# The impact of natural disasters on violent crime

(This is a working paper. Comments are welcome.)

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**Abstract**

This study addresses the following questions. Do crimes increase following natural disasters? Does an upcoming election or the presence of a strong local media, which potentially increases the incentive of the government to provide disaster relief, mitigate the effect of disasters on crime rates? I find that crime rates tend to increase following moderate to big disasters. Furthermore, a higher pre-disaster size and growth of newspapers has a mitigating effect on the crime response to disasters. Elections have a tempering effect on the crime response to low to moderate level disasters and this mitigating effect is lower in the years close to an election.

Keywords: crime rate, natural disaster, role of media and elections, developing country

JEL classifications: Q54, K42

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# 1 Introduction

Natural disasters impose tremendous economic and social losses on the affected regions. According to the Annual Disaster Statistical Review, in the year 2007 alone natural catastrophes cost the world at least $74,985.26 million and affected over 211,216,415 people worldwide.[1] While there have been several investigations into the economic impact of natural disasters, the social effects are relatively under-researched. This paper integrates two strands of literature: the economic literature on crime rates and the economic literature on natural calamities. The objective of this study is to answer the following questions in the context of a developing country. First, do violent crime rates (murder and dacoity) increase following natural disasters?[2] Second, does an upcoming election or the presence of a strong and vibrant local media, which potentially increases the incentive of the government to provide relief in the aftermath of disasters, mitigate the effect of disasters on crime rates.

Unlike the developed countries, a majority of the population in the developing countries does not have access to natural disaster insurance. Informal arrangements for mutual insurance are not very effective when it comes to dealing with collective risks (Dreze and Sen, 1989). Social order often breaks down and people resort to crime in desperation. For instance, following the floods of 2008 in the Indian state of Bihar, the *Bihar Times* reported, "criminals and anti-social elements are looting abandoned houses and robbing hapless evacuees at gun point". This suggests that in the case of India social costs of natural disasters are non-negligible. Large parts of India are prone to recurrent natural calamities from multiple hazards (see Figure 1). This study focusses on three inland states (Uttar Pradesh, Uttaranchal, and Bihar) and three coastal states (Tamil Nadu, Orissa, and Bihar).

Anecdotal evidence suggests that prompt government action in the aftermath of disasters is crucial for curtailing disaster losses. Government activism, however, can take multiple forms ranging from air drops of food to establishment of relief camps. I do not observe

[1] The Annual Disaster Statistical Review is published by the Center for Research on Epidemiology of Disasters (CRED).

[2] Dacoity is a kind of armed robbery in India committed by a gang of five or more individuals

these directly. Hence, I investigate whether election timing and the size of the local media have a tempering effect on the response of crime rates to disasters. In the Indian context, there is evidence that politicians increase developmental expenditures in the years close to an election. For instance, Khemani (2004) finds that incumbent politicians augment the mileage of national highways in the years close to an election. While this can have an independent effect on crime rates by changing the marginal return to legal work, it can also have an additional effect in the face of a disaster, through the provision of disaster relief. Another factor which can favorably affect the quantity and quality of disaster mitigation services is the size of local media. In a recent paper on India, Besley and Burgess (2002) finds that a higher pre-dissater circulation of newspapers in regional languages is associated with a higher level of calamity relief expenditures of the state governments. Media could also influence other aspects of disaster management, for instance, ensuring that law and order is maintained. A higher level of aid and disaster management services could translate into fewer incidences of looting and murders in the aftermath of disasters. This hypothesis is put to test in the empirical section of the paper.

The primary findings are the following. I find that crime rates, property crimes in particular, do tend to increase following moderate to big disasters (as measured in terms of magnitude as well as human deaths). The results suggest that a higher pre-disaster size and growth of newspapers is effective in curbing the spurt in crime rates in response to disasters. Plausibly, big events get a lot of coverage in local papers and this translates into greater relief and lower crime rates. I also find that the spurt in crime rates in response to disasters is lower in the years that are farther away from an election year, at least for moderate to low magnitude events.

Section 2 briefly reviews the literature on the economics of crime and natural disasters. Section 3 discusses the theory. Section 4 explains the empirical model and section 5 describes the data. In section 6, I discuss the results. Section 7 concludes the paper.

## 2 Review of Literature

**The literature on crime** The existence of crime in the economy can be explained by the economic theory of crime (Becker, 1968; Ehrlich, 1973), which argues that an individual indulges in criminal activities if the net marginal return from illegal activities exceeds the net marginal benefit from legal activities. Sociologists offer alternate explanations for the presence of crime in the society. They argue that people indulge in criminal activities when unsuccessful individuals feel frustrated at their situation relative to those who are successful (Merton's strain theory) or when mechanisms of social control are weakened and the community fails to regulate the activities of some of its members (Shaw and McKay's social disorganization theory). The literature on crime is vast. Hence, I discuss results from a handful of papers that are closely related to my analysis.

In the context of India, Dreze and Khera (2000) was one of the first papers to explain the cross-sectional variation in crime rates. Using district level data on homicides, the paper demonstrates that districts with higher literacy levels have lower incidences of crime rates. On the other hand, crime rates are higher in districts which have a higher proportion of Scheduled Tribes population, and those with a lower level of female to male ratio.[3] The authors argue that the relationship between ST proportion and crime rates is driven partly by the economic motive and partly by the fact that conviction rates are higher for poor people who do not have resources to defend themselves in the court of law. Prasad (2009), demonstrates that the benefits of IMF induced economic liberalization program were not limited to the economic sphere. The paper utilizes the time variation in the spread of gold price between London Stock Exchange and Bombay Stock Exchange to show that economic liberalization, which reduced the profitability of smuggling, also reduced the incidences of murders related to the maintenance of turf ground. Iyer et al. (2009) explores whether crimes against women decline with a greater political representation of women at the local and the state level. The paper finds that crimes against women decline under a female

[3]Scheduled Tribes population refers to a section of the economically backward class of people

Chief minister but increase with the share of local female leaders. The results suggest that a greater representation of women at the local level improves the reporting of crime and this plausibly accounts for the counter-intuitive positive sign.

**The literature on natural disasters** Kahn (2005) identifies income, democracy and geography of a nation to be important determinants of death toll associated with natural disasters. The study finds inverse relationship between disaster losses and the income of a country as well as its level of democracy. The role of good institutions such as trade openness and education in mitigating disaster losses has been confirmed by other studies as well, for instance, Skidmore and Toya (2006).

Among other studies, the politics associated with natural disasters have particularly attracted the attention of economists. In a recent paper, Besley and Burgess (2002), the authors investigate whether a greater circulation of regional newspapers is instrumental in raising the state government's responsiveness to floods and famines. Government activism is measured by plan and non-plan expenditure on calamity relief. The need for governmental activism is instrumented by rainfall shocks. They theorize that a higher media presence increases the incumbent politician's incentive to exert effort as media enables him to reduce the information asymmetry between affected and non-affected groups about his effort level following disasters. They find that a greater circulation of local newspapers enhances government activism following impending famines and actual floods (measured by rainfall shocks). Healy and Malhotra (2009) show that politicians under-invest in disaster-preparedness expenditure vis-a-vis post-disaster aid. They attribute this to voter myopia, which rewards incumbents for investing in the latter. Anbarci, Escaleras and Register (2005) try to explain why countries fail to provide enough "disaster preparedness" by developing a political economy model. The paper argues that as income increases, the benefits of collective action to curtail disaster losses outweighs the benefits from private action. However, income inequality can create a rift in the preferences of the voters. This reduces the likelihood that collective action will be the outcome under majority voting.

**Do crime rates respond to natural disasters in the Indian context?** To explore whether natural disasters result in either a hike or decline in crime rates, I plot crime rates (murder rate and armed robbery rate) against the occurrences of big disasters in Figures 3 and 4. I use an indicator variable, which takes a value of 1 if the number of annual disaster related deaths exceed 5 or more per 100,000 populace. This captures the set of major calamities (such as the 1999 Super Cyclone and the 2004 Tsunami). The objective is to see whether there is a big spurt or dip in the crime rates in the disaster year or in the year following the disaster. The first two graphs (Kendrapara and Puri district) trace the movement of crime rates before and after the Super Cyclone of 1999, which hit the Orissa coast on Oct 29th. This was the deadliest storm that hit India since 1971. The figures suggest that property crime surged upward in the disaster year or in the year following that. The homicide rate surged in Kendrapara but declined in Puri district. The next two graphs in each of the figures, illustrate the impact of the Tsunami of 2004. It hit the state of Tamil Nadu on December 24 and claimed the lives of hundreds of people. Armed robbery rate increases slightly in Kanniyakumari but remained unchanged in Cuddalore. Homicide rates do not seem to have been affected by the event. Finally, the last two graphs focus on a major landslide event (Nilgiri district of Tamil Nadu) and a severe flood (affecting Lucknow district of Uttar Pradesh). There is clear evidence of a rise in both homicide and armed robbery rates in the Nilgiris district following the landslide. Murder rates rose in Lucknow following the flood but not armed robbery.

