Do natural disasters increase the risk of communal violence in India? A natural experiment.

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ABSTRACT

This article aims to test whether the likelihood of low-level violence increases in areas that have recently been hit by climate-related natural disasters. This is done by comparing the frequencies of Hindu-Muslim riots in disaster-affected areas in India (1980-1995) to the frequencies in the same areas before disaster struck. In this sense, the analysis takes the form of a natural experiment (or a series of natural experiments), where it is assessed whether natural disasters display a systematic tendency of affecting the likelihood of riots in disaster-affected areas. For conducting the analysis, geo-referenced data containing information on spatial and temporal distance from disaster areas to riots is used. The results indicate a weak short-term tendency of more Hindu-Muslim riots in disaster-affected areas, but the effect is too weak to draw any conclusions about a systematic relationship.

Paper prepared for INDNOR workshop, PRIO, Oslo, 14-15.06.2011
Work in progress: please do not cite.

1. Introduction

The rates of climate-related natural disasters have increased in India and worldwide over recent decades, and evidence is accumulating that climate changes can be expected to further increase the frequency and severity of extreme weather events, which are the triggers of such disasters (Brown et al., 2008, Knutson et al., 2010, Wigley, 2009, Aalst, 2006). Large-scale urbanization also appears likely to contribute to increasing the rates of natural disasters, as it increases the number of people that live in areas which are exposed to natural hazards. If suggestions that environmentally induced adversity increase the risk of large-scale violence in affected areas (Burke et al., 2009, Homer-Dixon, 1999, Miguel et al., 2004, Nel and Righarts, 2008) are correct, then existing trends in disaster frequencies give reason for concern in themselves. These concerns are further deepened when taking the anticipated effects from climate changes into account.

This article aims to test whether rates of Hindu-Muslim riots in India have displayed systematic tendencies of increasing or decreasing after climate-related natural disasters such as floods, storms and droughts in the past (1980-1995). The analysis takes the form of a natural experiment (or, rather, summarizing a series of natural experiments), where the rates of violence in areas that have been affected by disasters are compared to the rates in the same areas before disaster struck. This is done using geo-referenced data with high temporal resolution, where the geographic distances and number of days from each disaster area to each incidence of violence are measured. These data are used for assessing whether the probability of observing violence in disaster-affected areas is different than it was in the same areas before disaster struck.

At first glance, the results appear to support the proposition that natural disasters should increase the risk of communal violence. However, this impression is driven by what appears to be a special case of reverse causality: the number of riots in affected areas is not unusually high after disasters, but it appears to be unusually low just *before*. Unlike earthquakes and tsunamis, most climate-related natural disasters, such as storms and floods, offer some forewarning, mainly via weather forecasts. An impending disaster appears to reduce people’s propensity to engage in riots, and unless this is controlled for, the return to normal rates can be confused with a significant post-disaster increase. Once this effect is taken into account by imposing a 20-day lag on the pre-disaster comparison periods, the riot-inducing effect of climate-related natural disasters largely evaporates. The results still display a certain tendency of more Hindu-Muslim riots after disasters than before, but the effect is short-lived, weak and is not robust to specification tests. Further, the tendency is short-lived: for the full year after disaster, there is a consistent tendency of fewer riots than the year before disaster struck.

The remainder of the article is structured as follows: the next sections discuss what a disaster is and introduce two main, contradictory approaches to how disasters can be expected to affect the risk of violent conflict. These are disaster sociology, which expects a reduced likelihood of communal violence, and the environmental security perspective, where adversity is expected to generate more conflict. Following this, the data and method is presented before proceeding to the results and conclusion.

2.1 What is a disaster?

Environmental shocks in this study are defined as severe deviations from natural phenomenas' ordinary patterns which lead to substantial destruction and/or loss of life. Although human-induced phenomena such as intense pollution and environmental destruction also fit this category, the focus in this article is on shocks that have been triggered by natural hazards (such as storms, droughts or floods). If they are sufficiently severe, these shocks are labeled as natural disasters.

Although natural hazards serve as triggers and exposure to these hazards is a necessary condition, the main component in the disaster triangle is human vulnerability. Vulnerability is mainly - but not exclusively - a social construct, which is related to institutional strength, economic conditions and, not least, political priorities. For example, introducing and enforcing strict building codes and preventing habitation in high-exposure areas can substantially reduce the likelihood that natural hazards turn into disasters. Similarly, effective warning and evacuation procedures can also substantially reduce the amount of damage caused.

