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Disaster, aid, and crime: a county study in the United States

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Abstract. Based on county-level panel data from 2005-2019, this paper examines the impact of natural disasters (including severe storms, floods, hurricanes, fires, and tornadoes) and subsequent federal assistance on local crime rates. By constructing multiple regression model and controlling for loss per capita, GDP per capita, crime rate in earlier period and fixed effect of year, this paper finds that most disasters do not significantly increase crime rate in the first year, but significantly reduce property crime rate in the second year. Further analysis shows that the overall impact of post-disaster assistance (both personal and public assistance) on crime rates is weak and heterogeneous: some assistance is even slightly positively correlated with crime rates. This study expands the spatiotemporal dimension and disaster types of the relationship between disasters and crime, and provides empirical evidence for post-disaster policy evaluation.

Keywords: natural disaster, post-disaster assistance, crime rate, FEMA, county-level panel data

1. Introduction

Every year, many kinds of disasters occur in the United States, and these disasters affect various aspects of local counties. Gall et al. [1] reported that floods, severe storms and other disasters accounted for about 75% of the total losses. Damage from hurricanes and floods has tripled over the past 50 years. This paper studies the impact of disasters on local crime rates, and further explores the impact of disaster assistance on local crime rates. Specifically, our research object is the counties affected by disasters in the United States from 2005 to 2019. The types of disasters, severity of disasters and follow-up assistance in these counties vary. We collect data on these aspects and analyze the changes in crime rates after disasters in these counties in combination with crime data of counties.

The local impact of a disaster on local residents is multiple. These disasters not only directly cause huge economic losses, reduce residents 'housing inventory, and destroy enterprises' productive capital, but may also have long-term impacts on society. Post-disaster reconstruction and assistance are important measures to deal with these impacts, and the Federal Emergency Management Agency (FEMA) helps disaster areas recover through post-disaster personal assistance (such as housing assistance) and public assistance (such as infrastructure repair). Crime rate, as an important index to measure social stability, may be affected by disasters. On the one hand, the effects of disasters lead to an increase in poverty rates and population outflows [2]; on the other hand, the social structure of the community and the psychological state of the residents are changed under the external shock of disasters, which brings psychological trauma to people. In addition, people may turn to cooperation and mutual assistance more in disasters, and the police force and external attention are increased. Whether post-disaster assistance can effectively improve people's situation and reduce crime has also become a problem worthy of study.

This study focuses on the following two issues. (1) The impact of different types of disasters on crime rates. (2) Whether the personal assistance and public assistance provided by the government through FEMA have a significant mitigation effect on the crime rate after the disaster. In this paper, multiple regression analysis method is used to analyze violence crime, property crime and total crime. The model controls for regional average property losses, GDP per capita, crime rates in the previous period, and year factors. The underlying hypothesis is that we believe that whether a disaster occurs and subsequent amounts of aid affect crime rates in affected counties. We found that most disasters reduce rather than increase local crime rates, and that crime rates drop more dramatically in the second year after a disaster. For the crime rate of disaster year, when the per capita loss is high, the violent crime of flood, fire and tornado decreases by 0.046 percentage point and the property crime decreases by 0.058 percentage point on average. By performing additional regressions on the one-period lag crime rate, we found that the crime rate decreased further over time after one year. Most of the coefficients were significant (severe storm and flood reduced property crime by 0.135 and 0.180 percentage points respectively, $p < 0.01$). Post-disaster aid research shows that aid has different effects on crime rates under different disasters, not reducing crime rates as a whole, and even some coefficients are positive and significant, and the effect of aid is relatively small (for example, an increase of \$100 per person in personal aid during a hurricane, an additional violent crime per 100,000 people, $p < 0.01$). Furthermore, the one-stage lag regression results show that the impact of aid weakens further over time.

This paper has made the following contributions to the related research fields of disaster and crime. First, previous studies of related crime disasters have focused on the impact of a major disaster, with specific states and regions. Our article deals with counties in the United States that suffered disasters between 2005 and 2019, including severe storms, floods, hurricanes, fires and tornadoes. Disaster types are more complete. Second, we provide empirical evidence that disasters reduce crime rates over time. Moreover, our study fills a gap in the existing literature where there is little discussion of the impact of post-disaster assistance on crime rates. A detailed comparison of the interaction between disaster and aid types (public/private) is made to examine whether post-disaster aid affects violence and property crime through different channels. In terms of research methods, we control the fixed year effect, and better deal with the impact of disasters occurring at different time points in a year, and then use the crime rate of the current year or the crime rate of the next year as the outcome variable, reducing the confusion in measurement time series.

Section 2 introduces the background and related literature. Section 3 describes the data sources for county-level observations. Section 4 describes how the data are processed and the design of the measurement model. Section 5 presents the results of our empirical analysis of disaster and post-disaster assistance for different types of crime rates and provides a brief analysis of the mechanisms. Robustness is discussed in Section 6. Section 7 is the conclusion.