Overall the figures suggest that periods facing huge disaster related deaths are associated with a change in the movement of crime rates. Moreover, the direction of change in the crime rates varies across the events. This suggests that public goods provision plausibly varied from event to event. For instance, the Tsunami of 2004 received a lot of media attention due to its size as well due to the fact that it affected several countries. This might have a led to a timely response in the aftermath of the event. In contrast to this, according to *Outlook*, dated November 15, 1999, "Four days after the super-cyclone hit Orissa, food, potable water and building material are nowhere in sight. Every time an Indian Air Force (IAF) helicopter drops food, there is a murderous rush to grab the packets. Despair is driving many rural people to loot trucks passing through National Highways 5 and 6. The cyclone has come and gone but the devastation it has left behind has benumbed the administration."

# 3 Theoretical Framework

To help organize ideas, I discuss a model of crime and natural disasters. I divide it into two steps. Step A describes how one arrives at a regional crime rate equation, starting from individual utility maximization problem. In the next step, I discuss the channels through which natural disasters affect crime rates in my model.

**Step A** This has already been worked out in Durlaf, Navarro and Rivers (forthcoming, *Journal of Econometrics*). I briefly summarize the basic idea. Consider an individual 'i' in locality/district, 'l' at time 't'. I assume that an individual either devotes all his time to crime or to work. He chooses to commit crime if the return from work is less than crime commission. Let the expected utility associated with choice, $\omega_{it}$; $\omega = \{1$ for crime, $0$ for work$\}$ be given by:

$$U_{i,t}(\omega_{i,t}) = X_{i,t}\omega_{i,t}\beta_1 + Z_{l,t}\omega_{i,t}\beta_2 + \eta_{l,t}(\omega_{i,t}) + \epsilon_{i,t}(\omega_{i,t}) \tag{1}$$

I have suppressed the index for 'l' in the U, X and $\epsilon$ term to avoid clutter. Here $U^{\omega}$ is the random utility associated with the choice of $\omega^{th}$ alternative; $X_{i,t}$ is a set of individual specific characteristics such as education and race; $Z_{l,t}$'s include region-specific factors such as state laws, local employment opportunities, and probability of getting caught. The terms $\epsilon$ and $\eta$ represent individual and location specific heterogeneity. An individual will commit crime if the utility of crime commission is greater than the utility of not committing a crime.

$$X_{i,t}\beta_1 + Z_{l,t}\beta_2 + \eta_{1,t}(1) - \eta_{l,t}(0) > \epsilon_{i,t}(1) - \epsilon_{i,t}(0) \tag{2}$$

Next, assume that

$$E(\epsilon_{i,t}(1) - \epsilon_{i,t}(0)) = 0 \tag{3}$$

$$\epsilon_{i,t}(1) - \epsilon_{i,t}(0) \text{ are independent of } \eta_{l,t}(1) - \eta_{l,t}(0) \tag{4}$$

$$\epsilon_{i,t}(1) - \epsilon_{i,t}(0) \text{ are independent of } X_{it}, Z_{lt} \tag{5}$$

Under the model assumptions, the individual choices are stocastic given the $X_{i,t}$, $Z_{l,t}$ and $(\eta_{l,t}(1) - \eta_{l,t}(0))$. Suppose that the $(\epsilon_{i,t}(1) - \epsilon_{i,t}(0))$'s follow the uniform distribution with probability distribution function, g(.) and cumulative distribution function, G(.). The probability that an individual commits crime is given by $P(U^C > U^W)$.

$$P_{i,t}(U^C > U^W) = P_{i,t}(X_{i,t}\beta_1 + Z_{l,t}\beta_2 + \tilde{\eta_{l,t}} + \tilde{\epsilon_{i,t}} < 0) = G(X_{i,t}\beta_1 + Z_{l,t}\beta_2 + \tilde{\eta_{l,t}}) \tag{6}$$

where $\tilde{d} = d(1) - d(0)$. Next, suppose that the distribution of $X_{it}$ in any locality, 'l' is uniformly distributed with F(.) being the associated c.d.f. The expected crime rate,

$$E(C_{l,t}|\eta_{l,t}, Z_{l,t}, F_X) = \int G(X^{\omega}_{i,t}\beta_1 + Z_{l,t}\beta_2 + \tilde{\eta_{l,t}})dF_X \tag{7}$$

Let C be the realized crime rate. Then,

$$C_{l,t} = \overline{X_{l,t}}\beta_1 + Z_{l,t}\beta_2 + \rho_{l,t} \tag{8}$$

where $\rho_{l,t}$=$\tilde{\eta_{l,t}} + \underbrace{C_{l,t} - E(C_{l,t}|\eta_{l,t}, Z^{\omega}_{l,t}, F_X)}_{\text{prediction error}}$ and $\overline{X_{i,t}}$ is the mean of $X_{i,t}$ within district 'l' at time 't'.

**Step B** Consider a country with benevolent government, which offers mitigation services following disasters.

$$C_{l,t} = \alpha_1 \overline{X_{i,t}} + \alpha_2 Z_{l,t} + e_{1l,t} \tag{9}$$

$C_{l,t}$ is the district crime rate, $\overline{X_{i,t}}$ is a subset of variables which affect crime rates (for instance, average literacy level in the district), $Z_{l,t}$'s are another set of district specific variables which affect criminality within a district. Let us suppose that Z stands for net return to legal work attributed to district -specific factors. I assume that:

$$Z_{l,t} = \beta_1 nd_{l,t} + e_{2l,t} \tag{10}$$

$$nd_{l,t} = \gamma_1 m_{l,t} + \gamma_2 m_{l,t} a_{l,t} + e_{3l,t} \tag{11}$$

$$a_{l,t} = \delta_1 g_{l,t} + e_{4l,t} \tag{12}$$

Here $nd_{l,t}$, and $m_{l,t}$ denote the loss and size of disastrous event respectively, while $a_{l,t}$ denotes the assistance provided by the government after a disaster. The amount of disaster assistance meted out to people depends on government activism ($g_{l,t}$). Note that $g_{l,t}$ could be in the form of food relief as well as maintenance of law and order. The reduced form crime rate equation is of the form:

$$C_{l,t} = \pi_1 \overline{X_{l,t}} + \pi_2 m_{l,t} + \pi_3 m_{l,t} g_{l,t} + \nu_{l,t} \text{ where } \pi_2 = \alpha_2 \gamma_1 \beta_1 \text{ and } \pi_3 = \alpha_2 \gamma_2 \beta_1 \delta_1 \tag{13}$$

**Expected sign and interpretation of $\pi_3$** If $\gamma_2$ <0 (the marginal effect of aid on disaster losses; equation 11), then the sign of $\pi_3$ (equation 13) depends on $\delta_1$, the structural coefficient on $g_{lt}$ (the marginal effect of government intervention on disaster aid; equation 12). If $g_{l,t}$ has no mitigation effect, then $\pi_3$=0; on the other hand, if it enhances assistance level, then $\pi_3$ <0. The partial effect at the average (PEA) of natural disasters on crime is $(\pi_2 + \pi_3 g_{l,t})$ while the PEA of $g_{l,t}$ is $(\pi_3 m_{l,t})$.

# 4 Empirical Strategy

I estimate linear equations of the following form:

$$C^j_{l,t} = \beta_0 + \beta^j_1 m_{l,t} + \beta^j_2 G_{l,t} + \beta^j_3 m_{l,t} * G_{l,t} + \alpha^j_t k_t + \mu^j_l + \epsilon^j_{l,t} \tag{14}$$

The dependent variable $C^j_{l,t}$ is the $j^{th}$ category crime rate ( murder, armed robbery) per 100,000 people in district, $l$ at time, $t$. The district fixed effects ($\mu_i$'s) capture time invariant factors which affect the marginal return to crime commission in a district. These include the probability of getting caught, disaster risk in a region, racial and educational composition of districts (i.e. $\overline{X_{lt}}$=$\overline{X_l}$). The time dummies ($k_t$'s) capture any aggregate shock that affected all the districts in any year, for example, liberalization of the economy. The natural disaster measures are denoted by $m_{l,t}$. The election and media variable are denoted by $G_{l,t}$. This distinguishes the election and the media variables from factors which have an effect on crime rates only through disaster mitigation. Note that newspaper circulation and elections can have an effect on crime rates even in disaster free periods. Hence, I include $G_{l,t}$ directly as well as interactively with the natural disaster variables. The need for disaster relief arises only in periods affected by natural calamities. If $G_{l,t}$ is election timing, then $\beta_2$ captures the marginal effect of elections on crime rates in the absence of disasters. If disasters bring out an incremental effect of elections ($\beta^j_3$) above the usual effect, then ($m_{l,t} * G_{l,t}$) is potentially capturing the provision of relief services. For instance, through an expansion of national highways which improves the quality of disaster mitigation as in Khemani (2004). A strong and active media can also augment the incentives of the incumbent politicians to provide disaster mitigation services Besley and Burgess (2002).

