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

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Abstract

The consensus that disasters do not cause an increase in crime rates is receiving renewed attention. In recent years, research has emerged that challenges this consensus by positing that crime rates and the type of crime may vary depending on the phase of the emergency. To address this, this research utilizes comprehensive crime data from the National Incident-Based Reporting System and hazard event data from the Spatial Hazard Events and Losses Database for the United States. Employing regression discontinuity design principles, swaths of linear regression models across different time scales are fitted, yielding nearly 200 statistically significant coefficients. The findings reveal correlations between certain natural hazard types and changes in crime rates. For instance, a correlation between winter weather hazard events and a subsequent drop in crime rates is observed whereas severe thunderstorms were associated with an increase in crime rates. Additionally, an increase in crime rates following natural hazard events that were observed in the shorter time scales (e.g., hail, tornadoes) did not persist into the longer time scale, where, in fact, negative treatment effects and a negative change in trend were found. These results shed light on the complex relationship between natural hazards and crime rates, providing valuable insights for policymakers, law enforcement agencies, and other stakeholders. Given that the intensity and frequency of natural hazards are on the rise, a better understanding of these dynamics can increase the efficiency of resource allocation for public safety and target the deployment of law enforcement more effectively.

Keywords: Crime Rates, Natural Hazards, Regression Design Discontinuity, Linear Regression

1 Introduction

Fear of crime and looting is a frequently cited reason when residents do not evacuate in the face of an approaching natural hazard such as a hurricane or a flood Kuhlman et al. (2022). The disaster research community has gone as far as labeling this (mis-)perception a "disaster myth" Aguirre (2020), meaning an untruth, due to long-standing research documenting a different phenomenon, i.e., an increase in altruistic and pro-social behavior Lemieux (2014). Some disaster case studies, though, suggest that this notion may no longer hold true and that in fact antisocial behavior (e.g., fraud) and violent crimes are emerging post-disaster as seen after hurricanes Hugo and Katrina Brown (2012) or the COVID-19 pandemic.

Natural hazard events pose a significant threat to communities and critical infrastructure, often resulting in substantial costs and damages Diaz and Pulwarty (1997). Notably, the frequency and intensity of these events have been on the rise (2021), with no apparent respite in the foreseeable future. This alarming trend has translated into escalating losses, affecting a growing number of properties and vital infrastructure each year Iglesias et al. (2021).

Simultaneously, law enforcement agencies are grappling with critical challenges, including staffing shortages and funding constraints Young et al. (2022); Villafranca (2022). Surveys conducted among law enforcement professionals consistently highlight recruitment and retention as paramount concerns International Association of Chiefs of Police (2021). Indeed, in those same surveys, 78% of agencies polled reported having difficulty in recruiting qualified candidates and 65% indicated they did not have enough candidates applying to be law enforcement officers. This crisis is exacerbated by a rising number of police officers leaving the force through resignation or retirement.

The COVID-19 pandemic further increased the strain on law enforcement entities. For example, research findings revealed a troubling correlation between the pandemic and an increase in incidents of partner violence (IPV) Buttell and Ferreira (2020). Lockdowns, social distancing measures, restricted travel, and closures of essential community services coincided with a marked surge in reported cases of domestic violence worldwide Campbell (2020). Notably, domestic disturbances and domestic violence calls are recognized as among the most perilous situations police officers respond to Tucker (2022). This surge in domestic violence extends beyond global pandemics, as seen in research linking it to events like the Black Saturday bushfires in Victoria, Australia Parkinson (2019). It is feasible that an increase in these types of crimes may need to be addressed by optimal resource allocation or hiring additional law enforcement officers.

In this study, spatio-temporal variations in crime rates categorized by crime type following natural hazard events are examined. The investigation encompasses both violent crime rates and overall crime rates without segmentation by type. Leveraging data from the National Incident-Based Reporting System (NIBRS) and natural hazard event data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), regression discontinuity design (RDD) is employed to assess whether statistically significant changes in crime rates occur in the aftermath of a hazard event. This approach, particularly when compared to the existing body of research, leverages more fine-grained spatio-temporal crime and disaster data to investigate changes in crime rates across monthly, weekly, biweekly, and quarterly time scales.

Discovering associations between changes in violent crime rates and certain types of hazard events may help law enforcement agencies prepare to optimally allocate resources to various areas affected by such hazards. For example, if a drastic rise in crime rates was observed in the aftermath of severe storm hazard events, such agencies may choose to provide further resources, either through more agents in the area or greater funding to departments, in the affected areas. Thus, this research seeks to offer practical information through findings pertaining to violent crime that law enforcement agencies may implement. Additionally, associations found between unsegmented crime rate data (property crime, violent crime, and all others) and hazard events will serve to fill a void in the academic literature.

1.1 Background

Conceptually speaking, there are three broad theories of disaster and crime: a) the emergence of altruistic behavior Gemeinschaft Dynes (1970), b) acceleration of lawlessness as a product of pre-disaster trends, historical inequalities, and social vulnerability Van Brown (2019), and c) the opportunity for crime as part of routine activities Chamberlain and Hipp (2015). In addition, there are a multitude of behavioral studies on the topic of response and recovery actions (e.g., evacuating v. staying behind) influenced by the perception or fear of crime alone Kuhlman et al. (2022). Some of these early behavioral studies revealed, for example, a disparity between public perception and empirical observations of human behavior in the aftermath of natural hazards Tierney et al. (2006). These studies, which primarily focused on individual events, challenged prevailing beliefs by suggesting that widespread looting and increased crime were often misconceptions and that in fact, social solidarity dominates post-disaster behaviors Auf der Heide (2004).

However, consensus on the relationship between disasters and crime remains elusive as diverse findings characterize the field. While some studies have reported an increase in prosocial behaviors and a decrease in crime rates during natural hazard events in affected areas Trainor et al. (2006), others have arrived at contrasting conclusions, suggesting an uptick in crime Blakeslee and Fishman (2018). The effects of space (e.g., neighborhoods, regions), time (e.g., emergency phases), hazard type and its characteristics (e.g., acute, complex), and crime types (e.g., property theft, domestic violence) add complexity. For example, some research Berrebi et al. (2021) found that crime decreases within disaster-stricken areas but rises in surrounding regions Berrebi et al. (2021) whereas Zahran et al. (2009) documented a reduction in reported property and violent crimes but an increase in domestic violence incidents. Another study found that there was essentially no change in crime patterns Zahnow et al. (2017).

