Effects of Natural Hazards on Spatio-Temporal Patterns of Crime in the United States

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Introduction: Team Members

Associate Prof. Dr. Petar Jevtic - Passionate about mathematical conceptualizations of risk. Special interests in emerging risks such as cyber risk and climate risk.

Assistant Prof. Dr. Melanie Gall - Studies the interaction between natural hazards and society. Focus on risk metrics, hazard mitigation, and climate change.

Dr. Esther Boyle - earned her doctorate in Statistics at ASU in the fall 2023. Interests include risk analysis and impacts of natural hazards.

Cody Delos Santos - Ph.D. student in applied mathematics at ASU. Received master's degree from SFSU in mathematics. Interests include machine learning, big data, and analysis of crime patterns.

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Objective

- Use extensive FBI crime data and premiere natural hazard data (SHELDUS) .
- Combine datasets to investigate crime rates before and after a hazard event.
- Detect notable changes in crime rates after hazard.

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Motivation

- Natural hazards pose significant threat.
  - *Damage to communities and infrastructure.*

- Such events often result in substantial costs and damage and are expected to increase over time.[1,2]

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Motivation

- Law enforcement agencies are grappling with critical staffing shortages and funding constraints [3,4]
- 78% of agencies are having difficulty in recruiting qualified candidates and 65% claimed to not have enough applicants [5].

Motivation

- Discovering associations between crime rates and natural hazards.
  - *May enable optimal resource allocation.*

- Findings may be used to inform law enforcement entities where to send more agents.

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Background

- Broad theories:
  - *The emergence of altruistic behavior.*
  - *The acceleration of lawlessness as a product of pre-disaster trends, historical inequalities, and social vulnerability.*
  - *The opportunity for crime as a part of routine activities.*
- There is not consensus on which theory is true.

Background

- Findings have been diverse and, in some cases, contradictory. [6,7,8]
    - *Trainor et al. Disaster Realities in the Aftermath of Hurricane Katrina: Revisiting the Looting Myth found prevalence of prosocial behavior*
    - *Blakeslee's Weather shocks, agriculture, and crime: Evidence from India found an uptick in crime.*
    - *Berrebi's Individual and community behavioral responses to natural disasters found that in affect area, crime decreases, but surrounding area crime increased*
    - *Zahnow's Disasters and Crime: The Effect of Flooding on Property Crime in Brisbane Neighborhoods found no change in crime.*

- Past research has been limited in scope either spatially or temporally. [9,10]
    - *Crime Prediction Using Twitter Sentiment and Weather*
    - *Hurricane Alex Impact on Crime Rates in Houston, Texas*
    - *Collective Resources and Violent Crime Reconsidered: New Orleans Before and After Hurricane Katrina*
    - *All focus on single event*

Background

- Our contributions:
  - Examine nearly three decades of crime and disaster data for the U.S.
    - *1991-2018*
  - Investigate multiple time scales.
    - *Weekly*
    - *Biweekly*
    - *Monthly*
    - *Quarterly*
  - Deploy well-established analytical methods.
    - *Regression-discontinuity design*

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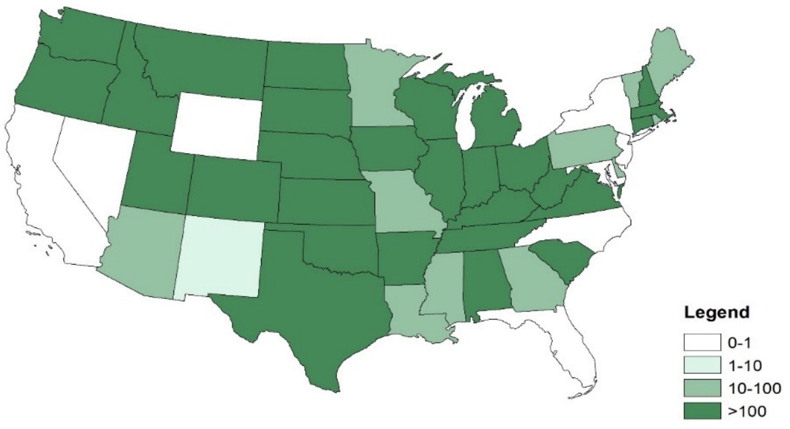
Crime Data: NIBRS

- The National Incident-Based Reporting System (NIBRS) is the national standard for law enforcement in the United States. [11,12]
  - Details on every crime incident in the U.S.
  - This research drew data exclusive from the Offense Segment.

