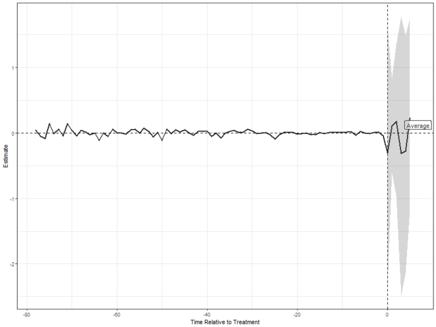
- Weight constraints:

$$\sum_{j \in \mathcal{D}} w_{ij} = 1, \quad w_{ij} \geq 0$$

- Software: `multisynth` package in R
- **Enhancement:** Include LASSO-selected covariates to improve pre-treatment fit

Key Results – Violent Crime

- Optimal hyperparameter: $\nu = 0.7209$
- Pooled RMSE: 0.2005 (pre-treatment fit)
- Average ATT: $\hat{\tau} = -0.064$ (SE $= 0.237$)
- **Interpretation:** Small, statistically uncertain effect
- Imbalance reductions:
  - Global: 96.9%
  - Unit-specific: 81.3%



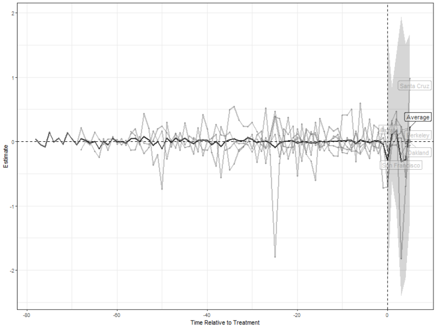
Unit-Specific RMSE

Table: Root Mean Squared Error (RMSE) for Separate SCM

Treated Unit	RMSE
Arcata	0.4014
Berkeley	0.1727
Oakland	0.1282
San Francisco	0.1132
Santa Cruz	0.1584

Placebo Test – Violent Crime

- Random assignment of treatment across units
- Placebo ATTs also fluctuate around zero
- Placebo ATT estimates resemble main results → not distinguishable
- **Conclusion:** No significant impact of policy on violent crime



Robustness – Varying ν

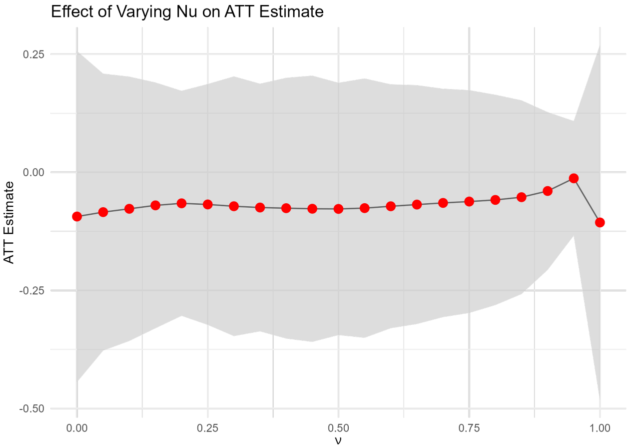
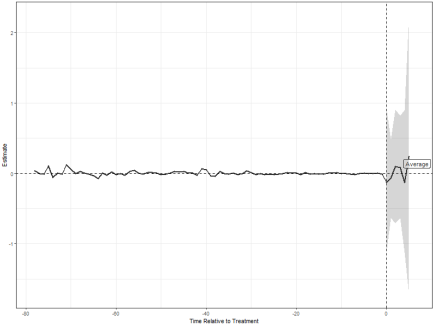


Figure: Varying ν from 0 to 1

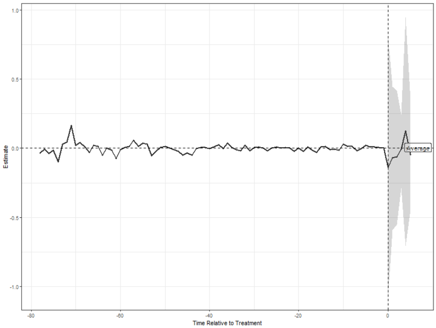
Robustness – Violent Crime (Excluding Arcata)

- Arcata had poor pre-treatment fit (RMSE $= 0.4014$)
- Exclusion improves pooled RMSE to 0.0816
- New ATT: 0.018 (SE $= 0.114$)
- **Conclusion:** Still no significant impact after exclusion



Key Results – Property Crime

- Optimal hyperparameter: $\nu = 0.5828$
- Pooled RMSE: 0.0959
- Average ATT: -0.031 (SE = 0.156)
- Imbalance reductions:
    - Global: 98.1%
    - Unit-specific: 90.2%
- **Conclusion:** Minimal, non-significant effect



Unit-Specific RMSE

Table: Root Mean Squared Error (RMSE) for Separate SCM

Treated Unit	**RMSE**
Arcata	0.1822
Berkeley	0.0946
Oakland	0.0476
San Francisco	0.0650
Santa Cruz	0.0671

