International Journal of Security Studies & Practice

Volume 2 | Issue 1 Article 3

2022

Disaster, Social Disorganization, and Crime in the Largest Cities in Texas

Daniel Augusto
University of Arizona Global Campus, daniel.augusto@uagc.edu

Jared Linebach
Shorter University, jlinebach@shorter.edu

Disaster, Social Disorganization, and Crime in the Largest Cities in Texas

Daniel Augusto[1] and Jared Linebach[2]

[1]University of Arizona Global Campus

[2]Department of Social Sciences, Shorter University

Author Note

Daniel Augusto, PhD, EdD, MS, CPP, is an assistant professor at the University of Arizona Global Campus, and is a retired law enforcement officer with 22 years of combined experience in law enforcement, homeland security, and emergency preparedness. He has been involved in disaster preparedness planning, exercises, and response. He also investigated disaster fraud as part of a federal disaster crime working group. Daniel Augusto earned his PhD in Criminal Justice and Homeland Security from Liberty University; his EdD from Northeastern University; and his MS in Emergency Management from Jacksonville State University. His research focus is on disaster crime.

Jared Linebach, PhD, CLC, is an associate professor of criminal justice at Shorter University. He received a MA in and a PhD from the California School of Forensic Studies in forensic psychology, and a BA from Clearwater Christian College. Among his publications are Evil: a psychological exploration (2021) *Christus Cultura: The Journal of Christianity and the Social Sciences,* A Scriptural view of crime, *Christus Cultura: The Journal of Christianity and the Social Sciences*, Inaugural Issue, and *Nonparametric Statistics for Applied Research* (2013) Springer Science+Business Media New York. He is the CEO and Editor-in-Chief of Verisega Books, LLC, Rome, GA. He is also a Subject Matter Expert in Forensic Psychology and Theories

of Crime, and a thesis/dissertation advisor for the Helms School of Government at Liberty University. His main research interest is in campus law enforcement, and works with doctoral candidates regarding their methodological and statistical approaches to research.

Correspondence concerning this article should be addressed to Daniel Augusto, e-mail: daniel.augusto@uagc.edu

Abstract

This study uses multiple regressions and moderation analysis to examine the relationship between disaster and crime in the 10 largest cities in Texas. The regressions revealed that yearly days with disaster significantly predicted Robbery, Murder, Rape, Burglary, and Auto Theft. Additionally, social disorganization and population density were often found to predict crime. Moderation analysis revealed that social disorganization increases the effect of yearly days with disaster on Burglary rates, which serve as a proxy for looting. These findings indicate that, on average, disaster responders, public safety, and security personnel in large cities can expect increases to crime as days with major weather events and disasters increase, particularly when those increases are paired with high levels of social disorganization in a city. Future security and disaster research should incorporate disaster phase timing, as well as compliance with disaster warnings to better understand the relationship between disaster, crime, and security.

Disaster, Social Disorganization, and Crime in the Largest Cities in Texas

Hurricane Harvey struck coastal Texas in August of 2017. Upon its conclusion, after adjusting for inflation, Harvey was the second most costly hurricane in United States (U.S.) history (NOAA, 2020), and caused the highest number of direct deaths from a tropical cyclone in Texas since 1919 (Blake & Zelinski, 2018). Despite Hurricane Harvey's impacts, it is only one of several disasters and major weather events that have struck coastal Texas during the last few decades. Texas is certainly not the only region of the U.S. afflicted by recurring major weather events and disasters. Florida faced more than 50 named weather events and hurricanes in 2004 and 2005 alone, and the Northeastern region of the U.S. has a history of consistently battling major weather events (NOAA, n.d.).

Many major metropolitan areas also face major weather events and disasters. The greater Houston, Texas area serves as an example of a major metropolitan area that experienced several major weather events and disasters during recent decades. Hurricane Harvey struck Houston in 2017 and Hurricane Ike hit Houston almost exactly ten years earlier. Individual disasters and major weather events have been associated with increases to some crime rates and decreases to other crime rates (HCFCD, 2018). However, despite several regions and urban areas facing repeated major weather events, Prelog (2016) is the only researcher located in recent years who studied disaster frequency as part of disaster crime research, and no research was located covering the relationship between number of days per year with a major weather event or disaster and crime.

Additionally, much of the recent research covering crime and security during disasters is focused on individual disaster events and, although necessary, that focus has also created a research gap relative to days with major weather events and disasters, despite days with disaster being a critical component of disaster research. Finally, another research gap exists relative to urban areas or cities as the unit of analysis on longitudinal disaster crime research. Some disaster crime studies have focused attention on one single city after a single disaster, such as New Orleans after Hurricane Katrina (Frailing & Harper, 2017). However, much of the recent longitudinal research, or research covering multiple points in time, uses the county as the unit of analysis (Spencer, 2017; Prelog, 2016). However, disaster impacts are likely to be most magnified in large urban areas, where the human-nature interface is most pronounced, since cities face increased exposure to risks and hazards (UNISDR, 2017). That research gap is also problematic for security and public safety personnel since so much of their focus is often on those same large urban areas.

This research is intended to address the research gaps listed above, and provide insight by using a longitudinal approach to examine the relationship between days with disaster and crime at the city level. The study regressed the number of days per year with a major weather event or disaster onto Index Crime rates in Texas' largest cities from 2000 through 2017, while incorporating Social Disorganization, Population Density, and Disaster Consequences into the models.

Literature Review

The study of disasters is an ever evolving and interdisciplinary endeavor that falls within an overarching paradigm called disaster risk reduction (DRR) research (Staupe-Delgado, 2019). Environmental science, urban planning, economics, psychology, biology, and many other fields of study have a role to play in DRR research. One component of DRR relates to the secondary risks and protective factors created by humans surrounding disasters. Disaster crime is one such secondary risk stemming from disasters.

Disaster sociologists have long recognized the importance of studying criminal activity associated with disasters (Prelog, 2016; Frailing & Harper, 2017). Eventually, criminologists also added to the body of work (Frailing & Harper, 2017). By researching what is now becoming known as disaster criminology, sociologists, criminologists, economists, and others are attempting to better understand society's reactions to disaster, particularly related to crime, in hopes of gaining knowledge to help mitigate the negative impacts of disaster on society (Prelog, 2016; Frailing & Harper, 2017).

Social Disorganization, Disaster, and Crime

Taken together, Social Disorganization Theory researchers have identified several factors that are thought to reflect higher degrees of Social Disorganization. School dropout rates represent disruptions to family and educational systems (Shaw & McKay, 1942), and other authors found socioeconomic factors such as poverty and unemployment to be key Social Disorganization factors related to increased crime (Frailing & Harper, 2017; Nogami, 2018).

Some researchers view disasters as another factor adding to social disorganization, particularly related to low socioeconomic status and instability, which can impact crime (Davila et al., 2005; Zahran, et al., 2009). Certainly, death and family disruption occur during disasters, which were key components of Social Disorganization Theory from its inception (Sampson, 1986). Disasters can disrupt unity and collective efficacy in the community, reducing community self-policing, and increasing antisocial behavior (Prelog, 2016). The research on violence and crime against displaced families at shelters may bolster that assertion. Nguyen (2019) found increased rates of post-disaster violence against women and girls in the Philippines, particularly when Social Disorganization was prominent prior to the disaster. Seddighi et al. (2019) found a similar trend in a systematic review of almost 700 papers.

