AFTER THE STORM SURGE: HURRICANES, LOCAL CRIME RATE AND FEDERAL DISASTER RELIEF

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AFTER THE STORM SURGE: HURRICANES, LOCAL CRIME RATE AND FEDERAL DISASTER RELIEF

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Hurricanes are the costliest natural disasters in the US. Not only is the direct economic loss significant, but the negative externality that come with the hurricanes are substantial as well. In this paper, I estimate the effect of hurricanes on one social impact that is overlooked - local crime rate. My results show that a hurricane increases larceny or other stolen property crime by 7.2%, burglary by 9.9%, robbery by 19.6% and property crime in general by 6.7%, yielding a social cost of $27,960 per county on average. I also find that such increase in crime tend to happen more often in areas that have lower socioeconomic status and higher racial heterogeneity. Besides, government's response to hurricanes matter. I study the efficiency and effectiveness of current federal assistance program and estimate the benefit of mitigation project investment.

BIOGRAPHICAL SKETCH

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CHAPTER 1

INTRODUCTION

1.1 Motivation and Research Questions

Damage cost due to weather and climate disasters in the US is significant. Of the 258 U.S. weather disasters since 1980, tropical cyclones or hurricanes have caused the most damage. According to NOAA Office for Coastal Management, economic loss due to a hurricane on average is estimated at $21.5 billion, which is almost the same size as Iceland 2020 GDP.

However, the short run impact of natural hazards does not just stop at the property and mortality loss. As a matter of fact, the human response to a natural disaster, such as mismanagement, underdevelopment, profiteering and politics, can exacerbate its impact, even more than the event itself [28, 24, 23]. While some sociology literature focuses more on the macro-level policy effect on the disaster recovery, the human response I am looking into is more on a micro level: criminal behavior.

Intuitively speaking, as people lose their belongings, properties and even jobs from the disaster, it would be easier for them to make a living by breaking the social order, i.e. commit a crime such as stealing, burglary, and robbery etc. To them, it is not crime, but survival mode. Such criminal behavior not only induces extra physical loss, but also extends a deleterious effect on both social and economic development. For example, crime promotes insecurity and anxiety which later drives people to lose mutual trust in the community, discourage social cohesion, inhibit local regeneration and eventually catalyse a downward spiral in neighborhood status [1, 19, 12]. Crime offsets the economic development efforts as it hinders productivity, reduces local property values and imposes substantial cost on local communities and nations [11, 15, 5]. Therefore, rebuilding damaged properties is not the only necessary task to help affected communities recover from catastrophes, allocating limited resources to remain social order and restore economic growth is a difficult yet overlooked job. That is why it is important to correctly examine the effect of hurricanes on local crime and understand the mechanism behind the change.

While news often covers stories about looting, burglaries, or even violent crime such as assault and rape after natural hazards [29, 21], the actual impact of natural hazards on social order is obscure as current literature that tries to link disaster and crime rate shares contradictory results. There are some studies find that disaster has a positive impact on crime activities such as looting, sexual assault and rape on women, murder, robbery, and motor vehicle theft [9, 26, 13]. At the same time, some literature concludes that there is no significant impact or even negative impact on criminal behaviors [30, 27, 14]. The contradictory results can be drawn on three sociological theories: the therapeutic community, social disorganization theory, and routine activities theory [20]. The therapeutic community thesis proposed by [10] argues that the disaster leads to communal restoration, altruistic behavior and an increase in social cohesion overall. Hence, crime in the affected areas is expected to decrease. On the other hand, social disorganization, characterized by low socioeconomic status, ethnic and racial heterogeneity, residential mobility, family disruption, and urbanization, disrupts the social cohesion and subsequently increases local crime rate [22, 25]. Finally, routine activity theory predicts that if a disaster event increases the likelihood of suitable targets, motivated offenders or absence of proper guardianship, the affected communities would experience an increase in crime [2, 7].

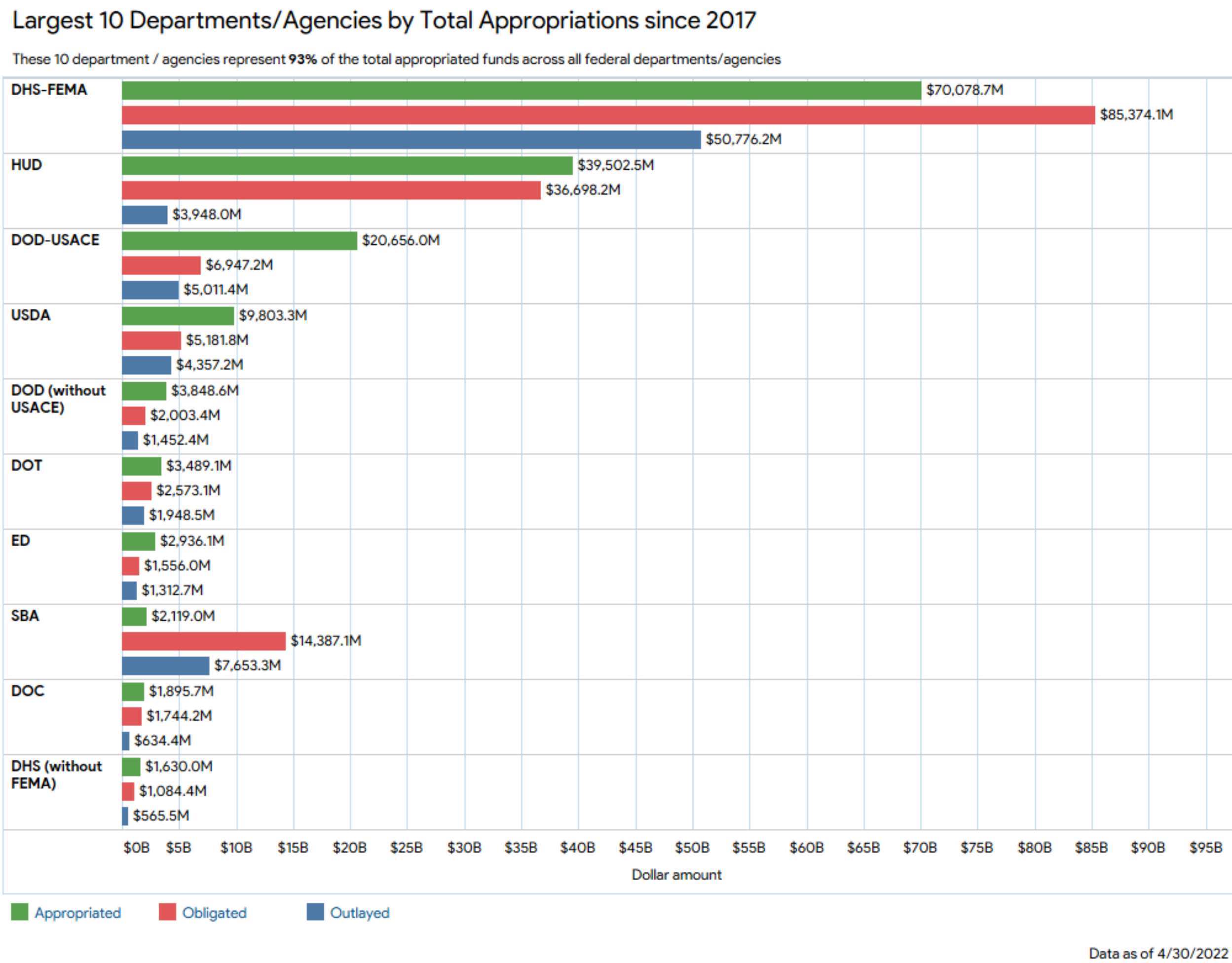
People's response to a disaster varies with its level of destruction. While most current literature that I am aware of focuses on the most destructive hurricanes, less attention has been put on the effect of smaller scaled yet non-negligible hurricanes. This paper fills in the gap by developing a causal framework to estimate the changes in property crime rate at an agency level followed by relatively smaller and exogenous climate shocks.

Besides individual's response, government's response to a disaster is also an important research topic. It goes without saying that the role of federal government in disaster assistance is crucial for both individuals and businesses as it leads the entire nation to prepare for and recovery from natural disasters. Not only does the government provides fund, but also it makes deliberate decision on who gets the assistance, exactly how much they are getting, and when they are getting the fund. Another important role the federal government takes is communication as it facilitate communication of responsibilities among agencies and collaborate with stakeholders and supporters to raise financial support [8]. In order to accomplish tasks, federal government has spent billions of dollars when facing natural disasters. Figure 1.1 shows when facing just 2017 and 2018 disasters, the sum of the largest 10 agencies outlay amount exceeds $75 billion, which is almost 0.4% of 2017 US total GDP. Therefore, it is important for researchers to study whether such large amount of money has been put into good use. Another set of questions this paper attempts to answer are: (1)how federal fund is allocated? (2) Is the current allocation reasonable and effective?

