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The impact of natural disasters on crime

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Abstract

This study addresses the following questions in the context of a developing country. 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 growth of newspapers has a mitigating effect on the crime response to disasters. Elections also influence the crime response to disasters. Crimes are more likely to rise following disasters in the years that are close to an election year.

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

JEL classifications: Q54, K42

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. The objective of this study is to answer the following questions in the context of India. First, do crime rates tend to increase following natural disasters? 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, influence the crime response to disasters? Natural disasters occur at regular intervals in developing countries and throw the population into deeper levels of poverty. A spurt in the 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.[2] Due to data limitations most studies on natural disasters have been able to use only state level or national level data. However, the effects of natural disasters are often localized and a state or a country level analysis is not likely to be very informative.

India is a good test ground for exploring the link between crime and natural disaster. Geographic location is an important determinant of the disaster risk faced by a region. The Northern tropic passes through the central part of India. This makes India prone to recurrent natural calamities (see Figure 1).[3] Furthermore, there is a lot of regional variation in the crime rates across India. India is also the most populous democracy in the world with a well functioning and independent press.

The study is focussed on three inland states (Uttar Pradesh, Uttaranchal, and Bihar) and

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

[2]Administratively, India is divided into various states, which are subdivided further into districts.

[3]Most natural disasters are concentrated in the region flanked by the Tropic of Cancer and the Tropic of Capricon.

three coastal states (Tamil Nadu, Orissa, and West Bengal). The primary findings of this study are the following. I find that crime rates, property crimes in particular, tend to increase following moderate to big disasters. The results suggest that a higher pre-disaster growth of newspapers is effective in curbing the spurt in crime rates following disasters, particularly moderate to high intensity disasters. Plausibly, these events get a lot of coverage in local papers and this translates into greater relief and lower crime rates. Elections also influence the crime response to disasters. The crime response to disasters is lower in the years that are farther away from an election year, at least for the low magnitude events.

The paper is organized as follows. Section 2 briefly reviews the economic literature on crime and natural disasters. Section 3 explains the empirical model followed by a description of the data in Section 4. I discuss the results in Section 5. Section 6 concludes the paper.

2 Review of Literature

The literature on natural disasters Economic studies on natural disasters can be broadly divided into three groups. One set of papers have identified factors such as income, democracy, and geography (Kahn, 2005) and trade openness and education (Skidmore and Toya, 2006) to be important determinants of disaster damages. Another group of studies tries to assess the impact of disasters on individual decision making and on the economy. Finlay (2009), for instance, finds that big earthquakes are capable of generating a fertility response. Finally, there are studies that explore the determinants of disaster relief. In this set of papers, the politics associated with natural disasters have particularly attracted the attention of economists. 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. 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 in India. The authors theorize that a higher media presence reduces the information asymmetry between affected and non-affected groups about the incumbent politician's effort level and this motivates the incumbent politician to respond to disasters. The paper finds evidence that a greater circulation of local newspapers enhances government activism following disasters. The link between media coverage and disaster related relief has been established in the context of international aid as well (Eisensee and Stromberg, 2007). These papers (Besley and Burgess, 2002; Eisensee and Stromberg, 2007) provide the argument for using media presence as a determinant of disaster aid in the current paper.

The literature on crime The literature on crime is vast. I discuss a handful of papers that are closely related to my analysis. In the context of India, Dreze and Khera (2000) find that higher literacy levels, a lower share of SCST population, and a low female to male ratio reduces the incidences of homicides in the cross-section of Indian districts. Prasad (2009), demonstrates that the IMF induced economic liberalization program, 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 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.

This paper integrates the literature on crime and natural disasters and considers whether elections and media have a tempering effect on the crime response to disasters. The use of elections is motivated by Levitt (1997) and Khemani (2004). The latter paper is focussed on India and 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 better disaster preparedness. Analogously, a higher media presence can influence the crime response to disasters though post-disaster relief efforts as well as their ability to cope with disasters.

Do crime rates respond to natural disasters in the Indian context? To explore whether natural disasters influence crime rates, I plot crime rates (murder rate and armed robbery rate) against the occurrences of big disasters in Figures 2 and 3. 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 (focussed on Kendrapara and Puri district) trace the movement of crime rates before and after the Super Cyclone of 1999, which hit the Orissa coast on October 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 illustrate that periods affected by disasters experience a change in the movement of crime rates. The direction of change 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.[4] 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 Empirical Strategy

I estimate panel data regressions for the jth category crime rate in district l in year t.

$$C^j_{l,t} = \beta^j_0 + \beta^j_1 m_{l,t} + \beta^j_2 G_{l,t} + \beta^j_3 m_{l,t} * G_{l,t} + \beta^j_4 Z_{l,t} + \alpha^j_t k_t + \mu^j_l + \epsilon^j_{l,t} \tag{1}$$

The district fixed effects (μ^j_l's) capture the time invariant factors which affect the marginal return to crime commission in a district. These include the probability of getting caught, and disaster risk in a region. The time dummies (k_t's) capture any aggregate shock that affected all the districts in any year, for example, trade liberalization of the economy; $m_{l,t}$ is the set of dummy variables indicating the occurrence of low, medium or high intensity disasters. The base category is non-occurrence of disasters. The variable $G_{l,t}$={years until next state election, entry of newspapers in the district}.[5] The coefficient β^j_2 may be interpreted as the marginal effect of $G_{l,t}$={media, elections} in disaster free periods. The partial effect at the average of natural disasters on crime is ($\beta^j_1 + \beta^j_3 \overline{G_{l,t}}$). However, the need for disaster relief arises only in periods affected by natural calamities. The coefficient β^j_3 is incremental effect of $G_{l,t}$ on crime in periods affected by disasters. If elections and newspapers mitigate

[4] The Outlook is a weekly magazine from India

[5] An alternate measure of presence of newspapers in a region is the existing size of newspapers.

the crime response to disasters, then β_3^j should be negative. This could be attributed to the provision of post-disaster relief measures as well as to better disaster preparedness, for instance through better connectivity to other parts of the country. In a recent paper, Besley and Donaldson (2010) demonstrate that railroads were helpful in curtailing the outbreaks of famine in British India. If $G_{l,t}$ is set to zero, the partial effect of natural disaster on crime would be β_1^j.