Residential instability, including that found in disaster, can cause substance use to increase as well as reduced social support networks (Prelog, 2016), which could increase crime. Varano et al. (2010) also found evidence that Hurricane Katrina crime patterns were affected by the displacement of evacuees to other areas such as Houston, San Antonio, and Phoenix. They found that several factors associated with disaster were connected to Social Disorganization Theory, including economic disadvantage, separation from social networks, and other stressors. Thus, one could argue that disasters, by their nature, can have a mirroring effect to that of disorganized communities.

The findings relative to Social Disorganization and disaster are particularly troubling when combined with other authors' findings that disasters have been known to have disproportionately adverse impacts on communities that exhibit characteristics that are commonly associated with Social Disorganization (Ogie & Prahdan, 2019). Indeed, the impact of a disaster is most pronounced on the most vulnerable communities, which often share demographics, social support, and educational characteristics with socially disorganized communities (Ogie & Prahdan, 2019). That increased vulnerability in socially disorganized communities is often referred to as 'social vulnerability' (Sun et al., 2017; Frigerio et al. 2018; Aksha et al. 2019).

It follows that the increased vulnerability of socially disorganized communities to disasters could also contribute to crime rates during and after disasters, while disrupting social unity and weakening the public response to crime (Spencer, 2017). Frailing and Harper's (2017) findings related to the importance of Social Disorganization Theory in disaster crime are relevant. They determined that the combination of socioeconomic stability and the Routine Activities Theory factor of Guardianship kept the Burglary rate increases low in New Orleans after a major storm in 1947. Overall, Frailing and Harper (2017) found that New Orleans socioeconomic factors, including high inequality rates, account for a significant increase in Burglaries after Hurricane Katrina.

However, other researchers found an opposite trend, that disasters bring people together, thereby reducing Social Disorganization, at least temporarily (Kuroishi & Sawada, 2019; Whitehouse et al., 2017). However, Leitner et al. (2011) found declines in crime rates in Orleans Parish after Hurricane Katrina, which eventually increased to post-weather levels, and even higher in some instances. The eventual increase to a level above pre-Katrina timeframes, particularly in violent crimes, would later be attributed to changes in drug markets throughout New Orleans after Katrina (Frailing et al., 2015).

Although some studies have incorporated Social Disorganization factors (Prelog, 2016; Frailing & Harper, 2017), further questions remain concerning the role of specific Social Disorganization factors in disaster crime. Additionally, no longitudinal research was found specifically focusing on the city as the unit of analysis, despite the high populations of large urban areas as key nexus points between humans and nature (UNISDR, 2017), and having increased social vulnerability to disasters (Aksha et al., 2019). This study addresses those gaps by using a longitudinal design to study urban areas while incorporating Days with Disaster, Disaster Consequences, Population Density, and Social Disorganization factors.

Research Method

The study analyzed overall Index Crime, violent Index Crime, and property Index Crime as well as Social Disorganization factors that play a role. All Index Crimes except Arson were analyzed for the time period from January 1, 2000, through December 31, 2017. City boundaries for each of the 10 largest cities in Texas were used as the grouping parameter, since the sources of data can be applied at that level. The study does not analyze data from suburban police agencies that border the larger cities or campus police departments within the cities. Alphabetically, the 10 largest cities are Arlington, Austin, Dallas, Corpus Christi, El Paso, Fort Worth, Houston, Laredo, Plano, and San Antonio. Texas Department of Public Safety (DPS) data were used to collect yearly

Index Crime rates for the ten most populous cities in Texas. The National Oceanic and Atmospheric Administration (NOAA) Weather Events Database was used for data on the number of days per year with a major weather event or disaster. Government data was used to incorporate the potential Social Disorganization factors such as unemployment rates, poverty, and school dropouts to identify if such factors have a mediating, moderating, or confounding effect on crime rates, similar to the format used by Frailing and Harper (2017). The two Research Questions (RQs) are listed below:

RQ 1: Does number of days with major weather events or disasters significantly predict Index Crime rates in the ten most populated cities in Texas?

RQ 2: Do Social Disorganization factors moderate the relationship between number of days with major weather events or disasters, and Index Crime rates in the ten most populated cities in Texas?

Variables

All variables were continuous. The dependent variables (DVs) were specific yearly Index Crime rates in each city, collected from the Texas DPS Crime in Texas Online database (2020). The crimes included were Murder, Rape, Robbery, Aggravated Assault, Burglary, Larceny, and Auto Theft. Arson was not included in the analysis because initial review of the data revealed few instances of Arson. The independent variable (IV) was Days with Disaster, and it consisted of the number of days per year with a major weather event or disaster reported by the NOAA Weather Events Database for each city. This manner of operationalizing the variable also parallels Social Disorganization Theory, since the Theory emphasizes the importance of factors in an environment and systems within the environment that people experience. Establishing a variable reflecting the number of days with disasters or major weather events also parallels that emphasis on the environment, since it reflects the proportion of a year the city was exposed to a major weather event or disaster and all the social and environmental changes and stressors that come with that disaster exposure.

A Social Disorganization composite variable, a Disaster Consequences composite variable, and a Population Density variable served as control variables (CVs). The two composite CVs were mean composites, where each construct of the variable was averaged along with the others for a total mean score representing the composite score for each year. Yearly unemployment rates, school dropout rates, and poverty rates were the socioeconomic factors combined into a mean composite variable and used as the Social Disorganization proxy for each city. Yearly unemployment rates and yearly poverty rates were used from the Department of Labor (DOL) database. Each city's school dropout rates served as a proxy for disruption to family and educational systems described by Shaw and McKay (1942). Dropout rates for each city were collected from the Texas Education Agency (TEA) Public Education Information Management System (PEIMS) (TEA, 2020). Yearly dropout rates from 8th grade to 12th grade were used from the TEA. The Disaster Consequences composite variable was comprised of direct deaths and direct injuries reported by the NOAA Weather Events Database (2020). The yearly Population Density variable for each city was calculated using yearly population counts collected from the Texas DPS Crime in Texas Online database (2020) and publicly available data on the total square miles of each city.

Sample

The sample for this study included all Index Crimes, disaster and major weather event totals, disaster and major weather event casualty totals, and Social Disorganization factor totals in the listed cities from 2000 through 2017. Regardless of the source of the data, all complete data relevant to each research question and hypothesis was used for analysis. Thus, the sampling groups were all the relevant data for each city. The U.S. Census Bureau (USCB) population estimates for 2000, and 2010 through 2019 were used to identify the ten most populous cities in Texas (USCB, 2013; 2020), and the data indicated that the 10 most populous cities in Texas remained the same throughout the time-period of this study. Urban areas in Texas, as opposed to another state, or multiple states, were chosen because they represent large urban areas in the U.S. Three of the cities fall within the top 10 most populous cities in the U.S. (NLC, 2020), six of the 20 most populous U.S. cities (NLC, 2020), and the cities are spread across a large portion of the landmass of the continental U.S.

Index Crimes other than Arson were included in the study since the use of these crimes will facilitate future comparisons with existing research. Additionally, Index Crimes are often thought of as among the most serious crimes, making them a priority to study. The study covered yearly data from 2000 through 2017 in an effort to capture a large pool of data while including time frames with and without major weather events and disasters. The crime data sampling was limited to the Texas DPS crime data related to total yearly reports provided for each city. Data for the IVs and CVs were yearly data associated with the relevant city for that year.