Just as every disaster is unique due to the nature of the hazard and the community itself as characterized by levels of social vulnerability and/or community resilience Cutter et al. (2008), so could be the linkages between a hazard, the community, and post-event crime patterns. In fact, more recent disaster case studies suggest that these theories are not mutually exclusive and may exist either sequentially Aguirre (2020) or concurrently post-disaster. Thus, more comprehensive and nuanced research is needed to answer critical questions related to the nature and extent of the association between natural hazards, crime and potentially confounding factors.

The inconclusive state of research on this topic may, in part, be attributable to methodological shortcomings related to limited spatial and temporal extents of the analysis, data resolution, or analytical methods. In addition, findings derived from a singular case study may not be non-transferable to other hazard events. Since the majority of the existing literature represents either case studies examining fear of crime and/or post-disaster crime patterns for a single single event Chen et al. (2015); Zahnow et al. (2017); Harris (2016); Weil et al. (2021), more advanced methodologically approaches warrant exploration.

To advance the field, some researchers have adopted a geographically broader scope and analyzed entire countries and multiple disasters Blakeslee and Fishman (2018). Others have relied on highly aggregated (annual) crime data or data with limited time scales, which impeded the detection of nuanced spatio-temporal crime patterns Berrebi et al. (2021). These choices, while insightful in regard to the specific time scales chosen, are inherently limited by the breadth of the findings. For instance, studies examining weekly crime incident counts have unveiled temporal evolution in spatio-temporal crime patterns post-disaster, such as a 10% increase in property crime in the first week, followed by a 2% decrease the subsequent week Jacob et al. (2007). Conversely, investigations based on monthly crime data revealed that post-flood property crime in Brisbane exceeded historical trends Zahnow et al. (2017). Some research has explored yearly aggregations of crime incidents to estimate expected counts, revealing proportional increases as temperatures rise Chen et al. (2015).

From a statistical modeling perspective, the most commonly used method was binomial regressions Zahran et al. (2009); Weil et al. (2021). Spatio-temporal analytics–such as the use of spatio-temporal cluster methods and Kulldorff's scan statistic to identify crime clusters associated with hazards Leitner and Helbich (2011)–are scarce. Notably, qualitative approaches have included large surveys to assess changes in crime rates following natural hazard events, although these often yield results that are challenging to implement in a predictive manner. Weil (2020).

2 Methods

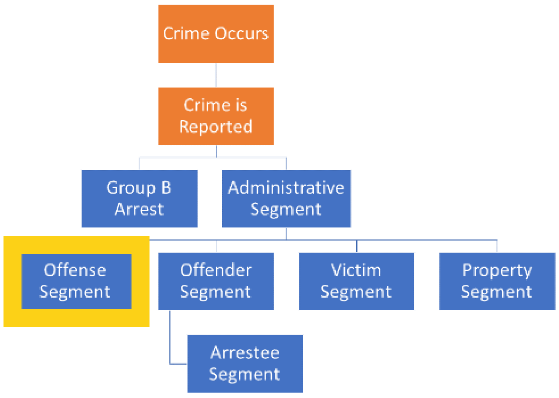
2.1 Crime and Hazard Data

The National Incident-Based Reporting System (NIBRS), the national standard for law enforcement crime data reporting, captures details on every crime incident in the United States FBI (2018); (2022). Figure 1 Kaplan (2021) visualizes the structure and process of NIBRS data generation. The data for this study originates from the offense segment and was downloaded as ASCII file from the National Archive of Criminal

Justice Data (NACJD) (1978) for the years 1991 through 2018. An asciiSetupReader R package Kaplan (2021) was utilized to convert the ASCII file into a CSV file type and import it into a Jupyter Notebook environment.

Upon concatenating data for each individual year and removing non-relevant variables, the resulting Python Pandas data frame consisted of size 109,936,357 rows and 7 columns with rows representing crime incidents and columns representing the following variables: state, OAI (Originating Agency Identifier), incident date, offense code, FIPS, population of county, and crime type. These variables detail for each crime incident, where the crime occurred, the state and jurisdiction of the crime, when the crime occurred (yyyy/mm/dd), which crime occurred, what type of crime occurred (violent, property, or non-index), and the population of the county the crime occurred in.

Fig. 1: Structure of the National Incident-Based Reporting System (NIBRS) data. Study data originate from the offense segment only (highlighted in yellow) [image from Jacob Kaplan's 'National Incident-Based Reporting System (NIBRS) Data: A Practitioner's Guide']



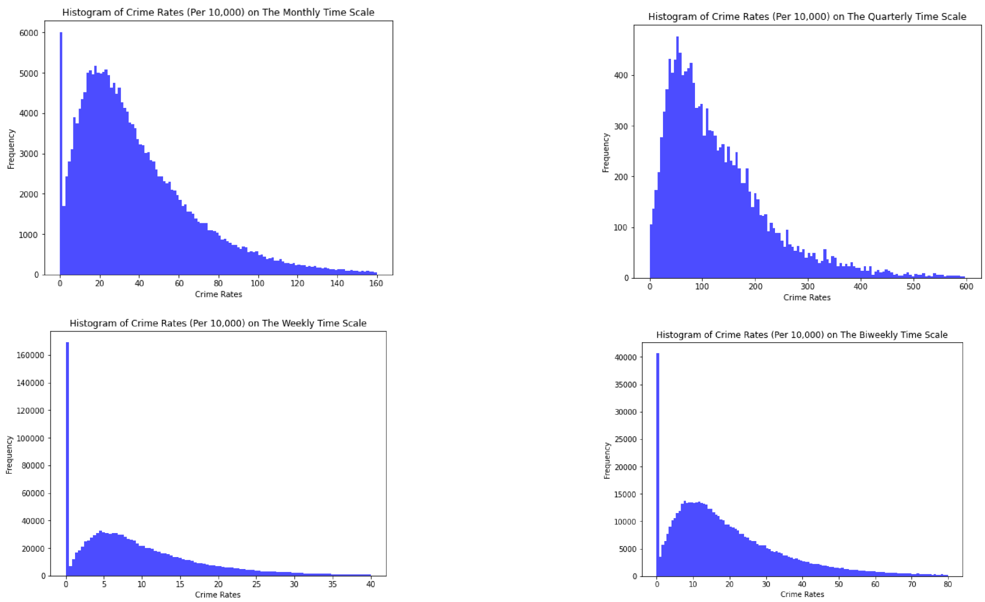
Information on hazard occurrence, or more specifically the occurrence of a direct loss (monetary or human) caused by a natural hazard was sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) Version 21. SHELDUS is a U.S. county-level hazard and loss dataset that includes direct losses (injuries, fatalities, property and crop damage) caused by one or more natural hazards (broadly categorized into 18 hazard types such as thunderstorms, hurricanes, wildfires, floods, etc.) Arizona State University and Security (2023). Version 21 covers the years 1960 through 2021, which subset to the time period and jurisdictions available for this study (1991-2018) resulted in a download of 215,933 loss records. SHELDUS data contains variables pertaining to direct losses (injury and fatality counts as well as current year and inflation-adjusted monetary losses), hazard type(s), the beginning and end date of a loss event, and the affected county. A direct property damage threshold of at least USD 1,000 was applied to exclude low-impact hazard events. SHELDUS data have been used elsewhere in the analysis of crime patterns Berrebi et al. (2021), albeit primarily at a yearly time scale and with aggregated hazard event counts.