2. Background and literature review

2.1. Changes in economic indicators and psychological factors after disasters

The occurrence of a disaster will have a profound impact on various aspects of the local county economy. Severe natural disasters (measured by the number of deaths, e.g., more than 25) lead to a significant increase in county-level net emigration rates by 1.5 percentage points, a decrease in median housing prices and rents by

2.5 to 5.0 percent, and an increase in local poverty rates within a decade after the disaster [2]. In this paper, the authors construct a 90-year (1920-2010) county-level federal panel data on natural disasters in the United States, and identify the impact of disaster events on various economic indicators using panel data models that include county-level fixed effects and state-specific time trends.

In addition, Gallagher et al. [3] examined the impact of FEMA's personal assistance programs on post-disaster household economic behavior. The study compared differences between families in tornado-affected areas who received and did not receive personal assistance funds. The empirical results show that cash subsidies significantly reduce the credit card debt level of affected families. Aid funds were used primarily as a substitute for high-cost borrowing, thereby effectively improving the balance sheet structure of households when they faced financial crisis. Economic indicators of a region (unemployment rate, household finances) tend to correlate closely with crime rates [4]. These studies suggest possible pathways for disasters to contribute to crime rates, giving hints to our research.

In terms of psychological pathways, research has confirmed that the socioeconomic impact of disasters (loss of loved ones, injuries, property losses) can significantly increase an individual's risk of extreme behavior [5]. In another study of earthquakes, the authors described in more detail the trend in suicide rates over time after earthquakes. The population was divided into "high exposure group" (hard-hit areas) and "low exposure group" (non-hard-hit areas in the same county). The results showed that suicide rates in the high-exposure group soared immediately after the earthquake and gradually fell back to baseline levels within 10 months [6]. This shows that at the psychological level, the occurrence of disasters affects people's mental health and increases people's tendency to violence. If the post-disaster assistance fails to effectively alleviate the psychological impact of disasters on people, it may lead to an increase in crime rates.

2.2. Debate on the impact of disasters on crime rates

There are two kinds of theories about the influence of disasters on crime, one is positive and the other is negative. The representative theory that disasters reduce crime rates is the therapeutic community theory [7], which holds that disasters promote cooperation among community members, increase trust among them, and a set of mechanisms for crime prevention is established at the community level, resulting in lower crime rates. On the other hand, the theory of social disintegration [8] can be used for analysis. In this theory, Shaw and McKay propose an explanatory framework of "social disintegration" based on juvenile delinquency data from different districts of Chicago. Communities are characterized by poverty, race, and population mobility, which weaken the community's ability to control society and induce individual delinquency. After the disaster, the characteristics of these communities change, the community structure is destroyed, and the crime rate increases.

These two different views are also supported at the empirical level. Lee Y [9]. studied crime, victimization and traumatic stress before and after the 1994 Northridge earthquake and found that crime rates remained relatively stable. Lemieux [10] found a slight decrease in the incidence of property crime during the Quebec ice storm of 1998. Sammy Zahran et al. [11] A study of Florida county data from 1991-2005 found that a natural disaster reduced the expected number of crimes in the authors' constructed index by 0.0037%, and disaster frequency reduced the expected number of violent crimes by 0.0051% and property crimes by 0.0037%, respectively.

On the other hand, there is evidence that crime rates increase rather than decrease after disasters. Auto thefts following Hurricane Carla in Galveston, Texas increase by 30 percent [12]. Mike Jiafang Huang [13] studied smaller hurricanes that landfall during the 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 the east side of the US.

Burglaries rose 9.9 percent and robberies rose 19.6 percent. However, eight months after the hurricane, crime rates were lower than pre-disaster levels, consistent with our findings.

Existing documents focus more on the impact of a disaster on crime rates and the geographical scope of the study is relatively small. This paper expands the time scale, geographical scope and disaster types of the study, and tries to consider the changes of crime rate after disasters more comprehensively.

2.3. The role of post-disaster assistance

Mike Jiafang Huang [13] pointed out that higher damaged areas always receive higher public assistance during the post-disaster period. Moreover, for FEMA disaster reduction investment in the studied counties, an increase of 1% in advance expenditure will reduce 3 property crimes per 100,000 residents. There is relatively little literature available to consider the impact of post-disaster assistance on crime rates, but there are some discussions on the relationship between cash intervention and violence in non-disaster situations that can provide reference for our research. Daiane Borges Machado et al. [14] examined interventions in violence in a number of cash assistance programmes, and in Brazil, increased coverage in Bolsa Familia was associated with a 0.3 per cent reduction in homicide rates. In Argentina, the Unemployed Heads of Household Programmes reduced property crime by 2.7 per cent. Cash interventions (especially cash+ models combined with other support) have the potential to prevent multiple forms of violence. Disasters often destroy the economy and order of a region, and the aid effect after disasters is a topic with research value.