Data Collection Process

All the needed data were available to the public on each respective agency's public-facing website. Index Crime data were collected from the Texas DPS Crime in Texas Online database. DOL and TEA provide Social Disorganization data through their websites. Additionally, public data for each city's square mileage were combined with Texas DPS data to calculate Population Density. The Days with Disaster data came from the NOAA database mentioned above.

Data Analysis

Data for each city were converted into the ratio per 100,000 residents for uniformity. Intellectus Statistics (IS) software was used to conduct the analysis. Multiple linear regression analysis was used to answer RQ 1 and the Baron and Kenny (1986) method of moderation analysis was used to answer RQ 2. Multiple linear regressions were used to analyze relationships between the sets of continuous IVs, continuous CVs, and continuous DVs (Field, 2018), and to answer the RQs and determine if the IVs and CVs predict the DVs. Additionally, power analysis for a multiple regression with four predictors was conducted in G*Power to determine a sufficient sample size using an alpha of 0.05, a power of 0.80, and a medium effect size ($f^2 = 0.15$) (Faul et al., 2013). Based on the aforementioned assumptions, the desired sample size of 85 is well below the sample size of this study (n = 180).

Bias was addressed by testing for assumptions associated with multiple linear regressions (Field, 2018). The assumptions of normality of residuals, homoscedasticity of residuals, absence of multi-collinearity, and lack of outliers were assessed. Additionally, since time series data were used, the Durbin Watson test was used with a critical values table (Notre Dame, n.d.) to test for statistically significant serial autocorrelation or independent errors. The potential for aggregation bias is addressed in this study by incorporating visual analysis of the data at a disaggregated level, to look for any patterns that could indicate within-individual variation in the data (Martin & Legault, 2016; Pollett et al., 2015). Additionally, since the potential for aggregation bias cannot be completely negated, inferences made from the findings reflect an increased level of caution to avoid the ecological fallacy that the overall findings necessarily apply directly to any one city in the study.

Multiple Linear Regressions

Standard multiple linear log-log regressions were used as described by Field (2018). The standard method enters all independent variables (predictors) simultaneously into the model. For significant predictors, every 1% increase in the predictor, the dependent variable will increase or decrease by the magnitude of the unstandardized beta coefficient, also represented as a percentage (UCLA, 2021).

Moderation

Moderators effect the direction or strength of the relationship between an IV and a DV (Baron & Kenny, 1986). Baron and Kenny's (1986) approach to moderation through regression analysis was conducted using IS software, to determine if a third variable moderates the relationship between the IV and the DV. A linear regression model was used to determine if there is significant a relationship between the IV and the DV. If the first condition is met, the second condition requires that the model with the interactions between the IV and the moderator must explain significantly more variance than the model without the interaction. If both conditions are met, then moderation is supported.

Potential Threats to Validity

Finally, research has shown that officers might re-calibrate their application of officer discretion during disasters, to determine how to handle police actions (Augusto, 2020). In short, offenses that would normally result in an arrest may become a lower priority when compared to life-threatening situations common in disasters. If so, it follows that arrest statistics would be under representative of the amount of disaster crime actually occurring. It also follows that a higher potential for mistakes or unreported violations, particularly related to minor offenses, would create decreased internal validity before the data were even collected by the agency. However, this phenomenon would only increase the likelihood of a Type I error, making positive associations between increased crime and days with disaster to be even more of a reality.

Results

Table 1 lists the summary statistics for all the variables in the study. The table reports summary statistics for the number of crimes reported per 100,000 people, per year. Summary statistics for Population Density, Days with Disaster, Disaster Consequences, and Social Disorganization reflect the yearly data for each variable, using the measurement process described above.

Table 1. Summary Statistics for all Variables.

Variable	*M*	*SD*	*n*	SE_M	Min	Max	Mode	*Mdn*
Murder	6.57	4.47	180	0.33	0.37	20.62	3.80	5.48
Rape	45.10	17.01	180	1.27	8.68	87.72	31.45	42.18
Robbery	198.45	153.84	180	11.47	33.87	685.28	110.07	148.66
Burglary	913.10	408.92	180	30.48	188.33	1882.29	1029.09	936.60
Assault	367.99	144.60	180	10.78	68.29	726.07	454.90	351.77
Larceny	3456.57	1142.92	180	85.19	820.71	5695.47	4914.47	3503.85
Auto Theft	445.79	303.71	180	22.64	65.22	1600.98	478.76	409.11
Social Disorganization	8.12	2.41	180	0.18	2.30	13.70	8.57	8.15
Disaster Consequences	0.43	1.50	180	0.11	0.00	13.56	0.00	0.05
Population Density	2976.88	1051.85	180	78.40	1126.40	8873.43	2072.30	2868.06
Days with Disaster	17.33	7.92	180	0.59	1.00	36.00	18.00	17.00

RQ 1: Does Number of Days with Major Weather Events or Disasters Significantly Predict Index Crime Rates in the Ten Most Populated Cities in Texas?

Overall, the findings reflect that Days with Disaster significantly predicted Robbery, Murder, Rape, Burglary, and Auto Theft. Days with Disaster did not significantly predict Larceny or Assault. Additionally, Social Disorganization and Population Density were often found to predict crime in several of the models. *Table 2* summarizes the models where Days with Disaster was a significant predictor of a crime.

Table 2. Results of Linear Regression Models Where Days with Disaster Predicted Crime.

Models	R^2	*F*	*DF*	*B*	*SE*	β	*t*	*p*
Model Predicting Robbery	**.20**	**10.86**	**4,175**	**-**	**-**	**-**	**-**	**< .001**
Days with Disaster	-	-	-	0.40	0.09	0.32	4.33	< .001
Social Disorganization	-	-	-	0.86	0.16	0.40	5.39	< .001
Population Density	-	-	-	0.39	0.16	0.17	2.41	.017
Disaster Consequences	-	-	-	0.08	0.12	0.05	0.68	.499
Model Predicting Murder	**.19**	**10.17**	**4,175**	**-**	**-**	**-**	**-**	**< .001**
Days with Disaster	-	-	-	0.30	0.10	0.23	3.01	.003
Social Disorganization	-	-	-	1.01	0.17	0.44	5.96	< .001
Population Density	-	-	-	0.35	0.17	0.14	2.02	.045
Disaster Consequences	-	-	-	0.15	0.13	0.08	1.17	.242
Model Predicting Rape	**.14**	**7.35**	**4,175**	**-**	**-**	**-**	**-**	**< .001**
Days with Disaster	-	-	-	0.18	0.05*	0.27	3.61	< .001
Social Disorganization	-	-	-	0.31	0.31*	0.26	2.33	.021
Population Density	-	-	-	-0.23	0.11*	-0.18	-1.99	.048
Disaster Consequences	-	-	-	0.04	0.67*	0.05	0.66	.513
Model Predicting Burglary	**.12**	**5.75**	**4,175**	**-**	**-**	**-**	**-**	**< .001**
Days with Disaster	-	-	-	0.28	0.07	0.30	3.82	< .001
Social Disorganization	-	-	-	0.38	0.12	0.23	3.01	.003
Population Density	-	-	-	-0.01	0.13	-0.01	-0.10	.924
Disaster Consequences	-	-	-	0.11	0.09	0.08	1.13	.258
Model Predicting Auto Theft	**.11**	**5.31**	**4,175**	**-**	**-**	**-**	**-**	**< .001**
Days with Disaster	-	-	-	0.18	0.09	0.16	1.98	.049
Social Disorganization	-	-	-	0.67	0.16	0.32	4.19	< .001
Population Density	-	-	-	0.34	0.16	0.16	2.11	.037
Disaster Consequences	-	-	-	0.10	0.12	0.06	0.87	.386

**Robust Standard Errors*
Note: Days with Disaster did not predict Larceny or Assault, so they were excluded from this summary table.