The merging process of hazard data from SHELDUS and crime data from NIBRS yielded four datasets: monthly (244591 rows x 7 columns), quarterly (15656 rows × 7 columns), biweekly (707785 rows × 7 columns), and weekly data (1497720 rows × 7 columns). Before using the data contained in this dataframe to fit a linear regression model, the column 'CrimeCount' was transformed into crime rates per 10,000 individuals, using data in a population dataframe. The distribution of crime rates may be found in Figure 2, along with the seven variables.

Table 1: A preview of the monthly dataframe. The indexing column has been omitted.

EventID	Jurisdiction	StartDate	EndDate	HazardType	TimePeriod	CrimeCount
54	AR0010000	2007-02-24	2007-02-24	Tornado	-14.0	7.0
54	AR0010000	2007-02-24	2007-02-24	Tornado	-13.0	10.0
54	AR0010000	2007-02-24	2007-02-24	Tornado	-12.0	15.0
54	AR0010000	2007-02-24	2007-02-24	Tornado	-11.0	12.0
...	...	...	...	...	...	...
20646	WVWSP9000	2008-06-04	2008-06-04	Flooding	8.0	1.0

Fig. 2: The distribution of crime data across each time scale for monthly, quarterly, weekly, and biweekly data respectively.



2.2 Data Processing

Additional variables were added to the concatenated crime dataframes that serve to flag specific analytical criteria and to aid in data cleaning. The added variables accounted for the population of jurisdiction, the FIPS code associated with that jurisdiction, and the type of crime (violent, property, non-index) that was committed for each crime incident. The crimes contained in the violent crime type are shown in Table 2. The categorization of crimes into crime types was based primarily on publications from the U.S. Department of Justice Morgan (2022).

NIBRS-reporting agencies only document the occurrence of a crime incident. Consequently, NIBRS incident-level data does not have an inbuilt way to identify an absence of crime. However, it is crucial to account for time periods (months, weeks, and quarters) when no crimes occurred in a jurisdiction. In order to achieve this, absent entries would need to be classified as *true zero* or *missing data*, with the former indicating a lack of reporting to NIBRS because there were truly zero crime incidents in a jurisdiction and the latter indicating a lack of reporting to NIBRS for any other reason. The methodology by Haas Haas et al. (2012) was followed to classify zeros as either true zeros or missing data. This approach relies on monthly occurrences of zeros. A thus a new dataframe (with 1,220,499 entries) that consisted of monthly counts of crime incidents for each jurisdiction was generated. Zeros were imputed for months over the course of the study with missing observations resulting in 3,186,960 entries. Using population and crime type variables, zeros were then labeled as true zeros or missing data according to the guidelines in Haas et al. (2012).

To detect outliers in our data, the *ratio to median test* was used Haas et al. (2012). The algorithm takes the form: $Y_i = \frac{x_i}{\tilde{x}}$ such that x_i is the monthly crime count for a jurisdiction and $\tilde{x}$ is the median crime count for 12 months composing a year. Y_i is then compared to a critical value $\alpha = 4$. If $Y_i > \alpha$, the entire year for that jurisdiction as missing data is flagged. This means that this data is not subject to consideration in the merging stage, where the hazard loss data and crime data are linked. The final dataframe containing eligible data for merging, data that passed the guidelines and the median to ratio test, contained 997,441 entries. This process finalized the NIBRS data cleaning.

Table 2: UCR Offense Codes and Crime Types

UCR Offense Code	Crime Type
Murder/Nonnegligent Manslaughter	Violent
Forcible Rape	Violent
Aggravated Assault	Violent
Robbery	Violent
Rape	Violent
Sexual Assault With An Object	Violent
Sodomy	Violent
Forcible Sodomy	Violent

To isolate hazard loss events temporally and prevent overlaps in time–which could disrupt the model's attempt to measure the crime rate pre- and post-event– separate hazard datasets were generated for each time scale: weekly, biweekly, monthly, and quarterly. For each dataset, events with fewer than 5 time periods (weeks, bi-weeks, months, quarters) on either side without a subsequent hazard event were removed. If another loss event happened within a range of 5 to 14 time periods before or after the given event, it was considered the maximum window of crime incidents from NIBRS that would be chosen for that haard event.

Next, the two datasets were cross-joined, so that for each hazard event in a given jurisdiction, a record of all crimes in a window of 14 time points before and after that event could be taken. However, if another hazard occurred within 5-14 time periods of that given hazard, only crime incidents after or before that preceding or anteceding event were considered. All crime incidents that occurred during the event were removed in order to get a clear perspective of the change before and after.

For each time scale (weekly, biweekly, monthly, quarterly) dataset, crime data were grouped in a window around the respective hazard up to the corresponding time scale resulting in 93,274 events for the weekly, 50,586 for the biweekly, 20,646 for the monthly, and 2,113 events for the quarterly time scale. A condensed version of this procedure is shown in Table 3.

Table 3: The Procedure for Merging NIBRS Data with SHEDLUS Data

Step	**Description**
1. Initial Event Removal	1. Remove events with less than $1,000 (2022 USD) in property losses.
2. Temporal Isolation	2. Remove events that have a subsequent event occur in fewer than five time periods on either side.
3. Maximum Window Definition	3. If another hazard event occurred between 5 and 14 time periods before or after a given event, this sets the maximum window for crime incidents to consider.
4. Cross-Joining Datasets	4. Each hazard event in a jurisdiction was cross-joined with all crimes occurring within a 14-time-point window before and after the event unless otherwise specified in the above step.
5. Removing Crimes at the Threshold	5. Remove crime incidents that occurred during the hazard event.

2.3 Research Design

Regression-discontinuity design (RDD) is traditionally a pretest-posttest program-comparison group strategy Trochim (1990). RDD segments data into two groups, pre-threshold (treatment) and post-threshold (treatment). In the context of this research, the treatment is the occurrence of a natural hazard event, set at $t = 0$. RDD implements regression analysis to estimate the effect of a predictor(s) on some outcome variable. Essentially, RDD takes advantage of naturally occurring thresholds to formulate a quasi-experimental setting, insofar as treatment and control groups are determined by which side of the threshold they naturally occur in. This research utilizes regression methods to determine the effect of natural hazard events on crime rates.