3. Data

3.1. Disaster data from the Federal Emergency Management Agency (FEMA) website

FEMA provides information about disasters and project assistance, including the disaster code for each disaster, the date of the disaster, the name of the affected county, and the personal and public assistance provided.

(1) Individual assistance covers housing assistance and assistance for other needs, for which FEMA approves the total amount of aid funding provided through the Individual and Family Program. Housing assistance is used to help victims with housing problems (e.g. temporary shelter, house repair/reconstruction) and other needs assistance (to meet disaster-related essential expenses and serious needs (e.g. medical, dental, funeral, personal property, transportation, relocation storage, etc.). For individual assistance, the government identifies the affected area first, and victims in declared disaster areas can apply to the IHP for disaster assistance within 60 days of the declaration. People need to provide information including names, insurance coverage, addresses of affected homes, descriptions of damage, bank accounts, etc. FEMA assesses the type of loss, confirms insurance, and then fills in the gaps. Funds are distributed in two forms: direct transfer and postal cheque. FEMA also provides the number of people assisted in each disaster.

(2) Public assistance includes Category B emergency measures funds and Category C-G permanent restoration funds. Category B measures include emergency work to protect life, public health and safety, and to improve disaster-affected property (e.g., debris removal, protective equipment, emergency traffic control, provision of temporary public facilities, etc.). These categories involve the repair or reconstruction of damaged public facilities to their pre-disaster functional state.

3.2. Data on crime rates comes from the FBI's UCR (Federal Bureau of Investigation Uniform Crime Reporting) system

Criminal incidents are classified as violent crimes and property crimes. Violent crime consists of four crimes: murder and manslaughter, rape, robbery and aggravated assault. Property crimes include burglary, theft, motor vehicle theft and arson. The FBI does not collect data on its own initiative, but relies on voluntary reporting by law enforcement agencies across the country, with participating agencies submitting data through state UCR nodes or directly to the FBI. According to the FBI's official UCR methodology, if a law enforcement agency does not complete a full year's data report, but provides partial monthly data (3 to 11 months), the FBI will use standard estimation methods to calculate missing data; if the report is less than three months, it will refer to similar areas for estimation. Crimes are not reported because victims are unwilling to report them or because agencies do not report them. Vera Institute points out that there is a discrepancy between the FBI data and the National Crime Victimization Survey (NCVS), which found a certain proportion of unreported through sampling surveys. In 2018, only about 80% of organizations reported to the FBI in full. From 2021, the transition to the National Incident-Based Reporting System (NIBRS) replaces the previous Summary Reporting System (SRS), requiring law enforcement agencies to report each crime incident in detail, including victims, types of crimes, etc. As many as 40% of police departments did not submit any data in 2021 due to institutional system transitions or technical issues. So this study used data from before 2019, while still assuming that FBI data can reflect the true crime rate to some extent. Some counties have some data gaps for some years, and this study discard these data. A case study of the Brisbane floods in Australia found that community members witnessing neighborhood cooperation and police-community interaction after floods helped strengthen social cohesion and increase willingness to report crimes [15]. This study assumes that there is no positive correlation between data gaps and disaster occurrence.

3.3. GDP data from U.S. Bureau of Economic Analysis (BEA)

This study collected nominal gdp data for us counties from 2005 to 2019 and calculated real gdp for us counties from 2005 to 2019 using the us gdp deflator and the base year 2005. Population data for each year in each county were also collected.

3.4. Disaster losses and county-level population data from NOAA and NCEI

Some of the tables in this section do not provide the state of the affected county, and we had to delete all duplicate counties during the data integration process, which cost us nearly 40% of the data. But we don't think the disaster happened because one county had the same name as other counties.

4. Research design

This study used county-level data to answer this question: How do different disaster types and subsequent federal personal and public assistance affect violence, property, and overall crime rates? This study specified a multiple linear regression model (see equation (1)) that included the interaction between disaster type and aid type and controlled for annual fixed effects. Our identification strategy relies on differences in the occurrence of different disasters and the amount of aid received by different counties in the same disaster.

$$\begin{aligned} crime\_rate = \alpha + \textstyle\sum_k \gamma_k DisasterType(k) + \textstyle\sum_k \varphi_k(DisasterType(k) \times pubAid(k)) \\ + \textstyle\sum_k \lambda_k(DisasterType(k) \times pesAid(k)) + \beta_1 aver\_damage \\ + \beta_2 lndgp + \beta_3 crime\_rate\_lag + \gamma_t + \varepsilon \end{aligned} \tag{1}$$

$$crime\_rate\_after = \alpha + \sum_k \gamma_k DisasterType(k) \\ + \sum_k \varphi_k (DisasterType(k) \times pubAid(k)) \\ + \sum_k \lambda_k (DisasterType(k) \times pesAid(k)) + \beta_1 aver\_damage \\ + \beta_2 lndgp + \beta_3 crime\_rate\_lag + \gamma_t + \varepsilon \tag{2}$$

The dependent variable crime rate lag includes the county's annual violent crime rate, annual property crime rate, and annual total crime rate (violent crime rate, property crime rate, total crime rate), determined by dividing the county's annual crime count by the county's total population for that year. For example, the violent crime rate of the county Accomack in 2007 was 0.198%, and there were 198 violent crimes among 100,000 people in the county that year. Since the same person may be responsible for multiple violent crimes, it does not mean that 198 out of 100,000 people committed violent crimes. In addition, we also regress crime rate after (including violent crime rate after, property crime rate after, total crime rate after) of the next year's data of crime rate to explore the effect of disasters and assistance in the long term (see equation (2)).