- Initially drew from nearly 110 million records of crime incidents.

Law Enforcement Jurisdictions Reporting to NIBRS



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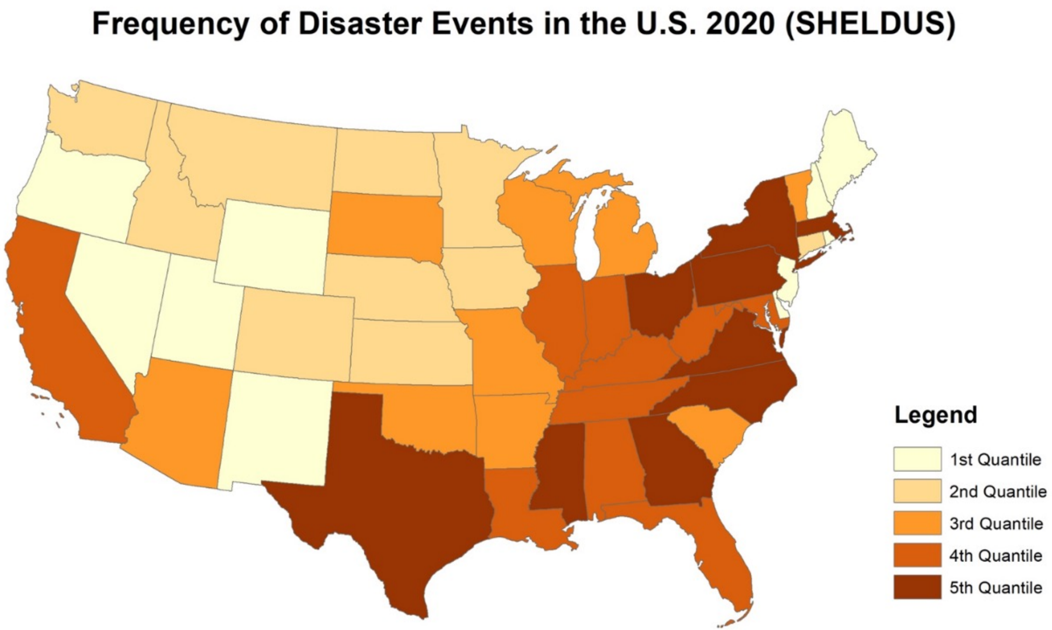
FEDERAL BUREAU OF INVESTIGATION
UNIFORM • CRIME • REPORTING
NIBRS
NATIONAL INCIDENT BASED REPORTING SYSTEM

Natural Hazard Data: SHELDUS

- The Spatial Hazard Events and Losses Database for the United States (SHELDUS):
  - *U.S. county-level hazard and loss dataset.*
  - *includes direct losses (injuries, fatalities, property and crop damage, etc.)* [13]
- Access to database for ASU researchers is free.
  - *936,783 hazard records*



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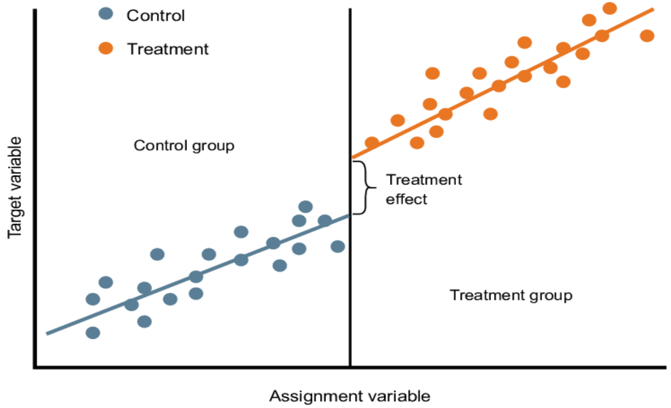
Data Cleaning