4 Data and descriptive statistics

Natural disaster (m_{it}) data The district level disaster information is compiled from *DesInventar* and *Disastrous Weather Events*.[6] The type of disastrous events covered in this study include climatological, hydrological, meteorological and geophysical events. I exclude droughts as the reaction time is much larger for this category of disaster. Based on the aforesaid sources, I construct indicator variables for the intensity of the disastrous event. The indicator variables in the *DesInventar* sample are based on the annual death toll in a district: (i) 1 if disaster related death toll (per 100,000 people) is less than equal to 0.06, 0 otherwise (ii) 1 if the disaster related death rate is greater than 0.06 but less than 1, 0 otherwise (iii) 1 if the disaster related death rate is greater than 1, 0 otherwise. The excluded category is disaster free periods. From the *Disastrous Weather Events* database, however, I record only the highest magnitude disaster affecting a district in any given year. For instance, if heavy rains precede flooding, I record only the latter event. This was done because unlike death toll, which is available for DesInventar database there is no natural way of aggregating across different types of disasters from the *Disastrous Weather Events*. The IMD assigns a categorical measure to each disastrous event (for instance, floods are categorized as flash floods, moderate floods, severe floods). A direct measure of loss is not available. Hence, I construct indicator variables based on this categorical measure of disaster intensity.[7] The

[6]Please refer to the data Appendix for details.

[7]The data is missing for the years 1990 and 1991 as the issues for these years were were not available in Indian Meteorological Department, Nagpur.

base category is non-occurrence of disastrous events. The advantage of using this database is that it is prepared by an independent agency which does not have an incentive to over report losses to attract federal aid. The DesInventar database is partially based on media reports and therefore is subject to some over-reporting. To deal with this issue, I construct another variable from the DesInventar database 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. The limitation of this measure is that one big event such as the Tsunami may cause more losses in a district than a multitude of small events. Hence, it is not clear whether multiple occurrences of natural disasters leads to more destruction than one such event. The DesInventar sample covers five states: Uttar Pradesh (1991-2006), Uttaranchal (2001-2006), West Bengal (1991-2006), Tamil Nadu (1978-2006) and Orissa (1973-2006). The DWE sample comprises of: Uttar Pradesh, West Bengal, Bihar, Orissa (1986-2006) and Uttaranchal (2001-2006).[8]

Before proceeding further, I demonstrate the the two datasets convey analogous information on disaster losses. In Table 3, I compare losses implied by low, medium and high magnitude events as constructed from the DWE sample with losses of dwellings (where reported) and human lives as recorded in the DesInventar database. Low magnitude events in the DWE sample primarily consist of events such as heavy rains in a district. The medium intensity events comprise of moderate earthquakes, flash floods to moderate floods and episodes of severe heat waves.[9] High magnitude events comprise of events such as severe flood, severe cyclonic events, and the Tsunami. To arrive at the statistics reported in Panel A of Table 3, I matched districts from the DWE sample with those in the DesInventar sample by year of occurrence of the disastrous event.[10] This exercise provides rough estimates of losses across

[8]The state of Uttaranchal was created from parts of Uttar Pradesh in 2001. The state of Jharkhand was created from parts of Bihar in 2001; however, the disaster related information in unavailable for Jharkhand, hence I drop Jharkhand districts from the sample.

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

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

the two samples since the DesInventar sample utilizes information on annual losses from all disasters, whereas the DWE sample is a record of the highest magnitude event only.

The figures show that low magnitude events are associated with much lower losses compared to medium or high magnitude events. It is also interesting to note that a large fraction of high magnitude disasters did not results in deaths. This suggests that perhaps factors such as topography also play an important role in determining 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. While these figures are informative of losses in an average Indian district, one may wish to repeat the exercise by focussing on any one district. In Panel B, I focus on Nadia district in West Bengal and compare the low, medium, and high intensity disasters based on the number of people affected by the disaster.[11] The figures from the Nadia district give me confidence that the categorization adopted by the IMD and more importantly my own categorization of the different disaster types (into low disaster, medium disaster, high disaster) captures the losses in the intended fashion.

How frequently do Indian districts get hit by disasters? Table 2 suggests that 52 % of the sample (the unit of observation is a district-year) experienced a natural disaster. However, a majority of these are low to medium intensity events. Only 6-7% of the sample experienced a high intensity disaster.

Crime data The crime categories considered in this study are murder, armed robbery, robbery, burglary, and theft. The crime rate is defined as incidence of crimes per 100,000 people. One might be concerned that certain crime categories such as thefts and burglaries are underreported. An added concern is whether the reporting of crime changes in periods affected by disasters. To the extent that crimes are under-recorded during these periods, equation (1) will under-estimate the crime response to disasters. According to Table 2, the

[11]The information on death toll and the number of damaged houses was not available for all the three years, hence the comparison is made on the basis of people affected

mean murder rate in the sample of DesInventar states (Orissa, Uttar Pradesh, Tamil Nadu, West Bengal, and Uttaranchal) is 3.55. 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. As expected the burglary and the theft rate is higher than the murder rate. In the Disastrous Weather Events sample, the murder rate is 3.88 but dacoity, henseforth, armed robbery rises to 0.98. This is partly due to the fact that the sample includes Bihar, which is well known in India for high incidences of crimes.

Media data Most Indian districts did not have local newspapers in the 1970's and 1980's. Over the years, several districts have experienced entry of newspapers in their district. The growth of newspapers is measured by the number of newly registered dailies in a district in any given year. To alleviate concerns about endogeneity, I use five year lagged values for this variable. The average number of new dailies in the sample is 0.349 in the DWE sample.

Election data The time until next state election is a count measure that takes a values of 0, 1, 2, 3 and 4 if the earliest election is scheduled to take place in 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 owning to deteriorating law and order situation in the state, in which case the governor dissolved the assembly.[12] 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

[12]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.

instrument and the actual election cycle diverge in the case of midterm elections. On average most districts in the sample are 2.26-2.37 years away from the next election. In the DWE (DesInventar) sample, actual elections and scheduled elections diverge in 43.8% (31.5%) of the cases.[13] The correlation between the actual cycle and the instrument is 0.90 and 0.88 in the DWE and DesInventar sample respectively.

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

Other Controls Previous studies have found that political competition is important determinant of public goods provision in the Indian context. In this study, political competition is measured by the index= 1-(Σparty shares^2). I use five year lagged values to construct this index. I club all the parties into four groups: Congress, Left, Hindu, and Regional.[14] The first two have been in the election scene since independence. Their dominance has declined in the recent years with the rise of regional parties and Hindu parties. The index of political competition is a measure of party concentration. The index ranges from 0 to 1. A lower value indicates that political competition in the state is low. The descriptive statistics suggest that there is moderate level (mean level of the index is 0.47-0.49) of political competition in the India states.