# 5 Data and descriptive statistics

This study uses data from several sources. Please refer to the data appendix for details.

**Natural disaster ($m_{it}$) data** The district level disaster information is compiled from *DesInventar* and *Disastrous Weather Events*. The type of disastrous events covered in this study include climatological, hydrological, meteorological and geophysical events. Based on the aforesaid sources, I construct indicator variables for the size of the disastrous event. The indicator variables in the*DesInventar* sample are based on annual death toll in a district: (i) the death rate (per 100,000 people) is less than equal to 0.06 (ii) the death rate is greater than 0.06 but less than 1 (iii) the death rate is greater than 1. The excluded category comprises disaster free periods.[4] Analogously, based on *Disastrous Weather Events* database I construct indicator variables based on the categorical measure assigned by the Indian Meteorological Department.[5] The limitation of this database is that I do not observe a direct measure of disaster loss. The base category is non-occurance of disastrous events. Figure 2 illustrates the geographical and temporal coverage of the two samples.

In Table 2, I compare losses implied by low, medium and high magnitude events as constructed from DWE with losses of dwellings (where reported) and human lives as recorded in DesInventar database. Low magnitude events in the DWE sample primarily consist of events such as heavy rains in a district. The medium magnitude events comprise of moderate earthquakes, flash floods to moderate floods and episodes of severe heat waves.[6] High magnitude events comprise events such as severe flood, severe cyclonic events, and the Tsunami. I record only the highest magnitude event if multiple events such as heavy rains followed by floods affect a district. To arrive at death rate and damage rate, I matched districts in DWE and in DesInventar by year.[7] These are rough estimates since DesInventar reports aggregate annual losses from all disasters, while DWE sample is a record of the highest magnitude

[4]One can construct another variable based on the frequency of disastrous events. The advantage of using frequency of disasters is that it is less prone to measurement errors compared to actual losses from disasters. Another advantage of using this variable is that it is exogenously determined. However, one big event such as the Tsunami may cause more losses in a district than a multiple small events.

[5]The data is missing for the years 1990 and 1991 as the issues for these years were were not available in IMD, Nagpur.

[6]Heat waves can claim over 700 lives in India annually

[7]Owning to large number of missing values for houses damaged in disasters, the reported mean is for non-zero observations.

events. The statistics suggest that low magnitude events are associated with much lower losses compared to medium or high magnitude events. It is also interesting to note that death rate is zero even for high magnitude events. This suggests that other factors such as topography are important determinants of disaster related deaths. Another explanation is that in the case of some disasters such as cyclones, death toll can be contained by timely evacuation, but the same is not true for property damage. In Panel B, I use the data supplied to me by Natural Disaster Management Unit, West Bengal to tie it to the categorical measures of size of the disasters. The figures from the Nadia district give me confidence that on average, the categorization adopted by IMD captures disaster losses in the intended fashion. Table 3, suggests that 25% of the sample experienced some form of natural disaster as measured by the biggest such event in the district. The DesInventar sample, which includes all the disastrous events in a sample suggest that the most common type of events are of moderate magnitude.

**Crime data** I focus on five crime categories: murder, armed robbery(dacoity), robbery, burglary and theft.[8] Although the information on other crime categories such as theft and burglary is available, they are likely to be underreported. Hence, I will focus more on the sign of the coefficients compared to the actual estimate.

According to Table 3, the mean murder rate in the sample of DesInventar states (Orissa, Uttar Pradesh, Tamil Nadu, West Bengal, and Uttaranchal) is 3.55 per 100,000 populace. The armed robbery rate is 0.55. The murder rate surpasses armed robbery rate due to the fact that dacoity is a very special type of armed robbery involving violence. The incidence of burglary and theft surpasses murder rates. In the Disastrous Weather Events sample, the murder rate is 3.87 but dacoity, henseforth, armed robbery rises to 0.98. This is partly due to the fact that we include Bihar, a high crime state in India. In India there is a lot of inter-district variation in crime rates. For instance, even within the state of Uttar Pradesh-a high crime state, murder rate is as low as 1.5 in Balrampur and five times as high at 7.5 in

[8]Dacoity is defined as a special type of armed robbery involving a gang of 5 or more members.

Bareily.

The circulation of newspapers in a district is captured by the media index=1-1/exp(-number of registered dailies). This construct gives a smaller weight to each additional newspapers as the size of newspapers in a district continues to increase. The growth of media is measured by the new papers, which came up in the district over the past years. I use five year lagged values of these variables. The average number of newspapers in a district is 7(this translates into a media index of 0.47 and 0.48 in the DWE and DesInventar sample respectively). The average number of new newspapers is 0.43.

The time until next election, is a count measure that takes a values of 0, 1, 2, 3 and 4 if the date of election is the current year, one year away, two years away and so on. According to the Constitution of India, state elections in India are to be held every five years. However, on several occasions an elected government has failed to last the full term due to shifting political alignment or because the governor dissolved the assembly owning to deteriorating situation of law and order in the state.[9] This calls into questions the assumption of exogeneity of the timing of the elections. Following Khemani (2004), I use an instrument for the election timing. Table 1 describes the construction of this variable. The scheduled and midterm elections are denoted by S and M respectively. According to the table, in period 4, midterm elections take place but instead of treating it as an election year, the instrument assigns it a value of 2. Every year that follows an election year is assigned a value of 4 in the instrument variable. The instrument and the actual election cycle diverge in the case of midterm elections. On average most districts are 2.26-2.37 years away from the next election. In the DWE (DesInventar) sample, 43.8% (31.5%) of the elections were midterm elections or those which were held a year later than the scheduled date due to the imposition of President's rule. The correlation between the actual cycle and the instrument is 0.90 and 0.88 in the DWE and DesInventar sample.

[9] Midterm elections usually take place when the party at the federal level and that at the state level are non-aligned. For midterm election to take place, the governor of the state would have to dissolve the state legislature.

Table 1: Construction of the election variable

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Election | S | | | M | | | | | S | | | |
| Instrumented years to election | 0 | 4 | 3 | 2 | 4 | 3 | 2 | 1 | 0 | 4 | 3 | 2 |

Previous studies in India have found that political competition is important in the Indian context. Political competition is measured by the index= 1-absolute value of (share of party with highest seats in the state legislature-share of runner up). This was used in Besley and Burgess (2002). The descriptive statistics suggest that there is moderate level of political competition in the India states.

Finally, I use year dummies to capture any other time varying factor, for instance economic shocks or elections to the national parliament, which can affect the returns to crime. The district dummies capture the time invariant features of the district. These include $\overline{X_{lt}}$ such as average literacy, provision of public goods in a district, and disaster risk.

# 6 Results

## 6.1 Crime and natural disasters: evidence from *Disastrous Weather Events* sample

Table 4 reports the baseline results on the impact of disasters on crime rates. In this model, I assume away the presence of omitted disaster relief variables. The other controls include district and time fixed effects and the population density of the districts.[10] The results suggest that murder rates tend to decline following low magnitude disasters. Property crimes, however, increase by 0.203-0.832 points following high intensity events depending on whether one is looking at armed robbery or burglary. Recall that high magnitude events in this sample consist of severe flooding, severe cyclonic storms and other such events, which are

[10]The population density changes within the sample overtime due to the growth of population and due to the formation of new districts.

likely to cause substantial economic losses in a district. Unlike other property crimes, armed robbery tends to increase following both medium as well as high disaster size categories. Given that the mean armed robbery rate is 0.988 in this sample, this represents an increase of 21% for high magnitude events, and 15% for moderately sized events. In reality, however, the response of crime rates to disasters can depend on the provision of disaster mitigation services. Omission of relief variables can lead to underestimating the link between crime rate and natural disasters. In the next set of regressions, I re-estimate the relationship between crime and natural disasters after controlling for factors which might affect the provision of disaster mitigation services. Note that a greater level of political competition is associated with lower crime incidence.

**Crime response to natural disasters and the timing of elections** In Table 5, I explore whether an upcoming election (as measured by the years until next elections) mitigates the impact of disasters on crime rates. Elections can have an independent effect on crime rates, through greater policing (Levitt, 1997; 2002) or through an increase in developmental expenditures, for instance on national highways (Khemani, 2004). These activities might affect the relative return to legal work. I want to investigate whether elections affect the crime response to disasters in a favorable way or unfavorable way. Theoretically, the relation between years until elections and incumbent effort is ambiguous. Elections can have a motivating effect as well as demotivating effect. Under symmetric information between voters and politician, an incumbent politician, who discovers in the last period of his term that he is of low type relative to the challenger may exert lower effort in this term relative to earlier terms. The results suggest that crime rates are lower in the years close to an election. This can be explained by higher levels of policing or higher levels of developmental expenses or both. The coefficient on $G_{it} * m_{it}$ suggests that crime tends to increase in response to big disasters in the years farther away from an election. Note, however that for low to medium sized events the coefficient on $G_{it} * m_{it}$ is either insignificant or negatively significant. For instance, incidence of robbery increases following low magnitude events but the crime response to low magnitude events in lower in the years close to an election. This suggests that the crime response to elections varies with the magnitude of the disastrous event, which might capture people's perception about his type.