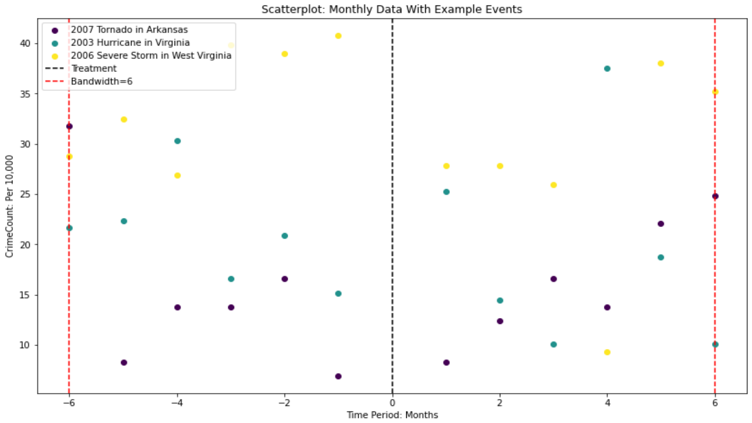
- Started with all of NIBRS and SHELDUS data.
  - *Aggregated to monthly level*
  - *Added zeros to determine missing data or true zeros*
  - *3,186,960 entries*

- Removed *missing data.*
- Only *true zeros* remained.
  - *Left at 997,441 entries*
- Excluded hazard events that were too close temporally.
- Only considered hazard events with at least $1000 in property loss.

Approach/Methodology: Regression-Discontinuity Design

- A statistical method to compare two groups of data before and after certain event.
- Segmented crime data into pre-hazard event and post-hazard event.
- Disaster events act as a treatment with resulting effect on crime patterns.





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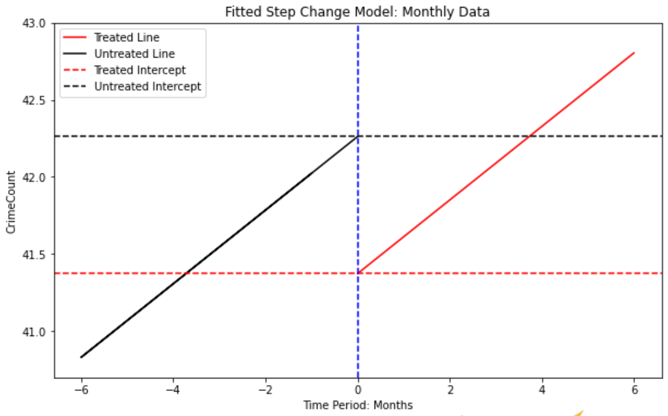
Approach/Methodology

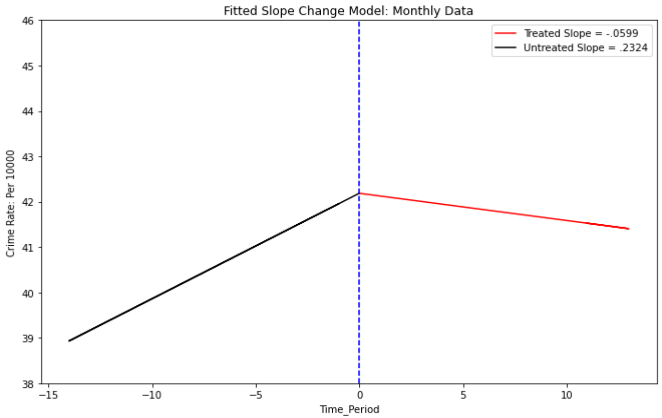
Step Change Model

- Quantify to what extent natural hazard events immediately impact crime rates.
- 'Jump' in intercepts of lines (*treatment effect).*



Slope Change Model

- Focus on estimating the changes in the *trend* of crime rates immediately following a natural hazard event.
- Change in slopes of lines.



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Models: Step Change

With N independent variables (predictors) a **step** change model takes the form of:

$$Y_{it} = \alpha_0 + \beta_0 * t + \alpha_1 * I_{it}^1 + \alpha_2 * I_{it}^2 + \cdots + \alpha_N * I_{it}^N + \epsilon_{it}$$

- Y_{it} - the value of outcome
- α_0 - intercept of the model before treatment
- β_0 - estimates the general trend of crime rates before the treatment
- I_{it}^n - indicator variable (1 or 0)
- α_n - **estimates how a hazard event immediately impacted crime rates**
- ϵ_{it} - error term

Models: Slope Change

With N independent variables (predictors) a **slope** change model takes the form of:

$$Y_{it} = \alpha_0 + \alpha_1 * t + \beta_1 * I_{it}^1 * t + \beta_2 * I_{it}^2 * t + \cdots + \beta_N * I_{it}^N * t + \epsilon_{it}$$