The explanatory variable DisasterType(k) is a dummy variable set containing the five hazards (Severe Storm, Flood, Hurricane, Fire, and Tornado) in the FEMA disaster declaration. Other hazards such as Tropical Storm and tsunami are less common in FEMA records (fewer than 20 samples). We did not analyze these disasters and removed these county-level samples.

For each disaster, FEMA provides the corresponding amount of aid, number of people assisted and name of assisted county. pesAid(k) is the average amount of personal assistance for a disaster, resulting from dividing the total amount of personal assistance for the disaster by the number of people assisted. pubAid(k) is the county average amount of aid to public facilities after a disaster(k). This study count the number of assisted counties and divide the total amount of public aid by the number of assisted counties.

The interaction terms DisasterType(k) × pubAid(k) and DisasterType(k) × pesAid(k), such as the interaction term Hurricane pubAid interaction for personal assistance after a hurricane, are used as explanatory variables for regression. We were thus able to capture the heterogeneity of disaster effects. The norm ensures that the estimated impact of assistance is not averaged across different disaster settings, thereby providing more accurate evidence of what assistance mitigates crime in what disasters.

Among the control variables, aver damage is the county's annual property loss per capita. This study collected the total losses of all disasters in this county for that year. Divide the total loss by the number of people in the county for that year to get aver damage. lngdp is the logarithm of the actual gdp per capita of the county in that year.

γ_t is a year dummy variable. The trend of crime rate in each county with year was controlled.

This study also include crime rate lag (violent_crime_rate_lag, property crime rate lag, total crime rate lag) from the period before the disaster.

To better measure the impact of disasters and aid on crime rates, this study aggregated the data in a form similar to the "school year" (July 1 of year n - 1 to June 30 of year n). Disaster events within each "school year" affect crime rates for the year in which the school year ends (i.e., year n). When combining crime rate data, we determine the "school year" of a disaster based on the month in which it occurs. Therefore, we retain each county-level disaster event as an observation. Each disaster event needs to be associated with its annual crime rate (i.e. dependent variable), gdp per capita, property damage per capita, and crime rate for the previous year, all of which are for normal years; disaster dummy variables, aid variables, etc., are for "school years".

Some counties may experience multiple disasters in a given "school year". For different disasters, our model estimates the impact of disasters and aid on crime rates separately. For the same type of disaster, we aggregate the aid as if the disaster occurred only once in the school year.

5. Empirical results and mechanisms

5.1. Current effects of disasters on crime rates

Table 1 is the regression result of equation (1), which shows the effect of disaster type, personal assistance and public assistance on crime rates (violent crime, property crime and total crime) under different disasters. We observed that floods, fires and tornadoes had negative coefficients for all nine of the three crime indicators. In the year following floods, fires, and tornadoes, violent crime decreased by 12, 16, and 24 per 100,000 people, respectively, and property crime decreased by 26, 55, and 58 per 100,000 people, respectively. These results were not statistically significant. However, the hurricane did not reduce the crime rate. On the contrary, it increased the property crime rate by 0.057%.

The explanation for this variation in crime rates across disasters is that hurricanes destroy communities more systematically than other disasters. The most direct evidence for this view comes from calculating property losses per capita for each disaster, when we exclude the smallest disasters (losses less than $1 per capita). We found that hurricanes cause twice as much damage to property on average ($115) as floods ($66), three times as much as fires ($49), and ten times as much as tornadoes ($11).

For localized disasters (floods, fires, tornadoes), the effects are more consistent with the therapeutic community theory [7]. Disasters, as an external threat, activate altruism and cooperative norms within communities, strengthen links between people in communities in the short term, and thus inhibit crime. However, hurricanes and similar severe storms are regional catastrophes. Using the theory of social disintegration [8], the scale of the disaster was large enough to destroy community structures and economic bases and cause population outmigration [2]. Significant changes in community characteristics (poverty, population mobility) create a large number of crime opportunities, resulting in a net increase in crime.

Disaster samples with average loss less than 1 dollar (aver damage < 1) accounted for 28.56% of the total samples. We eliminated these samples and regressed the remaining 903 data points (i.e., severe disasters) again. As shown in Table 2, some coefficients began to show statistical significance. Compared with before elimination, we found that the negative coefficient of disaster increased obviously. This suggests that severe disasters may amplify the impact of disasters and post-disaster assistance on crime rates.