This can be illustrated by the different impacts of the cyclones Sidr and Nargis. Sidr was a category 5[1] cyclone which struck a densely populated and highly exposed part of Bangladesh in May 2008. It caused between 3,500 and 10,000 fatalities. One may only speculate on what the fatality rate had been if the Bangladeshi government had not organized the evacuation of

[1] Measured on the Saffir-Simpson hurricane scale, which ranges from 1-5.

around two million people from the impact area before the cyclone made landfall. Cyclone Nargis struck unprepared Burma in November 2007, and led to the death of approximately 140,000 people, despite being less powerful than Sidr. Hence, although it is nature that triggers disasters, institutions and infrastructure appear crucial for determining whether hazards turn into disasters.

This has clear implications for how disasters are measured in analyses. In particular for cross-sectional time series analyses, differences in vulnerability across time and units can cause problems for analysis. This study, although focused on a single country and a limited time period, attempts to take this into account by using disaster data where actual damage rather than physical characteristics are used as inclusion criteria. These are derived from the EM-DAT Disaster database (CRED 2007) and are further introduced in section 3.

2.2 Why would disasters affect conflict risk?

I distinguish between two main ways disasters may affect the risk of violent conflict. The first, 'push'-factors, work mainly on the individual and group levels. The second, 'pull'-factors are factors that influence external constraints against the use of violence. The boundaries between these are fluent and they should be seen more as heuristic devices than objective differences.

2.2.1 Push

‘Push’ factors are located at the individual and group levels, and refer to disaster-induced changes in the likelihood that individuals and groups will resort to violence. They may both increase and reduce the probability of violence. Case studies have found that environmental stress increases the risk of violent conflict (Homer-Dixon, 1999, Kahl, 2006), while studies aimed specifically at analyzing post-disaster behavior have found that the common fate shared by disaster victims tends to increase social cohesion and reduce conflict risk (Fritz, 1996, Quarantelli and Dynes, 1976). Despite the different outcomes, these approaches are not necessarily mutually exclusive. The former studies are conducted in developing countries, while the latter are mainly from western, industrialized states – primarily the US. Hence, these states are not where one would expect to find violent civil conflict, as democratic institutions are mostly able to settle conflicts without any part resorting to violence.

The common fate that is reported to unify disaster victims may be a double-edged sword: if disaster exposure follows social or ethnic divides, then this increased cohesion may contribute to exacerbating between-group conflicts. If all are affected equally, on the other hand, the opposite may happen. Aside from this suggestion, which has found extensive support within disaster sociology (Fritz, 1996), most theoretical connections between disasters and the risk of violence emphasize an increased risk of violence after disasters. In particular, absolute and relative scarcity of important resources, including perceived misdistribution, has been suggested as a potential connection between environmentally induced adversity and violent conflict (Homer-Dixon, 1999).

Further, it has been suggested that the emotional trauma of disaster can cause those affected to be more likely to resort to violence. This appears particularly plausible in situations where a single group or actor can be perceived as responsible for the adversity, either by triggering the adversity, contributing to make it more severe or preventing a just distribution of aid and reconstruction efforts after the disaster. This form of aggression appears particularly likely to be directed against political authorities, but may in principle be directed against any individual, group or institution that is perceived blamable. This can be illustrated by the killings of ‘witches’ who were thought responsible for crop failure and bad weather in the 15th century Europe, or in current rural Tanzania (Behringer, 2010:128ff, Miguel, 2005). Such sentiments, possibly combined with political actors that seek to improve on their own position by stoking intergroup conflict (Baechler, 1998, Homer-Dixon, 1999:136), can provide yet another ‘push’ factor connecting natural disasters and the risk of violent conflict.

2.2.2 Pull

‘Pull’ factors refer to disaster-induced changes external to the actors, such as changed state capabilities or other changes in the opportunity structure. As with ‘push’-factors, these may both increase and reduce the likelihood that violence erupts. State capacity is perhaps the most important factor here: as disasters are likely to overstrain authorities’ ability to enforce rule of law and provide aid, actors that aim to strike a competing ethnic group or instigate an insurgency become more able to do so (Drury and Olson, 1998, Homer-Dixon, 1999:133, Wilkinson, 2006). That being said, the ability to instigate an insurgency can also be hampered by disasters, as damaged infrastructure may also prevent insurgents’ freedom of action. Further, the pool of recruits may be diminished as people who might otherwise participate may be overburdened with the effect of the disaster, leaving no time or energy to participate in fighting.