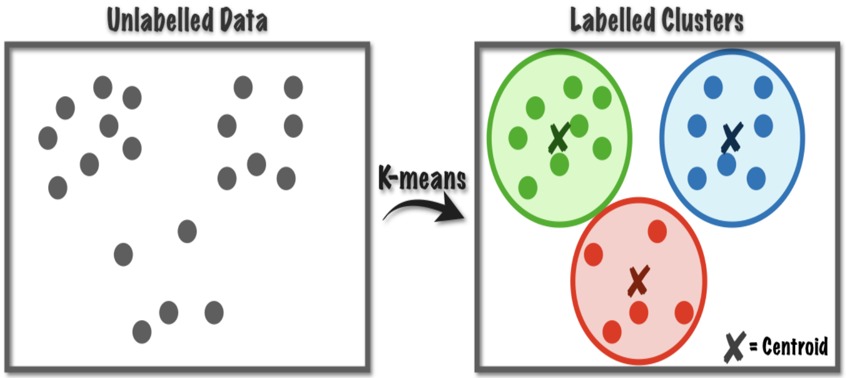
- α_1 - trend of crime data (increasing, decreasing, unchanging) before hazard event
- **β_n - estimates how the trend of crime data changes after hazard event**

Model Segmentation

Model Type Name	Description
General Crime Models	No data segmentation. Predictor - 1 if $t > 0$ or 0 if $t < 0$
Hazard Type Segmented Models	No crime data segmentation. Predictors - hazard types.
Violent Crime Type Models	Crime data is segmented by crime type.
Property Loss Segmented Models	No crime data segmentation. Predictors are categories of damage caused my disaster.
Crime Type and Property Loss Segmented Models	Crime data is segmented by crime type. Predictors - loss categories.
State Segmented Models	Data is segmented by state.

Approach/Methodology: Crime Rate Clusters

- Differences may exist in higher crime rate jurisdictions and lower crime rate jurisdictions.
- Categorize crime rates into similar groups.
  - *K-Means clustering*
- Separate models fitted for each group.
- Results have high utility in that different jurisdictions may find results specific to their crime rate.



Results: Big Picture

- 497 models were fitted. Total of 1865 coefficients produced.
- **280 coefficients statistically significant.**
- Results are sorted into easy-to-read tables.
  - *Broken down by timescale, model-type, crime rate group, and hazard type.*
- This analysis revealed variations in coefficients across different time scales and crime rate clusters.
- Some patterns did emerge consistently.

Biweekly				
Model	**Hazard Type**	**Coefficient**	**P-Value**	**Crime Rate Range (per 10000)**
Step	Lightning	0.0182	< .001	2.91-22.24
Step	SevereStorm/Thunder	0.077	< .001	2.91-22.24
Step	Tornado	0.0837	< .001	2.91-22.24
Step	WinterWeather	−0.1334	< .001	2.91-22.24
Step	Flooding	−0.1053	< .001	22.24-2346.37
Step	Lightning	0.2062	< .001	22.24-2346.37
Step	SevereStorm/Thunder	0.3806	< .001	22.24-2346.37
Step	Tornado	0.0976	0.01	22.24-2346.37
Step	Wind	−0.2974	< 0.001	22.24-2346.37
Step	WinterWeather	−0.2466	< 0.001	22.24-2346.37
Slope	Flooding	−0.0193	0.025	21.95-2346.37
Slope	Lightning	0.0673	< 0.001	21.95-2346.37
Slope	SevereStorm/Thunder	0.1053	< 0.001	21.95-2346.37
Slope	Tornado	0.0406	< 0.001	21.95-2346.37
Slope	Wind	−0.0747	< 0.001	21.95-2346.37
Slope	WinterWeather	−0.0509	< 0.001	21.95-2346.37
Slope	Lightning	0.0807	< 0.001	2.82-21.95
Slope	SevereStorm/Thunder	0.0231	< 0.001	2.82-21.95
Slope	Tornado	0.0252	0.004	2.82-21.95
Slope	Wind	−0.0134	0.013	2.82-21.95
Slope	WinterWeather	−0.0433	< 0.001	2.82-21.95

Note. Coefficients and p-values are presented as obtained from the statistical models. Crime rate ranges are provided per 10000 population for reference. P-values less than 0.001 are denoted as < 0.001.