5.2. Long-term effects of disasters on crime rates in the second year after disasters

Table 3 shows the regression results of equation (2). Due to the selection of a lag in the data tornado data is too small. It has less than 30 pieces of data. We ruled out tornadoes. Only the dependent variables were replaced and regression was performed on the remaining 1,009 data. We find that the absolute value of the hazard coefficient increases. In other words, the crime rate decreased significantly after one year, and it was statistically significant. Looking at the data, the main decrease is reflected in property crime. In the year following a severe storm, property crime fell by 135 per 100,000 people ($p < 0.01$). In the year after the flood, property crime fell by 180 per 100,000 people ($p < 0.01$). In the year after the fire, property crimes per 100,000 people decreased by 147 ($p < 0.01$). These are much larger than the previous year's results.

This is consistent with the results in Mike Jiafang Huang's [13] paper. The occurrence of disasters in a short period of time makes the property crime rate rise 6.7%, of which theft rises 7.2%, burglary rises 9.9%, robbery rises 19.6%. However, crime rates eight months later were lower than pre-disaster levels. Our data show more evidence of a long-term decline in crime. Disaster assistance has to some extent improved the economic situation of those affected. This economic distress may be related to the disaster or pre-existing (Gallagher, Hartley, and Rohlin [3] note that similar subsidies eased their debt distress). In the long run, people affected by disasters are no longer burdened by bad economic conditions. This finding also somewhat refutes the hypothesis that disasters reduce reporting of crime by agencies, as law enforcement agencies are more likely to be rehabilitated in the second year after a disaster, thereby increasing the likelihood of crime reporting.

5.3. Effects of personal and public assistance on crime rates after disasters

The coefficients of post-disaster assistance in Table 1 are generally very small, and the signs of the coefficients lack obvious positive and negative. The personal assistance factor for hurricanes was 0.00001 ($p < 0.01$), meaning that an additional \$100 in assistance per person would result in an additional violent crime per 100,000 people in the county that year (1.08 before rounding). Similarly, an additional \$100 per person in aid in the year of a severe storm adds 1 property crime per 100,000 people (1.16 before rounding). In public assistance, hurricanes reduce violent crime by a factor of 6.444×10^{-10}, although statistically significant. In Table 3, the impact of aid decreases further over time, with most coefficients approximating zero.

Hurricanes account for only 19.5% (244) of the 1,264 samples, but the aid relationship between hurricanes and violent crime is more significant than other disasters, reflecting some features of the post-hurricane aid effect on crime rates, and it is worth examining further the more specific allocation of aid in hurricanes. But for all disasters as a whole, we think it doesn't make a lot of sense to argue about whether aid has a positive or negative impact on crime as a whole in the face of these small coefficients. Nevertheless, post-disaster assistance cannot simply be assumed to have no effect on crime rates, and a coefficient close to zero is more likely to be the result of multiple mechanisms.

6. Discussion on robustness

In this study, the calculation method of public assistance is to divide FEMA's public assistance to disasters by the total number of assisted counties. A more reasonable method should be to use the population or area of each county as the index of county size, and distribute the amount of public assistance to each county by weight. Such results tend to emphasize metropolitan areas. Unfortunately, population-weighted averaging of public assistance is difficult because we cannot distinguish between districts with duplicate names. If complete information on the states in which the counties with duplicate names are located is available, consider calculating public assistance in a more rational way and adding state fixed effects to the model. In addition, the 1263 samples contain data on disasters in more than 600 counties across the United States, with each county experiencing an average of two disasters (Severe Storm, Flood, Hurricane, Fire, and Tornado) during the 14-year period. Finally, we need data over a longer time span to account for county heterogeneity.

We performed heteroscedastic robust standard error regression analysis on all models, taking into account how the error term might vary under different disaster and aid conditions (see Tables 4, 5, and 6 in the Appendix). There was no significant difference between the results of regression and those of general regression, and some coefficients decreased or increased significantly. In addition, separately, we regress counties where a particular disaster occurred (e.g. for all sample points where Severe Storm $i = 1$). We chose severe storm and hurricane (because they have the largest sample sizes of the five). Take severe storm as an example, multiple linear regression model:

$$
\begin{gathered}
rime\_rate = \alpha + \varphi(Severe\_Storm \times pubAid) + \lambda(Severe\_Storm \times pesAid) \\
+\beta_1 averdamage + \beta_2 lngdp + \beta_3 precrime + \varepsilon
\end{gathered} \tag{3}
$$

Tables 7 and 8 show the regression results using robust standard errors. It can be seen that the effect of post-disaster assistance is still relatively small for the counties affected by the same kind of disaster, and there is no big difference between the results of our initial model, and the positive and negative coefficients of different types to different crimes are irregular.