Robustness – Varying ν

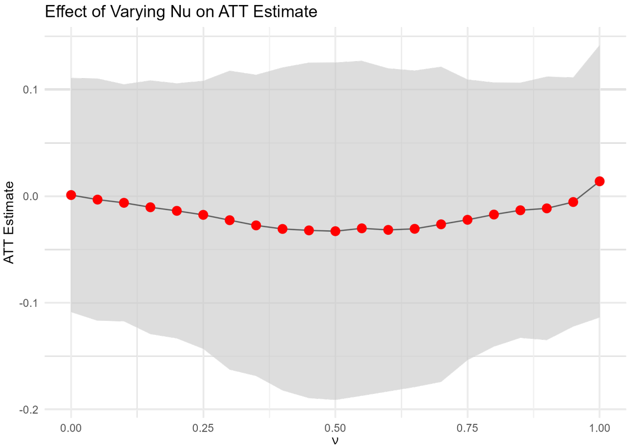
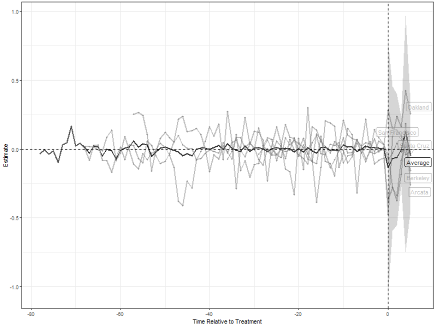


Figure: Varying ν from 0 to 1

Placebo & Robustness – Property Crime

- Placebo ATTs fluctuate around zero, and similar to main ATT
- Excluding Arcata improves pooled RMSE to 0.0565
- New ATT: 0.021 (SE = 0.163)



With Covariates – Violent & Property Crime

Table: Model Performance for Violent and Property Crimes (with Covariates)

	Violent	**Property**
ν	0.6596	0.4893
$\text{RMSE}_{\text{pooled}}$	0.2496	0.1327
$\text{RMSE}_{\text{Arcata}}$	0.4853	0.2361
$\text{RMSE}_{\text{Berkeley}}$	0.2066	0.1371
$\text{RMSE}_{\text{Oakland}}$	0.1659	0.0665
RMSE_{SF}	0.1242	0.0907
RMSE_{SC}	0.2266	0.1146
ATT	-0.079	0.001
SE	0.294	0.109

Sensitivity Check – Excluding Arcata (Covariates)

- Further drop Arcata from donor pool
- ATT (Violent): 0.009 (SE = 0.095)
- ATT (Property): 0.053 (SE = 0.258)
- Individual units imbalance was reduced:
  - Violent: 89.2% improvement
  - Property: 91.2% improvement

Crime Subcategories

Table: Crime Subcategory Statistics

	Homicide	Robbery	Rape	Assault	Burglary	Larceny	Vehicle Theft	Arson
ν	0.5278	0.6518	0.5745	0.6507	0.5461	0.4738	0.5660	0.5492
$\text{RMSE}_{\text{pooled}}$	0.4983	0.4871	0.5055	0.3675	0.2125	0.1383	0.2863	0.5867
$\text{RMSE}_{\text{Arcata}}$	0.4684	1.0509	0.9291	0.7507	0.3701	0.2376	0.5636	1.0048
$\text{RMSE}_{\text{Berkeley}}$	0.2315	0.3325	0.5124	0.2840	0.2055	0.1372	0.2497	0.5830
$\text{RMSE}_{\text{Oakland}}$	0.1937	0.1860	0.2172	0.2121	0.0992	0.0686	0.1120	0.3324
RMSE_{SF}	0.1613	0.1681	0.2388	0.1748	0.1733	0.1240	0.1604	0.2479
RMSE_{SC}	0.1643	0.3554	0.4666	0.2670	0.1768	0.1128	0.2218	0.7273
ATT	0.149	0.011	-0.082	-0.160	-0.029	-0.009	0.015	0.065
SE	0.494	0.102	0.283	0.536	0.209	0.103	0.237	0.235
Global L2 Imbalance	0.078	0.136	0.155	0.102	0.061	0.033	0.079	0.182
Std. L2 Imbalance	0.270	0.530	0.538	0.398	0.224	0.147	0.306	0.640

Key Findings Recap

- **Method:** Partially-pooled synthetic control on 5 CA cities
- **Main results:**
  - Violent crime ATT: -0.064 (SE $=$ 0.237)
  - Property crime ATT: -0.031 (SE $=$ 0.156)
  - Both estimates statistically insignificant
- **Conclusion:** Psychedelic decriminalization had no measurable impact on crime rates

Final Thoughts & Policy Relevance

- Aligns with broader literature: psychedelic decriminalization $\neq$ higher crime. Backed by Denver 2021 City Council study to review their 2019 policy effect on public safety
- Contrasts with mixed findings from cannabis reform
- Limitations:
  - Short post-treatment windows
  - Potential unobserved confounders
  - Many of the treated cities are in North California- so cautiously generalize the results
- **Policy implication:** Reforms need not compromise public safety
- **Future research:**
  - Longer-term impacts
  - Context-specific dynamics (psychedelic value chain)