Time Scale	Model	Hazard Type	Coefficient	P-Value	Crime Rate (per 10,000)
Monthly	Step	WinterWeather	−0.0882	0.044	0.04-7.46
Monthly	Step	WinterWeather	−1.1521	0.015	7.47-116.28
Monthly	Slope	WinterWeather	−0.4594	0.007	7.45-116.28
Monthly	Slope	WinterWeather	−0.0327	0.041	0.04-7.45
Monthly	Step	SevereStorm/Thunderstorm	0.2897	< 0.001	0.04-7.46
Monthly	Step	SevereStorm/Thunderstorm	1.254	0.001	0.04-7.46
Monthly	Slope	SevereStorm/Thunderstorm	0.3599	0.012	7.45-116.28
Monthly	Slope	SevereStorm/Thunderstorm	0.0943	< 0.001	0.04-7.45
Weekly	Step	Lightning	0.0419	< 0.001	0.01-2.12
Weekly	Step	Lightning	0.4706	0.026	6.70-23.70
Weekly	Slope	Lightning	0.0062	< 0.001	0.01-2.13
Weekly	Slope	Lightning	0.1247	0.001	6.71-23.70
Biweekly	Step	Wind	−0.1439	< 0.001	0.02-3.44
Biweekly	Step	Wind	−0.224	< 0.001	3.44-11.13
Biweekly	Slope	Wind	−0.0506	< 0.001	0.03-3.49
Biweekly	Slope	Wind	−0.0877	< 0.001	3.49-11.49

Note. Coefficients and p-values are presented as obtained from the statistical models. Crime rate ranges are provided per 10,000 population for reference. P-values less than 0.001 are denoted as < 0.001.

Monthly				
Model	**Hazard Type**	**Coefficient**	**P-Value**	**Crime Rate Range (per 10000)**
Step	Wind	−0.011	< .001	18.08-50.95
Step	Flooding	−0.0286	0.022	18.08-50.95
Step	WinterWeather	−0.0507	< .001	18.08-50.95
Step	SevereStorm/Thunder	0.1511	< .001	50.95-4285.40
Step	Wind	−0.1917	< .001	50.95-4285.40
Step	Flooding	−0.0906	< .001	50.95-4285.40
Step	WinterWeather	−0.1215	< .001	50.95-4285.40
Step	SevereStorm/Thunder	−0.0432	0.006	.11-18.08
Step	Wind	0.0923	< .001	.11-18.08
Step	WinterWeather	−0.0624	0.002	.11-18.08
Slope	SevereStorm/Thunder	0.0476	< .001	50.40-4285.40
Slope	Wind	−0.0612	< .001	50.40-4285.40
Slope	Flooding	−0.0275	< .001	50.40-4285.40
Slope	WinterWeather	−0.0288	< .001	50.40-4285.40
Slope	SevereStorm/Thunder	−0.0051	0.01	17.82-50.30
Slope	Wind	−0.0053	0.01	17.82-50.30
Slope	Flooding	−0.007	< .001	17.82-50.30
Slope	WinterWeather	−0.0052	0.014	17.82-50.30
Slope	SevereStorm/Thunder	−0.0059	0.01	.11-17.80
Slope	Wind	0.0058	0.012	.11-17.80
Slope	Flooding	−0.0074	0.002	.11-17.80
Slope	WinterWeather	−0.0179	< .001	.11-17.80

Note. Coefficients and p-values are presented as obtained from the statistical models. Crime rat ranges are provided per 10000 population for reference. P-values less than 0.001 are denoted a < 0.001.