2.4 Data Transformation

To address right-skewness in the outcome variable data across all time scales, a Box-Cox transformation was applied using the *scipy.special* package in Python. This transformation enhanced model fit and the quality of residual vs. fit analysis. A subsequent analytical pipeline constructed in Python optimized model parameters and facilitated K-means clustering on the target variable. The pipeline consisted of the following key steps:

- Bandwidth selection: In an RDD model, the bandwidth is defined as... . Here, an optimal bandwidth was determined to maximize R-squared values, as illustrated in Figure 3. This step set how much data the model would be fitted to.
- K-Means Clustering: We hypothesize that jurisdictions of different sizes with different crime patterns may have different effects following a disaster event. For this reason, K-means clustering was performed on the target variable to create multiple categories of crime rates. The choice of the number of clusters was guided by an elbow curve plot, a widely accepted technique in the literature Bartalotti and Brummet (2017); Joshi et al. (2017).
- Cluster-Specific Models: Clustering allowed each group of crime rates to have its own separate model. This approach enabled the detection of statistically significant treatment effects or changes in trends that might exist within specific clusters but not when analyzing all crime data collectively.
- Variable Bandwidths: Clustering the target variable before bandwidth selection ensured that each cluster had its own optimal bandwidth. Consequently, the bandwidth was not fixed across all clusters, accommodating potential variations in data characteristics.

Implementing this pipeline enhanced the robustness of the analysis and revealed nuanced relationships between hazard loss events and crime rates within distinct clusters of jurisdictions.

2.5 Modeling

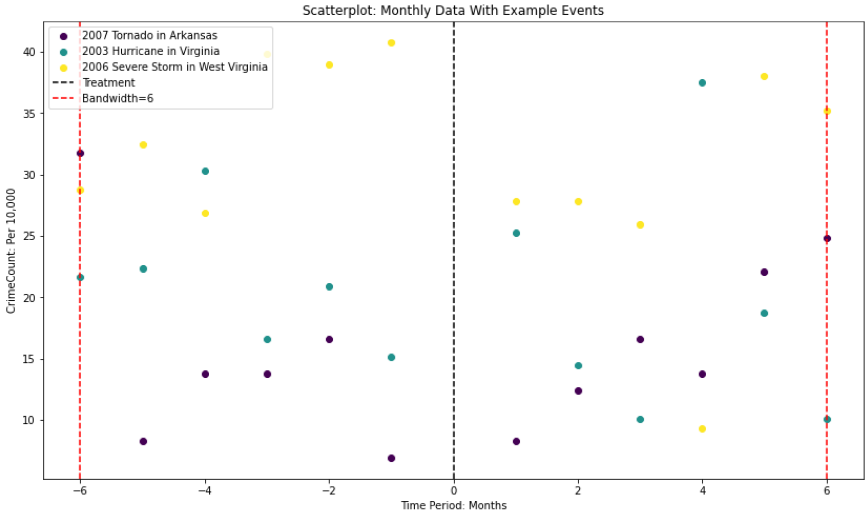
The identification of crime-hazard patterns is achieved by fitting linear regression models onto the data of each time-scale dataframe. Principles from the Regression Discontinuity Design (RDD) framework are adopted to investigate the causal impact of natural hazard events on crime rates. RDD, a well-established methodology in medical research, is adapted here to examine natural hazard events as interventions.

2.5.1 Model Categories

The models fall into two distinct categories, each serving a specific purpose:

- Step Change Models: These models estimate coefficients that quantify the treatment effect of independent variables on crime rates. In essence, these models elicit how natural hazard events immediately impact crime rates.
- Slope Change Models: In contrast, slope change models focus on estimating coefficients that capture changes in the trend of crime rates immediately following a

Fig. 3: An illustration of bandwidth. In this example, the bandwidth is set to 6. Bandwidth determines how much data the model is fitted to. A few natural hazard events and their corresponding crime rate data are given as an example.



natural hazard event. They provide insights into the evolving patterns of crime over time.

2.5.2 Estimating Technique

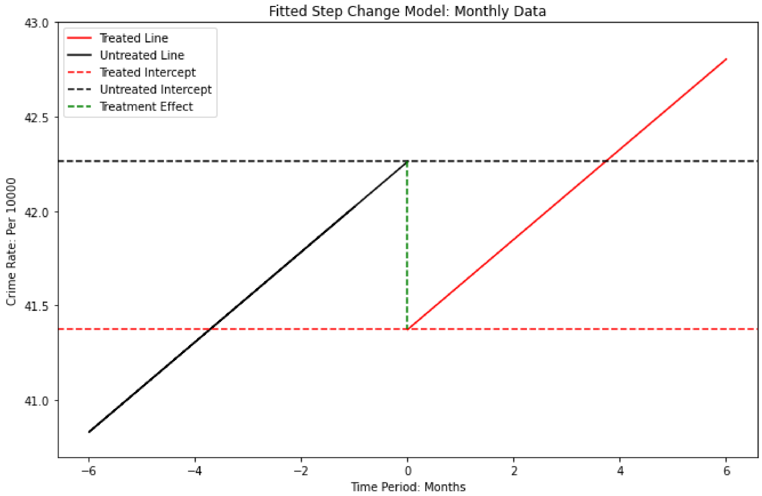
To estimate model parameters, Ordinary Least Squares (OLS) regression is employed. This choice allows for the straightforward addition or removal of predictors in the linear regression models, streamlining model manipulation. The models are implemented using the Python package statsmodels.api, which facilitates the estimation process. Our step change models follow the structure of Model (1), with N predictors, while the slope change models, also utilizing OLS and containing N predictors, adhere to the structure of Model (2). This modeling approach detects the immediate and trend-related effects of natural hazard events on crime rates, providing a comprehensive understanding of their impact. Similar model techniques have been used elsewhere Hawley et al. (2019).

$$(1)\ \ Y_{it} = \alpha_0 + \beta_0 \cdot t + \alpha_1 \cdot I^1_{it} + \alpha_2 \cdot I^2_{it} + \ldots + \alpha_N \cdot I^N_{it} + \epsilon_{it}$$

$$(2)\ \ Y_{it} = \alpha_0 + \alpha_1 \cdot t + \beta_1 \cdot I^1_{it} \cdot t + \beta_2 \cdot I^2_{it} \cdot t + \ldots + \beta_N \cdot I^N_{it} \cdot t + \epsilon_{it}$$

For model (1), Y_{it} is the value of outcome at time t surrounding event i. α_0 is the intercept that estimates the level of outcome just before the threshold at $t = 0$. In order to estimate the pre-treatment trend, β_0 is the slope. I^n_{it} takes on value 1 if $t > 0$ and $i = n$, else it takes on value 0. Next, α_n estimates the treatment effect for any $1 \leq n \leq N$. Finally, ϵ_{it} is the error term. In model (2) α_1 is now the slope that estimates the pre-treatment trend, β_n estimates the change in trend occurring immediately after the intervention for any $1 \leq n \leq N$. Notably, the multiplication of the indicator variable I^n_{it} by t transforms model (1) into model (2). A visualization of a step change model and a slope change model, both fitted to some of the data, may be seen in Figure 4 and Figure 5 respectively.