To measure crime, I employ data from the National Incident-Based Reporting System (NIBRS) for the years 2015 to 2019. Given most NIBRS data are collected from the east side of the US, I focus on hurricanes that made landfall in the eastern US between 2015 and 2019. I obtain hurricane data from NOAA including storm location, maximum sustained wind speed, and maximum extent of wind radius. I employ both differences-in-differences and event studies framework, comparing police agencies that experience hurricanes during the sample period with ones that do not, to estimate how hurricanes affect crime recorded by the local police. To provide context for these results and to understand the mechanisms that drive them, I also consider changes in police forces, population, household incomes, and employment status.

To measure government's response to natural disasters, I acquire data on federal

Figure 1.1: Federal Spending for 2017-2018 Disasters



source: https://recovery.fema.gov/spending-explorer

spending for individual assistance, ex-ante public assistance, and ex-post public assistance accordingly. Individual assistance is meant to meet individuals' basic needs and supplement disaster recovery efforts; Ex-ante public spending reduces long-term risk to people from future natural disasters; Ex-post public spending provides funds to help community recover from a large disaster

1.2 Contributions

I document several new and important facts. First, while most current literature mainly focuses on major hurricanes such as Katrina or Harvey, my results shows that smaller scaled hurricanes also has a significant impact on local crime. I estimate a hurricane increases larceny or other stolen property crime by 7.2%, burglary by 9.9%, robbery by 19.6% and property crime in general by 6.7%.

Second, I provide evidence on crime patterns against demographics. I find that property crime rate increases at a higher rate in counties that have higher poverty rate, higher unemployment rate, lower median household income, and higher percentage of black residents. At the same time, a hurricane has insignificant effect on crime in top 10 percent wealthiest counties in my sample. The finding partially reflects [14]'s study where they discover percentage of African Americans, the percentage of persons living below the poverty level have a positive relationship with the increase in burglaries after Hurricane Rita. It also resonates [13]'s study where they use differences-in-differences approach to estimate the effect of Hurricane Katrina evacuees on crime in host cities. They find dramatic increases in murder, assault, illegal possession of weapons and arson in areas lived by more disadvantaged evacuees compared to other areas.

Third, combining the results with estimates of average cost of each crime type estimated by [4, 3, 18], I show that hurricane can cause an additional cost of $27,960 in social cost on average per county. Moreover, such additional social cost caused by the increasing in property crime is over 10% of the median county-level property damages estimated by SHELDUS, suggesting a change in law enforcement during post-diaster period is necessary.

Finally, I evaluate the efficiency and effectiveness of federal disaster relief allocation. I find that areas that experienced higher damaged receive more public funding during recovery process. Regarding the individual assistance, more economically challenged households are more likely to be eligible to enroll in individual assistance program and receive more assistance comparing to richer families; When facing the same category of hurricane wind speed, areas that have mitigation constructions pre-hurricane landfall suffer less damages than areas that do not have any sort of storm preparation projects. More importantly, I have found that increasing ex-ante spending by 1% reduces property crime during post-disaster period by 3 incidents per 100,000 residents, which is more than the effect of increasing one dollar of community policing funding per resident in cities with population greater than 100,000 [31].

The rest of the paper is organized as follows. Chapter 2 provides background information on hurricanes, US crime, US federal disaster aid, and the data used for the analysis. Chapter 3 describes the empirical strategy. Chapter 4 presents and interprets the result. Chapter 5 concludes.

CHAPTER 2

BACKGROUND

2.1 Hurricanes

A hurricane starts with the sea surface temperature at or above 80 degrees near the equator. These warm water evaporate and create warm moist air which acts as fuel for the storm. Another key ingredient is the wind: the wind causes more warm water to evaporate in the air. As a matter of fact, many hurricanes in the US are caused by winds blowing across the Atlantic Ocean from Africa. The warm moist air over the ocean condensed into liquid water droplets and forms clouds. As the warm air continues rising upward, the winds begin blowing in a circular pattern around a center. The spiraling winds gather up a cluster of big thunderstorm clouds. Once the spinning winds reach 74 miles per hour, the storm has officially become a hurricane. Hurricanes can be 10 miles high and over 1,000 miles across. Once a hurricane hits land, its wind begin to weaken as it runs out of warm moist air. However it can still lead to tremendous economic loss.

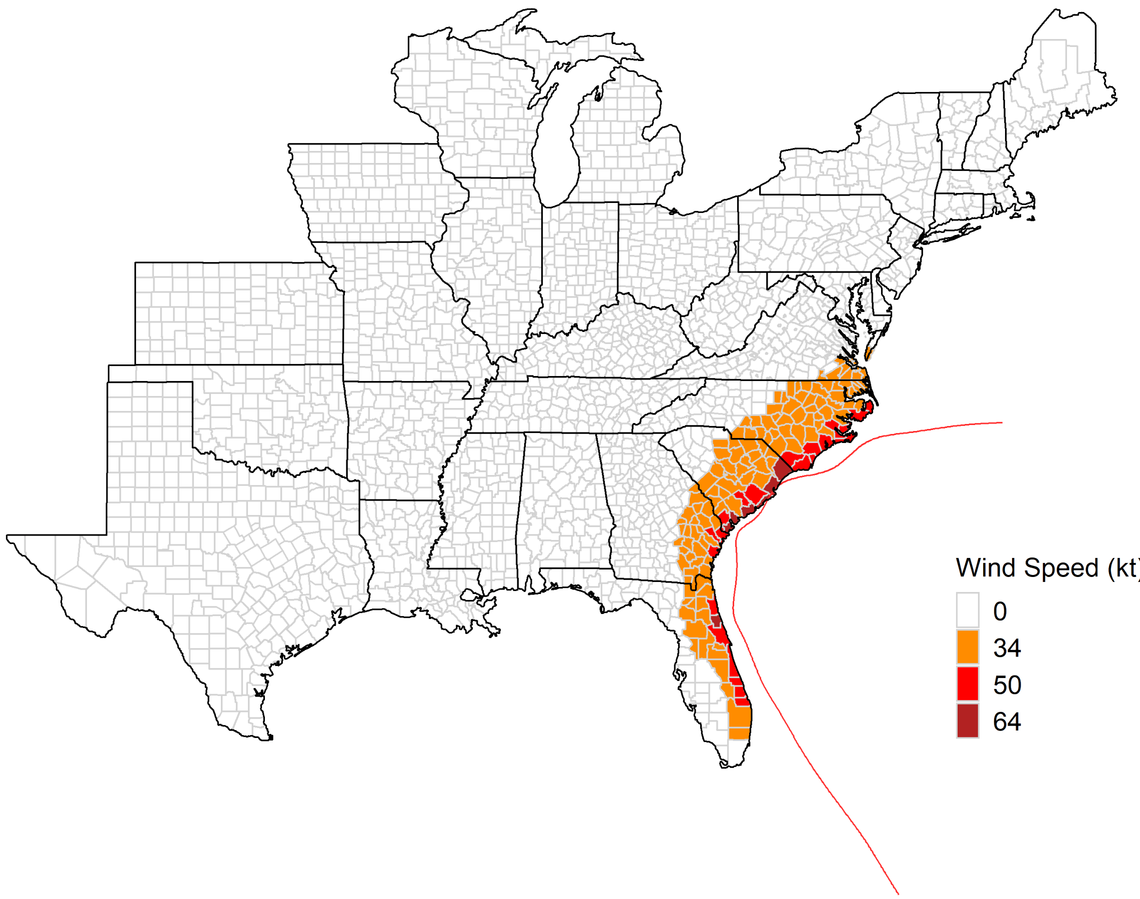
This paper includes hurricanes that landfall during 2015-2019 sample period: Hermine and Matthew in 2016, Irma in 2017 as well as Michael and Florence in 2018, all of which mainly affect east side of the US.

To track where hurricanes hit, I use revised Atlantic hurricane database (HURDAT2) provided by National Hurricane Center (NHC). It contains six-hourly information on storm center location, maximum sustained wind speed, central pressure and wind radii for each of the four quadrants. Maximum sustained wind is defined as the maximum average wind speed over a minute. The original radius gives the maximum extent of 34 knot, 50 knot and 64 knot in each quadrant. I then interpolate this data to every 15 minutes using linear interpolation. For each 15-minute point along the storm's track, I determine counties that fall within each wind radius as treatment counties, while counties that fall outside of any wind radius as control counties. Given that the data does not allow me to observe the actual maximum wind speed a county has experienced, I can only infer the wind intensity based on the highest wind speed radius. For example, if a county falls in maximum extent of 64 knot radius, then I conclude that it experiences at least 64-knot wind. Figure 2.1 displays storm track and affected counties by wind intensity for hurricane Matthew in 2016 as an example. The red solid line presents the interpolated storm track. The darker the filled color is, the higher wind speed a county has experienced. I assign agencies that experience 34 knots or higher to be treated group because 34-knot is a wind speed threshold for tropical storm.