Weekly				
Model	**Hazard Type**	**Coefficient**	**P-Value**	**Crime Rate Range (per 10000)**
Step	Wind	−0.0475	< .001	.98-11.10
Step	SevereStorm/Thunder	0.1034	< .001	.98-11.10
Step	Lightning	0.1161	< .001	.98-11.10
Step	WinterWeather	−0.1264	< .001	.98-11.10
Step	Tornado	−0.0475	< .001	.98-11.10
Step	Wind	−0.1727	< .001	11.10-1428.57
Step	SevereStorm/Thunder	−0.0352	< .001	11.10-1428.57
Step	Flooding	0.0462	< .001	11.10-1428.57
Step	WinterWeather	0.0493	< .001	11.10-1428.57
Step	Hail	−0.0457	0.001	11.10-1428.57
Slope	Wind	−0.0186	< .001	1.01-11.27
Slope	SevereStorm/Thunder	0.0345	< .001	1.01-11.27
Slope	Lightning	0.037	< .001	1.01-11.27
Slope	WinterWeather	−0.0432	< .001	1.01-11.27
Slope	Tornado	0.0247	< .001	1.01-11.27
Slope	Wind	−0.0492	< .001	11.27-1428.57
Slope	SevereStorm/Thunder	0.0869	< .001	11.27-1428.57
Slope	Lightning	0.0322	< .001	11.27-1428.57
Slope	WinterWeather	−0.0642	< .001	11.27-1428.57
Slope	Hail	0.0264	0.013	11.27-1428.57
Slope	Tornado	0.0435	< .001	11.27-1428.57

Note. Coefficients and p-values are presented as obtained from the statistical models. Crime rate ranges are provided per 10000 population for reference. P-values less than 0.001 are denoted as < 0.001

Results: Emergent Patterns

- Strong evidence suggests winter weather hazard events associated with a drop in crime rates.
- In contrast, severe storms were associated with an increase in crime rates.
- These held true across time scales and regardless of crime rates.

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Results: Emergent Patterns

- Property loss segmented models indicated a strong association with a decrease in violent crime in particular.
- This was true regardless of the crime rate cluster.

Results: Clear Picture

- Models segmented by state indicated that hazard events were associated with a decrease in crime rates.
- This was a clear result in Michigan and South Carolina.
- Emergent altruistic behavior in these state?
    - *Further research needed.*

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Results: Example Output

- Output of this research allows for highly specified recommendations based on:
  - *existing crime rates in the jurisdiction*
  - *hazard type*
  - *hazard event severity*
  - *which state the event took place in, in some cases*

Time Scale	Model	Hazard Type	Coefficient	P-value	Crime Rate (Per 10,000)
Monthly	Step	Winter Weather	-.0862	.014	.04-7.46
Monthly	Step	SevereStorm/ Thunderstorm	.2807	<.01	.04-7.46
…	…	…	…	…	…
Biweekly	Slope	Wind	-.0877	<.001	3.49-11.49

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Limitations

- On longer time scales, it is possible to miss valuable/important data at the threshold.
- Data at the threshold is not considered for analysis.
- On the longer time scales, monthly and quarterly, this risks the possibility of excluding data that may be insightful during the month and quarter containing the hazard event.
- Selection bias: Not all jurisdictions report to NIBRS.

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Discussion

- After natural hazard event law enforcement agencies require additional personnel to promptly respond to affected areas.

- Our research demonstrates that this is dependent on:
  - *Disaster type*
  - *Crime rate*
  - *Event severity (financially)*
  - *Location*

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Discussion: Impact for DHS

- Occurrence of a hazard event is followed by local and state law enforcement departments facing harsh struggles to maintain the safety of the public.[14]

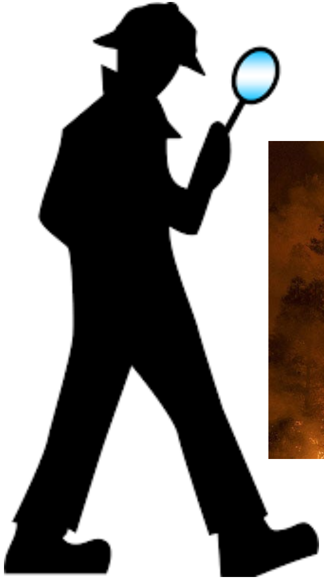
- Information campaigns may aid in dispelling possibly harmful ‘disaster myths’.

- Results didn’t indicate crime should universally be expected to rise after all disasters.

- Relationship between crime and natural hazards more nuanced.
    - *Findings capture nuance by using several types of models*

Discussion: Impact for DHS

- Output tables offer insight into specific disaster types.
- Information may be dispersed as seen fit to state and local law enforcement.
- Aid in disaster preparedness and response.
- Aid in optimal resource distribution.
  - *Some disasters strongly associated with drop in crime*
  - *Others a rise in crime*
  - *In face of various disasters, informed decisions may be made*



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Questions for the Researchers?

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