Days with Disaster Predicts Robbery

The results of the linear regression model were significant, $F(4,175) = 10.86$, $p < .001$, $R^2 = 0.20$, indicating that approximately 20% of the variance in Robbery is explainable by Days with Disaster, Population Density, and Social Disorganization. Days with Disaster significantly predicted Robbery, $B = 0.40$, $t(175) = 4.33$, $p < .001$. This indicates that on average, a 1% increase of Days with Disaster will increase the value of Robbery by .40%. As a result, the null hypothesis is rejected. Population Density significantly predicted Robbery, $B = 0.39$, $t(175) = 2.41$, $p = .017$, which indicates that, on average, a 1% increase of Population Density will increase the value of Robbery by .39%. Social Disorganization significantly predicted Robbery, $B = 0.86$, $t(175) = 5.39$, $p < .001$, indicating, on average, a 1% increase of Social Disorganization will increase the value of Robbery by .86%. Disaster Consequences did not significantly predict Robbery, $B = 0.08$, $t(175) = 0.68$, $p = .499$.

Days with Disaster Predicts Murder

The results of the linear regression model were significant, $F(4,175) = 10.17$, $p < .001$, $R^2 = 0.19$, indicating that approximately 19% of the variance in Murder is explainable by Population Density, Social Disorganization, and Days with Disaster. Days with Disaster significantly predicted Murder, $B = 0.30$, $t(175) = 3.01$, $p = .003$, which indicates that, on average, a 1% increase in Days with Disaster will increase the value of Murder by 0.30%. As a result, the null hypothesis is rejected. Population Density significantly predicted Murder, $B = 0.35$, $t(175) = 2.02$, $p = .045$, indicating that, on average, a 1% increase of Population Density will increase the value of Murder by 0.35%. Social Disorganization significantly predicted Murder, $B = 1.01$, $t(175) = 5.96$, $p < .001$, which indicates that, on average, a 1% increase in Social Disorganization will increase the value of Murder by 1.01%. Disaster Consequences did not significantly predict Murder, *B* = 0.15, *t*(175) = 1.17, *p* = .242.

Days with Disaster Predicts Rape

The results of the linear regression model were significant, *F*(4,175) = 7.35, $p < .001$, R^2 = 0.14, indicating that approximately 14% of the variance in Rape is explainable by Days with Disaster, Population Density, and Social Disorganization. Days with Disaster significantly predicted Rape, *B* = 0.18, *t*(175) = 3.61, $p < .001$. This indicates that on average, a 1% increase in Days with Disaster will increase the value of Rape by 0.18%. As a result, the null hypothesis is rejected. Population Density significantly predicted Rape, *B* = -0.23, *t*(175) = -1.99, *p* = .048. This indicates that on average, a 1% increase in Population Density will decrease the value of Rape by 0.23%. Social Disorganization significantly predicted Rape, *B* = 0.31, *t*(175) = 2.33, $p < .001$, which indicates that, on average, a 1% increase in Social Disorganization will increase the value of Rape by 0.31%. Disaster Consequences did not significantly predict Rape, *B* = 0.04, *t*(175) = 0.66, *p* = .513.

Days with Disaster Predicts Burglary

The results of the linear regression model were significant, *F*(4,175) = 5.75, $p < .001$, R^2 = 0.12, indicating that approximately 12% of the variance in Burglary is explainable by Days with Disaster and Social Disorganization. Days with Disaster significantly predicted Burglary, *B* = 0.28, *t*(175) = 3.82, $p < .001$, indicating that, on average, a 1% increase of Days with Disaster will increase the value of Burglary by 0.28%. As a result, the null hypothesis is rejected. Social Disorganization also significantly predicted Burglary, *B* = 0.38, *t*(175) = 3.01, *p* = .003, which indicates that, on average, a 1% increase of Social Disorganization will increase the value of Burglary by 0.38%. Population Density did not significantly predict Burglary, *B* = -0.01, *t*(175) =

-0.10, p = .924 and Disaster Consequences did not significantly predict Burglary, B = 0.11, t(175) = 1.13, p = .258.

Days with Disaster Predicts Auto Theft

The results of the linear regression model were significant, F(4,175) = 5.31, p < .001, R^2 = 0.11, indicating that approximately 11% of the variance in Auto Theft is explainable by Days with Disaster, Population Density, and Social Disorganization. Days with Disaster significantly predicted Auto Theft, B = 0.18, t(175) = 1.98, p = .049, which indicates that, on average, a 1% increase in Days with Disaster will increase the value of Auto Theft by 0.18%. As a result, the null hypothesis is rejected. Population Density also significantly predicted Auto Theft, B = 0.34, t(175) = 2.11, p = .037, indicating that, on average, a 1% increase of Population Density will increase the value of Auto Theft by 0.34%. Social Disorganization significantly predicted Auto Theft, B = 0.67, t(175) = 4.19, p < .001, which indicates that, on average, a 1% increase of Social Disorganization will increase the value of Auto Theft by 0.67%. Disaster Consequences did not significantly predict Auto Theft, B = 0.10, t(175) = 0.87, p = .386.

Days with Disaster Does Not Predict Larceny

The results of the linear regression model were significant, F(4,175) = 6.50, p < .001, R^2 = 0.13, indicating that approximately 13% of the variance in Larceny is explainable by Population Density and Social Disorganization. However, Days with Disaster did not significantly predict Larceny, B = 0.00, t(175) = 0.08, p = .933, resulting in failure to reject the null hypothesis. Disaster Consequences also did not significantly predict Larceny, B = 0.04, t(175) = 0.55, p = .586. Population Density significantly predicted Larceny, B = -0.22, t(175) = -2.46, p = .015, which indicates that, on average, a 1% increase in Population Density will decrease the value of Larceny by 0.22%. Social Disorganization also significantly predicted Larceny, B = 0.30, t(175) = 3.50, p

< .001, indicating that, on average, a 1% increase in Social Disorganization will increase the value of Larceny by 0.30%.

Days with Disaster Does Not Predict Assault

The results of the linear regression model were significant, $F(4,175) = 19.43$, $p < .001$, $R^2 = 0.31$, indicating that approximately 31% of the variance in Assault is explainable by Social Disorganization, while including Disaster Consequences, Days with Disaster, and Population Density in the model. Social Disorganization significantly predicted Assault, $B = 0.85$, $t(175) = 6.90$, $p < .001$, indicating that, on average, a 1% increase of Social Disorganization will increase the value of Assault by 0.85%. Disaster Consequences did not significantly predict Assault, $B = 0.05$, $t(175) = 0.54$, $p = .592$ and neither did Population Density, $B = -0.04$, $t(175) = -0.47$, $p = .641$. Additionally, Days with Disaster did not predict assault, $B = 0.10$, $t(175) = 1.59$, $p = .113$, resulting in failure to reject the null hypothesis.