7. Conclusion

This paper examines the effects of Severe Storm, Flood, Hurricane, Fire and Tornado disasters and post-disaster assistance on crime rates. We controlled disaster levels, gdp per capita and crime in previous years. One year after the disaster, some crime rates decreased to some extent after the disaster. In the second year after the disaster, the local crime rate decreased significantly. Post-disaster aid had a very small effect on crime rates. This paper provides new empirical results for the literature in the field of disaster and crime.

Follow-up studies could collect non-affected counties as a control group. These unaffected counties should have similar economic geography to the affected counties, allowing better exploration of the effect of disasters on crime rates. Additional studies could also be carried out on specific hazards to document changes in monthly crime rates and capture trends in crime rates more accurately. In terms of post-disaster assistance, the impact of assistance amounts can be studied on a person-by-person basis rather than on a county-by-county basis, providing empirical support for possible theoretical analysis.

Natural disasters are an enduring challenge to human society. Governments can build stronger recovery mechanisms for post-disaster law enforcement systems. A small finding that some aid may increase crime may suggest problems in the distribution of aid funds. The government needs to further reflect on and improve the post-disaster resource allocation mechanism.

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Appendix

Table 1. Regression results of equation (1)

Violent Crime Rate	Property Crime Rate	Total Crime Rate
Disaster Type Dummies		
Severe Storm -0.005 (0.019)	0.007 (0.085)	0.014 (0.091)
Flood -0.012 (0.020)	-0.026 (0.088)	-0.024 (0.094)
Hurricane 0.000 (0.019)	0.057 (0.085)	0.056 (0.090)
Fire -0.016 (0.024)	-0.055 (0.104)	-0.056 (0.111)
Tornado -0.024 (0.031)	-0.058 (0.136)	-0.067 (0.145)
Interaction Terms		
Severe Storm×pubAid -0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Severe Storm×pesAid -0.00000 (0.00000)	0.00001 (0.00000)	0.00001 (0.00000)
Flood × pubAid 0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Flood × pesAid -0.00000* (0.00000)	-0.00000 (0.00001)	-0.00000 (0.00001)
Hurricane × pubAid -0.00000** (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pesAid 0.00001** (0.00000)	-0.00000 (0.00001)	0.00001 (0.00001)
Fire × pubAid 0.00000 (0.00000)	-0.00000** (0.00000)	-0.00000* (0.00000)
Fire × pesAid 0.00000 (0.00000)	0.00001 (0.00001)	0.00001 (0.00001)
Tornado × pubAid -0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)

Table 1. Continued

Tornado × pesAid	-0.00000 (0.00001)	0.00001 (0.00003)	0.00001 (0.00004)
Control Variables			
aver damage	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
lngdp	-0.007* (0.004)	-0.031* (0.017)	-0.034* (0.018)
violent crime rate lag	0.819*** (0.016)		
property crime rate lag		0.849*** (0.013)	
total crime rate lag			0.867*** (0.012)
Year Fixed Effects	Yes	Yes	Yes
Observations	1,263	1,263	1,263
R-squared	0.741	0.823	0.842

Note: This table presents the regression results with standard errors in parentheses. */**/*** indicate significance at the 10%/5%/1% levels, respectively.

Table 2. Regression results of equation (1)(aver damage ≥ 1)

	Violent Crime Rate	Property Crime Rate	Total Crime Rate
Disaster Type Dummies			
Severe Storm	-0.015 (0.022)	-0.006 (0.103)	-0.010 (0.109)
Flood	-0.026 (0.023)	-0.054 (0.107)	-0.067 (0.113)
Hurricane	-0.019 (0.022)	0.078 (0.103)	0.058 (0.109)
Fire	-0.067** (0.033)	-0.078 (0.155)	-0.123 (0.163)
Tornado	-0.044 (0.034)	-0.041 (0.159)	-0.071 (0.168)
Interaction Terms			
Severe Storm × pubAid	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Severe Storm × pesAid	-0.00000 (0.00000)	0.00001** (0.00001)	0.00001* (0.00001)
Flood × pubAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Flood × pesAid	-0.00000* (0.00000)	0.00000 (0.00001)	-0.00000 (0.00001)
Hurricane × pubAid	-0.00000** (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pesAid	0.00001*** (0.00000)	-0.00001 (0.00002)	0.00001 (0.00002)
Fire × pubAid	0.00000* (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Fire × pesAid	0.00000 (0.00000)	0.00001 (0.00001)	0.00001 (0.00001)

Table 2. Continued

Tornado × pubAid -0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Tornado × pesAid 0.00000 (0.00001)	0.00008 (0.00007)	0.00009 (0.00007)
Control Variables		
aver damage 0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
lngdp -0.006 (0.005)	-0.033 (0.022)	-0.033 (0.023)
violent crime rate lag 0.770*** (0.020)		
property crime rate lag	0.829*** (0.017)	
total crime rate lag		0.849*** (0.016)
Year Fixed Effects Yes	Yes	Yes
Observations 903	903	903
R-squared 0.694	0.793	0.817