Fig. 4: A step change model fitted to unsegmented crime data on the monthly time scale. We can see the 'jump' that occurs at the threshold $t = 0$, which represents the treatment effect. For step change models, the slope of both lines is fixed, and the intercept is allowed to vary.

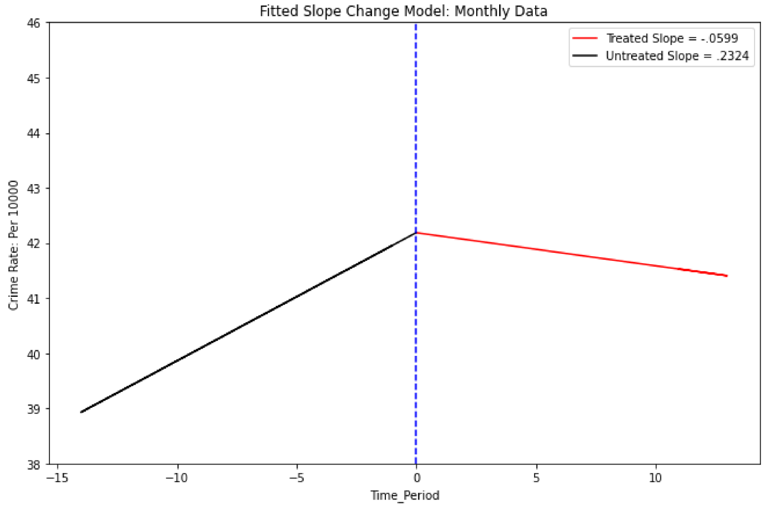


To explore the relationship between natural hazard events and crime rates, models were fitted using different predictors and data segmentation protocols. The different types of data segmentation and the different predictors used are shown in Table 4. In total, 497 models were fitted, yielding a total of 1,865 coefficients.

Table 4: The different types of models, categorized by data segmentation or predictors used.

Model Type Name	**Description**
General crime models	No data segmentation. The predictor used is a dummy variable that takes on value 1 if $t > 0$ and 0 if $t < 0$.
Hazard type segmented models	No data segmentation. The predictors are hazard type.
Violent crime type models	Data is segmented by crime type based on categories from Table 3. Violent crimes are extracted into their own dataframe.
Violent crime type and hazard type models	Data is segmented as in crime type models and predictors are drawn from hazard type models.
Property loss segmented models	No data segmentation. Predictors are drawn from K-means clustering performed on variable 'property loss' drawn from SHELDUS.
Crime type and property loss segmented models	Data is segmented as in crime type models and predictors are drawn from property loss models.
Location Segmented Models	Data is segmented by state. The same predictor from general models is used.

Fig. 5: A slope change model fitted to the same data as in Figure 4. The slope of each line may be seen in the legend. It follows that the 'change in trend', change in slope, immediately following the intervention at $t = 0$ is $-.2923$. For slope change models, the intercept of both lines is fixed, and the slope is allowed to vary.



Some hazard types were scarce and did not have high enough counts to be included in the modeling process. The hazard types that were used as predictors in the modeling process may be found in Table 5. Due to the nature of how we merged NIBRS and SHEDLUS data, the hazard types included were not consistent across time scales. For the crime type models, it was found that counts of 0 were exceedingly common to the point of poor model fit and undesirable residual vs. fit plots. This was due to how data was segmented from the larger dataframe down to the violent crime type dataframe. The larger dataframe contained instances of crimes of any type including non-index crimes and property crimes. In the process of extracting counts of crime of violent crime type, those instances of a crime being committed of crime type non-index or property were now reflected as a crime count of 0 in the violent crime type dataframe. It was decided to remove all events that had counts of 0 violent crime in order to fix this issue. This resulted in a dataframe that contained events where at least 1 violent crime took place based on the selection criteria detailed in section 2.2.

Table 5: The hazard types that were used as predictors for each time scale in the modeling process.

Time Scale	Hazard Types
Weekly	SevereStorm/ThunderStorm, Wind, Flooding, WinterWeather, Hail, Tornado.
Monthly	Wind, SevereStorm/ThunderStorm, Flooding, Lightning, WinterWeather.
Biweekly	Flooding, Lightning, SevereStorm/ThunderStorm, Tornado, Wind, WinterWeather.
Quarterly	Flooding, SevereStorm/ThunderStorm, Tornado, Wind.

Once a model was fitted, the p-values corresponding to each coefficient of interest were checked for statistical significance. Figure 6 provides an example of a printed model summary. If a coefficient was statistically significant, a record of the coefficient's name, its value, and other relevant metadata was created and incorporated into a table collating all statistically significant coefficients (subsequently referred to as the "significant coefficients table"). As part of the final procedures of the pipeline, a residual vs. fit plot was generated alongside a Q-Q plot to ensure the reliability of the models.

Fig. 6: The coefficients for 'Wind', 'SevereStorm/ThunderStorm', 'Lightning', 'WinterWeather', and 'Tornado' were all statistically significant.

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.3947	0.004	558.194	0.000	2.386	2.403
Time_Period	-0.0007	0.001	-0.487	0.626	-0.004	0.002
Wind	-0.0475	0.009	-5.355	0.000	-0.065	-0.030
SevereStorm/ThunderStorm	0.1034	0.007	15.020	0.000	0.090	0.117
Flooding	-0.0062	0.010	-0.594	0.553	-0.027	0.014
Lightning	0.1161	0.014	8.356	0.000	0.089	0.143
WinterWeather	-0.1264	0.011	-12.020	0.000	-0.147	-0.106
Hail	0.0056	0.017	0.323	0.747	-0.028	0.039
Tornado	0.0767	0.015	5.128	0.000	0.047	0.106

Omnibus:	14712.002	Durbin-Watson:	1.017
Prob(Omnibus):	0.000	Jarque-Bera (JB):	12619.908
Skew:	-0.498	Prob(JB):	0.00
Kurtosis:	2.440	Cond. No.	31.6

3 Results

In total, 198 coefficients were statistically significant. Each of these coefficients was stored in the significant coefficients table. The table consisted of columns 'Time Scale', 'Model Type' (step change or slope change), 'Hazard Type' (where applicable), 'Coefficient', 'P-Value', and 'Crime Rate' (for specified cluster).