**Impact of natural disasters on crime rates and the role of local newspapers** In this set of regressions, I explore whether the pre-disaster size of local newspapers, or the pre-disaster growth of newspapers affect the crime response to natural disasters. The results (Table 6, columns 1 and 2) suggest that the size of local media does not affect crime rates directly. The counter-intuitive positive sign for theft could due to better reporting of such events. If a higher level of media presence is helpful in receiving disaster aid, then we would expect that the crime response to natural disasters to be negative. The results are supportive of this hypothesis for theft and burglary for medium sized events. Although incidences of theft does not increase significantly following high magnitude events, a higher level of disaster aid (in the form of food or extra policemen) plausibly leads to a decline in thefts following moderately sized disasters.

**Impact of natural disasters on crime rates and the role of new newspapers** In Table 7, I explore whether the growth of newspapers affects the crime response to disasters. With the entry of new papers in the market, the papers have to compete for readership. This can favorably affect the quality of news reported in the papers. The results suggest that new papers help to reduce incidence of thefts by 8-10% following disastrous events when compared to the mean theft rate in the sample. The incidences of robbery decline by around 1% following moderately sized disastrous events when compared to the average robbery rate in the sample. Although crime rate increases significantly following moderate to high magnitude events for armed robbery and burglary, the entry of new papers does not seem to mitigate this in the aftermath of disasters.

## 6.2 Crime and natural disasters: evidence from *DesInventar* sample

**The impact of natural disasters on crime rates: the DesInventar sample** Unlike the DWE sample, the disaster size in this sample is measured by the annual number of people killed across all the disastrous events in a district. This is direct measure of disaster related loss. The indicator variables included in the model are low (1 if death rate>0 & <=0.06 per 100,000 people, 0 otherwise), medium (1 if death rate >0.06 & <=1, 0 otherwise), and high (1 if death rate >=1, 0 otherwise). The results found in this sample are not directly comparable with those in the DWE sample. This is due to the fact that the first reaction of the administration following a natural disaster is saving lives. With the exception of rare and highly destructive events such as the Tsunami and the Super Cyclone, it is possible to have a situation, where the property loss was immense but the death toll was low to moderate. Hence, a subset of high magnitude events in the DesInventar sample (death rate >=5) plausibly coincide with the high magnitude events in the DWE sample, but it is difficult to compare other disaster size categories across the two samples. The base category for disasters in the DesInventar sample is disaster-free periods.

Table 8 presents the baseline results between crime and natural disaster dummies. I control for political competition in the state, district and time fixed effects and the population density dummies. The results suggest that incidences of burglary tend to increase following moderately sized disasters. It is interesting to note that when death toll is used for categorizing disaster size, murder rates also tend to increase following natural disasters. The marginal effect of highly destructive events on murder rates is 0.296 (an increase of 8.3% over the mean level of murder rate in this sample). The coefficient estimates on the disaster variables could suffer from omitted variable bias, hence in the following set of regressions I explore whether the results are robust to inclusion of election and media variables. In both the DWE sample as well as in this sample, a greater level of political competition helps to reduce incidences of crime.

**Crime response to natural disasters and the timing of elections** In this set of regressions, I investigate whether election timing mitigates the effect of disasters on crime rates. The coefficient estimates in Table 10 suggest that crime rates tend to increase following disasters when measured by death toll. Armed robbery rate increases by 35% relative to the mean rate in the sample following big disasters. However, the increase in crime following disasters is likely to be lower in the years that are farther away from elections. The results are qualitatively similar for robbery and murder. Recall that when disaster size is measured using categorical measure, the result was opposite. One explanation of the divergence in the results is that the samples differ in temporal and geographical coverage. An alternate explanation is that failure to save lives conveys a negative signal about the incumbent politician's type compared to property damage. To check the validity of this assertion, I merged the the two samples and re -estimated this relationship. The results in the DWE suggest (Table 5, Panel A in author's webpage) that the crime response to disasters in the DWE sample is negative for low to medium type events. This suggests that disaster losses are associated with higher spurt in crime rates in the years closer to an election. As another test, I re-estimated this relationship using another exogenous measure of disasters: the number of disastrous events that occurred in a district. The results reported in Table 2 in author's webpage suggest that crime rates tend to increase following the occurrence of two or more disastrous events in a district after controlling for election timing and that this increase is lower in the years farther away from an election. For instance, murder rates tend to increase by 30% on average relative to the mean rate following the multiple occurrence of disastrous events in a district but the spurt in crime is lower in the years away from an election. This suggests that the discrepancy in the results in the sample is partially driven by different geographical coverage of the sample.

**Crime response to natural disasters and the role of local media: DesInventar sample** Like the DWE sample, the results in this sample support the hypothesis that a bigger media presence has a mitigating effect on crime rates following disasters. Disasters, which are associated with a high (moderate) death toll lead to a rise in both murder rates and robbery (see columns 1 and 3 and 4 in Table **??**). Compared to disaster free periods, occurrences of big disaster events increase murder rates by 0.522 points and robbery rate by 0.280 points. These represent an increase of 15% and 14% over the mean rates respectively. Thefts and burglary increase significantly following moderate to high magnitude disasters. Unlike the DWE sample, the DesInventar sample suggests significant mitigation for thefts for both medium and big disaster sizes. Moreover, there is evidence that thefts significantly increase in periods affected by disasters compared to disaster-free periods. The murder rate is least likely to suffer from reporting errors and hence one may be interested in the magnitude of crime mitigation as well. A higher media presence more than offsets the spurt in crime rates following high magnitude events.

In Table 11, I focus on the role of entry of number of new papers on disaster mitigation. The results (columns 1-5) suggest that crime rates significantly increase following big disasters. The results also suggest that there is a higher entry of newspapers significantly mitigates the crime response to disasters. If the number of disastrous events is used as a measure of disasters losses (Table 3 in author's webpage), I find that crime rates increase for all crime categories expect robbery. A higher entry of new papers mitigates the crime response to disasters for robbery and theft (and for burglary for the occurrence of one disastrous event).

To summarize, media seems to have a tempering effect on the crime response to disasters. The strongest evidence is found for thefts. The results is robust in both DWE as well as DesInventar sample. When death toll is used to measure disaster size, a higher media presence in instrumental is mitigating the crime response to multiple categories.

# 7 Conclusion

The objective of this study was to explore whether natural disasters lead to a rise in the crime rates and whether the crime response to disasters depends on the timing of elections and the strength of local media. Natural disasters occur at regular intervals in developing countries and throw the population into deeper levels of poverty. A spurt in crime rates during these trying times imposes additional burden on the affected regions. This paper deviates from other papers on natural disasters by using a district as the unit of analysis. Due to data limitations most studies on natural disasters have data only at the national level or at the state level. The effects of natural disasters are often localized and a state or a country level analysis is not likely to be very informative. The size of the natural disasters is measured using two different variables: an intensity measure of the event (and frequency of events as additional checks) and the number of disaster related deaths. The former is more exogenous and potentially also captures property losses in a district while the latter is a direct measure of loss of human lives.

I find that crime rates, property crimes, do tend to increase following moderate to big disasters. The results suggest that a higher pre-disaster size and growth of newspapers is effective in reducing the impact of disasters on crime, particularly for thefts. If a direct measure of disaster loss is utilized, I find that a higher pre-existing size and entry of newspapers puts a check on the spurt in crime following big disasters for almost all types of crimes. Plausibly, big events are covered in greater depth in local papers and this translates into greater relief and consequently lower crime rates. Elections, on average, seem to have a demotivating effect on incumbent politicians when faced with disasters (in terms of death toll). A higher distance from the election year is associated with significant mitigation of crime response to disasters.

Overall, the results support the hypothesis that natural disasters lead to a spurt in crime rates. The presence of media and electoral incentives which augment the relief efforts of the incumbent politicians are instrumental in mitigating the impact of disasters on crime rates.

Ideally, one would like to control for relief expenses of the government. Since it is difficult to identify factors which cause exogenous variation in this variable, the best we can do is to identify factors which affect the size of disaster relief. In this context, it may be useful to look at the role of road expansion in disaster mitigation. Expansion of roads is a policy variable for the government. A better road network, which improves the connectivity of the districts to other regions in the state and the country, can directly affect the return to crime but it can also have an additional beneficial effect during periods facing disasters, through a timely arrival of relief material or the timely evacuation of the affected population. Furthermore, this paper only focusses at the role of media in the home districts in crime mitigation. It may be useful to look at the impact of media in the adjoining districts in this context. A priori it is not clear whether it will be helpful in crime mitigation as some of the neighboring districts will be from a different state (targeted at a different population and possibly in a different language), which may/may not affect the electoral incentives of the incumbent politicians in the home states. This is left as a future exercise.