2.2 Crime

Most existed crime literature uses crime data from Uniform Crime Reporting (UCR) Program, which is known for its measurement error [17, 16]. Instead, I collect my crime data from National Incident-Based Reporting System (NIBRS), a crime reporting system that is initially implemented in 1989. Unlike UCR where they only provide aggregated monthly crime data, NIBRS contains detailed information on each crime incident including incident date and time, demographic details on victims and offenders, location information, and property descriptions etc. Moreover, it looks at more offense types than traditional UCR does: NIBRS collects data for 52 offenses, while UCR only collects 10. My primary focus is property crime. Existed literature has shown that unemployment rate will spike and personal income will drop in a short run. Combine with the fact that people lose their valuable properties from natural disaster, disaster survivors, especially the poor who needs money for subsistence, are pushed to commit property crime such as larceny, burglary and credit card fraud. Detailed information on offense type, location data and

Figure 2.1: Hurricane Matthew Track Map



Note: NOAA provides data on wind radii for each of four quadrants and storm center location every 6 hours. The original radius gives the maximum extent of three types of wind speed in each quadrant: 34 knot (characterized as tropical storm), 50 knot (characterized as storm) and 64 knot (characterized as a hurricane) I interpolated this data to every 15 minutes using linear interpolation. For each 15-minute point along the storm's track, I determined which counties fell within each wind radius. The red solid line presents the interpolated storm track. The darker the filled color is, the higher wind speed a county has experienced. I assign agencies that experience 34 knots or higher to be treated group because 34-knot is a wind speed threshold for tropical storm.

property descriptions allows me to acquire more comprehensive and accurate results.

However, the merit of NIBRS does not come without drawbacks. Law enforcement agencies are only encouraged but not required to submit their report on NIBRS. Therefore, the data is limited in states that have good variation in hurricane data. For example, none of the police agency in Florida reports to NIBRS; even though most agencies in Georgia and North Carolina reports their data, they only start to report in 2019; Also, there is a concern regarding under-reporting following a hurricane either because survivors do not have time to contact police agencies or because law enforcement authorities are too busy with recovering to report to NIBRS. To alleviate that concern, I limit police agencies to be consistently reporting every month throughout the entire study period, allowing me to observe whether there is a drop in crime type that should not be affected by hurricanes. I also limit a state to have at least 90% agencies contributing to NIBRS. These two exercises lead to a further drop in sample size. I finally end up with 1,752 agencies that cover just under 16% of the US population across 11 different states in the east. I am aware that decisions made by criminals might vary across different places and my sample data cannot represent the whole country. I interpret my results with this in mind.

2.3 Federal Disaster Assistance

Federal disaster assistance is a grant that in resources or monetary form to individuals and households for losses that are not covered by the insurance. A county is eligible to receive federal disaster aid under following conditions: (1) Affected state or tribe and Federal Emergency Management Agency (FEMA) regional office must complete Preliminary Damage Assessment (PCA), including the extent of the disaster, its impact on individuals and public, and the types of federal assistance needed (2) The governor or tribal chief executive of the affected state/tribe must submit a request to the US President within 30 days of the occurrence. (3) The US President approves the request.

There are three major category of federal disaster assistance: (1) Public Assistance that is meant to help repair public facilities and offer emergency services. It can be mainly considered as ex-post federal spending that includes debris removal, protective measures such as rescue and evacuation, permanent work such as fixing roads and bridges, restoration of utilities as well as management costs. (2) Hazard Mitigation Assistance can be mainly considered as ex-ante spending that funds mitigation projects that reduce long term risk to people and property from future natural disasters. In later analysis, I restrict the projects to be solely planned for facing strong wind speed and flood. That includes retrofitting, elevation private and public properties, flood control, flood proofing and structure stabilization. (3) Individual Assistance that is meant to help individuals and households. Under Individual Assistance, there are programs such as the Individuals and Households Program (IHP) that assures people have a safe and sanitary place to live, the Small Business Administration (SBA) that provides loans to homeowners and business, the Disaster Unemployment Assistance (DUA) programs that provides unemployment benefits and reemployment services up to 26 weeks after the Presidential declaration date, as well as other legal and counseling services. This paper mainly focuses on the IHP since it is the primary way FEMA assists disaster survivors. IHP Assistance is comprised of two provisions, Housing Assistance and Other Needs Assistance (ONA). Housing Assistance may be provided in the form of financial assistance (funds provided to an applicant) or direct assistance (housing provided to the applicant by FEMA). Examples for financial assistance are Lodging Expense Reimbursement, Home Repair/Replacement Assistance and Rental Assistance, while examples for direct assistance include placing disaster survivors in temporary housing units or other improved residential properties and providing construction and repair services.

After a state, tribe or territory receives a presidential declaration for a disaster and individual assistance programs are designated, disasters survivors may apply for assistance. Typically, they have a 60-day period to register for assistance via Disaster Recovery Center, online or phone calls. Within 10 days after their applications, FEMA will send inspector to verify disaster related damage. If it is eligible, applicants are expected to receive check or deposit within 10 days after inspectors' visits.

Both Public Assistance data and Hazard Mitigation Assistance data are provided at a project level: project name and type, approved and closed date, estimated project total costs and federal obligated share[1,2]. I obtain the data on IHP Assistance from FEMA Report and Data section[3]. The data set contains FEMA applicant-level data for the Individuals and Households Program. It provides information on corresponded disaster, each applicant's location information such as state, county and zip-code, demographics including household composition, age and gross income etc. Moreover, it takes record of each applicant's insurance status, estimated damage amount, eligibility of federal assistance programs, and the final assistance received.

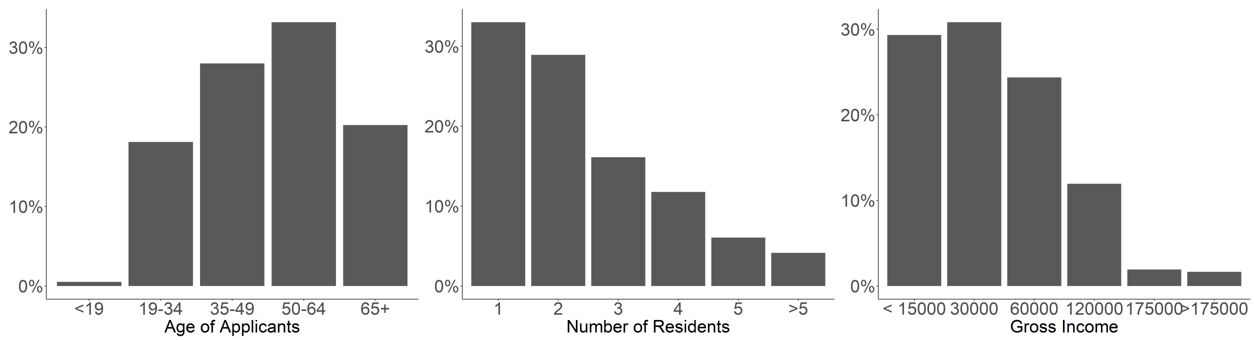
Figure A2 shows the spatial distribution of Public Assistance on average at county level for hurricane Matthew. Combine with the hurricane Matthew storm track map, we can observe a pattern that counties that experienced worse storm (higher wind speed), potentially suffered higher damages, received more federal ex-post spending to rebuild. Table 2.1 displays applicant-level summary statistics for hurricane Matthew in 2016, Irma in 2017 as well as Florence and Michael in 2018. Note that in response to those hurricanes, only residents in Florida, Georgia, South Carolina, North Carolina, and Virginia are eligible to apply for individual assistance. There are 3,160,976 households applied, among whom, 49% of the applicants own their properties, 33% of them have home owners insurance, 8% has flood insurance coverage; most applicant is at age of between 35 and 64,

[1]https://www.fema.gov/api/open/v1/PublicAssistanceFundedProjectsDetails
[2]https://www.fema.gov/api/open/v2/HazardMitigationAssistanceProjects
[3]https://www.fema.gov/openfema-data-page/individuals-and-households-program-valid-registrations-v1

Table 2.1: Applicant Summary Statistics for IHP Assistance

Statistic	Mean	St. Dev.	Min	Max	N
Ownership	0.49	0.50	0	1	3,160,976
Has Home Owners Insurance	0.33	0.47	0	1	3,160,976
Has Flood Insurance	0.08	0.28	0	1	3,160,976
Water Depth (inch)	0.48	3.80	0	480	3,160,976
Destroyed	0.001	0.03	0	1	3,160,976
Damage to Real Properties (USD)	292.17	2,473.97	0.00	338,581.20	3,160,976
Damage to Personal Properties (USD)	81.46	526.02	0	131,250	3,160,976
Eligible to IHP	0.29	0.45	0	1	3,160,976
Assistance from IHP (USD)	484.74	1,831.03	0.00	70,260.20	3,160,976

Figure 2.2: Applicants Demographics Density



lives with one or two people in the household, and earns less than or equal to $60,000 a year; the average depth of water affected the damaged dwelling is 2.6 inches; only 0.1 % of the registered property is totally destroyed by the disaster; the average FEMA-determined value of disaster-caused damage to real property components is around $300. This includes damage to floors, walls, access roads, and bridges etc; the average FEMA-determined value of disaster-caused damage to personal property is $81.46. This includes damage to home appliances and furniture; only 29% of the applicants are eligible to receive individual assistance, while the average assistance received is a little less than $500.