RQ 2: Do Social Disorganization Factors Moderate the Relationship Between Number of Days with Major Weather Events or Disasters, and Index Crime Rates in the Ten Most Populated Cities in Texas?

The findings indicate that Social Disorganization positively moderates the relationship between Days with Disaster and Burglary. However, moderation was not supported for any of the other Index Crimes in the study. The assumptions necessary of the moderation analyses were met.

Social Disorganization Moderates the Relationship Between Yearly Days with Disaster and Burglary

The first moderation condition was met since Days with Disaster significantly predicted Burglary, $B = 0.23$, $t(178) = 3.41$, $p < .001$. The second condition was assessed using a partial *F*-test to determine if the interaction model explained more variance in Burglary than the non-interaction model. The partial *F*-test, $F(1,176) = 5.85$, $p = .017$, indicated that the interaction model explained significantly more variance than the non-interaction model, so the second condition was met. Since Days with Disaster significantly predicted Burglary in the simple effects model (condition 1) and the interaction model explained significantly more variance of Burglary than the non-interaction model (condition 2) moderation is supported. The results of the simple, non-interaction, and interaction models are presented in *Table 3*.

Table 3. Moderation Analysis Table with Burglary Predicted by Days with Disaster Moderated by Social Disorganization.

Predictor	*B*	*SE*	β	*t*	*p*
Step 1: Simple Effects Model					
(Intercept)	6.06	0.19		32.12	< .001
Days with Disaster	0.23	0.07	0.25	3.41	< .001
Step 2: Non-Interaction Model					
(Intercept)	5.12	0.36		14.33	< .001
Days with Disaster	0.30	0.07	0.32	4.28	< .001
Social Disorganization	0.37	0.12	0.23	3.09	.002
Step 3: Interaction Model					
(Intercept)	6.72	0.04		168.36	< .001
Days with Disaster	0.22	0.08	0.23	2.87	.005
Social Disorganization	0.40	0.12	0.25	3.36	< .001
Days with Disaster : Social Disorganization	0.53	0.22	0.19	2.42	.017

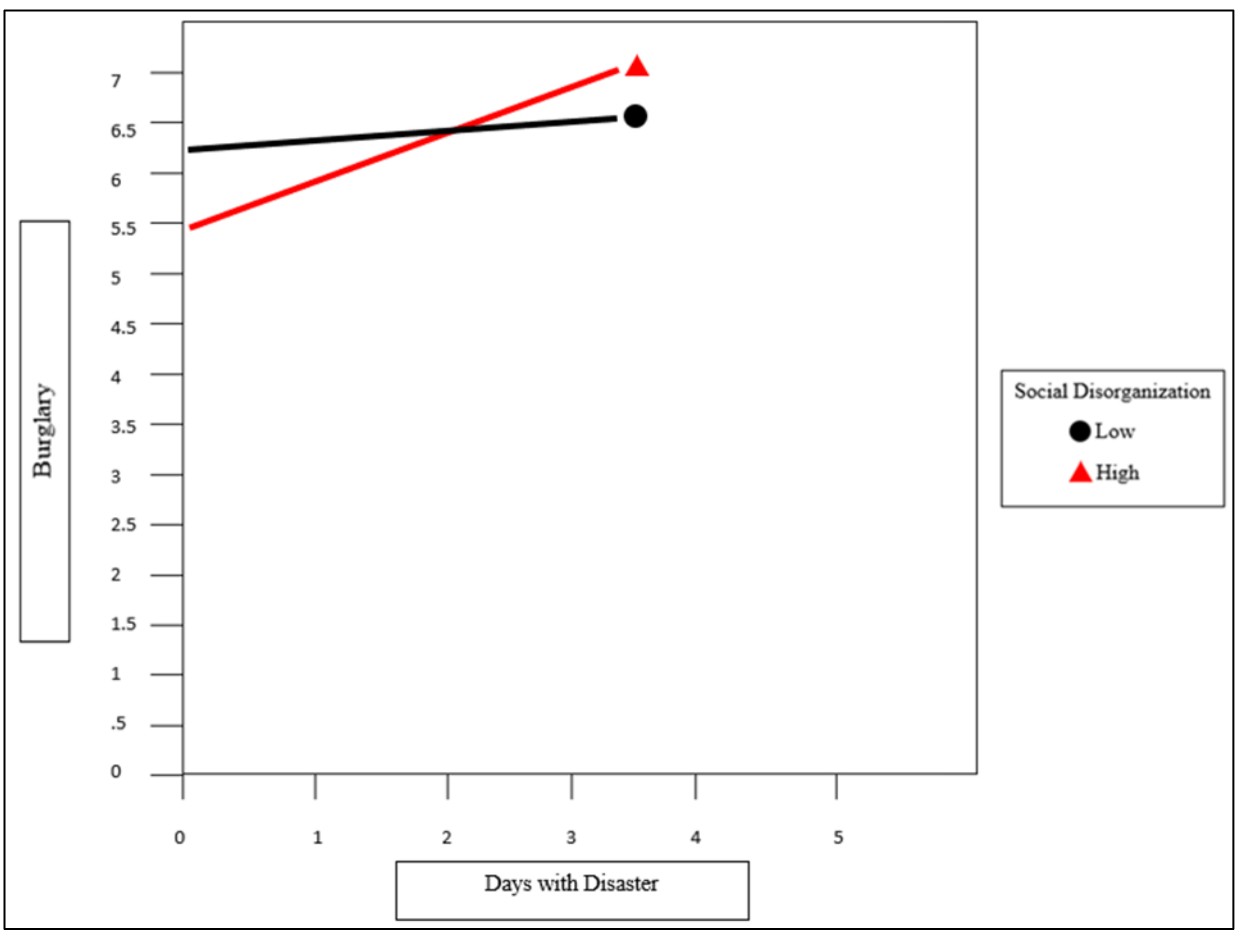
Social Disorganization significantly moderated the effect of Days with Disaster on Burglary, $B = 0.53$, $t(176) = 2.42$, $p = .017$. This indicates that on average, a 1% increase of Social Disorganization will cause a 0.53% increase in the slope of Days with Disaster on Burglary. *Table 4* presents a comparison of the non-interaction and interaction models.

Table 4. Linear Model Comparison Table between the Non-Interaction and Interaction Model.

Model	R^2	*F*	*df*	*p*
Non-Interaction	0.11			
Interaction	0.14	5.85	1	.017

In order to visualize the moderation analysis, Social Disorganization was dichotomized into High and Low categories at the median. *Figure* 1 shows the regression lines for Burglary predicted by Days with Disaster for the High and Low categories of Social Disorganization. The High category indicates all observations of Social Disorganization above the median, and the Low category indicates all observations of Social Disorganization below the median.

Figure 1. Regression Lines for Burglary predicted by Days with Disaster for the High and Low Categories of Social Disorganization.



Social Disorganization Does Not Moderate Relationships Between Days with Disaster and Other Index Crimes

Days with Disaster did not significantly predict Murder, $B = 0.18$, $t(178) = 1.86$, $p = .065$, Assault, $B = -0.05$, $t(178) = -0.82$, $p = .414$, Larceny, $B = -0.06$, $t(178) = -1.32$, $p = .189$, Auto Theft, $B = 0.12$, $t(178) = 1.36$, $p = .176$. Since the first moderation condition was not met, moderation was not supported for Murder, Assault, Larceny, and Theft. Analysis of the remaining variables, Rape and Robbery, indicated that the first moderation condition was met, but the second condition was not met.