# 8 Data Appendix

**Crime data** The source of crime data used in this analysis is Ministry of Home Affairs, Government of India, which publishes *Crime in India* on an annual basis since 1953. The district level data is available from 1971 onward.

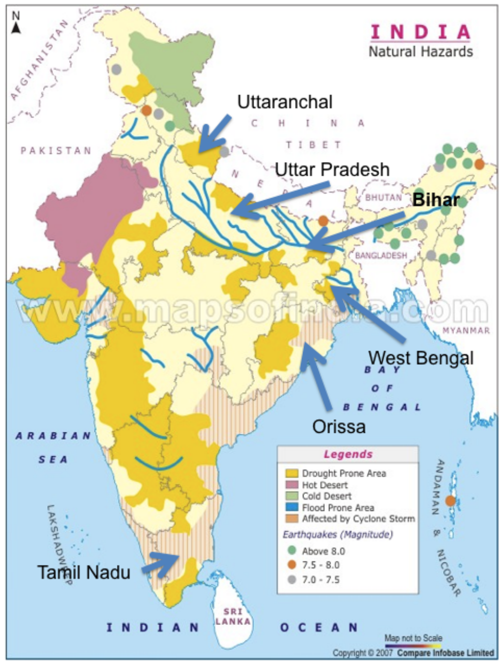
**Natural disaster data** The source of death toll in natural disasters is DesInventar database and the source of magnitude of disasters is *Disastrous Weather Events* (DWE) supplemented with disaster records maintained by the Geological Survey of India.. The former has district level information on the losses from all types of natural disasters (hydrological, climatological, meteorological and geophysical) experienced by districts of three Indian states, albeit for a limited number of years: Uttar Pradesh (1991-2005); Tamil Nadu (1976-2007); and Orissa (1970-2007). The data on Uttaranchal is publicly available on the state's disaster management website. I would like to thank the Government of West Bengal for sharing the confidential disaster data with me. The *Disastrous Weather Events* is published by the Indian Meteorological Department and maintains district level information on natural disasters in India.

**Election and media variables ($G_{it}$)** The election data is compiled EOPP stata dataset and the website maintained by Election Commission of India. [11] The data on the size of local/district media is available from "The Registrar of Newspapers for India". I use the information on the city of publication to identify the district to which it belongs. I also restrict my analysis to newspapers, which are published daily to avoid inclusion of literature devoted mainly to poetry and other such issues.

The information on population, population density of a district is available from the decennial Census of India, 1981,1991, and 2001.

[11] The author would like to thank Tim Besley and Robin Burgess for providing the EOPP stata dataset at their website.

Figure 1: Natural hazard map of india




Source: MapsofIndia website

Figure 2: Comparison of geographical and temporal coverage of the two samples

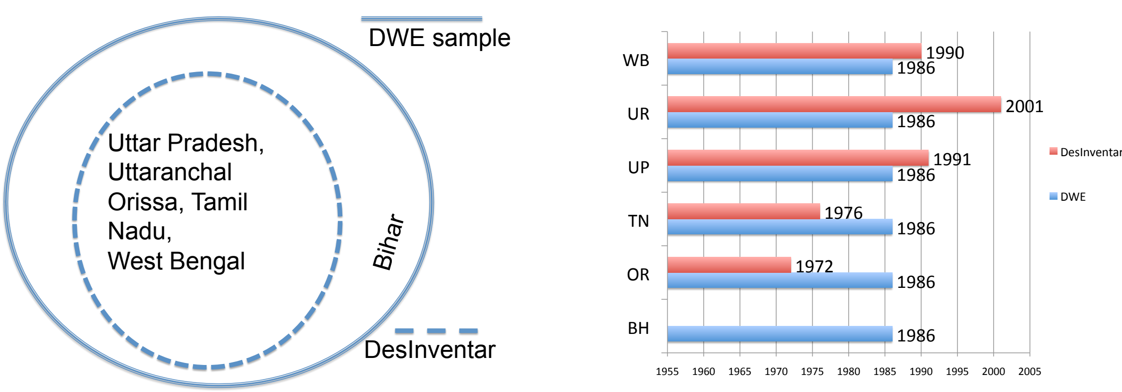


Figure 3: Murder rates and losses from natural disasters as measured by death toll per 100,000

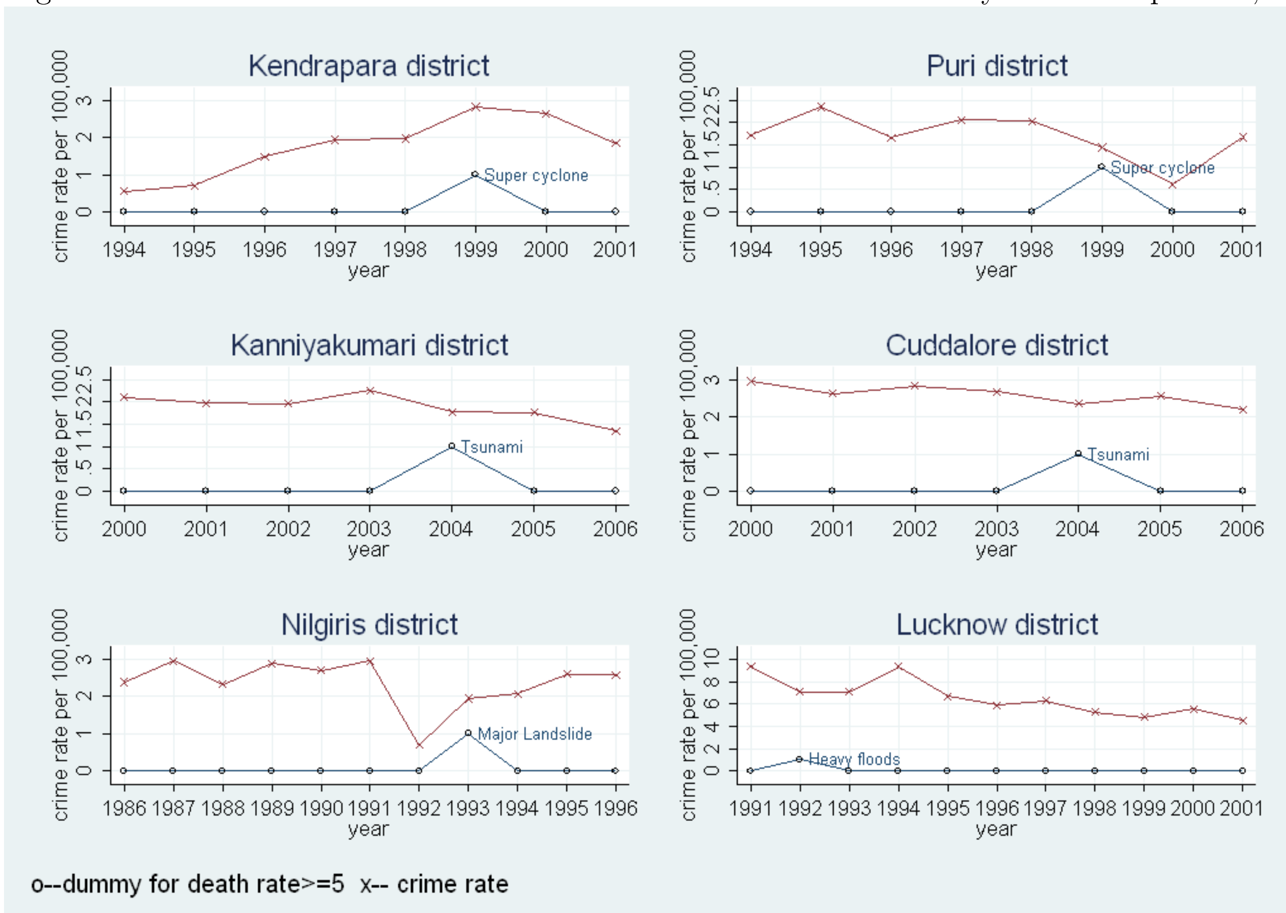


Figure 4: Armed robbery rates and losses from natural disasters as measured by death toll per 100,000