Note: This table presents the regression results with standard errors in parentheses. */**/*** indicate significance at the 10%/5%/1% levels, respectively. The model contains data for only aver damage ≥ 1

Table 3. Regression results of equation (2)

	Violent Crime Rate After	Property Crime Rate After	Total Crime Rate After
Disaster Type Dummies			
Severe Storm	-0.011 (0.009)	-0.135*** (0.042)	-0.145*** (0.045)
Flood	-0.022* (0.012)	-0.180*** (0.055)	-0.195*** (0.059)
Hurricane	0.015 (0.013)	-0.084 (0.061)	-0.086 (0.066)
Fire	-0.021 (0.019)	-0.147* (0.088)	-0.156* (0.095)
Interaction Terms			
Severe Storm × pubAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Severe Storm × pesAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Flood × pubAid	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Flood × pesAid	-0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pubAid	-0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Hurricane × pesAid	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Fire × pubAid	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Fire × pesAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Control Variables			
aver damage	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)

Table 3. Continued

lngdp	-0.008 (0.005)	-0.060*** (0.023)	-0.063** (0.025)
violent crime rate lag	0.790*** (0.020)		
property crime rate lag		0.770*** (0.017)	
total crime rate lag			0.802*** (0.017)
Year Fixed Effects	Yes	Yes	Yes
Observations	1,006	1,006	1,006
R-squared	0.682	0.732	0.758

Note: This table presents the regression results with standard errors in parentheses. */**/*** indicate significance at the 10%/5%/1% levels, respectively.

Table 4. Regression results for equation (1)(heteroscedastic robust)

	Violent Crime Rate	Property Crime Rate	Total Crime Rate
Disaster Type Dummies			
Severe Storm	-0.005 (0.014)	0.007 (0.052)	0.014 (0.054)
Flood	-0.012 (0.015)	-0.026 (0.053)	-0.024 (0.055)
Hurricane	0.000 (0.014)	0.057 (0.048)	0.056 (0.050)
Fire	-0.016 (0.017)	-0.055 (0.062)	-0.056 (0.066)
Tornado	-0.024 (0.018)	-0.058 (0.120)	-0.067 (0.124)
Interaction Terms			
Severe Storm × pubAid	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Severe Storm × pesAid	-0.00000 (0.00000)	0.00001 (0.00001)	0.00001 (0.00001)
Flood × pubAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Flood × pesAid	-0.00000* (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pubAid	-0.00000** (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pesAid	0.00001** (0.00000)	-0.00000 (0.00001)	0.00001 (0.00001)
Fire × pubAid	0.00000 (0.00000)	-0.00000** (0.00000)	-0.00000* (0.00000)
Fire × pesAid	0.00000 (0.00000)	0.00001 (0.00000)	0.00001 (0.00000)
Tornado × pubAid	-0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Tornado × pesAid	-0.00000 (0.00000)	0.00001 (0.00003)	0.00001 (0.00003)
Control Variables			
aver damage	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
lngdp	-0.007* (0.004)	-0.031* (0.017)	-0.034* (0.019)
violent crime rate lag	0.819*** (0.051)		
property crime rate lag		0.849*** (0.027)	
total crime rate lag			0.867*** (0.025)

Table 4. Continued

Year Fixed Effects Yes	Yes	Yes
Observations 1,263	1,263	1,263
R-squared 0.741	0.823	0.842

Note: This table presents the regression results with heteroskedasticity-robust standard errors in parentheses. */**/*** indicate significance at the 10%/5%/1% levels, respectively.

Table 5. Regression results for equation (1) (heteroscedastic robust)(aver damage ≥ 1)

Violent Crime Rate	Property Crime Rate	Total Crime Rate
Disaster Type Dummies		
Severe Storm -0.015 (0.016)	-0.006 (0.054)	-0.010 (0.057)
Flood -0.026 (0.017)	-0.054 (0.056)	-0.067 (0.060)
Hurricane -0.019 (0.016)	0.078 (0.050)	0.058 (0.054)
Fire -0.067** (0.026)	-0.078 (0.085)	-0.123 (0.093)
Tornado -0.044** (0.021)	-0.041 (0.131)	-0.071 (0.135)
Interaction Terms		
Severe Storm × pubAid -0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Severe Storm × pesAid -0.00000 (0.00000)	0.00001 (0.00001)	0.00001 (0.00001)
Flood × pubAid 0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Flood × pesAid -0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00001)
Hurricane × pubAid -0.00000** (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pesAid 0.00001** (0.00000)	-0.00001 (0.00002)	0.00001 (0.00002)
Fire × pubAid 0.00000** (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Fire × pesAid 0.00000 (0.00000)	0.00001 (0.00000)	0.00001 (0.00001)
Tornado × pubAid -0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Tornado × pesAid 0.00000 (0.00001)	0.00008 (0.00005)	0.00009 (0.00005)
Control Variables		
aver damage 0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
lngdp -0.006 (0.005)	-0.033 (0.021)	-0.033 (0.022)
violent crime rate lag 0.770*** (0.072)		
property crime rate lag	0.829*** (0.037)	
total crime rate lag		0.849*** (0.034)