Additionally, although the RQs and hypotheses did not require any additional analysis, moderation analyses were also conducted by reversing the variables to determine if Days with Disaster moderates the relationship between Social Disorganization and the crimes in this study. None of the moderation analyses were supported when the two predictor variables were rotated with one another.

Discussion

These findings reinforce other findings showing that certain crime increases are associated with disasters (Augusto et al, 2020; Augusto 2021; Prelog, 2016; Spencer, 2017; Spencer & Stobl, 2019; Weil et al., 2019; Zahnow et al., 2017). However, these findings also seem to refute some author's findings that indicate certain crime decreases during disaster (Augusto, 2020; Bretzke et al., 2018; Bretzke & Andresen, 2018; Herber, 2014; Zahnow et al., 2017). The seemingly contradictory findings among researchers are at least partially likely a reflection of different levels of measurement. This study focuses on city-level data, while others often focus on county-level data.

Additionally, some studies are limited to broad categories of Index Crimes like violent crimes or property crimes, while other studies, such as this one, parse out the crimes into individual

Index Crimes. Further inconsistencies probably occur when researchers study different constructs of a phenomenon, such as Disaster Frequency, Days with Disaster, or Disaster Consequences, all using different data. Additionally, comparing findings is also difficult when one researcher studies solely hurricanes while other researchers study natural disasters or, in the case of this research, major weather events and disasters. At face value, these studies might seem to report on the same factors, but the connections between study findings become much less concrete with so many discrete differences in study designs and data used.

In addition, this study focuses on yearly Days with Disaster where other studies focused on other constructs of one or more disasters, which might account for other seemingly contradictory findings. This reinforces the importance of research that relies upon longitudinal data to uncover general associations, in addition to studying a single disaster. Given past research findings, it seems reasonable that an increase in the number of disasters would be linked to an increase in crimes, since individual disasters were also paired with such increases. However, this study specifies a relationship between total days per year with a major weather event or disaster and specific Index Crime rates. That specific relationship is a unique addition that adds to a fuller picture of the disaster crime body of work. Although a single disaster will almost certainly have impacts on crime, this study indicates that the repeated battering of a city with frequent disasters and major weather events over the course of decades is a different phenomenon with unique impacts on crime rates.

One might also question why all the studied crimes showed a significant positive relationship between disaster and crime except Larceny and Assault. Larceny and Assault may differ from expectations since law enforcement officers reported a realignment of priorities toward life-saving tasks and major crimes during disasters (Augusto et al., 2020; Pollock & Augusto, 2021). Larceny and assault may be two crimes that go unreported or are de-prioritized among the major calls-for-service during disasters and major weather events.

Days with Disaster as a Social Disorganization Factor

RQ 1 findings reinforce Social Disorganization Theory as a way of explaining changes to crime. In every regression model, Social Disorganization was also the strongest significant predictor of crime above Days with Disaster, Disaster Consequences, and Population Density. These findings reinforce the importance of Social Disorganization in explaining crime, at least at the macro level.

The results indicated that Social Disorganization worsened the impacts of Days with Disaster on Burglary rates. The question remains regarding why Burglary was the only crime for which moderation was supported. Burglary is often considered to be a proxy for Looting in disasters (Frailing & Harper, 2017), so it seems reasonable that increased Days with Disaster would result in more instances of Burglary or Looting, and that trend is magnified in low income, disorganized areas due to a combination of increased need and increased vulnerability.

The findings of this study provide evidence for the argument that Days with Disaster should be added to the generally accepted Social Disorganization factors. This claim should perhaps be unsurprising given the history of disasters disproportionately impacting low-income communities (Hallegatte et al., 2020; SAMHSA, 2017). Poor people are more likely to face heightened impacts from natural disasters for a few reasons.

According to Hallegatte et al. (2020), at-risk areas may be more attractive to poor people because those areas are typically cheaper, and offer more opportunity and income, and provide relatively increased public services. Additionally, poor people often settle in low-income areas, which have less public infrastructure to protection against hazards. Lower income people are also more likely to have an increased percentage of their finances and assets depleted by damage from disasters, simply due to having less resources to begin with. In addition, people in poverty, with low incomes, and with less education have all been found to be less prepared for disasters than other groups and to have fewer resources to respond to official warnings or evacuations regarding incoming disasters (SAMHSA, 2017). One could assert that Socially Disorganized communities face the same increased vulnerability to disaster since Socially Disorganized communities have the same deteriorating infrastructure, unemployment, reduced education levels, and low income (Frailing & Harper, 2017; Nogami, 2018).

Indeed, several researchers have argued that Social Disorganization is increased with disaster and used Social Disorganization Theory as a foundation for their research (Frailing & Harper, 2017; Prelog, 2016). This nexus seems intuitive, since disasters are known to cause residential displacement, family upheaval, and negative economic impacts, with particularly negative outcomes in already disorganized urban areas with high social vulnerability (Hallegatte et al., 2020; SAMHSA, 2017). However, the above argument relates to a temporary phenomenon, albeit across the extended disaster cycle. The findings from this study suggest that the aforementioned argument should be extended, and Days with Disaster should be added as an ever-present, if perhaps undulating, Social Disorganization Factor, specifically in urban areas.

Study Implications

This research provides some additional insight and an enhanced evidence base to aid in decision making relative to policies and funding toward preemptive crime reduction measures. The findings of this study could potentially be used by police agencies, particularly in disaster-prone cities, to adjust current enforcement plans and procedures relative to disaster-related law enforcement activities. Additionally, the study could be of use to inform security initiatives and crime preparedness measures in organizations with facilities that are likely to face repeated disasters. The study also provides further insight into the role of Social Disorganization in explaining post-disaster crime rates, as Frailing and Harper (2017) argued occurred in New Orleans after Katrina, and as Davila et al. (2005) suggested occurred after two previous floods in Texas.

These findings also consistently showed the Social Disorganization composite variable as significantly linked to crime, which reinforces the role of Social Disorganization Theory factors in relation to crime. Social Disorganization significantly predicted every crime being studied and was found to worsen the impact of Days with Disaster on Burglaries. This is not surprising given the increases to Burglaries that have been observed during disasters (Augusto, 2020; Augusto, 2021; Frailing et al., 2021; Spencer, 2017; Spencer & Stoble, 2019). This study also supports an argument for the inclusion of frequent disaster as a bona fide Social Disorganization Theory factor.

Limitations and Recommendations for Future Research

This study does have some limitations. Timing and compliance with disaster warnings are likely a factor in disaster crime. This study would have benefited from incorporating warning timing and compliance into models, although locating such data across 10 cities is likely unrealistic. The use of aggregate data also limits the inferences one can make from this research. This study showed that most Index Crimes in the group of 10 largest cities in Texas increase as days with major weather event or disaster increase, even when incorporating Social Disorganization factors, Population Density, and Disaster Consequences. However, one risks ecological fallacy by interpreting these results to indicate that the findings necessarily apply to any one city.

Only major weather events and weather-related disasters were studied. Thus, other types of disasters, such as earthquakes, are not weather-related, and are not included in the study. Another limitation of the study relates to the time measurement used. Much of the disaster crime literature focuses on the impacts of individual disasters and relatively short periods of time. While the study of the narrow windows of time surrounding a disaster is an important part of the picture, this research is intended to uncover long-term, broad relationships between crime and number of days with weather events and disasters in large cities in Texas. As a result, this study also does not provide insight into county-level crime trends.