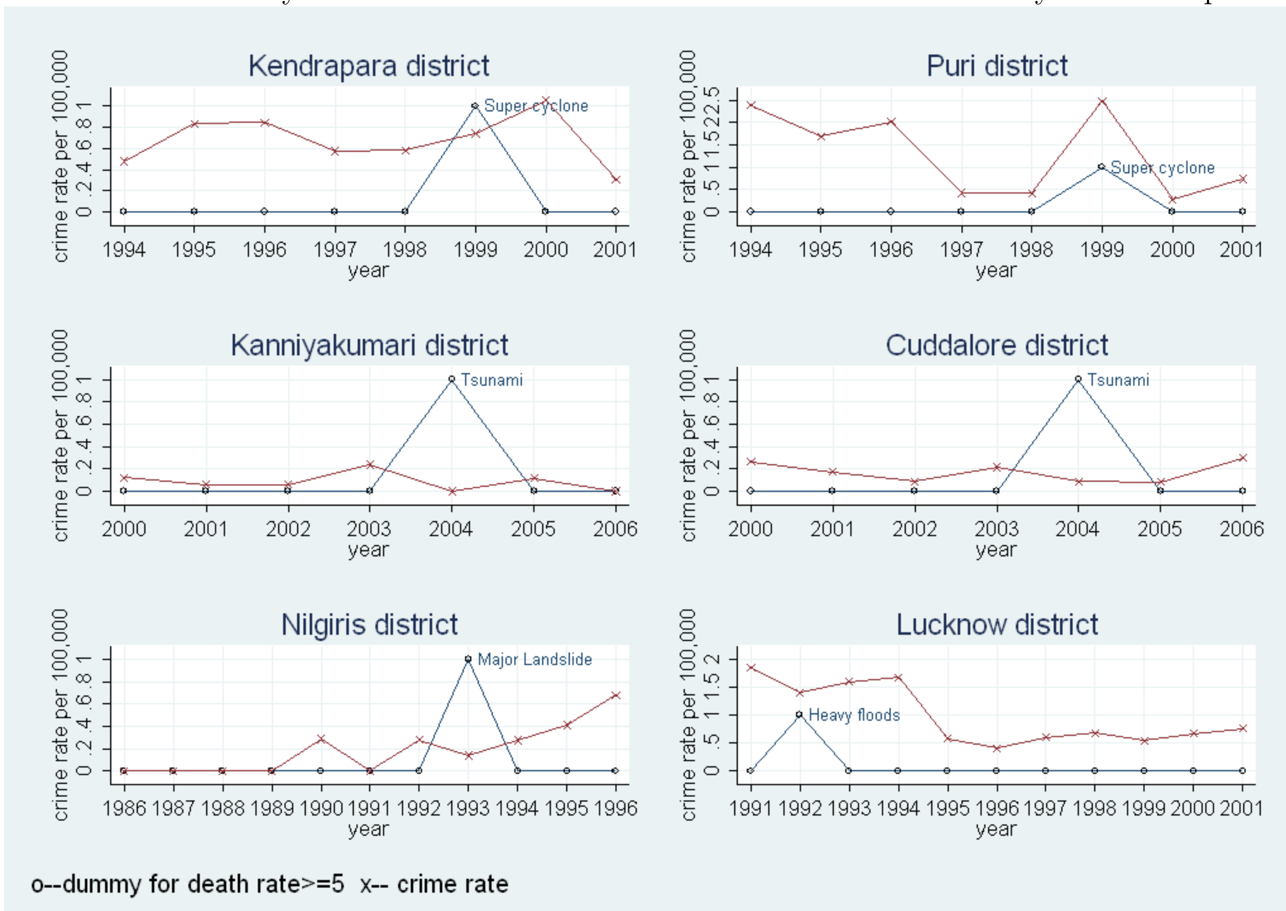


Table 2: Comparison of losses across DesInventar and DWE sample

| Panel A: in the common sample of DWE and DesInventar | | | | |
|---|---|---|---|---|
| Category of event (DWE) | Damage rate of dwellings | Death rate (DesInventar) | % Zero death cases | Maximum death toll |
| low | 684 | 5.66 | 43.95 | 77 |
| medium | 3141 | 13.3 | 38.35 | 332 |
| high | 6849 | 113.16 | 41.28 | 11653 |

Notes: Damage rate is number of houses damaged in disasters per 100,000 population
Death rate is number of disaster related deaths per 100,000 population

| Panel B | | | | |
|---|---|---|---|---|
| Event type | District | Disaster type | Year | People affected |
| low | Nadia, WB | heavy rains | 2005 | 238443 |
| medium | Nadia,WB | Rains and Flash floods | 2006 | 600000 |
| high | Nadia,WB | Severe Flood | 1999 | 1200000 |

Notes: Nadia is a district in West Bengal
Damage rate is calculated for a subset of the period, when the data was available

Table 3: Descriptive Statistics

| Variables | Description | Mean | Std. dev |
|---|---|---|---|
| DWE, N=3323 | | | |
| murder | murders per 100,000 people | 3.87 | 2.45 |
| dacoity (armed robbery) | dacoity per 100,000 people | 0.98 | 1.14 |
| robbery | robberies per 100,000 people | 2.30 | 2.17 |
| burglary | burglaries per 100,000 people | 7.37 | 6.04 |
| theft | thefts per 100,000 people | 19.21 | 17.19 |
| low | low intensity events | 0.07 | 0.26 |
| medium | medium intensity events | 0.12 | 0.33 |
| high | high intensity events | 0.06 | 0.25 |
| years until election | years until next state election | 2.26 | 1.35 |
| media | index of existing size of newspapers in the district | 0.47 | 0.46 |
| new papers | 5 period lagged newpapers in the district | 0.33 | 1.19 |
| political competition | 1-absolute value of (share of party with highest seats in the state legislature-share of runner up). | 0.49 | 0.16 |
| DesInventar, N=2782 | | | |
| murder | murders per 100,000 people | 3.55 | 2.39 |
| dacoity (armed robbery) | dacoity per 100,000 people | 0.55 | 0.59 |
| robbery | robberies per 100,000 people | 1.94 | 1.81 |
| burglary | burglaries per 100,000 people | 9.03 | 7.74 |
| theft | thefts per 100,000 people | 22.58 | 19.66 |
| low | low intensity events | 0.15 | 0.35 |
| medium | medium intensity events | 0.29 | 0.45 |
| high | high intensity events | 0.08 | 0.26 |
| years until election | years until next state election | 2.37 | 1.33 |
| media | index of existing size of newspapers in the district | 0.48 | 0.46 |
| new papers | 5 period lagged newpapers in the district | 0.36 | 27.92 |
| political competition | 1-absolute value of (share of party with highest seats in the state legislature-share of runner up). | 0.36 | 1.24 |

Note: media is defined as $1-\frac{1}{e^{(\text{5 year lagged size of newspaper})}}$

Table 4: Fixed effect regression of natural disasters on crime rate: using categorical measure

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| Mean of Y | 3.87 | 0.98 | 2.30 | 7.37 | 19.21 |
| | (1) | (2) | (3) | (4) | (5) |
| low | -0.144** | 0.078** | 0.024 | 0.132 | -0.295 |
| | [0.065] | [0.036] | [0.088] | [0.215] | [0.491] |
| medium | -0.078 | 0.147*** | 0.014 | 0.271 | -0.382 |
| | [0.060] | [0.040] | [0.076] | [0.175] | [0.508] |
| high | -0.090 | 0.203*** | 0.137 | 0.832*** | 0.285 |
| | [0.092] | [0.057] | [0.138] | [0.280] | [0.684] |
| political competition | -1.866*** | -0.490** | -4.303*** | -7.185*** | -5.608** |
| | [0.379] | [0.238] | [0.531] | [1.060] | [2.425] |
| Constant | 4.348*** | 1.934*** | 4.846*** | 15.433*** | 33.498*** |
| | [0.305] | [0.145] | [0.442] | [0.748] | [1.569] |
| Observations | 3323 | 3323 | 3323 | 3323 | 3323 |
| $R^2$ | 0.239 | 0.391 | 0.270 | 0.536 | 0.412 |
| Number of districts | 227 | 227 | 227 | 227 | 227 |

Robust standard errors in []; *** p<0.01, ** p<0.05, * p<0.1. The sample period is 1986-2006

The excluded category corresponding to the disaster variables (low, medium and high) is "no disasters".