Table 5. Continued

Year Fixed Effects Yes	Yes	Yes
Observations 903	903	903
R-squared 0.694	0.793	0.817

Note: This table presents the regression results with heteroskedasticity-robust standard errors in parentheses. */**/*** indicate significance at the 10%/5%/1% levels, respectively. The model contains data for only aver damage ≥ 1

Table 6. Regression results for equation (2)(heteroscedastic robust)

	Violent Crime Rate After	Property Crime Rate After	Total Crime Rate After
Disaster Type Dummies			
Severe Storm	-0.011 (0.008)	-0.135*** (0.044)	-0.145*** (0.047)
Flood	-0.022** (0.010)	-0.180*** (0.056)	-0.195*** (0.059)
Hurricane	0.015 (0.014)	-0.084 (0.064)	-0.086 (0.068)
Fire	-0.021 (0.013)	-0.147* (0.083)	-0.156* (0.089)
Interaction Terms			
Severe Storm × pubAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Severe Storm × pesAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Flood × pubAid	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Flood × pesAid	-0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)
Hurricane × pubAid	-0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Hurricane × pesAid	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Fire × pubAid	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Fire × pesAid	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Control Variables			
aver damage	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
lngdp	-0.008 (0.005)	-0.060*** (0.022)	-0.063** (0.024)
violent crime rate lag	0.790*** (0.062)		
property crime rate lag		0.770*** (0.025)	
total crime rate lag			0.802*** (0.024)
Year Fixed Effects	Yes	Yes	Yes
Observations	1,006	1,006	1,006
R-squared	0.682	0.732	0.758

Note: This table presents the regression results with heteroskedasticity-robust standard errors in parentheses. */**/*** indicate significance at the 10%/5%/1% levels, respectively.

Table 7. Regression results for severe storm (heteroskedasticity-robust standard errors)

	Violent Crime Rate	Property Crime Rate	Total Crime Rate
Disaster Aid Interactions			
Severe Storm × Public Aid	-0.00000 (0.00000) (0.00000)	-0.00000 (0.00000) (0.00000)	-0.00000 (0.00000) (0.00000)
Severe Storm × Personal Aid	-0.00000 (0.00000) (0.00009)	0.00001 (0.00001) (0.00818)	0.00001 (0.00001) (0.00843)
Control Variables			
Average Damage	0.000 (0.000) (0.000)	0.000 (0.000) (0.000)	0.000 (0.000) (0.000)
Log GDP per capita	-0.010** (0.005) (0.005)	-0.072** (0.031) (0.031)	-0.076** (0.033) (0.033)
Violent Crime Rate (lag)	0.780*** (0.078) (0.078)		
Property Crime Rate (lag)		0.817*** (0.041) (0.041)	
Total Crime Rate (lag)			0.837*** (0.039) (0.039)
Observations	718	718	718
R-squared	0.690	0.748	0.779

Note: This table presents regression results for Severe Storm disasters with heteroskedasticity-robust stan- dard errors in parentheses. Ordinary standard errors are on the right and robust standard errors are below. */**/*** indicate significance at the 10%/5%/1% levels, respectively. (Only data satisfying severe storm = 1 are used for regression)

Table 8. Regression results for hurricane (heteroskedasticity-robust standard errors)

	Violent Crime Rate	Property Crime Rate	Total Crime Rate
Disaster Aid Interactions			
Hurricane × Public Aid	-0.00000** (0.00000) (0.00000)	0.00000 (0.00000) (0.00000)	0.00000 (0.00000) (0.00000)
Hurricane × Personal Aid	0.00001*** (0.00000) (0.00000)	0.00001 (0.00001) (0.00001)	0.00002 (0.00001) (0.00001)
Control Variables			
Average Damage	-0.000 (0.000) (0.000)	-0.000*** (0.000) (0.000)	-0.000*** (0.000) (0.000)
Log GDP per capita	-0.012 (0.010) (0.010)	-0.166*** (0.054) (0.054)	-0.177*** (0.059) (0.059)
Violent Crime Rate (lag)	0.975*** (0.042) (0.042)		
Property Crime Rate (lag)		0.866*** (0.034) (0.034)	
Total Crime Rate (lag)			0.892*** (0.037) (0.037)
Observations	245	245	245
R-squared	0.816	0.776	0.800

Note: This table presents regression results for Hurricane disasters with heteroskedasticity-robust standard errors in parentheses. Ordinary standard errors are on the right and robust standard errors are below. */**/*** indicate significance at the 10%/5%/1% levels, respectively. (Only data satisfying Hurricane = 1 are used for regression)