2.3 Summary

The arguments presented above imply that if disasters increase the risk of violence, the risk appears greatest in developing countries with unstable political institutions and existing tensions between social groups. If violence is triggered, it is not necessarily framed within the context of disaster: several of the suggested theoretical connections imply that eruptions of violence may be triggered within existing conflicts, or erupt due to disaster-induced changes in the opportunity structure. Only studying conflicts where the discourse centers around recent disasters would therefore risk missing relevant cases.

The theoretical arguments do not give explicit suggestions for where and when the risk of post-disaster violence is most likely to be affected. If factors such as shock, frustration, lack of governmental intervention or unity in common destiny are driving the risk of violence, the effects should be expected to be most evident in and near the disaster area in the first period after disaster has struck. This time-space domain will be the main focus of the analysis in this study.

3. DATA

Hindu-Muslim riots in this dataset are violent confrontations between two or more communally identified groups representing Hindus and Muslims, recorded mainly from the Mumbai edition of the Times of India (Wilkinson, 2006:255). The data are reported to be cross-checked against a number of other sources to ensure that reporting bias is avoided (ibid:248f). As outlined in the theory section, natural disasters have been suggested as likely triggers of intergroup conflict (Baechler, 1998, Homer-Dixon, 1999:136). In India, such a connection appears likely to increase the risk of conflict between Hindus and Muslims. This variable is included to test whether this is the case.

Coordinates were assigned based on the location reported in the dataset (village, town or city), and coordinates were assigned using GeoMaker (2009). Of 733 events, 30 were excluded as the location could not be positively identified and two more because they were located in Pakistan. Data from 1980 until the set ends in 1995 are used. The riots occur in most of India, although the concentration is greatest in Gujarat and the states along the western coast (illustrated in Figure 1, below).

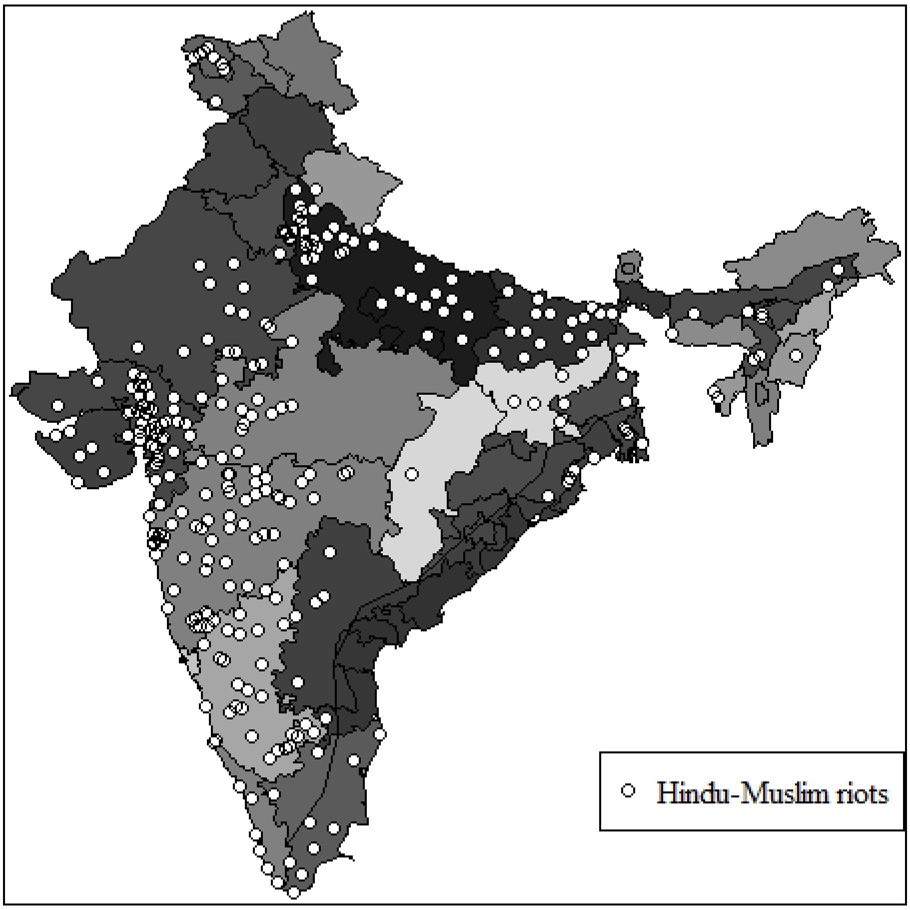
Compared to civil war, Hindu-Muslim riots are far more common and have substantially lower start-up costs. This lower ‘activation threshold’ should make such forms of violence more sensitive to changes in the motivations, levels of grievances and feasibility for conducting violence, thereby making systematic trends between disasters and the likelihood of violence easier to detect. This does, however, come at the cost of not knowing to what extent findings on these forms of violence are transferable to other forms of violence, such as civil war[2]. A second issue relating to transferability of findings in this study is, obviously, whether the findings are valid for other countries than India.