One might be concerned that the media variables are picking up the role of factors such as urbanization. To deal with this, I include population density dummies in the regression. I also control for the district literacy levels in the districts as reported in decennial census. Additionally, I include two variables which vary over time at the state level: Total police

[13]This divergence is attributed primarily due to midterm elections and in a miniscule of cases due to the imposition of President's rule which can postpone elections.

[14]The regional parties are primarily dominant in home states whereas the Congress, Left have presence in almost all the states. The importance of Hindu bent parties varies from state to state.

strength per km^2 lagged by one period, and the fraction of state's total expenditure devoted to development related expenses, lagged by one period. These variables are intended to capture the existing quality of infrastructure just before the disaster hit, which in turn can affect the provision of relief services. One might be concerned that past shocks to crime affect police strength and development expenses, hence I include them only as a part of robustness checks. The final sample comprises of an unbalanced panel of 228 districts in the DWE sample and 117 districts in the DesInventar sample. Several Indian districts split during the period covered by this study. If a district retains its original name or inherits most of the area of the original district, I treat is as the old district. All the other newly created districts are included in the sample from that point onward. As a part of robustness check, I also create composite districts, which are the original districts from the newly created districts. This gives me a balanced panel of districts within each state.

5 Results

5.1 A: Basic Results

The baseline regression results of crime on natural disaster are reported in Table 4. The results reported in Panel A uses the categorical measure of disasters from the DWE sample, while Panel B and Panel C utilise the death toll measure and frequency measure respectively from the DesInventar sample. The explanatory variables include the natural disaster dummies, year dummies, district density dummies district literacy levels, and political competition at the state level. Robust standard errors are reported throughout. The regressions omit the election and media variables. The results reported in Panel A provides evidence that armed robbery and burglary rate tend to increase following medium to large disasters. Murder rate tends to decline following low intensity disasters. In the DesInventar sample (Panel B), murder rate decreases following small disasters but increases in response to big disasters. Panel C offers further evidence that natural disasters influence the movement of crime rate. Relative to disaster free periods, the occurrence of a disaster is associated with a rise in burglaries. The other crime categories do not seem to be influenced by the frequency of disasrers. However, if the availability of disaster relief influences the crime response to disasters, then the coefficients on the disaster variables suffer from the omitted variable bias. In the regressions that follow, I use elections and media as possible influencers of disaster relief and preparedness.

Crime response to natural disasters and years until next elections The existing evidence on India suggests that public goods provision is higher in the years close to an election. The results in this study are supportive of this hypothesis. Note, for instance (Table 5, DWE and DesInventar sample), that the farther away is the next election, the higher are the crime rates. This is true in the case of murder rates as well as property crimes such as robberies and thefts. The coefficient on the disaster dummies informs us about the crime response to disasters in the election year (i.e. when the time until next election=0). Panels A and B suggest that crime rates tend to increase following low to medium intensity disasters. The results also suggest that proximity to elections influences the crime response to disasters. According to Panel A, the robbery rate significantly increases by 0.255 (an increase of 11% above the mean) points following low intensity disasters; however, the marginal effect of low intensity disasters at the average on robbery is 0.012 and is insignificant.[15] In the DesInventar sample (Panel B), the marginal effect of low intensity disaster on the robbery rate in the election year is 0.348. Moving from the election year to a situation where the next election is four years away, the marginal effect drops to -0.256. Panel C uses the frequency measure of disasters. The marginal effect of multiple disasters changes from 0.397 in the election year to -0.207 when elections are four years away. Let us focus on murder and armed robbery rate. The results in Panel C imply that relative to disaster free periods, the occurrence of multiple disasters in a district is associated with 0.534 and 0.143 points increase in the murder rate

[15] This refers to the marginal effect evaluated at average level of G, in this case, G is years until next election

and armed robbery rate respectively in the election year. However, the partial effect at the average of multiple disasters on the murder rate and the armed robbery rate is insignificant. The results from the DWE and DesInventar sample diverge for the crime response to big disasters. Panels B and C suggest that the crime rates increase following disasters whereas Panel A suggests the opposite. The marginal effect of high intensity disasters at the average on murder rate is 0.259 and significant in Panel B whereas it is -0.090 and insignificant in Panel A. The temporal and geographic coverage of the samples differ and plausibly this explains the differences in the results. Conventional wisdom suggests that the crime response to disasters should be lower in the years close to an election as the incumbent politicians strive to maximize their chances of an reelection. However, it is possible that the electorates hold the politicians responsible for events outside their control (Cole, Healey and Werker, 2008) and this might have a demotivating effect on the politicians.

Impact of natural disasters on crime rates and newspapers In Panels A-C of Table 6, I explore whether the growth of newspapers affects the crime response to disasters. Unlike elections, the entry of papers into the districts does not seem to influence crime rates in the disaster free periods, except for armed robbery in the DWE sample. Recall, that I use five year lagged value of this variable to allay concerns about endogeneity. According to Panel A, low intensity disasters are associated with a decline in the murder rate. Armed robbery rate and burglary rate increases following medium to large disasters. For instance, medium intensity disasters are associated with a 0.348 points and 0.506 points increase in the burglary rate in Panel A and Panel B respectively. Even though this increase is small when compared to the mean crime rate, during periods of disasters even slight increases in crime rate could generate unrest among people. The marginal effect at the average of a medium intensity disaster on the burglary rate is 0.292 and 0.409 respectively in Panels A and B. Thefts tend to increase following high intensity (Panel B) and multiple occurrences of disasters (Panel C). This represents an increase of around 6% over the mean rate. However, the entry of new papers is associated with a decline in thefts and burglaries in the face of disasters. The reduction in thefts is evidenced from Panel B as well. According to Panel B, high intensity disasters lead to a 1.260 points increase in thefts in the absence of entry of new dailies, however newspapers tend to moderate this effect. The partial effect at the average of response of thefts to high intensity disasters is insignificant. Murders tend to decline following small disasters (Panels A and C). According to Panel B, disasters associated with huge death toll are associated with an increase in the murder rate but a newspapers help to curb this rise. With the entry of new papers in the market, the newspapers have to compete for readership. This can favorably affect the quality of news reported in the papers. Thus, apart from the possibility that these regions are able to attract higher post-disaster aid, these regions are also likely to have a greater provision of public goods, for instance good quality roads. This in turn could improve disaster preparedness of the region. An alternate measure of presence of newspapers in a district is the existing number of dailies. The results not reported here suggest that the pre-disaster size of newspapers is helpful in reducing thefts in the face of disasters.