CHAPTER 3

EMPIRICAL STRATEGY

To estimate the effect of a hurricane on crime up to 12 months after its landfall, I first adopt three model specifications from [6]'s framework: a flexible event study, a concise event study and a specification that accounts for pretrends by allowing outcomes in hurricane-affected counties to follow a different linear trend and subsequently estimates whether hurricanes cause a shift in the mean and /or a change in the trend. Throughout the analysis, the identifying assumption is that, conditional on location and time, treatment group in the absence of the hurricane occurrence will follow the same trend as the control group post-disaster period. This is reasonable because the occurrence of a hurricane is uncorrelated with the unobservables: hurricane hits are as good as random.

3.1 Basic Approach

The first hurricanes my sample counties experienced are Hurricane Hermine and Matthew in 2016. However, the last time these counties were hit by a hurricane is back in 2011. The five years of hurricane free period provides an identifiable shock period for analysis. Besides using only hurricanes that made landfall between 2015 and 2019, I borrow [6]'s set-up and use only the first instance of a hurricane in my estimation. In other words, I ignore hurricanes that occurred prior to 2015 or after 2019 as well as any hurricanes that occurred between 2015 and 2019 in a county that had already experienced a hurricane during that sample period.

To maintain a consistent sample, I require that none of the following key variables are missing for an agency-year observation to be included in the estimation: population that an agency is responsible for, total number of officers, and total number of civilians. To maintain a balanced agency-level crime record across different offense categories, I fill in zeros for agencies that consistently report every month but have no record on certain offense categories.

I first employ a flexible event study framework, which is helpful to observe the pattern of the impact of a hurricane on crime. Such pattern allows me to identify whether the pre-trend assumption is violated, which directly determines the validity of later difference-in-differences analysis. To implement the event study, I regress agency-level-outcomes on a set of hurricane indicators ranging from twelve months before to twelve months after a hurricane. Given the treatment is assigned at county-year-month level, I include county and year-month fixed effects. I also control for total officers, population and hurricane occurrence outside the time interval of interest. Besides, I include year indicators interacted with each of the following 2015 (one year before the first hurricane occurrence) characteristics: poverty rate, median household income, unemployment rate, and shares of the population that are black. Specifically, the estimating equation is

$$\begin{aligned} O_{it} = & \sum_{\tau=-12,\tau\neq-1}^{12} \beta_\tau H_{c\tau} + \gamma X_{it} + \alpha_c + \alpha_t + \psi'_{c,2015}\alpha_t \\ & + \beta_{-13} H_{c,-13} + \beta_{13} H_{c,13} + \epsilon_{it} \end{aligned} \tag{3.1}$$

where O_{it} is some outcome for agency i in year t, such as the log of crime per capita or log of crime count (Poisson regression). The variable $H_{c\tau}$ is a hurricane indicator equal to 1 if the county at time t, experienced a hurricane $-\tau$ months ago. I normalize the effect in the month before the hurricane ($\tau = 0$) as zero. The variables α_c and α_t are county and year-month fixed effects accordingly. Besides, I include agency-level control variables such as total number of officers and population that are covered by each agency. Additionally, the set of interactions $\psi'_{c,2015}\alpha_t$ allows the year-month fixed effects to differ by linear 2015 characteristics at a county level. Finally, $H_{c,-13}$ and $H_{c,13}$ control for whether a county experience another hurricane before or after the window of interest. I cluster standard errors by county and weight the observations by population that each agency is responsible for. The coefficient β_τ reflect the mean effect on outcome O_{it} at time τ, relative to one month before a hurricane landfall.

To obtain a more concise to increase the power of the estimates, I then combines 12-month post treatment period into three groups: 1-3 months after, 4-7 months after and 8-12 after a landfall, assuming there is no differences between affected and unaffected counties in the 12 months prior to hurricane. The estimating equation has the similar setup

$$\begin{aligned} O_{it} &= \beta_1 H_{c,1 \text{ to } 3} + \beta_1 H_{c,4 \text{ to } 7} + \beta_2 H_{c,8 \text{ to } 12} + \gamma X_{it} + \alpha_c + \alpha_t \\ &+ \psi'_{c,2015}\alpha_t + \beta_{-13} H_{c,-13} + \beta_{13} H_{c,13} + \epsilon_{it} \end{aligned} \tag{3.2}$$

where $H_{c,\text{n to m}} = \sum_{\tau=n}^{m} H_{c\tau}$. Recall that I only use the first instance of a hurricane in my estimation, hence $H_{c,\text{n to m}}$ and $H_{c,\text{n to m}}$ can be interpreted as a indicator that equals to 1 for affected counties that fall in between n months after and m months after interval accordingly. The coefficient β_1 indicates the average treatment effect in months 1-3 after the hurricane, relative to month during hurricane; β_2 indicates the average treatment effect in months 4-7 after the hurricane while the coefficient β_3 indicates the average treatment effect 8-12 months after the hurricane.

The last specification [6] does is to control for differential trends between treatment and control group during the sample period.

$$\begin{aligned} O_{it} &= \beta_1 H_{c,0 \text{ to } 12} + \beta_2 H_{c,0 \text{ to } 12} \times \tau + \beta_3 H_{c,\text{-12 to } 12} \times \tau \\ &+ \gamma X_{it} + \alpha_c + \alpha_t + \psi'_{c,2015}\alpha_t + \beta_{-13} H_{c,-13} + \beta_{13} H_{c,13} + \epsilon_{it} \end{aligned} \tag{3.3}$$

where $H_{c,0 \text{ to } 12} = \sum_{\tau=0}^{12} H_{c\tau}$, $H_{c,\text{-12 to } 12} = \sum_{\tau=-12}^{12} H_{c\tau}$, and τ indicates the number of months since a hurricane landfall. Our variable of interest, β_1, represents the average treatment effect during the entire post treatment period relative to twelve months before a hurricane.β_2 represents the change in the linear growth rate of O_{it} between treated counties during the entire post-treatment period, with respect to control counties. β_3 represents the overall trend difference in O_{it} between treated and control counties. The rest set-up is the same as before.