3.1 General Crime Models

The general crime models saw a statistically significant treatment effect and change in the trend of crime rates immediately following a hazard event for all time scales. On the monthly time scale, the cluster having a moderate crime rate of 17.54 to 49.65 per 10,000 saw a negative treatment effect and a negative change in the trend of -.0278 and -.005 respectively meaning a reduction in crime post-hazard. The cluster of the lowest crime rate of .11 to 17.75 has a statistically significant negative change in trend. On the biweekly time scale, a statistically significant change in trend was observed in the clusters that had crime rates 22.33-2348.18 and 2.93-22.31 with values -.0057 and -.0116. In contrast, on the weekly and biweekly time scales, clusters with the lowest crime rates of .0009-.99 and .0009-2.84 had statistically significant treatment effects of positive value meaning an increase in crime post-hazard. On the quarterly time scale, one statistically significant negative change in the trend of crime rates was observed in crime rate .18-36.96. Thus, the increase in crime rates following natural hazard events that were observed in the shorter time scales did not persist into the longer time scale, where, in fact, negative treatment effects and a negative change in trend were found. Table 6 shows the results of the general models.

Table 6: Statistically Significant Coefficients and Corresponding Metadata for General Crime Models

Time Scale	Model	Coefficient	P-Value	Crime Rate Range (per 10000)
Monthly	Step	-0.0278	0.044	17.54-49.65
Monthly	Slope	-0.005	0.002	17.76-50.11
Monthly	Slope	-0.0305	< 0.001	0.11-17.75
Weekly	Step	0.0304	< 0.001	0.001-0.990
Weekly	Slope	-0.0035	< 0.001	1.008-11.31
Weekly	Slope	0.0075	< 0.001	0.001-1.010
Biweekly	Step	0.028	0.003	0.001-2.840
Biweekly	Slope	-0.0057	0.043	22.33-2348.18
Biweekly	Slope	0.0102	0.034	0.001-2.930
Quarterly	Slope	-0.0432	0.001	0.180-36.960

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.

3.2 Hazard Type Segmented Models

On the monthly time scale, the hazard types that had statistically significant negative treatment effects on crime rates were wind, flooding, winter weather, and severe storms/thunderstorms. Monthly crime data was clustered with K-means clustering into three groups, based on the elbow curve. In each cluster, statistically significant coefficients were observed. Notably, in all clusters, the coefficient 'WinterWeather' was negative and statistically significant. In two of the three clusters, the coefficient 'Flooding' was both statistically significant and negative. Similarly, in the slope change models, 'WinterWeather' was again negative and statistically significant in all clusters of crime rates. Further, 'Flooding' was negative and statistically significant in all clusters in the slope change model.

On the weekly time scale, the fitted hazard-type slope model had coefficient 'SevereStorm/Thunderstorm' statistically significant across two clusters of crime rates 11.27-1427.57 and 1.01-11.26. In both cases the coefficient was positive, indicating a positive change in the trend of crime rates following such a natural hazard event. Additionally, this held true for the coefficient 'Lightning', which also had a positive treatment effect in the low crime cluster of crime rate .98-11.10. On the biweekly time scale, the same held true for 'Lightning' and 'SevereStorm/Thunderstorm' coefficients. In both step change and slope change models, both coefficients were positive and statistically significant over clusters with rates 2.82-22.24 and 21.95-2346.37. Again, 'WinterWeather' was statistically significant and negative across several clusters in both step change models and slope change models on the biweekly timescale.

Much like on the monthly scale, the coefficient 'Flooding' was negative on the quarterly time scale. This was true for both step change and slope change models

Table 7: Monthly Statistically Significant Coefficients and Corresponding Metadata for Hazard Type Segmented Models

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 rate ranges are provided per 10000 population for reference. P-values less than 0.001 are denoted as < 0.001.

and for the cluster of lowest crime rate range of -.18-58.54. When seen as a whole, the fitted models indicate an association between natural hazard events that include severe storming and thunderstorms, and an increase in the trend of crime rates. This association persisted across multiple time scales. Additionally, the models provided some evidence that decreased crime rates and natural hazard winter weather events are indeed correlated. Tables 7,8,9, and 10 depict the statistically significant coefficients for the hazard type models.

3.3 Violent Crime Type Models

The violent crime type models fitted using violent crime data yielded at least one statistically significant coefficient across each time scale. Of the five coefficients that were statistically significant, four were observed in the slope change models. Of those four, three were negative. The coefficients and their corresponding metadata are shown in Table 11. On the longer time scales of monthly and quarterly, a negative change in the trend of violent crime rates was observed in the cluster of low crime rates of .05-4.81 and .7-12.86 respectively. However, on the weekly time scale, a positive change in the trend of rates of violent crime was observed in the cluster of crime rates .01-2.82.

Table 8: Weekly Statistically Significant Coefficients and Corresponding Metadata for Hazard Type Segmented Models

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.

3.4 Violent Crime Type And Hazard Type Models

The violent crime type and hazard type models were fitted in order to see if particular natural hazard event types were correlated to any effect on rates of violent crime. Several coefficients, at each time scale, were statistically significant. Notably, the hazard type 'WinterWeather' was correlated with a negative change in trend and a negative treatment effect, on the monthly level, across multiple clusters. Additionally, the coefficient 'SevereStorm/Thunderstorm' had a positive value across multiple clusters in both slope change and step change models. On the weekly timescale, natural hazard-type lightning had a positive value in all instances of statistical significance and appeared in several clusters across both classes of models. In the models fitted to the biweekly data, the natural hazard-type wind had a negative treatment effect and was associated with a negative change in the trend of crime rates in all but one cluster the coefficient was statistically significant in. This held across step change and slope change models for multiple clusters. An extracted portion of the table containing some of these coefficients may be seen in Table 12.

3.5 Property Loss Segmented Models

Property loss is one variable in the SHELDUS database. K-means clustering was used alongside an elbow curve plot to cluster property losses into three clusters. This

Table 9: Biweekly Statistically Significant Coefficients and Corresponding Metadata for Hazard Type Segmented Models

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.