5.2 B: Robustness

The results reported above utilize variations in the elections timing and media as a proxy for disaster relief. In the following regressions, I include additional controls,which might affect the crime response to disasters. The first control is one year lagged police strength per km square at the state level. The second control is the share of development expenditure in the state lagged by one year. A district is likely to cope with disasters better in the years when the state spent more on the law and order and other development projects. To save space, I report results from the DWE sample only. First I focus on elections (Table 7). The robbery rate tends to rise following low intensity disasters but this response is higher in the years closer to an election. The coefficient on the interaction variable changes only slightly when compared to Table 5. However, the coefficient on the low disaster dummy is smaller and is significant at 10% level only. The moderating role of elections for low intensity disasters holds for murder rates as well. Overall, the coefficients on the disaster dummies seem to be muted in this regression when compared to Table 5. The results from the death toll and the frequency measure (not reported here) are qualitatively similar to that in Table 5. Murder, armed robbery, robbery and thefts tend to increase following disasters and a bigger media presence helps to curb this rise. In Table 8, I revisit the link between crime and natural disasters and newspapers. The coefficient on the big disaster dummy increases slightly in the armed robbery and burglary equation. The mitigating effect of newspapers on crime is evidenced in this set of regressions as well. The results from the DesInventar sample are again qualitatively similar to that found in Table 6. High intensity disasters are associated with a rise in the crime rates (murder rate, robbery and theft rate when death toll measure is used and armed robbery and theft rate when the frequency measure is utilized). The strong mitigation in the case of thefts and high intensity disasters is found in this set of regressions as well.

Another concern associated with previous regressions is that several districts split during the sample period. Two of the controls included in the previous regressions political competition and density of a district are likely to influence the creation of new districts. Yet, one might worry that there are omitted factors that are driving the results. To allay such concerns, I calculate crime rate and other controls for the original districts throughout the sample period. If results are driven by primarily by omitted factors then one would not be able to reproduce the results found above. The downside of this procedure is that the fixed effect procedure is only able to account for time invariant omitted factors in the composite districts. Potentially districts grow differently after the split and this can result in a bias in the regression results. This sample has 117 districts followed from 1986-2006 in the DWE sample and 93 districts in the DesInventar sample with a sample size of 1914. Panel A in Table 9 offers evidence that elections have a role in moderating the effect of disasters on crime. For instance, the burglary rate significantly increases by 0.421 points in these super-districts following low intensity disasters in the election year, however this partial effect is insignificant when evaluated at the average. The results from the DesInventar sample (the results are not reported here), suggest that the increase in crime following disasters in the years closer to an election if not limited to property crimes but extends to murders as well. The results remain qualitatively unchanged if police strength and share of development expenditure is included in the model.

In Panel B, there is evidence that armed robbery, robbery, and burglary tend to rise following low intensity disasters. Media has a moderating influence on this relationship in the case of murder rate, robbery and theft rate. In the DesInventar sample (the results are not reported here), murders and robbery (thefts) tend tend to rise following high (moderate) intensity disasters when measured by death toll. Media plays a role in crime mitigation following disasters in the case of burglary (in the case of low intensity disasters) and theft (in the case of low level to moderate disasters). Relative to disaster free periods, the occurrences of disasters are associated with increases in burglaries (in the case of one disaster) and theft (in the case of multiple disasters). A higher entry of papers helps to mitigate this response in the case of thefts for both single and multiple occurrences of calamities. This result that a higher media presence helps in moderating the spurt in crime in the face of disasters is robust to the inclusion of police strength and share of development expenditure in the model. This is true in the case of both the death toll and the frequency measure.

6 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. I find that crime rates, property crimes in particular, tend to increase following moderate to big disasters. The results suggest that a higher pre-disaster growth of newspapers is effective in reducing the impact of disasters on crime, particularly for thefts. Plausibly, disasters are covered in greater depth in local papers and this translates into greater relief and consequently lower crime rates. Alternatively, a bigger media presence is associated with a higher pre-disaster infrastructure, which augments the ability to cope with disasters. Elections seem to have a demotivating effect on incumbent politicians when faced with low intensity disasters. A greater distance from the election year is associated with a lower spurt in the crime rates following disasters. Elections seem to influence the crime response to disasters in the case of murders and robberies whereas thefts and burglaries seem to be influenced by the presence of media.

This study highlights the role of media as a watchdog that possibly increases the accountability of the politicians and thereby affects the crime response to disasters. Furthermore, the study highlights the importance of electoral incentives in eliciting a quick response to disasters. If voters hold the incumbents responsible for events outside their control, then it opens up the possibility that relief efforts will be lower and crime rates higher in the years close to an election.

I conclude with some caveats and directions for future research. Due to the annual nature of the crime data and also due to the low probability of occurrence, I am unable to distinguish between the crime response to events such as floods, which primarily affect the poor and events such as earthquakes, which affect the entire population. Furthermore, I ignore the heterogeneity in the response to crime rates across the states. The study ignores the role of newspapers in the neighboring districts. A priori it is not clear whether newspapers in the neighboring districts are 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.

In the future, it may be useful to look at the role of road and railroad expansion in disaster mitigation. A better connectivity of the districts to other regions in the state and the country, can directly affect the return to crime but it also improves disaster preparedness.

Data Appendix

District crime data and state police strength The source of district crime data and police strength at the state level 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 DesInventar database is available at www.desinventar.org. The *Disastrous Weather Events* (DWE) is published by the Indian Meteorological Department. This was supplemented with disaster records maintained by the Geological Survey of India. The low type events in the DWE sample comprise of depression, heavy rains, moderate heat waves. The moderate type events cover floods (flash floods, moderate floods, severe floods), landslides, earthquake, severe heat waves. High type events comprise of severe floods and very severe cyclonic storms.

Election and media variables (G_{it}) The election data is compiled from the EOPP stata dataset and the website maintained by Election Commission of India.[16] I largely follow the categorization of parties adopted in Besley and Burgess (2000). For instance, "Left parties" in this study comprise of Soft Left and Hard Left parties in Besley and Burgess (2000). The "Hindu parties" comprise of BJP and the RSS. The "Congress and its allies" have been grouped into the category Congress in my study. All other parties including independents are clubbed into the "Regional parties" category. The data on the size of local/district media is available from "The Registrar of Newspapers for India".