CHAPTER 4

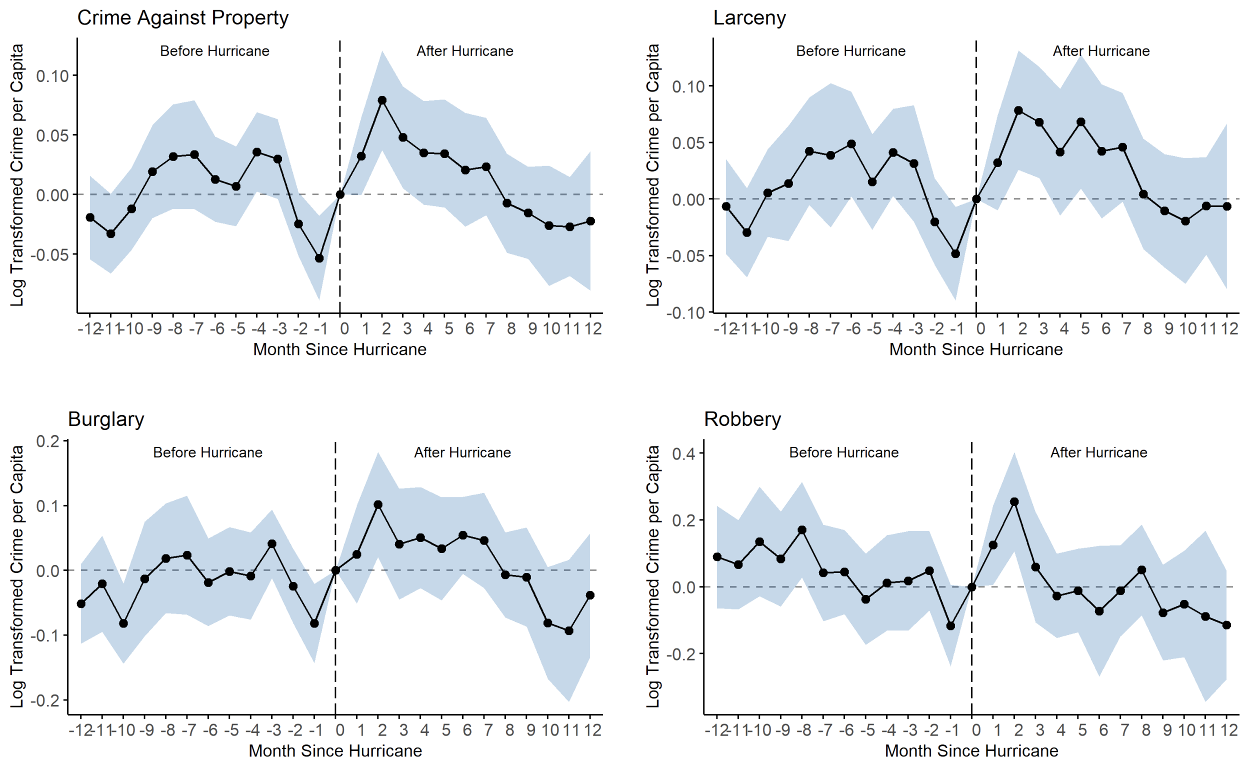
RESULTS

4.1 Change in Crime Followed by A Hurricane

Event study estimates of the effect of hurricane on crime per capita are shown in Figure 4.1. Under specification 3.1, crime rates in property crime, larceny, burglary and robbery starts to increase just one months after the landfall and reaches its peak two months after before it starts to decrease. In the short run, property crime in total increases by 7%; larceny and other stolen property crime increases by 8%; burglary increases by 10%; robbery increases dramatically by 30%. However, the gap in crime rate begins to dissipate shortly after its peak. Moreover, eight months after the hurricane hit, treated counties fall below the pre-hurricane period as they actually experience less crime than control counties, despite it is not conclusive. In Section **??** I will examine whether such decreasing trend in the long run is caused by federal disaster relief. There are no significant pretrend violation as most coefficients of pre-treatment periods are wiggling around zero. The down tick in crime preceding the storm event may due to a decrease in opportunities for crime. For example, police and firefighters are active in the streets directing residents in preparation for the storm, or people are outside boarding up windows and tying things down. The increasing chances of getting caught disincentives potential criminals to commit crime. The drop one month before storm hit may also be explained by the fact that police simply do not respond to or report crimes preceding storms since storm preparation efforts are given priority.

Corresponding estimates from the more concise models, equation 3.2 and 3.3, are shown in Table 4.1 and 4.2. These results confirm the results of the event study. All crimes shown in Figure 4.1 experience a significant increase 1-3 months after a hurricane strikes,

Figure 4.1: The Effect of Hurricanes on Crime - Event Studies



Note: Only the first instance of a hurricane in my estimation. The x axis indicates how many months have passed since the last hurricane strike rather actual calendar time. Each point implies the difference in log transformed crime incident per 1,000 residents between treated counties and control counties, comparing to the difference in months during hurricane. The window of interest is within 12 months before and 12 months after a hurricane, so estimates of $H_{c,-13}$ and $H_{c,13}$ are not shown in the figure. The estimates in all panels are from the same regression, but with different sub-sample. All panels account for county, year-month fixed effects. Standard errors in all panels are clustered at the county level. All regressions are weighted by the population each police agency is responsible for. and state-by-hurricane levels.

a less significant increase 4-7 months after, and insignificant decrease after 8 months a hurricane strikes. The significant negative estimates for post-hurricane trend difference indicates the dissipating gap in crime between treated and control agencies. Finally, the insignificant estimates for overall trend imply the positive crime effect becomes less significant as time goes by.

It seems that a hurricane has a swift yet significant effect on property crime in general. To see whether the short run increase in crime rates followed by a hurricane is due to people loss of properties and jobs, it would be better if I could observe the monthly trends

Table 4.1: The Effect of Hurricanes on Crime - Concise I

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
1-3 months after hurricane	0.0508***	0.0496***	0.0721***	0.1431***	0.0529
	(0.0142)	(0.0178)	(0.0234)	(0.0398)	(0.0764)
4-7 months after hurricane	0.0253	0.0385*	0.0611***	0.0042	-0.1660*
	(0.0168)	(0.0201)	(0.0194)	(0.0373)	(0.0923)
8-12 months after hurricane	-0.0209	-0.0163	-0.0300	-0.0197	-0.1955***
	(0.0162)	(0.0183)	(0.0297)	(0.0466)	(0.0643)
Fixed-effects					
data_year-month_incident	Yes	Yes	Yes	Yes	Yes
County FIPS	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	96,512	93,896	76,160	28,500	6,287
R^2	0.57835	0.52261	0.63205	0.61283	0.77974
Within R^2	0.09700	0.05124	0.14236	0.22224	0.14937

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

Note: Data are estimated using equations 3.2. Standard errors are clustered at county level. Controls include county fixed effects, year-month fixed effects, trends linear in 2015 county characteristics, and dummies for hurricane occurrence outside of the time window of interests.

for economic indicators such as poverty rate, household income, and unemployment rate. For example, it would be a rather concrete evidence to show economic indicators drives up the property crime rate if income drops drastically or unemployment rate spikes up at the same time crime rate increases. Unfortunately, due to data limitation, the data on economic indicators is only available at year, not month level. However, I am still able to use the data on socioeconomic status, and racial heterogeneity to test the social disorganization theory. Recall that disorganization theory claims that a shock is more likely to break the social cohesion in an area with low socioeconomic status and racial heterogeneity. The key variables I use for socioeconomic status are poverty rate, median household income, and unemployment rate. I use the percentage of black residents in each county as a proxy for racial heterogeneity. In order to see a clearer pattern in crime, I grouped my sample counties by 10^{th} percentile of each variable. That is, I compare

Table 4.2: The Effect of Hurricanes on Crime - Concise II

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Post-hurricane indicator	0.0673***	0.0724***	0.0986***	0.1958***	0.0075
	(0.0185)	(0.0228)	(0.0295)	(0.0399)	(0.1131)
Post-hurricane trend difference	-0.0083***	-0.0069***	-0.0149***	-0.0109	-0.0210**
	(0.0025)	(0.0026)	(0.0041)	(0.0071)	(0.0102)
Overall Trend	-6.72×10^{-5}	-0.0007	0.0020	-0.0079**	0.0006
	(0.0014)	(0.0017)	(0.0026)	(0.0040)	(0.0076)
Fixed-effects					
data_year-month_incident	Yes	Yes	Yes	Yes	Yes
County FIPS	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	96,512	93,896	76,160	28,500	6,287
R^2	0.57835	0.52260	0.63205	0.61286	0.77938
Within R^2	0.09699	0.05122	0.14235	0.22231	0.14799

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

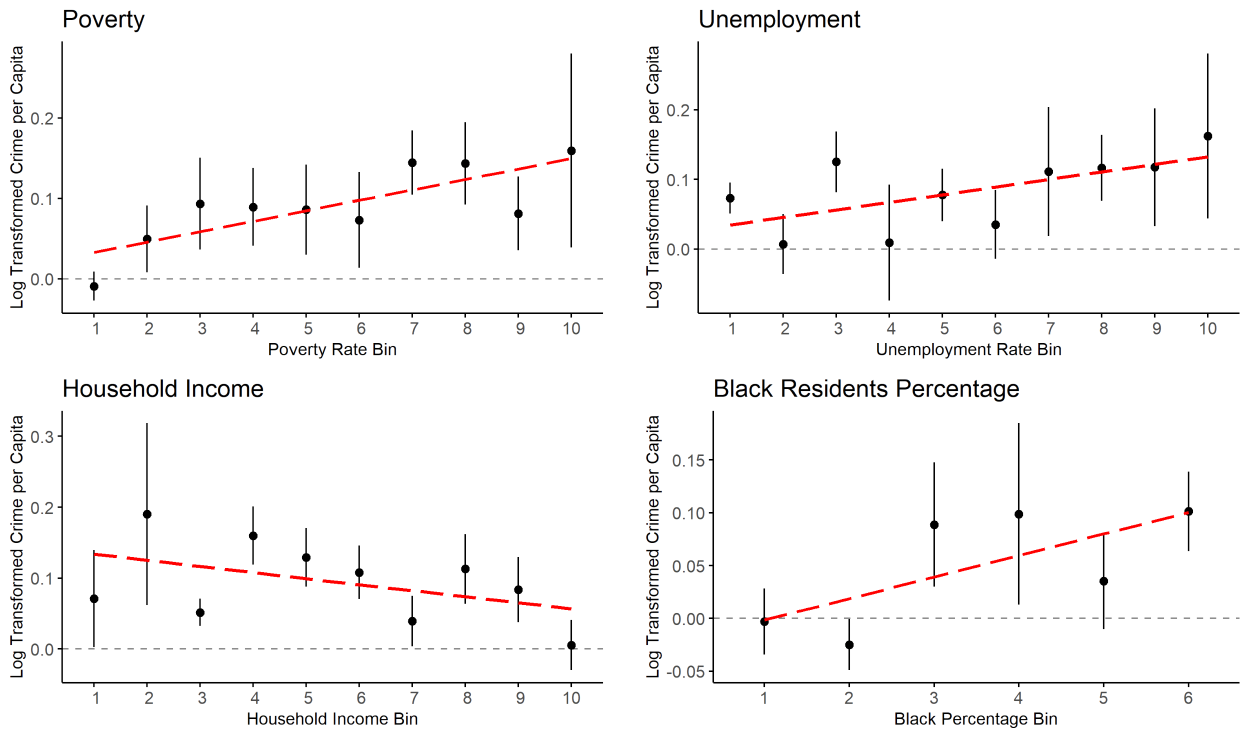
Note: Data are estimated using equations 3.3. Standard errors are clustered at county level. Controls include county fixed effects, year-month fixed effects, trends linear in 2015 county characteristics, and dummies for hurricane occurrence outside of the time window of interests.