Other controls include district and time fixed effect, and population density dummies

Table 5: Impact of elections on the crime response to disasters

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| Mean of Y | 3.87 | 0.98 | 2.30 | 7.37 | 19.21 |
| | (1) | (2) | (3) | (4) | (5) |
| low | 0.007 | 0.090 | 0.246* | 0.532 | -0.397 |
| | [0.124] | [0.069] | [0.130] | [0.483] | [1.114] |
| medium | -0.119 | 0.102 | -0.083 | 0.400* | -0.432 |
| | [0.097] | [0.066] | [0.102] | [0.224] | [0.653] |
| high | -0.325** | 0.008 | -0.525*** | -0.122 | -1.403 |
| | [0.133] | [0.085] | [0.149] | [0.356] | [0.910] |
| years to election | 0.044** | 0.004 | 0.052** | 0.225*** | 0.444*** |
| | [0.018] | [0.012] | [0.021] | [0.057] | [0.112] |
| election*low | -0.069 | -0.007 | -0.105** | -0.193 | -0.002 |
| | [0.046] | [0.024] | [0.045] | [0.172] | [0.420] |
| election*medium | 0.021 | 0.021 | 0.047 | -0.059 | 0.032 |
| | [0.041] | [0.028] | [0.037] | [0.097] | [0.291] |
| election*high | 0.101* | 0.085* | 0.287*** | 0.406** | 0.708 |
| | [0.053] | [0.044] | [0.080] | [0.177] | [0.434] |
| political competition | -1.904*** | -0.497** | -4.348*** | -7.355*** | -5.995** |
| | [0.374] | [0.238] | [0.527] | [1.065] | [2.407] |
| Constant | 4.266*** | 1.923*** | 4.740*** | 15.022*** | 32.728*** |
| | [0.302] | [0.144] | [0.428] | [0.720] | [1.499] |
| Observations | 3323 | 3323 | 3323 | 3323 | 3323 |
| $R^2$ | 0.242 | 0.392 | 0.278 | 0.541 | 0.416 |
| Number of districts | 227 | 227 | 227 | 227 | 227 |

Robust standard errors in []; *** p<0.01, ** p<0.05, * p<0.1. The sample period is 1986-2006
The excluded category corresponding to the disaster variables (low, medium and high) is "no disasters".
Other controls include district and time fixed effect, and population density dummies

Table 6: Fixed effect regression of natural disasters on crime rate and size of media: using categorical measure

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| Mean of Y | 3.87 | 0.98 | 2.30 | 7.37 | 19.21 |
| | (1) | (2) | (3) | (4) | (5) |
| low | -0.033 | 0.060 | 0.008 | 0.332 | 0.082 |
| | [0.100] | [0.049] | [0.110] | [0.262] | [0.579] |
| medium | -0.080 | 0.132* | -0.065 | 0.577** | 0.971 |
| | [0.100] | [0.067] | [0.113] | [0.257] | [0.824] |
| high | -0.127 | 0.192* | 0.219 | 1.096* | 0.570 |
| | [0.184] | [0.113] | [0.240] | [0.578] | [1.076] |
| index of media size | -0.183 | -0.220 | -0.319 | 0.070 | 4.892*** |
| | [0.255] | [0.216] | [0.356] | [0.819] | [1.645] |
| media*low | -0.217 | 0.035 | 0.031 | -0.414 | -0.787 |
| | [0.133] | [0.065] | [0.156] | [0.417] | [1.033] |
| media*medium | 0.004 | 0.032 | 0.157 | -0.617* | -2.724** |
| | [0.145] | [0.086] | [0.172] | [0.365] | [1.102] |
| media*high | 0.066 | 0.025 | -0.133 | -0.508 | -0.741 |
| | [0.241] | [0.146] | [0.347] | [0.740] | [1.634] |
| political competition | -1.838*** | -0.462** | -4.255*** | -7.201*** | -6.319*** |
| | [0.382] | [0.228] | [0.536] | [1.066] | [2.372] |
| Constant | 4.395*** | 1.990*** | 4.926*** | 15.396*** | 32.217*** |
| | [0.312] | [0.166] | [0.437] | [0.774] | [1.465] |
| Observations | 3323 | 3323 | 3323 | 3323 | 3323 |
| $R^2$ | 0.242 | 0.392 | 0.278 | 0.541 | 0.416 |
| Number of districts | 227 | 227 | 227 | 227 | 227 |

Robust standard errors in []; *** p<0.01, ** p<0.05, * p<0.1. The sample period is 1986-2006

The excluded category corresponding to the disaster variables (low, medium and high) is “no disasters”.

Other controls include district and time fixed effect, and population density dummies

Table 7: Fixed effect regression of natural disasters on crime rate and growth of media: using categorical measure

| VARIABLES | (1)<br>murder | (2)<br>armed robbery | (3)<br>robbery | (4)<br>burglary | (5)<br>theft |
|---|---|---|---|---|---|
| low | -0.138** | 0.076** | 0.017 | 0.233 | 0.510 |
| | [0.069] | [0.038] | [0.091] | [0.214] | [0.515] |
| medium | -0.089 | 0.143*** | 0.077 | 0.350* | 0.318 |
| | [0.061] | [0.043] | [0.076] | [0.183] | [0.505] |
| high | -0.091 | 0.213*** | 0.156 | 0.935*** | 0.835 |
| | [0.099] | [0.061] | [0.146] | [0.297] | [0.704] |
| new papers | -0.016 | 0.027** | -0.009 | -0.000 | -0.026 |
| | [0.023] | [0.012] | [0.042] | [0.104] | [0.296] |
| new papers*low | -0.010 | 0.001 | 0.001 | -0.246 | -1.907*** |
| | [0.023] | [0.012] | [0.047] | [0.258] | [0.341] |
| new papers*medium | 0.024 | 0.003 | -0.125*** | -0.178 | -1.529*** |
| | [0.053] | [0.015] | [0.048] | [0.140] | [0.380] |
| new papers*high | 0.003 | -0.030 | -0.062 | -0.320 | -1.782*** |
| | [0.066] | [0.031] | [0.084] | [0.279] | [0.491] |
| political competition | -1.852*** | -0.513** | -4.287*** | -7.144*** | -5.282** |
| | [0.377] | [0.237] | [0.527] | [1.055] | [2.404] |
| Constant | 4.347*** | 1.935*** | 4.841*** | 15.416*** | 33.364*** |
| | [0.305] | [0.145] | [0.442] | [0.745] | [1.494] |
| Observations | 3323 | 3323 | 3323 | 3323 | 3323 |
| $R^2$ | 0.240 | 0.392 | 0.271 | 0.537 | 0.423 |
| Number of districts | 227 | 227 | 227 | 227 | 227 |

Robust standard errors in []; *** p<0.01, ** p<0.05, * p<0.1

The excluded category corresponding to the disaster variables (low, medium and high) is “no disasters”.

Other controls include district and time fixed effect, and population density dummies

Table 8: Fixed effect regression of natural disasters on crime rate: using death toll measure

crime rate

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| mean of Y | 3.55 | 0.55 | 1.94 | 9.03 | 22.58 |
| | (1) | (2) | (3) | (4) | (5) |
| low | -0.084 | 0.025 | 0.039 | 0.280 | 0.481 |
| | [0.064] | [0.028] | [0.081] | [0.248] | [0.776] |
| medium | 0.028 | 0.018 | -0.030 | 0.419** | 0.127 |
| | [0.057] | [0.022] | [0.073] | [0.206] | [0.582] |
| high | 0.296** | 0.054 | 0.201 | 0.126 | 0.528 |
| | [0.121] | [0.041] | [0.137] | [0.332] | [0.640] |
| political competition | -1.308*** | -0.446*** | -1.810*** | -2.561*** | -1.540 |
| | [0.390] | [0.123] | [0.356] | [0.883] | [2.985] |
| Constant | 2.894*** | 0.747*** | 1.350*** | 24.915*** | 47.250*** |
| | [0.403] | [0.190] | [0.504] | [1.621] | [3.890] |
| Observations | 2782 | 2782 | 2782 | 2782 | 2782 |
| $R^2$ | 0.349 | 0.298 | 0.289 | 0.634 | 0.522 |
| Number of districts | 177 | 177 | 177 | 177 | 177 |

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. The sample period is 1972-2006

The excluded category for disaster variables is "no disasters"

Table 9: Fixed effect regression of natural disasters on crime rate and election timing:using death toll measure

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| mean of Y | 3.55 | 0.55 | 1.94 | 9.03 | 22.58 |
| | (1) | (2) | (3) | (4) | (5) |
| low | 0.283** | 0.058 | 0.334*** | 0.189 | 0.986 |
| | [0.114] | [0.037] | [0.097] | [0.352] | [0.946] |
| medium | 0.411*** | 0.065* | 0.207** | 0.427 | 0.630 |
| | [0.105] | [0.036] | [0.101] | [0.290] | [0.880] |
| high | 0.851*** | 0.191*** | 0.544*** | 0.412 | 0.019 |
| | [0.188] | [0.071] | [0.148] | [0.494] | [1.031] |
| years to election | 0.218*** | 0.020* | 0.158*** | 0.125 | 0.293 |
| | [0.038] | [0.012] | [0.037] | [0.117] | [0.242] |
| election*low | -0.161*** | -0.014 | -0.130*** | 0.041 | -0.230 |
| | [0.042] | [0.013] | [0.037] | [0.120] | [0.292] |
| election*medium | -0.170*** | -0.021 | -0.104*** | 0.005 | -0.198 |
| | [0.041] | [0.014] | [0.040] | [0.116] | [0.243] |
| election*high | -0.258*** | -0.059** | -0.163*** | -0.139 | 0.169 |
| | [0.070] | [0.028] | [0.056] | [0.178] | [0.363] |
| political competition | -1.327*** | -0.424*** | -1.859*** | -2.819*** | -2.304 |
| | [0.391] | [0.124] | [0.355] | [0.884] | [2.983] |
| Constant | 2.368*** | 0.684*** | 0.981* | 24.646*** | 46.867*** |
| | [0.374] | [0.194] | [0.499] | [1.541] | [3.758] |
| Observations | 2782 | 2782 | 2781 | 2781 | 2781 |
| $R^2$ | 0.360 | 0.300 | 0.296 | 0.628 | 0.511 |
| Number of districts | 177 | 177 | 177 | 177 | 177 |

Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

The excluded category for disaster variables is "no disasters"

These regressions control for year and population density dummies.