Table 10: Quarterly Statistically Significant Coefficients and Corresponding Metadata for Hazard Type Segmented Models

Quarterly				
Model	**Hazard Type**	**Coefficient**	**P-Value**	**Crime Rate Range (per 10000)**
Step	Flooding	-0.1154	< 0.001	58.54-165.44
Step	SevereStorm/Thunder	-0.2505	< 0.001	.18-58.54
Step	Tornado	0.1395	0.039	.18-58.54
Step	Wind	0.1363	0.02	.18-58.54
Step	Tornado	0.2722	< 0.001	165.48-8653.85
Slope	Flooding	-0.0216	< 0.001	55.72-157.77
Slope	SevereStorm/Thunder	0.0103	0.027	55.72-157.77
Slope	Tornado	0.0729	< 0.001	157.79-8653.85
Slope	Flooding	-0.0248	0.006	.18-55.70
Slope	SevereStorm/Thunder	-0.0478	< 0.001	.18-55.70

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.

Table 11: Statistically Significant Coefficients and Corresponding Metadata for the Violent Crime Type Models

Time Scale	Model	Coefficient	P-Value	Crime Rate (per 10,000)
Quarterly	Step	0.5279	0.032	0.17-13.177
Monthly	Slope	-0.0153	0.002	0.05-4.81
Weekly	Slope	0.002	0.001	0.01-2.82
Biweekly	Slope	-0.0243	0.003	3.49-11.45
Quarterly	Slope	-0.1056	< 0.001	0.17-12.86

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.

Table 12: Statistically Significant Coefficients from the Violent Crime Type and Hazard Type Models

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.

allows the segmenting of natural hazard events into clusters by severity, with property losses acting as a proxy for a severity metric. In the property loss models, statistically significant coefficients were found across the monthly, biweekly, and quarterly time scales only. On the monthly level, only the cluster of property loss range $15 Million to $55 Million was statistically significant. This same cluster had positive coefficients on the slope change models for crime rates 12.63-31.90 and 68.09-4285.39, with coefficient values of .0067 and .0063 respectively, indicating strong evidence that natural hazard events resulting in losses within that range are associated with an increase in the trend of crime across all clusters of crime rates. The loss models fitted to the biweekly data and quarterly data indicated a negative change of trend in crime rates in the clusters of loss ranges $1,010-$70,000,000 and $1,136.36-$7,000,000 respectively. All of the statistically significant coefficients are shown in Table 13.

Table 13: Statistically Significant Coefficients and Corresponding Metadata for Property Loss Segmented Models

Time Scale	Model	Loss Range	Coefficient	P-Value	Crime Rate (per 10,000)
Monthly	Step	$15,000,000$-$55,000,000$	-0.0557	0.007	30.63-65.97
Monthly	Step	$15,000,000$-$55,000,000$	0.3091	< 0.001	66.08-4285.39
Monthly	Slope	$15,000,000$-$55,000,000$	0.0067	0.039	12.63-31.90
Monthly	Slope	$15,000,000$-$55,000,000$	0.0063	< 0.001	68.09-4285.39
Monthly	Slope	$15,000,000$-$55,000,000$	-0.0127	< 0.001	31.97-67.97
Biweekly	Step	$15,000,000$-$55,000,000$	0.2901	< 0.001	3.01-22.42
Biweekly	Slope	$1,010$-$7,000,000$	-0.0041	0.003	1.63-13.61
Quarterly	Step	$14,000,000$-$20,000,000$	0.2909	0.019	163-8655.18
Quarterly	Slope	$1,136.36$-$7,000,000$	-0.0408	0.001	0.18-56.98

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.

3.6 Property Loss And Crime Type Models

Segmenting the dataframe that data was drawn from in the property loss models to include violent crime incidents only and then fitting the crime type and loss models yielded several statistically significant coefficients. On the monthly time scale, one cluster of property loss range $15 million-$55 million had a negative treatment effect over two clusters of crime rates .05-4.67 and 4.67-13.44. In the fitted slope change model, that same cluster's coefficient was associated with a negative change in trend immediately following a natural hazard event for the crime rate range of .05-4.81. On the quarterly time scale, the largest quantity of statistically significant coefficients was observed (Table 14).

Table 14: Statistically Significant Coefficients and Corresponding Metadata for Property Loss and Crime Type Models

Time Scale	Model	Loss Range	Coefficient	P-Value	Crime Rate (per 10,000)
Monthly	Step	$15,000,000$-$55,000,000$	-0.1241	0.003	.05-4.67
Monthly	Step	$15,000,000$-$55,000,000$	-0.206	0.036	4.67-13.44
Monthly	Slope	$15,000,000$-$55,000,000$	-0.0273	$< .001$	.05-4.81
Weekly	Step	$116,400,000$-$500,000,000$	-0.1767	$< .001$	.01-2.83
Weekly	Slope	$1,010$-$113,000,000$	0.002	0.001	.01-2.82
Weekly	Slope	$116,400,000$-$500,000,000$	-0.0216	$< .001$	.01-2.82
Biweekly	Step	$80,000,000$-$500,000,000$	-0.4139	$< .001$	.02-5.58
Biweekly	Slope	$80,000,000$-$500,000,000$	-0.0505	$< .001$	.02-5.58
Quarterly	Step	$14,000,000$-$20,000,000$	-14.7991	0.025	21.38-118.40
Quarterly	Slope	$1,136.36$-$7,000,000$	-0.242	0.005	.17-21.36
Quarterly	Slope	$14,000,000$-$20,000,000$	-0.0984	$< .001$	21.38-118.40
Quarterly	Slope	$1,136.36$-$7,000,000$	-2.4846	0.005	21.38-118.40

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.

3.7 Location Models

The location models included step change models and slope change models that were fitted to segmented data by state. On the monthly, weekly, biweekly, and quarterly time scales, there were 34, 38, 37, and 25 states included in the merged natural hazard and crime incidents dataframes. The number of events that took place, in sum total across all time scales, may be seen in Table 15. Sorted by descending order of event counts, models were fitted for roughly the first quartile of states.

Table 15: The total number of unique events that took place in each state across any time scale.

State	Value	State	Value
Michigan	15940	Utah	1552
South Carolina	7578	Oregon	1136
Tennessee	7740	South Dakota	926
Virginia	5961	Texas	1507
Kansas	3527	Wisconsin	1013
Idaho	1966	Montana	466
Kentucky	2571	Connecticut	1056
Iowa	4130	Rhode Island	821
Colorado	1653	Illinois	624
New Hampshire	2442	Vermont	798
Arkansas	2774	Louisiana	407
Ohio	3015	Maine	152
North Dakota	1940	Delaware	577
West Virginia	2378	Missouri	120
Oklahoma	1681	Alabama	33
Massachusetts	4042	Mississippi	29
Washington	1376	Indiana	15
Georgia	2		

Of the models that had any statistically significant coefficients, all values were negative. Given that the segmented data by states was both less skewed and of a significantly smaller size, clustering and Box-Cox transformations were not performed on the crime rates. Notably, models fitted to the Michigan data yielded statistically significant results on the monthly, weekly, and biweekly levels. On said time scales, a decrease in the trend of crime rates in Michigan was observed with coefficient values -.8008, -.1066, and -.2201, respectively. Similarly, models fitted to data from South Carolina showed similar results. Natural hazard events had both a negative treatment effect and were associated with a decrease in the trend of crime rates immediately following a natural hazard event. These results are shown in Table 16.