Additionally, the interpretation of these findings relies upon the R Squared score for each model to reflect how much variance in the dependent variable is explained by the predictor variables. This study found that five of the seven Index Crimes being studied were positively associated with yearly Days with Disaster, but the models all reported relatively low R Squared scores. Thus, criminological researchers hoping to uncover the factors that predict large portions of the variance in crime will need to continue their search. However, since the primary goal of this study is to better understand the relationship between Days with Disaster and crime, the relatively low effect sizes indicated by the low R Squared scores do not negate the significance of the results. These findings are still useful in explaining the relationships between yearly Days with Disaster and particular Index Crimes. Additionally, Wuensch (2019) cautioned researchers against discounting low effect sizes, since even trivial effect sizes may be a large effect size when applied in a different context.

Further research should build upon this study and apply these findings as important context for future disaster crime research. The body of work would also benefit from a study comparing these results to a set of 10 cities with less days with disasters. Additionally, the body of work would benefit from research that delineates crime rates during the pre-disaster, disaster, and disaster recovery periods to better understand changes to crime through the disaster cycle. In any case, future research should focus on timing and compliance of disaster warnings in relation to crime.

Conclusion

Overall, this study found that Days with Disaster significantly predicted Robbery, Murder, Rape, Burglary, and Auto Theft, but did not significantly predict Larceny or Assault. Additionally, Social Disorganization was also often found to predict crime, and the results indicated that Social Disorganization, on average, worsened the impacts of Days with Disaster on Burglary rates in the cities studied. These findings indicate that, on average, security and public safety personnel in large cities can expect increases to crime as days with major weather events and disasters increase, particularly when those increases are paired with high levels of Social Disorganization. The findings advance the body of disaster research and carry several practical and theoretical implications.

Additionally, although this research presents important general associations between disaster and crime in urban areas, disaster researchers can more systematically advance the body of work by studying their chosen disaster from multiple units of analysis and with varied frequency of data. Future disaster crime research should also incorporate disaster phases, and timing, as well as compliance with disaster warnings.

References

Aksha, S. K., Juran, L., Resler, L. M., & Zhang, Y. (2019). An analysis of social vulnerability to natural hazards in Nepal using a modified social vulnerability Index. *International Journal of Disaster Risk Science 10*(1), 103–116. https://doi.org/10.1007/s13753-018-0192-7

Augusto, D. (2020). Change-point analysis of Houston crime during Hurricane Harvey. *JASR: An International Journal of Police - Security Operations & Practices*, *16*(1), 1-18. https://doi.org/10.1080/19361610.2020.1857170

Augusto, D. (2021). Strengthening disaster response through analysis of crime during hurricane Ike. *Journal of Homeland Security and Emergency Management, 18*(4). https://doi.org/10.1080/19361610.2020.1857170

Augusto, D., Pollock, E., & Flick, S. (2020). The push of disasters and pull of pandemics: Law Enforcement Officers' perspectives on crime and policing during disasters and the COVID-19 Pandemic. *International Public Safety Association Journal, 5*(1), 1-37. Retrieved December 1, 2021 from https://www.joinipsa.org/resources/IPSA%20Journal/IPSA%20Journal%20Fifth%20Edition%20-%20December%202020.pdf

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(1), 1173-1182.

Blake, E. S. & Zelinski, D. A. (2018, May 9). *National Hurricane Center Tropical Cyclone Report Hurricane Harvey*. Retrieved November 3, 2020 from https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf

Breetzke, G. D., King, M., & Fabris-Rotelli, I. (2018). The impact of the Canterbury Earthquakes on the temporal and spatial patterning of crime in Christchurch, New Zealand. *Australian & New Zealand Journal of Criminology*, *51*(1), 135–156. https://doi.org/10.1177/0004865816679687

Breetzke, G. D. & Andresen, M. A. (2018). The spatial stability of alcohol outlets and crime in post-disaster Christchurch, New Zealand. *New Zealand Geographer, 74*(1), 36-47. https://doi.org:10.1111/nzg.12182

Davila, M., Marquart, J., & Mullings, J. (2005). Beyond mother nature: Contractor fraud in the wake of natural disasters. *Deviant Behavior*, *26*(1), 271–293. https://doi.org/10.1080/01639620590927623

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2013). G*Power Version 3.1.9.7 [computer software]. Uiversität Kiel, Germany. Retrieved June 7, 2020 from http://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower.html

Field, A. (2018). *Discovering statistics using SPSS* (5th ed.). Thousand Oaks, CA: Sage.

Frailing, K., Harper, D. W., & Serpas, R. (2015). Changes and Challenges in Crime and Criminal Justice After Disaster. *American Behavioral Scientist*, *59*(10), 1278–1291. https://doi.org/10.1177/0002764215591184

Frailing, K., & Harper, D. W. (2017). *Toward a Criminology of Disaster: What we Know and What we Need to Find Out.* Palgrave-MacMillan.

Frailing, K., Zawisza, T., & Harper, D.W. (2021). Whirlwinds and Break-Ins: Evidence Linking a New Orleans Tornado to Residential Burglary. *Journal of Crime and Justice*, *44*(1), 119-130. https://doi.org/10.1080/0735648X.2020.1782249

Frigerio, I., Carnelli, F., Cabinio, M., & De Amicis, M. (2018). Spatiotemporal pattern of social vulnerability in Italy. *International Journal of Disaster Risk Science 9*(2), 249–262. https://doi.org/10.1007/s13753-018-0168-7

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From poverty to disaster and back: A review of the literature. *Economics of Disaster and Climate Change 4*(1), 223–247. https://doi.org/10.1007/s41885-020-00060-5

Harris County Flood Control District (HCFCD). (2018). *Hurricane Harvey: Impact and Response in Harris County*. Retrieved January 1, 2021 from https://www.hcfcd.org/Portals/62/Harvey/harvey-impact-and-response-book-final-re.pdf

Herber, E. (2014). Dealing with the aftermath of Japan's triple disaster: Building social capital through crime prevention. *Asian Journal of Criminology*, *9*(2), 143-159. https://doi:http://dx.doi.org.ezproxy.liberty.edu/10.1007/s11417-014-9183-9

Kuroishi, Y., & Sawada, Y. (2019). Motivations behind prosocial behavior: Evidence from the Philippines. *Journal of Asian Economics*, *1*(1). https://doi:10.1016/j.asieco.2019.06.003

Leitner, M., Barnett, M, Kent, J. & Barnett, T. (2011). The Impact of Hurricane Katrina on Reported Crimes in Louisiana: A Spatial and Temporal Analysis. *The Professional Geographer*, *63*(2), 244-261. https://DOI: 10.1080/00330124.2010.547156

Martin, R. A., & Legault, R. L. (2016). Systematic measurement error with state-level crime data: Evidence from the "More guns, less crime" debate. *The Journal of Research in Crime and Delinquency*, *42*(2), 187-210. https://doi.org/10.1177/0022427804270052

National League of Cities (NLC). (2020). *The 30 Most Populous Cities*. Retrieved August 12, 2021 from https://www.nlc.org/the-30-most-populous-cities

NOAA. (n.d.). *Historical Hurricane Tracks.* Retrieved September 3, 2020 from https://oceanservice.noaa.gov/news/historical-hurricanes/.