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

Development expenditure and total expenditure of the states This data is compiled EOPP stata dataset and Database on the Indian Economy maintained by the Reserve Bank of India.

[16]The author would like to thank Tim Besley for providing the EOPP stata datasets at his website.

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Table 2: Descriptive Statistics

	Mean	Std. Dev.	Mean	Std. Dev.
	DWE sample		DesInventar sample	
Murder rate	3.880	2.460	3.542	2.392
Armed robbery rate	0.986	1.159	0.550	0.588
Robbery rate	2.301	2.172	1.931	1.815
Burglary rate	7.350	6.034	9.007	7.737
Theft rate	19.136	17.144	22.532	19.640
1 natural disaster (f1)	–	–	0.271	0.445
>= 2 disasters (f2)	–	–	0.252	0.434
Low	0.072	0.259	0.160	0.367
Medium	0.126	0.332	0.291	0.454
High	0.064	0.244	0.073	0.260
Years until state elections	2.255	1.354	2.370	1.329
New dailies*	0.349	1.205	0.403	1.374
Political competition*	0.493	0.162	0.477	0.177
Share of developmental expenditure**	0.582	0.074	0.591	0.083
Literacy	49.365	15.806	51.948	15.512
Total police per km^2**	0.525	0.182	0.497	0.214
	N=3357		N=2792	

Notes: * and ** implies 5 year and 1 year lagged values are used

Table 3: Comparison of losses across DesInventar and DWE sample

Panel A: in the common sample of DWE and DesInventar				
DWE variables	DesInventar variables			
(Event type)	Damage rate of dwellings	Death rate	% 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
Panel B: from West Bengal database				
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; death rate is number of disaster related deaths per 100,000 population. Damage rate is number of houses damaged in disasters per 100,000 population and is calculated for a subset of the period, when the data was available.

Table 4: Baseline results on crime and natural disasters

Y=	murder	armed robbery	robbery	burglary	theft
	(1)	(2)	(3)	(4)	(5)
Panel A DWE sample: Categorical measure					
low	-0.129**	0.088**	0.028	0.142	-0.212
	[0.065]	[0.037]	[0.087]	[0.213]	[0.482]
medium	-0.051	0.182***	0.036	0.286*	-0.283
	[0.065]	[0.052]	[0.077]	[0.173]	[0.513]
high	-0.082	0.208***	0.146	0.845***	0.344
	[0.093]	[0.057]	[0.138]	[0.280]	[0.686]
N	3357	3357	3357	3357	3357
R squared	0.236	0.384	0.269	0.535	0.408
Districts	228	228	228	228	228
Panel B DesInventar sample: Death toll measure					
low	-0.128*	0.027	-0.003	0.224	0.256
	[0.074]	[0.027]	[0.080]	[0.240]	[0.746]
medium	0.006	0.020	-0.054	0.371*	-0.108
	[0.060]	[0.023]	[0.076]	[0.194]	[0.576]
high	0.304**	0.038	0.220*	0.218	0.460
	[0.118]	[0.041]	[0.132]	[0.312]	[0.636]
N	2792	2792	2792	2792	2792
R squared	0.342	0.297	0.285	0.628	0.511
Districts	177	177	177	177	177
Panel C DesInventar sample: Frequency measure					
1 disaster (f1)	-0.074	0.010	-0.046	0.313*	-0.135
	[0.058]	[0.018]	[0.064]	[0.177]	[0.526]
>= 2 disasters (f2)	0.104	0.054	0.057	0.292	0.522
	[0.096]	[0.035]	[0.114]	[0.288]	[0.858]
N	2792	2792	2792	2792	2792
R squared	0.345	0.296	0.287	0.628	0.511
Districts	177	177	177	177	177

Notes: The other controls include district and time fixed effect, literacy, political competition in the state, district density dummies.
*** p<0.01, ** p<0.05, * p<0.1.

Table 5: District fixed effect regression of crime on disasters: role of elections

Y	murder	armed robbery	robbery	burglary	theft
mean Y_{DWE}	3.879	0.986	2.300	7.350	19.135
mean $Y_{DesInventar}$	3.542	0.550	1.932	9.007	22.531
Panel A: Categorical measure of natural disaster and election variables					
low	0.032	0.097	0.255**	0.533	-0.230
	[0.123]	[0.069]	[0.127]	[0.477]	[1.108]
medium	-0.109	0.088	-0.084	0.399*	-0.442
	[0.097]	[0.064]	[0.100]	[0.219]	[0.635]
high	-0.294**	0.030	-0.505***	-0.087	-1.482
	[0.133]	[0.085]	[0.149]	[0.356]	[0.917]
years to election	0.045**	0.007	0.053**	0.226***	0.448***
	[0.018]	[0.012]	[0.021]	[0.057]	[0.113]
election*low	-0.073	-0.007	-0.108**	-0.189	-0.039
	[0.045]	[0.024]	[0.044]	[0.170]	[0.418]
election*medium	0.030	0.046	0.058	-0.052	0.083
	[0.040]	[0.035]	[0.038]	[0.095]	[0.286]
election*high	0.090*	0.077*	0.282***	0.395**	0.766*
	[0.053]	[0.043]	[0.078]	[0.176]	[0.434]
Panel B: Death toll measure of natural disaster and election variables					
low	0.345***	0.089**	0.348***	0.264	1.045
	[0.113]	[0.036]	[0.101]	[0.371]	[0.922]
medium	0.418***	0.069**	0.206**	0.415	0.551
	[0.106]	[0.034]	[0.102]	[0.292]	[0.859]
high	0.908***	0.221***	0.534***	0.562	-0.042
	[0.184]	[0.068]	[0.142]	[0.487]	[0.996]
years to election	0.230***	0.026**	0.164***	0.146	0.354
	[0.038]	[0.011]	[0.037]	[0.117]	[0.247]
election*low	-0.203***	-0.027**	-0.151***	-0.013	-0.342
	[0.040]	[0.013]	[0.037]	[0.114]	[0.279]
election*medium	-0.178***	-0.021	-0.111***	-0.007	-0.253
	[0.041]	[0.014]	[0.040]	[0.115]	[0.238]
election*high	-0.274***	-0.078***	-0.147***	-0.159	0.176
	[0.067]	[0.025]	[0.052]	[0.177]	[0.351]
Panel C: Frequency measure of natural disaster and election variables					
1 disaster (f1)	0.377***	0.054*	0.214**	0.303	0.031
	[0.093]	[0.029]	[0.092]	[0.284]	[0.751]
>= 2 disasters (f2)	0.534***	0.143***	0.397***	0.468	1.710*
	[0.139]	[0.044]	[0.118]	[0.413]	[0.901]
years to election	0.229***	0.023**	0.172***	0.138	0.429*
	[0.038]	[0.011]	[0.038]	[0.121]	[0.255]
f1*elections	-0.193***	-0.018	-0.110***	0.010	-0.058
	[0.036]	[0.011]	[0.035]	[0.099]	[0.218]
f2*elections	-0.193***	-0.039**	-0.151***	-0.064	-0.474*
	[0.044]	[0.016]	[0.044]	[0.144]	[0.247]