the change in property crime rate between treatment and control counties that are in the same group. As for model specification. I regress property crime rate on the interaction of treatment assignment and the key variable group.

$$O_{it} = \sum_{g=1}^{10} \beta_g H_{c,0 \text{ to } 12} \mathbb{1}[G = g] + \alpha_c + \alpha_t + \psi'_{c,2015}\alpha_t + \beta_{-13} H_{c,-13} + \beta_{13} H_{c,13} + \epsilon_{it} \tag{4.1}$$

$\mathbb{1}[G = g]$ is an indicator equal to 1 if county c is in group g, while the rest of the set up remains the same. Figure 4.6 presents a set of crime rate estimates against groups in poverty rate, unemployment rate, median household income, and black residents percentage. The red dashed lines are the best linear fits. It is clear to observe that the crime rate increases at a higher rate in groups that have higher poverty rate, higher unemployment rate, lower

Figure 4.6: Bin Regression - Demographics



Note: Point estimates from equation4.1 and 95 percent confidence intervals are shown. The demographic variable is displayed above and below the corresponding panel. Standard errors are clustered at county level. Controls include county fixed effects, year-month fixed effects, trends linear in 2015 county characteristics, and dummies for hurricane occurrence outside of the time window of interests. The reason why there are only six bins in Figure 4.5 is due to lack of treatment group in some bins.

household income, and higher black residents percentage. This finding perfectly reflects the disorganization theory. The reason why there are only six bins in Figure 4.5 is due to lack of treatment group in some bins. It is also interesting to note that a hurricane has an insignificant effect on crime rate in counties that have the lowest poverty rate, highest household income and lowest black residents percentages. At the same time, the magnitude of the treatment effect is the largest in counties that have the highest poverty rate, unemployment rate, and black residents percentage.

4.2 Federal Government's Response

4.2.1 Individual Assistance

The disaster relief aids data covers Hurricane Matthew, Irma, Florence and Michael. As described in Section 2.3, victims in federal disaster declared regions are allowed to apply for disaster relief aids from the IHP within 60 days after the declaration. IHP assistance is not designated to restore applicant's properties to pre-disaster status, but to provide uninsured or under-insured necessary expenses and serious needs. They may or may not be eligible to receive the fund, depending on FEMA's inspection. If they are eligible, applicants are expected to receive their assistance within 10 days after the inspection. Given detailed information on applicant's demographics, insurance status, estimated damage amount, eligibility of federal assistance programs, and the final assistance received for each corresponded disaster, I now estimate a pattern of the federal assistance by different income group. Specifically, I try to answer (1) Who are more likely to receive the fund? (2) How much assistance do they receive from FEMA? (3) What are some characteristics of the applicants and how do they explain the eligibility and the amount of assistance?

To answer the first question, I perform a linear probability regression and regress the eligibility indicator on income groups while controlling for household composition, estimated damage amount as well as flood and homeowners insurance status. The exact specification is:

$$\text{Eligibility}_i = \sum_{g=1, g\neq 3}^{6} \beta_g \mathbb{1}[G = g] + \gamma X_i + \alpha_c + \alpha_d + \epsilon_i \tag{4.2}$$

Eligibility is a binary variable that takes value of 1 if an applicant is approved to enroll in IHP assistance. The income group is divided by five thresholds: \$15,000, \$30,000, \$60,000,

\$120,000, and \$175,000. I end up with six income groups, and I normalize the third income group to zero. $\mathbb{1}[G = g]$ takes the value of 1 if applicant i falls in income group g. X_i contains applicant-level information that is mentioned before. I also add in county fixed effects and disaster fixed effects to control for unobserved characteristics that may affect eligibility across different counties and disasters.

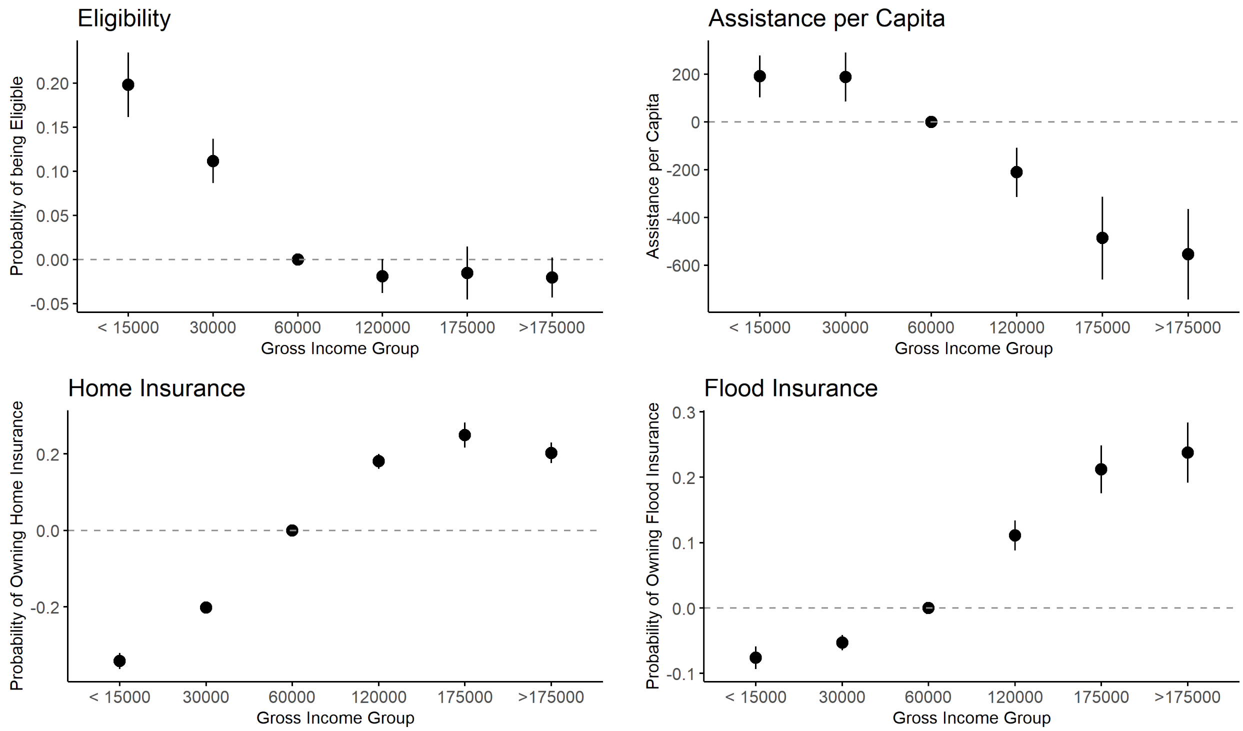
To answer the second question, I use the ratio between assistance received and estimated damage amount as a proxy for the level of assistance. I then regress the ratio on income groups and include the same controls and fixed effects as in equation 4.3.

$$\frac{\text{Assistance}_i}{\text{Damage}_i} = \sum_{g=1, g \neq 3}^{6} \beta_g \mathbb{1}[G = g] + \gamma X_i + \alpha_c + \alpha_d + \epsilon_i \tag{4.3}$$

Figure 4.7 shows a decreasing trend against income group. Controlling for the same household composition and estimated damage level, applicants who earn less than \$15,000 a year are almost 20% more likely to receive federal assistance, comparing to an applicant that earns \$60,000 every year. Moreover, applicants who fall in the first two income group on average receive around \$200 more assistance per capita, comparing to applicants who earn \$60,000 a year and keeping everything the same. It is also interesting to notice that applicants who earn \$175,000 or higher on average receive \$400-\$600 less. Given the fact that average IHP assistance is \$484, the result implies that rich families are not likely to enroll in the individual assistance program.