NOAA. (2020). *U.S. Billion-Dollar Weather and Climate Disasters.* Retrieved November 12, 2020 from https://www.ncdc.noaa.gov/billions/

NOAA. (2021). *NOAA Weather Events Database*. Retrieved Sep 3, 2020 from https://www.ncdc.noaa.gov/weatherevents/

Nguyen, H. (2019). Gendered vulnerabilities in times of natural disasters: Male-to-female violence in the Philippines in the aftermath of super typhoon Haiyan. V*iolence Against Women, 25*(4), 421–440. https://doi.org/10.1177/1077801218790701

Nogami, T. (2018). Disaster myths among disaster response professionals and the source of such misconceptions. *Journal of Contingencies and Crisis Management*, *26*(4), 491-498. https://doi-org.ezproxy.liberty.edu/10.1111/1468-5973.12218

Notre Dame University. (n.d.). *Durbin Watson Significance Tables.* Retrieved December 12, 2020 from https://www3.nd.edu/~wevans1/econ30331/Durbin_Watson_tables.pdf

Ogie, R. I., & Pradhan, B. (2019). Natural hazards and social vulnerability of place: The strength-based approach applied to Wollongong, Australia. *International Journal of Disaster Risk Science*, *10*(1), 404-420. http://dx.doi.org.ezproxy.liberty.edu/10.1007/s13753-019-0224-y

Pollet, T. V., Stulp, G., Henzi, S. P., & Barrett, L. (2015). Taking the aggravation out of data aggregation: A conceptual guide to dealing with statistical issues related to the pooling of individual-level observational data. *American Journal of Primatology*, *77*(7), 727-740. https://doi.org/10.1002/ajp.22405

Pollock, L. D. & Augusto, D. (2021). Protecting others, compassion, and sacrifice: The toll of disaster policing on law enforcement officers in the United States. *The Police Journal.* https://doi.org/10.1177/0032258X211044708

Prelog, A. J. (2016). Modeling the Relationship between Natural Disasters and Crime in the United States. *Natural Hazards Review, 17*(1), 1-11. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000190

SAMHSA. (2017). Greater impact: How disasters affect people of low socioeconomic status. *Disaster Technical Assistance Center Supplemental Research Bulletin.* Retrieved September 3, 2020 from https://www.samhsa.gov/sites/default/files/dtac/srb-low-ses_2.pdf

Sampson, R. (1986). Crime in cities: The effects of formal and informal social control. In A. Reiss Jr. & M. Tonry. (Eds.), *Communities and crime* (pp. 271–311). University of Chicago Press.

Seddighi, H., Salmani, I., Javadi, M., & Seddighi, S. (2019). Child abuse in natural disasters and conflicts: A systematic review. *Trauma, Violence & Abuse, 1*(1), 1-22. https://doi.org/10.1177/1524838019835973

Shaw, C., & McKay, H. (1942). *Juvenile delinquency and urban areas.* The University of Chicago Press.

Spencer, N. O. (2017). Look what the hurricanes just blew in: Analyzing the impact of the weather on criminal activities. *Journal of Crime and Justice*, *40*(1), 417-429. https://doi.org/10.1080/0735648X.2016.1168749

Spencer, N. O. & Stoble, E. (2019). Crime watch: Hurricanes and illegal activities. *Southern Economic Journal*, *86*(1), 318-338. https://doi-org.ezproxy.liberty.edu/10.1002/soej.12376

Staupe-Delgado, R. (2019). Analysing changes in disaster terminology over the last decade. *International Journal of Disaster Risk Reduction*, 101161, 1-5. https://doi.org/10.1016/j.ijdrr.2019.101161

Sun, Y., Chau, P. H., Wong, H., & Woo, J. (2017). Place-and age responsive disaster risk reduction for Hong Kong: Collaborative place audit and social vulnerability Index for elders. *International Journal of Disaster Risk Science 8*(2), 121–133. https://doi.org/10.1007/s13753-017-0128-7

Texas DPS Crime in Texas Online database (2020). *Crime in Texas Online*. Retrieved August 23, 2020 from https://txucr.nibrs.com/SRSReport/AnnualSRSSummary

Texas Education Agency. (2020). Public Education Information Management System. Retrieved August 23, 2020 from https://tea.texas.gov/reports-and-data

UCLA. (2021). *SAS FAQ*. UCLA Institute for Digital Research & Education. Retrieved August 23, 2021 from https://stats.idre.ucla.edu/sas/faq/how-can-i-interpret-log-transformed-variables-in-terms-of-percent-change-in-linear-regression/.

UNISDR. (2017). *UNISDR Terminology on Disaster Risk Reduction 2017*. Retrieved August 23, 2021 from https://www.preventionweb.net/english/hyogo/gar/2015/en/home/GAR_pocket/Pocket%20GAR_3.html.

U.S. Census Bureau. (2013). *Census 2000 Gateway*. Retrieved January 14, 2021 from https://www.census.gov/main/www/cen2000.html.

U.S. Census Bureau. (2020). *City and Town Population Totals: 2010-2019.* Retrieved January 14, 2021 from https://www.census.gov/data/tables/time-series/demo/popest/2010s-total-cities-and-towns.html

U.S. Department of Labor. (2021). *BLS Dataset Viewer*. Retrieved January 14, 2021 from https://beta.bls.gov/dataViewer/view/timeseries/LAUCT482400000000003

Varano S., Schafer J., Cancino J., Decker S., & Greene J. (2010). A tale of three cities: Crime and displacement after Hurricane Katrina. *Journal of Criminal Justice 38*(1), 42–51. https://docs.rwu.edu/cgi/viewcontent.cgi?referer=&httpsredir=1&article=1026&context=sjs_fp

Weil, F. D., Barton, M., Rackin, H., Valasik, M., & Maddox, D. (2019). Collective Resources and Violent Crime Reconsidered: New Orleans Before and After Hurricane Katrina. *Journal of Interpersonal Violence, 1*(1), 1-25. https://doi.org/10.1177/0886260518822345

Whitehouse, H., Jong, J., Buhrmester, M. D., Gómez, Á., Bastian, B., Kavanagh, C. M., & Gavrilets, S. (2017). The evolution of extreme cooperation via shared dysphoric experiences. *Scientific Reports, 7*(1), 44292. https://dx.doi.org.ezproxy.liberty.edu/10.1038/srep44292

Wuensch, K. (2019). *Cohen's Conventions for Small, Medium, and Large Effects.* East Carolina University. Retrieved January 19, 2021 from http://core.ecu.edu/psyc/wuenschk/docs30/EffectSizeConventions.pdf

Zahnow, R., Wickes, R., Haynes, M. & Corcoran, J. (2017). Disasters and crime: The effect of flooding on property crime in Brisbane neighborhoods. *Journal of Urban Affairs, 39*(6), 857-877. https://DOI.org/10.1080/07352166.2017.1282778

Zahran, S., Shelley, T. O., Peek, L., & Brody, S. (2009). Natural disasters and social order: Modeling crime outcomes in Florida. *International Journal of Mass Emergencies and Disasters, 27*(1), 26–52. https://www.researchgate.net/publication/228348077_Natural_Disasters_and_Social_Order_Modeling_Crime_Outcomes_in_Florida

.