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: District fixed effect regression of crime on disasters: role of new dailies

Y	murder	armed robbery	robbery	burglary	theft
mean Y_{DWE}	3.879	0.986	2.300	7.350	19.135
mean $Y_{DesInventar}$	3.542	0.550	1.932	9.007	22.531
Panel A: Categorical measure of natural disaster and entry of new papers					
low	-0.126*	0.081**	0.008	0.276	0.640
	[0.069]	[0.039]	[0.091]	[0.214]	[0.528]
medium	-0.062	0.184***	0.079	0.348*	0.389
	[0.068]	[0.056]	[0.076]	[0.179]	[0.509]
high	-0.052	0.212***	0.158	0.937***	0.784
	[0.099]	[0.059]	[0.147]	[0.296]	[0.659]
new papers	0.003	0.027*	0.013	0.083	0.207
	[0.029]	[0.015]	[0.049]	[0.118]	[0.291]
new papers*low	-0.010	0.009	0.028	-0.290	-1.818***
	[0.024]	[0.016]	[0.037]	[0.241]	[0.300]
new papers*medium	0.019	-0.007	-0.090*	-0.157	-1.519***
	[0.054]	[0.015]	[0.053]	[0.129]	[0.363]
new papers*high	-0.079	-0.011	-0.036	-0.272	-1.351*
	[0.062]	[0.030]	[0.088]	[0.254]	[0.735]
Panel B: Death toll measure of natural disaster and entry of new papers					
low	-0.113	0.026	0.018	0.334	1.070
	[0.077]	[0.028]	[0.079]	[0.244]	[0.773]
medium	0.033	0.025	-0.000	0.506**	0.781
	[0.063]	[0.024]	[0.075]	[0.208]	[0.479]
high	0.370***	0.063	0.336***	0.443	1.260*
	[0.123]	[0.043]	[0.127]	[0.331]	[0.674]
new papers	-0.019	-0.004	0.024	0.068	0.745
	[0.034]	[0.015]	[0.050]	[0.116]	[0.508]
new papers*low	-0.034	0.006	-0.035	-0.247**	-2.015**
	[0.044]	[0.014]	[0.052]	[0.120]	[0.801]
new papers*medium	-0.063	-0.012	-0.118*	-0.240	-1.867**
	[0.038]	[0.017]	[0.062]	[0.149]	[0.876]
new papers*high	-0.181***	-0.072**	-0.314***	-0.576***	-1.891***
	[0.061]	[0.030]	[0.071]	[0.207]	[0.684]
Panel C: Frequency measure of natural disaster and entry of new papers					
1 disaster (f1)	-0.046	0.014	-0.007	0.461**	0.771
	[0.060]	[0.019]	[0.062]	[0.185]	[0.501]
>= 2 disasters (f2)	0.128	0.059*	0.112	0.419	1.383*
	[0.100]	[0.035]	[0.111]	[0.285]	[0.780]
new papers	-0.019	-0.003	0.025	0.064	0.723
	[0.035]	[0.015]	[0.051]	[0.116]	[0.503]
f1* newpapers	-0.069*	-0.010	-0.090	-0.328***	-2.119***
	[0.039]	[0.014]	[0.063]	[0.095]	[0.710]
f2* newpapers	-0.059	-0.013	-0.126*	-0.210	-1.742*
	[0.043]	[0.018]	[0.065]	[0.177]	[0.908]

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Crime response to disasters and elections: Robustness checks (DWE sample)

	(1)	(2)	(3)	(4)	(5)
Y	murder	armed robbery	robbery	burglary	theft
Low	0.059	0.092	0.253*	0.487	-0.212
	[0.134]	[0.069]	[0.131]	[0.474]	[1.091]
Medium	-0.037	0.079	-0.071	0.330	-0.382
	[0.100]	[0.065]	[0.102]	[0.217]	[0.643]
High	-0.134	0.056	-0.344**	0.169	-1.259
	[0.135]	[0.086]	[0.148]	[0.339]	[0.929]
Years to election	0.053***	0.006	0.055***	0.220***	0.455***
	[0.018]	[0.012]	[0.020]	[0.056]	[0.114]
Election*low	-0.081*	-0.005	-0.107**	-0.175	-0.045
	[0.048]	[0.024]	[0.045]	[0.171]	[0.412]
Election*medium	-0.000	0.049	0.051	-0.030	0.057
	[0.039]	[0.035]	[0.038]	[0.094]	[0.289]
Election*high	0.058	0.066	0.233***	0.295*	0.710
	[0.054]	[0.043]	[0.078]	[0.171]	[0.439]
Share of state development expenditure	-6.466***	0.537	-1.846*	3.860*	-5.892
	[0.874]	[0.410]	[0.988]	[2.257]	[5.382]
Literacy	-0.010	0.001	-0.008	-0.015	0.071
	[0.009]	[0.007]	[0.014]	[0.033]	[0.051]
1 period lagged police strength per km^2	-3.368***	-1.567*	-6.479***	-14.769***	-6.774
	[0.967]	[0.843]	[1.509]	[3.332]	[9.421]
Political competition	-2.161***	-0.701***	-4.930***	-8.815***	-7.714***
	[0.343]	[0.226]	[0.530]	[1.151]	[2.314]
Low density district dummy	0.635*	0.069	0.380	1.617*	-2.619
	[0.329]	[0.267]	[0.487]	[0.948]	[2.356]
Moderate density district dummy	0.148	0.284**	-0.030	-0.358	-1.180
	[0.188]	[0.111]	[0.241]	[0.531]	[1.226]
Constant	10.904***	2.346***	9.700***	20.545***	38.323***
	[0.987]	[0.442]	[1.144]	[2.332]	[4.564]
Observations	3357	3357	3357	3357	3357
R^2	0.269	0.388	0.293	0.547	0.413
Number of districts	228	228	228	228	228

Notes: Time dummies are also included.