Table 10: Fixed effect regression of natural disasters on crime rate and size of media:using death toll measure

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| mean of Y | 3.55 | 0.55 | 1.94 | 9.03 | 22.58 |
| | (1) | (2) | (3) | (4) | (5) |
| low | -0.027 | 0.037 | 0.081 | 0.540 | 1.437* |
| | [0.089] | [0.041] | [0.104] | [0.345] | [0.849] |
| medium | 0.138 | 0.048 | 0.064 | 0.685** | 1.751*** |
| | [0.093] | [0.037] | [0.096] | [0.337] | [0.628] |
| high | 0.522*** | 0.079 | 0.280* | 0.547 | 2.093** |
| | [0.173] | [0.064] | [0.163] | [0.453] | [0.858] |
| index of media size | 0.358 | -0.118 | 0.103 | 0.058 | 4.922** |
| | [0.290] | [0.159] | [0.322] | [0.796] | [2.365] |
| media*low | -0.100 | -0.024 | -0.074 | -0.514 | -1.773 |
| | [0.146] | [0.054] | [0.177] | [0.461] | [1.410] |
| media*medium | -0.228* | -0.065 | -0.191 | -0.489 | -3.181** |
| | [0.132] | [0.054] | [0.156] | [0.429] | [1.251] |
| media*high | -0.560** | -0.058 | -0.173 | -1.005 | -3.431* |
| | [0.282] | [0.093] | [0.363] | [0.713] | [1.777] |
| political competition | -1.377*** | -0.432*** | -1.845*** | -2.767*** | -2.705 |
| | [0.393] | [0.125] | [0.367] | [0.881] | [2.827] |
| Constant | 2.794*** | 0.763*** | 1.312** | 24.864*** | 46.056*** |
| | [0.411] | [0.201] | [0.510] | [1.583] | [3.782] |
| Observations | 2782 | 2782 | 2781 | 2781 | 2781 |
| $R^2$ | 0.352 | 0.301 | 0.290 | 0.629 | 0.516 |
| Number of districts | 177 | 177 | 177 | 177 | 177 |

Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

The excluded category for disaster variables is "no disasters"

These regressions control for year and population density dummies.

Table 11: Fixed effect regression of natural disasters on crime rate and growth of media: using death toll measure

| Y | murder | armed robbery | robbery | burglary | theft |
|---|---|---|---|---|---|
| mean of Y | 3.55 | 0.55 | 1.94 | 9.03 | 22.58 |
| | (1) | (2) | (3) | (4) | (5) |
| low | -0.087 | 0.024 | 0.043 | 0.389 | 1.367* |
| | [0.064] | [0.029] | [0.075] | [0.259] | [0.738] |
| medium | 0.039 | 0.020 | 0.008 | 0.542** | 1.134** |
| | [0.058] | [0.023] | [0.070] | [0.215] | [0.502] |
| high | 0.335*** | 0.071* | 0.290** | 0.360 | 1.483** |
| | [0.121] | [0.042] | [0.127] | [0.343] | [0.665] |
| new papers | 0.009 | 0.012 | 0.068 | 0.203 | 1.305** |
| | [0.037] | [0.017] | [0.053] | [0.151] | [0.629] |
| new papers*low | 0.014 | 0.002 | 0.000 | -0.249* | -2.165** |
| | [0.034] | [0.015] | [0.064] | [0.146] | [0.956] |
| new papers*medium | -0.033 | -0.008 | -0.106 | -0.259* | -2.420** |
| | [0.041] | [0.016] | [0.072] | [0.156] | [1.043] |
| new papers*high | -0.124** | -0.059** | -0.290*** | -0.710*** | -2.546*** |
| | [0.055] | [0.027] | [0.078] | [0.206] | [0.760] |
| political competition | -1.311*** | -0.454*** | -1.850*** | -2.783*** | -2.045 |
| | [0.387] | [0.124] | [0.349] | [0.890] | [2.787] |
| Constant | 2.890*** | 0.747*** | 1.338*** | 24.914*** | 46.934*** |
| | [0.404] | [0.189] | [0.502] | [1.617] | [3.869] |
| Observations | 2782 | 2782 | 2781 | 2781 | 2781 |
| $R^2$ | 0.350 | 0.300 | 0.295 | 0.630 | 0.526 |
| Number of districts | 177 | 177 | 177 | 177 | 177 |

Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

The excluded category for disaster variables is “no disasters”

These regressions control for year and population density dummies.

# References


**Anbarci, N., M. Escaleras, and C. Register**, 2005, "Earthquake fatalities: the interaction of nature and political economy," *Journal of Public Economics*, *89* (9-10), 1907-1933.

**Becker, G. S.**, 1968, "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, *76*, 169-217.

**Besley, T. and R. Burgess**, 2002, "The political economy of government responsiveness: theory and evidence from India," *Quarterly Journal of Economics*, *Nov*, 1445-1451.

**Chisholm, J. and C. Choe**, 2005, "Income variables and measures of gains from crime," *Oxford Economic Papers*, *57* (1), 112-119.

**Chisholm, J. and C. Choe**, 2003, "Trade and the Environment: Theory and Evidence," *Princeton Univ. Press*, Princeton, NJ, 2003.

**Centre for Research on the Epidemiology of Disasters**, 2007, "Annual Disaster Statistical Review: The Numbers and Trends".

**Dreze, J. and R. Khera**, 2000, "Crime, Gender, and Society in India: Insights from Homicide Data," *Population and Development Review*, *26* (2), 335-352.

**Dreze, J. and A, Sen**, 1989, "Hunger and Public Action," Oxford University Press.

**Durlauf, S. N., S. Navarro and D. Rivers**, "Understanding Aggregate Crime Regressions," *(forthcoming) Journal of Econometrics.*

**Ehrlich, I.**, 1973, "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation," *Journal of Political Economy*, *81*, 521-565.

**Healy, A. and N. Malhotra**, 2009, "Myopic Voters and Natural Disaster Policy," *American Political Science Review*, *103* 387-406.

**Hochrainer, S.**, 2009, "Assessing the Macroeconomic Impacts of Natural Disasters? Are there Any?", *World Bank Policy Research Working Paper 4968*.

**International Federation of Red Cross and Red Crescent Societies**, 2007, "World Disasters Report: Focus on Discrimination".

**Iyer, L., A. Mani, P. Mishra, and P. Topalova**, 2009, "Political Representation and Crime: Evidence from India's Panchayati Raj," Harvard Business School Working Paper.

**Kahn, M. E.**, 2005, "The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions," *Review of Economics and Statistics*, *87* (2), 530-539.

**Kelly, M.**, 2000, "Inequality and Crime," *Review of Economics and Statistics*, *87* (4), 530-539.

**Kellenberg, K. K. and A.M Mobarak**, 2008, "Does rising income increase or decrease risk from natural disasters?," *Journal of Urban Economics* , *63*, 788-802.

**Khemani, S.**, 2004, "Political cycles in a developing country effect of elections in the Indian States," *Journal of Development Economics, 73(1)*, 125-154.

**Levitt, Steven D.,** 1997, "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime," *American Economic Review, 87(3)*, 270-290.

**Levitt, Steven D.,** 2002, "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime: A Reply," *American Economic Review*, September, *92*, 1244-250.

**Merton, R.,** 1938, "Social Structure and Anomie," *American Sociological Review*, 672-682.

**Prasad, K.**, 2009, "Economic Liberalization and Violent Crime in India," *Working Paper*, Robert H. Smith School of Business. University of Maryland, College Park, MD.

**Schumacher, I. and E. Strobl**, 2008, "Economic Development and Losses due to Natural Disasters: The Role of Risk," Ecole Polytechnieque. Department of Economics Working Paper.

**Shaw, C., and H. McKay**, 1942, "Juvenile Delinquency and Urban Areas," Chicago: University of Chicago Press.

**Skidmore, M. and H. Toya**, 2006, "Economic development and the impacts of natural disasters," *Economics Letters*, *40* (94),20-25.

**Tol, R. and F. Leek**, 1999, "Economic analysis of natural disasters," In: Downing, T., Olsthoorn, A. and Tol, R. (Eds,), Climate Change and Risk, 308-327 *Routledge*, London.

**Voluntary Health Association of India**, 1993, "Turning disasters into development," 40, Institutional Area, New Delhi, 110016.