4 Discussion

This analysis revealed variations in coefficients across different time scales and crime rate clusters, yet certain patterns emerged consistently. Regardless of the model type or time scale considered, the coefficient associated with the 'WinterWeather' hazard

Table 16: The statistically significant coefficients and their metadata from models fitted to Michigan and South Carolina.

Time Scale	Model	State	Coefficient	P-Value
Monthly	Slope	Michigan	-0.8008	$< .001$
Weekly	Slope	Michigan	-0.1066	$< .001$
Biweekly	Step	Michigan	-0.6939	0.046
Biweekly	Slope	Michigan	-0.2201	$< .001$
Monthly	Slope	South Carolina	-1.35	$< .001$
Monthly	Step	South Carolina	-0.565	0.008
Biweekly	Step	South Carolina	-1.5337	0.015
Biweekly	Slope	South Carolina	-0.2538	0.049

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.

type consistently remained statistically significant and negative. This robust evidence suggests a strong correlation between decreased crime rates and this specific natural hazard type. Similarly, the 'SevereStorm/Thunderstorm' hazard type consistently exhibited a statistically significant positive coefficient across various settings. The 'wind' and 'lightning' hazard types also displayed sign consistency in their coefficients, albeit not universally.

When the losses that hazard events induced were introduced as a predictor, all statistically significant coefficients were positive. This was especially true on the monthly time scale when considering the slope change model. Indeed, across all the clusters, statistically significant variables were observed for hazard events that resulted in financial losses of $15 million to $55 million.

Considering the statistically significant coefficients observed in the crime type models, all coefficients were positive values. This held true across all time scales. However, this only held true for very low crime rates and mostly in the slope change models. This indicates a positive change in the clusters with the lowest crime rates.

Due to the nature of regression discontinuity design, data at the threshold, $t = 0$ in this case, is not included in the model fitting process. While it is highly unlikely that any meaningful difference in the data may be excluded for consideration on the weekly and biweekly time scales, as we would only be excluding one week or two for each event, respectively, it is possible that on the monthly and quarterly time scales some relevant change in data may have been overlooked.

Perhaps most importantly, these findings have practical implications for law enforcement agencies. The incorporation of clustering techniques focusing on crime rates and hazard types as predictors allows for the targeted implementation of our findings following natural hazard events. It appears that the extent of natural hazards, meaning their area of impact, influences crime rates. During winter weather, for example, large areas tend to be affected with residents staying home, schools and offices closed, etc.. This may consequently immobilize or disincentivize potential perpetrators to commit crimes.

By contrast, severe thunderstorms, tornadoes, and flood events are highly localized. While some neighborhoods in a community experience damage, the majority of the community tends to remain unscathed. As a result, public safety resources are immediately deployed to the affected areas. This seems to create a "window of opportunity" for crime to occur either because potential perpetrators perceive it as such and increase their activity and/or law enforcement presence outside of the impact area is reduced and therefore unable to protect and prevent criminal activities. Weisburd (2021) and others Petersen et al. (2023) have documented a connection between police presence and crime rates, which seems to be relevant in the linkage between natural hazards and crime rates.

These findings suggest that law enforcement agencies need additional personnel immediately following a natural hazard event to respond to the areas affected by a hazard while remaining present in other areas of the community. Although law enforcement departments tend to surge personnel via support from neighboring jurisdictions, it may be time to consider multiple avenues to create surge capacity post-disaster in the public safety realm. Hurricane Sandy, for instance, triggered the activation of the Department of Homeland Security (DHS) Surge Capacity Force (6 U.S.C. § 711), i.e., the deployment of federal employees in the aftermath of a major incident and managed by the Federal Emergency Management Agency (FEMA), for the first time. Similarly, the Emergency Management Assistance Compact (EMAC) offers a well-established and effective state-to-state mechanism to create surge capacity but it is generally only activated after major disasters. Law enforcement personnel were first "EMACed" during the 2004/2005 hurricane season Rojek and Smith (2007). In order for law enforcement personnel to possess the power of arrest, though, officers must be immediately sworn in when they arrive in the requesting state and the EMAC agreement between the sending and requesting state must first stipulate such power NEMA (2018).

What may be missing are surge capacity mechanisms at the local level when natural hazards do not cause impacts that exceed state, or perhaps even local, capacities. Establishing procedures and agreements that allow for the swift deployment of, for instance, other law enforcement from neighboring jurisdictions or local government employees to supplement activities in the affected area could free up or support law enforcement resources elsewhere in the community. Based on the findings of this study, such surge capacity should be activated swiftly after a natural hazard event and not just for catastrophic events.

5 Conclusion

This research addresses a critical gap in the existing literature on the intersection of natural hazards and crime. While numerous scholars have made significant contributions in this field, their work has often been constrained by limitations in temporal or spatial data coverage Weil (2020); Zahran et al. (2009); Berrebi et al. (2021); Chen et al. (2015). By leveraging extensive crime data from NIBRS, spanning multiple decades and states in the US, alongside comprehensive natural hazard event data from SHEDLUS, this study developed new insights by identifying previously unrecognized variations in crime patterns following natural hazard events is pivotal in shaping effective law enforcement resource allocation strategies.

Through the use of clustering techniques, the analytical approach accommodated crimes of varying crime rates. Some clusters experienced a positive treatment effect and a shift in trends following natural hazard events, while others exhibited a negative treatment effect and a decline in crime rates immediately after such events. However, some hazard types were consistently either associated with an increase in crime rates or a decrease in crime rates. This is most clear when considering severe storm hazard events and winter weather hazard events, whereby the former was clearly associated with a rise in crime rates in most cases, and the latter was associated with a decrease in crime rates. Notably, models fitted to data segmented by states indicated that all statistically significant treatment effects and changes in the trend of crime rates were negative. This was true for Michigan and South Carolina, both of which had large quantities of data the models could fit.

By providing comprehensive tables that illustrate such associations for a plethora of different hazard types, these findings provide a thorough examination of the relationship between changes in crime rates and hazard events. In the broader context of natural hazards research, these findings illuminate a critical aspect of public safety and the need for swift deployment of surge capacity.

Acknowledgments. This material is based upon work supported by the U.S. Department of Homeland Security under Grant Award Number 17STCIN00001-05-00.

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