To answer the third question, I perform another linear probability model and regress the insurance status indicator for homeowner insurance and flood insurance on income groups while controlling for household composition, county fixed effects and disaster fixed effects. It has the exact same set up as in specification 4.7. Figure 4.9 and 4.10 display an exact opposite pattern as in Figure 4.7 and 4.8. The likelihood of having homeowner or flood insurance increases as the applicant moves from lower income group to

Figure 4.11: Bin Regression - IHP



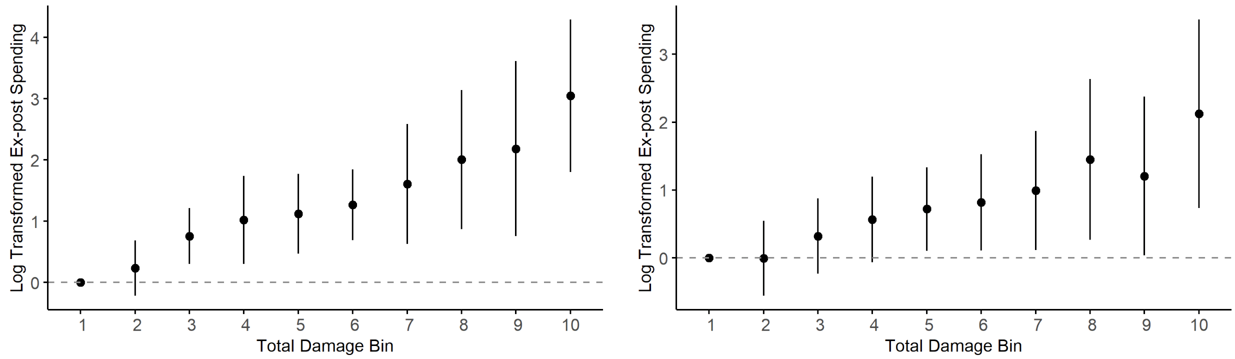
Note: Data are estimated from equations 4.2 and 4.3. Point estimates and 95 percent confidence intervals are shown. The omitted category for each panel is 3. The outcome variable is displayed above and below the corresponding panel. Standard errors are clustered at county level. Controls include county fixed effects, disaster fixed effects, and applicant-level information including household composition, age, FEMA estimated damage cost.

higher income group, until it reaches the kink at $175,000 threshold. Notice that the kink in Figure 4.9 and 4.10 matches the kink in Figure 4.7 and 4.8, suggesting the status of insurance is another crucial factor besides income.

4.2.2 Public Assistance

Another question I ask when evaluating the government response to a disaster is: Does government spend more on ex-post funding in counties that has experienced higher damages from a disaster? I use two separate measures to quantify county-level-damages: households personal damages estimated by FEMA inspectors and direct losses in a

Figure 4.14: SHELDUS



Note: Point estimates from equation 4.4 and 95 percent confidence intervals are shown. The omitted category for each panel is 1. The outcome variable is displayed below the corresponding panel. Standard errors are clustered at state level. Controls include state fixed effects and disaster fixed effects.

county provided by Spatial Hazard Events and Losses Database for the United States (SHELUDS). I aggregate each household's estimated damage cost up to county level to stay consistent. To see a clearer pattern, I again divide either personal damages or SHELDUS estimated damges into deciles and then regress the log transformed federal ex-post spending for county c, disaster d on the damage bins, while controlling for state and disaster fixed effects:

$$\log(\text{ex-post spending}_{cd} + 1) = \sum_{g=1}^{10} \beta_g \mathbb{1}[G = g] + \alpha_s + \alpha_d + \epsilon_{cd} \tag{4.4}$$

The increasing trend shown in Figure 4.12 is almost monotonic in both personal damages and SHELDUS direct losses, indicating higher damaged area always receive higher public assistance during post-disaster period.

4.2.3 Hazard Mitigation and Future Crime

Next I analyze how effective is hazard mitigation projects and whether such ex-ante spending reduces future crime. For simplicity, I only use hurricane Matthew as an example. The ex-ante spending is any projects that are approved after hurricane Sandy-2012 but before Matthew-2016. I restrict mitigation projects to be only planned for facing strong wind speeds or flooding by manually selecting the project types to be: retrofitting, elevation private and public properties, flood control, flood proofing and structure stabilization. The four-year-window allows most approved projects to be completed before hurricane Matthew stoke in 2016.

My hypothesis is that higher damages are more likely to motivate criminal behavior as storm is more likely to demolish their properties. If the pre-landfall invested projects are able to reduce future damages, people may not have an incentives to commit crime during post-disaster period. In other words, crime may not increase as much if mitigation projects work effectively. I prove my hypothesis in three steps by asking three questions: (1) Is crime rate higher in areas that have higher damage? (2) Does government-funded mitigation projects reduce future property loss? (3) Does ex-ante spending reduce crime during post-disaster period? I estimate the relationship among crime, total damages, and federal ex-ante spending using the following models:

$$
\begin{aligned}
\text{Crime per Capita}_{it} = {} & \beta_1 H_{c,0\text{ to }12} + \\
& \beta_2 (H_{c,0\text{ to }12} \times \text{Total Damages}_c) + \\
& + \gamma X_{it} + \alpha_c + \alpha_t + \psi_{c,2015}\alpha_t + \beta_{-13} H_{c,-13} + \beta_{13} H_{c,13} + \epsilon_{it} \qquad (4.5)
\end{aligned}
$$

$$
\begin{aligned}
\text{Total Damage per Capita}_c = {} & \beta_1 \text{Observed Wind Speed}_c + \\
& \beta_2 (\text{Observed Wind Speed}_c \times \mathbb{1}[\mathit{Mitigation}]_c) + \alpha_s + \epsilon_c \qquad (4.6)
\end{aligned}
$$

$$
\begin{aligned}
\text{Crime per Capita}_{it} = {} & \beta_1 H_{c,0\text{ to }12} + \\
& \beta_2 (H_{c,0\text{ to }12} \times \log(\text{ex-ante spending})_c) + \\
& + \gamma X_{it} + \alpha_c + \alpha_t + \psi_{c,2015}\alpha_t + \beta_{-13} H_{c,-13} + \beta_{13} H_{c,13} + \epsilon_{it} \qquad (4.7)
\end{aligned}
$$

where the total damages are estimated by SHELDUS, $\mathbb{1}[\mathit{Mitigation}]_c)$ takes value of 1 if county c has at least one mitigation project completed before hurricane Matthew hit. The variable of interests are the interactive terms in each equation.

Table 4.3 displays the estimates for β_2s. Each column corresponds to each model specification. The coefficient in the first column tells me that crime in treated areas would increase by 1 for every 100,000 residents if the damage increases by 1 million dollars. The treatment here is whether got hit by hurricane Matthew. The coefficients in the second column tell us, controlling for the observed wind speed, counties that have mitigation projects before hurricane Matthew would experience lower damages from Matthew. Moreover, the higher the wind speed is, the more future damages are saved. The third column tells us at treated counties, increasing 1% of ex-ante spending would reduce 3 property crimes every 100,000 residents, which is almost the effect of increasing community policing funding[1][31].

[1]Given the average ex-ante spending in my data sample is $2,041,264, increasing 1% of that means an additional $20,000 reduces property crime by 3. [31] claims that in cities with populations greater than 10,000, an increase in one dollar of hiring grant funding per resident contributed to a corresponding decline of 21.63 property crimes per 100,000 residents. In other words, $20,000 reduces property crimes by 4.326 at most per 100,000 residents.

Table 4.3: Ex-ante Spending, Future Damages and Future Crime

Dependent Variables:	Crime per Capita	Total Damage Per Capita	Crime per Capita
Model:	(1)	(2)	(3)
Variables			
I(Treatment) X Total Damages	0.0138***		
	(0.0025)		
I(0 < Observed Wind Speed < 34 knots) X I(Mitigation)		-11.23**	
		(5.279)	
I(34 < Observed Wind Speed < 50 knots) X I(Mitigation)		-156.2	
		(131.8)	
I(50 < Observed Wind Speed < 64 knots) X I(Mitigation)		-214.6**	
		(104.1)	
I(Treatment) X Ex-Ante Spending			-0.0301*
			(0.0178)
Fixed-effects			
Year-Month	Yes		Yes
County FIPS	Yes		Yes
State		Yes	
Fit statistics			
Observations	58,371	2,396	58,371
R^2	0.55836	0.06332	0.55749
Within R^2	0.15985	0.03365	0.15820

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Data are estimated using equations 4.5, 4.6, and 4.7. The estimates and their standard errors are shown in column accordingly. The first column shows the marginal increase in crime incidents per 1,000 residents when total damages increase by $1 million. The second column shows the effect of having mitigation projects before hurricane landfall on post-hurricane damage. The third column shows the marginal effect on crime when increasing 1% ex-ante spending.