Table 8: Crime response to disasters and entry of papers: Robustness checks (DWE sample)

Low	-0.121*	0.078**	0.003	0.252	0.639
	[0.069]	[0.039]	[0.089]	[0.207]	[0.526]
Medium	-0.052	0.181***	0.076	0.322*	0.392
	[0.068]	[0.056]	[0.074]	[0.176]	[0.507]
High	0.031	0.214***	0.207	0.960***	0.879
	[0.100]	[0.058]	[0.146]	[0.289]	[0.658]
New papers	-0.007	0.028*	0.011	0.092	0.199
	[0.026]	[0.014]	[0.047]	[0.116]	[0.293]
New papers*low	-0.007	0.009	0.031	-0.285	-1.813***
	[0.023]	[0.016]	[0.035]	[0.233]	[0.295]
New papers*medium	0.021	-0.007	-0.090*	-0.161	-1.518***
	[0.052]	[0.015]	[0.054]	[0.124]	[0.360]
New papers*high	-0.075	-0.010	-0.030	-0.261	-1.343*
	[0.060]	[0.030]	[0.090]	[0.264]	[0.725]
Share of state development expenditure	-6.418***	0.543	-1.793*	4.176*	-5.718
	[0.857]	[0.404]	[0.983]	[2.220]	[5.519]
Literacy	-0.011	0.000	-0.010	-0.019	0.068
	[0.009]	[0.007]	[0.014]	[0.034]	[0.053]
1 period lagged police strength per km^2	-3.499***	-1.658**	-6.848***	-15.401***	-7.921
	[0.966]	[0.840]	[1.522]	[3.318]	[9.370]
Political competition	-2.122***	-0.712***	-4.902***	-8.704***	-7.238***
	[0.345]	[0.225]	[0.533]	[1.150]	[2.275]
Low density district dummy	0.660**	0.084	0.412	1.738*	-2.350
	[0.331]	[0.270]	[0.491]	[0.945]	[2.334]
Moderate density district dummy	0.163	0.293***	-0.009	-0.287	-1.028
	[0.190]	[0.111]	[0.243]	[0.534]	[1.228]
Constant	11.051***	2.431***	10.035***	21.139***	39.508***
	[1.000]	[0.445]	[1.159]	[2.329]	[4.539]
Observations	3357	3357	3357	3357	3357
R^2	0.267	0.387	0.288	0.544	0.418
Number of districts	228	228	228	228	228

Notes: Time dummies are also included.

Table 9: District fixed effect regression of crime on natural disasters in the original districts

Y=	murder	armed robbery	robbery	burglary	theft
Mean	3.894	1.211	2.352	7.262	19.039
	(1)	(2)	(3)	(4)	(5)
Panel A: Effect of elections					
low	0.122	0.155*	0.421***	1.318**	0.235
	[0.145]	[0.087]	[0.148]	[0.535]	[1.212]
medium	-0.075	0.111	0.065	0.637***	-0.274
	[0.086]	[0.072]	[0.108]	[0.236]	[0.650]
high	-0.334**	-0.023	-0.429**	0.136	-0.740
	[0.153]	[0.088]	[0.171]	[0.425]	[1.066]
years to election	0.045**	0.003	0.059**	0.250***	0.487***
	[0.022]	[0.015]	[0.026]	[0.071]	[0.158]
election*low	-0.112**	-0.013	-0.135***	-0.395**	-0.044
	[0.050]	[0.030]	[0.050]	[0.190]	[0.482]
election*medium	0.001	0.040	0.009	-0.161	-0.101
	[0.039]	[0.032]	[0.043]	[0.099]	[0.303]
election*high	0.074	0.090**	0.229***	0.395*	0.553
	[0.054]	[0.043]	[0.079]	[0.210]	[0.493]
Panel B: Effect of entry of papers					
low	-0.121	0.141***	0.137	0.630***	0.900*
	[0.074]	[0.044]	[0.087]	[0.209]	[0.464]
medium	-0.069	0.228***	0.152*	0.290	-0.174
	[0.061]	[0.049]	[0.083]	[0.201]	[0.583]
high	-0.102	0.192***	0.127	1.080***	0.837
	[0.109]	[0.064]	[0.145]	[0.355]	[0.742]
new papers	0.016	0.040	0.013	-0.002	-0.131
	[0.055]	[0.026]	[0.082]	[0.175]	[0.432]
new papers*low	-0.033	-0.017	-0.030	-0.289	-1.009*
	[0.038]	[0.019]	[0.062]	[0.200]	[0.514]
new papers*medium	-0.017	-0.056**	-0.111*	0.003	-0.587
	[0.047]	[0.024]	[0.065]	[0.151]	[0.430]
new papers*high	-0.119*	-0.000	-0.039	0.012	-0.495
	[0.061]	[0.032]	[0.080]	[0.240]	[0.688]
Observations	2671	2671	2671	2671	2671
R^2	0.285	0.422	0.323	0.585	0.392
Number of districts	117	117	117	117	117

Notes: *** p<0.01, ** p<0.05, * p<0.1.

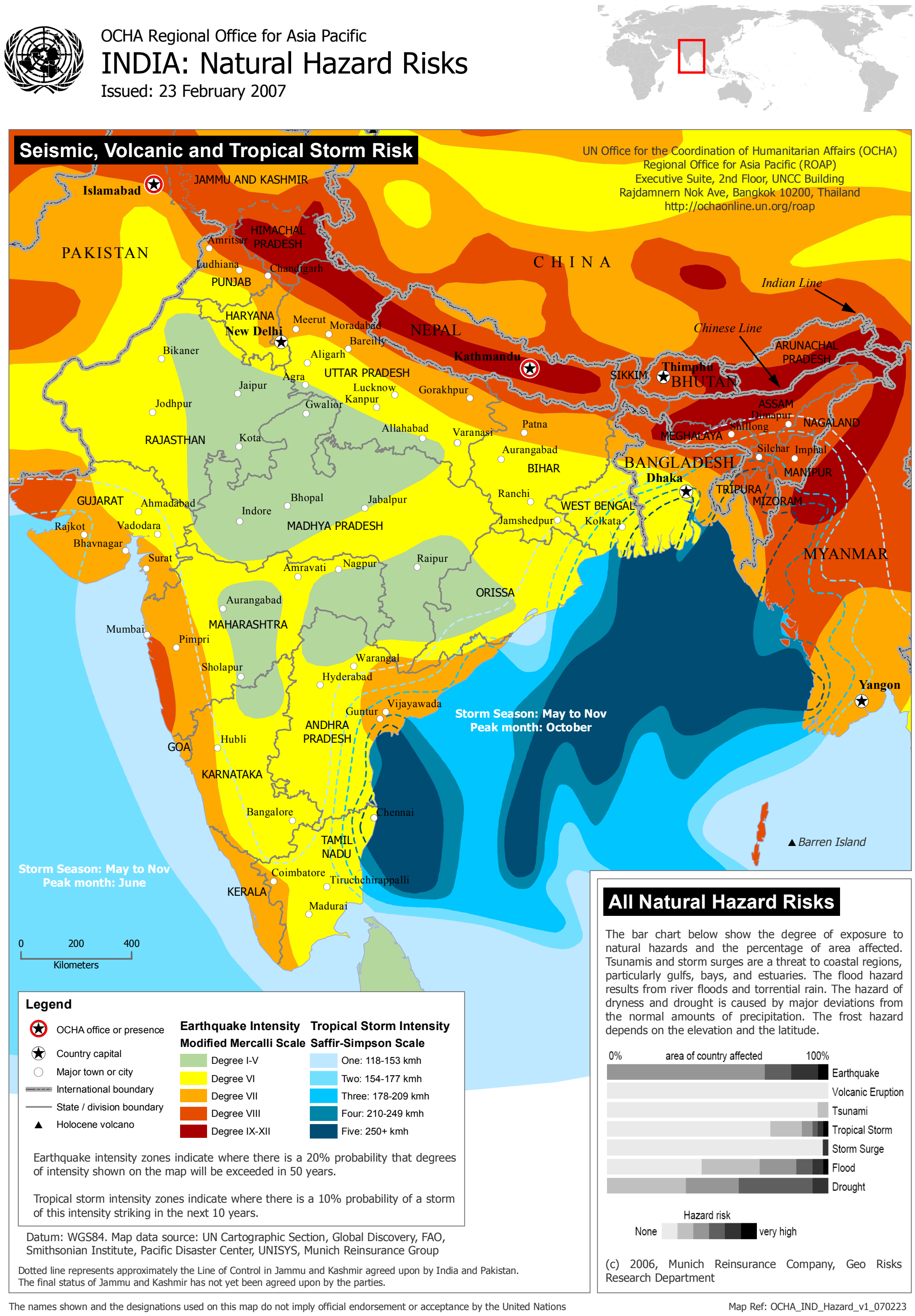

Figure 1: India disaster risk

Figure 2: Murder rates and natural disasters (death toll per 100,000)

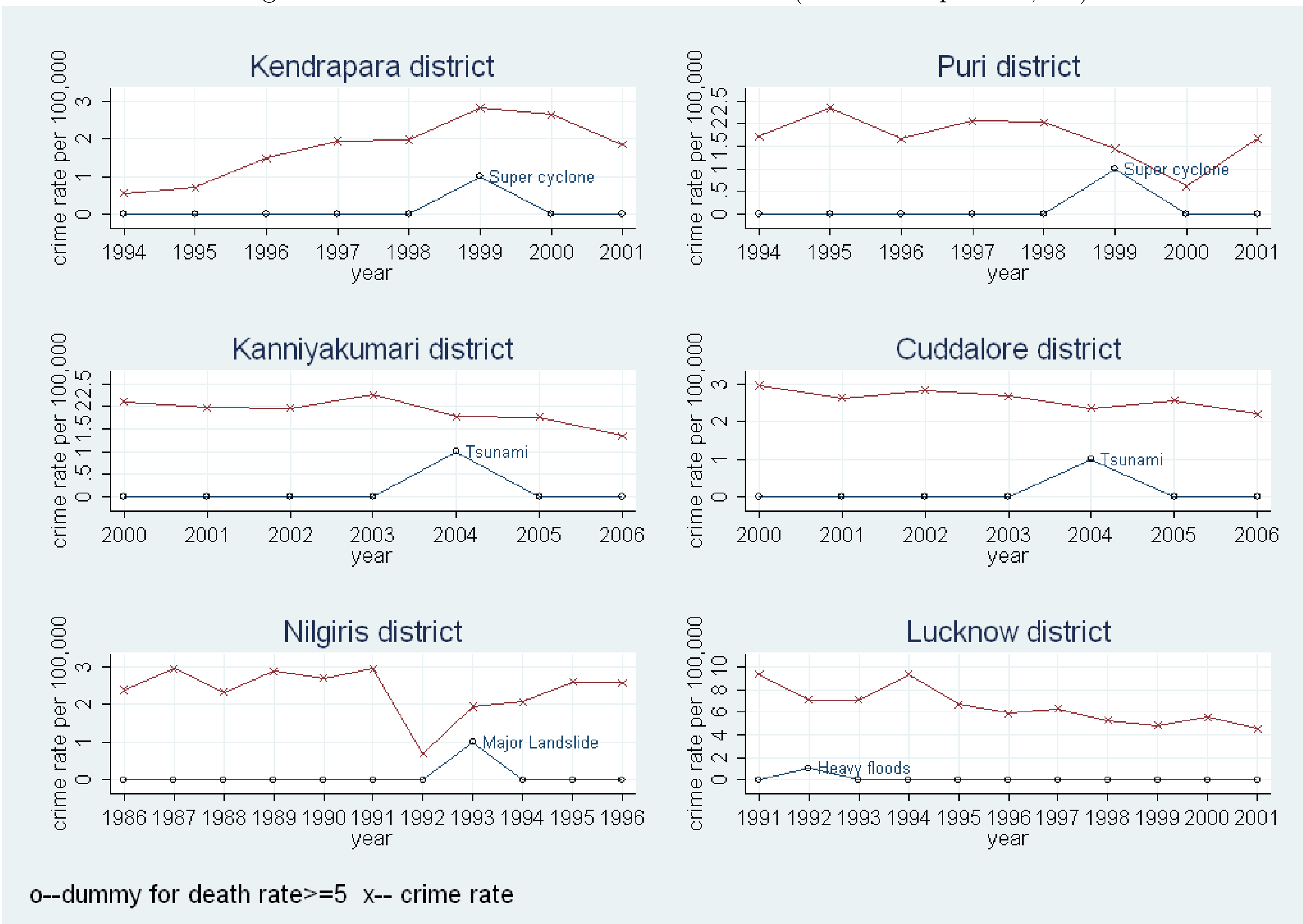

Figure 3: Armed robbery rates and natural disasters (death toll per 100,000)