CHAPTER 5

CONCLUSIONS

In this paper, I find that even smaller-scaled hurricanes would have substantial short-run positive effect on local crime. Even though the increasing trend only lasts for two months, such crime increase causes non-negligible social loss. Combine the average cost of each crime [4, 3, 18] with my estimates in Table 4.2, I show that smaller-scaled hurricanes can cause an additional $27,960 in social cost on average per county[1]. While the median county-level property damages throughout the sample period is around $195,000, monetary loss from the increasing crime takes over 10%. In order to maximize the police deterrence effect, more police force should be allocated to areas that has high poverty rate, low median household income, high unemployment rate, and high racial heterogeneity.

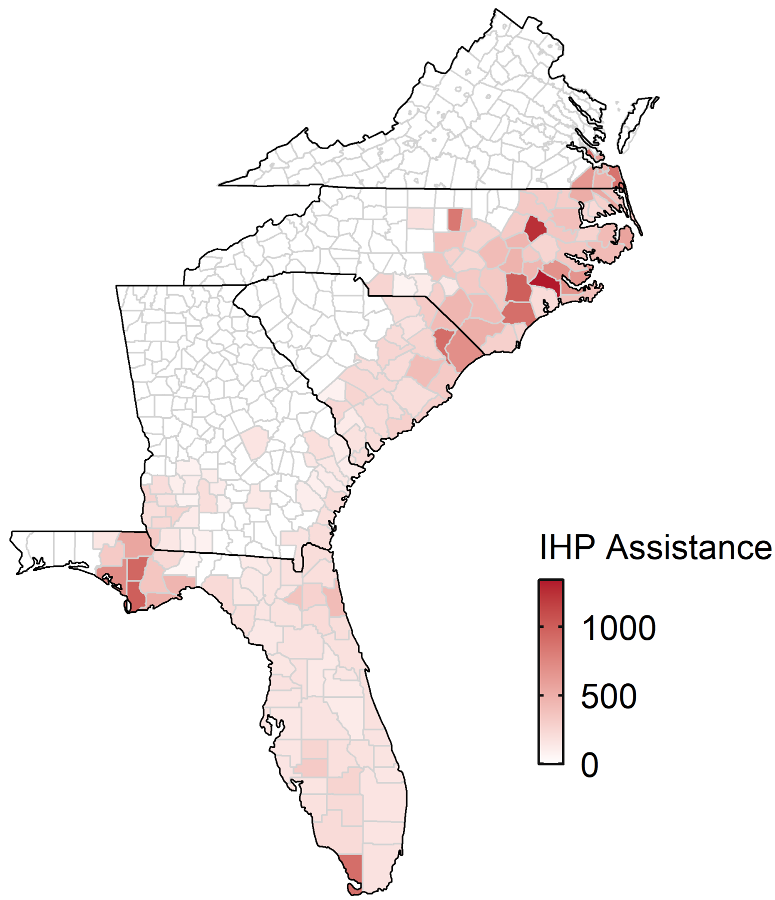
This paper also evaluates current federal disaster relief allocation. It confirms that both current public and individual allocations are reasonable. More severely damaged areas receive more funds during the recovery period. More economically-challenged families are more likely to enroll in the assistance program and receive higher assistance. More importantly, I show the benefit of mitigation projects investments. With the ex-ante spending on hurricane Matthew, not only do I find areas that have mitigation constructions pre-hurricane landfall suffer less damages than areas that do not have any sort of storm preparation projects, but also I discover that ex-ante spending has similar effect on future crime rate comparing to community police funding.

[1]The literature shows that an average cost of larceny, burglary, and robbery is $3,015.41, $18,461.81, and $94,842.33 accordingly.

APPENDIX A

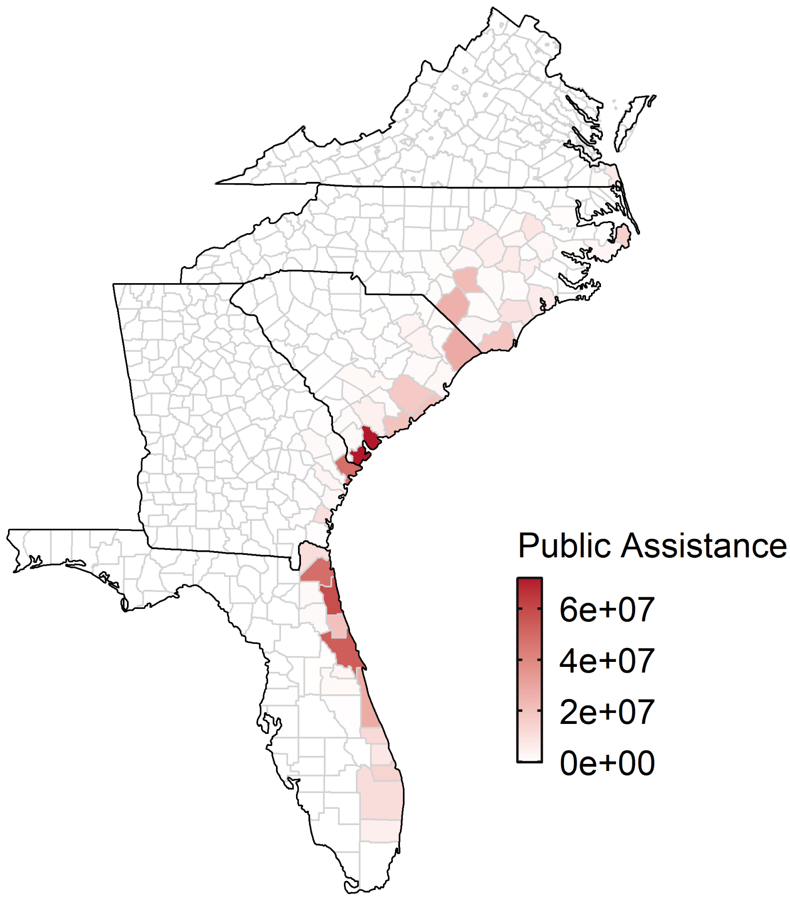
APPENDIX

Figure A1: Average IHP Assistance Received at Household Level



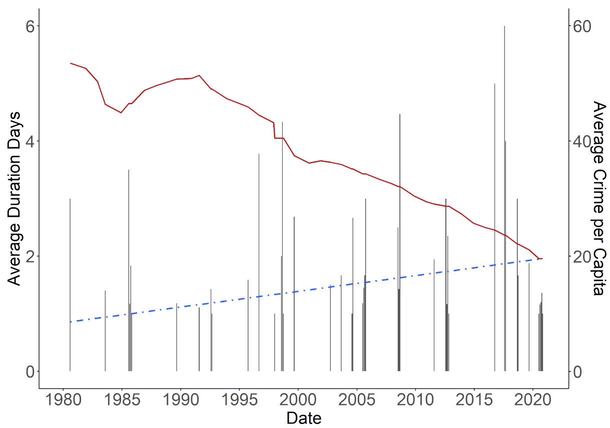
The figure shows the spatial distribution of average IHP Assistance received at household level. The darker the filled color is indicates higher average IHP Assistance.

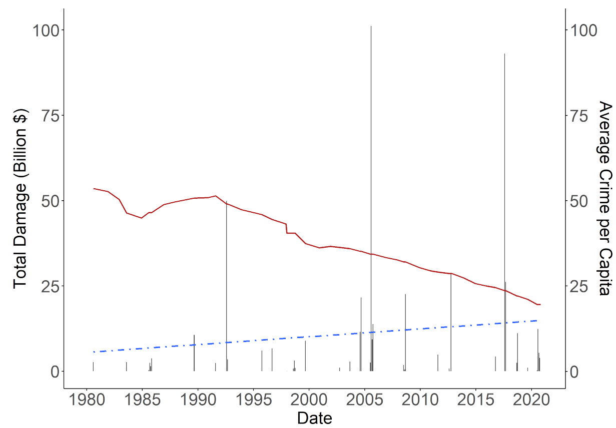
Figure A2: Average Public Assistance at County Level



The figure shows the spatial distribution of average Public Assistance received at county level. The darker the filled color is indicates higher average Public Assistance.

Figure A5: Total Damages in Billion USD





Panel A displays average hurricane duration days and average crime per capita against time from 1980 to 2020. The red solid line indicates the change in crime across time. Black bars indicate occurrence of at least one hurricanes of that year. The height of each bar indicates how many days on average a hurricane last in that year. Blue dashed line is the best linear fit for duration days and time. Panel B displays total damage in billion $ and average crime per capita against time from 1980 to 2020. Black bars indicate the monetary loss due to hurricane in a specific year. Everything else remains the same as Panel A.

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