The data on natural disasters are derived from the EM-DAT Emergency events database (CRED, 2007) include 118 climate-related natural disasters in India for 1980-1995. Floods constitute more than half the reported disasters, storms about a quarter, while landslides and extreme temperatures cover almost another quarter. Two droughts, one wildfire and one tidal wave are also reported. The disasters are represented as geo-referenced polygons covering the areas that are reported to have been affected by each disaster.

The EM-DAT database includes only severe weather events that are categorized as disasters by causing ten or more deaths, affecting 100 or more persons, leading to the declaration of a state of emergency and/or a call for international assistance. This implies dependence on a relatively arbitrary cutoff point for what is considered a disaster, but at the same time ensures that only events that actually caused substantial damage are included. This is considered as an advantage as the vulnerability to extreme weather events can vary substantially across time and space. The disasters are geo-referenced as polygons covering all locations reported to have been affected by each disaster[3]. The geographic distribution of disasters is illustrated in Figure 1, below.

[2] That being said, it should be recalled that Hindu-Muslim riots in India have turned extremely deadly on several occasions, indicating that studying these riots is merited in itself.
[3] The geo-referencing was done by Jan Ketil Rød and assistants.

Figure 1: Distribution of Hindu-Muslim riots and climate-related natural disasters in India, 1980-1995



Darker map shading indicates more disasters

In order to assess the robustness of the findings and gauge whether there is a difference in risk in rich or poor and densely or sparsely populated areas, grid-resolution data on population size per 1*1 degree-sized grid-cell as well as 'gross cell product' (Nordhaus et al., 2006) is used. The tests consist of running the analyses without the upper or lower quartiles of economy and population per grid cell (measured in the cell where the violence occurs). A further robustness test is conducted by running the analysis without the cold season, pre-monsoon, monsoon and post-monsoon.

4. METHOD

For the analyses, a dataset with all combinations of Hindu-Muslim riots and disasters (dyads) is constructed, and the temporal and spatial distances from each riot to each disaster are then measured. This yields roughly 82 000 dyads in, although the vast majority of these are not directly relevant for analysis due to that the geographic distance within dyads is too great, or that the violence took place before the disaster. However, as will be outlined in the following, the 'irrelevant' dyads can serve as interesting bases of comparison.

By assuming that disasters may affect the risk of violence but not vice versa, these data can be used as the basis of a natural experiment where it is investigated if the likelihood of observing violence in disaster-affected areas immediately after disasters is systematically different from immediately before. This is done by first counting the number of violent events that occur within 1 to x days after a disaster, and y kilometers or less from the disaster area. Second, this is compared to the number of violent events that occurred within 1 to x days and y kilometers *before* the disaster. Given that climate-related natural hazards often can be anticipated some days in advance there is, however, a risk that imminent hazards may affect the likelihood of riots. The post-disaster riot distributions are therefore also compared to pre-disaster distributions that are lagged 20 days. This lag period is considered sufficiently long that there should be no direct effect on the likelihood of riots this long before the hazard strikes, while it is still expected to be short enough that the pre-disaster periods remain comparable to the post-disaster periods.

For example, the number of incidences within 25 kilometers and 30 days or less after a disaster is compared to the number of incidences in the same area for the last 30 (or 21-50 if lagged) days before disaster struck. This procedure is repeated for all dyads where the temporal and spatial distances fall within x days and y kilometers. A number of different x and y thresholds are tested. For a frame of 25 kilometers and 30 days at kilometer-day resolution, there are 25*30=750 possible space-time 'locations'. For each 'location', the number of violent events taking place there is recorded, and the pre- and post-disaster distributions are compared using the t-test. The tests are run for combinations of 10, 20, 30, 50, 90, 140, 180 and 360 days and 10, 25, 50, 100 and 250 km, yielding 40 time-distance combinations to be tested for each type of violence.

The economic situation and population size in an area may also be suspected of affecting the likelihood of post-disaster violence. For additional robustness excluding the upper and lower quartiles on 'grid cell product' and population size (measured in the cell where the violence happens) is also tested. Religious festivals can trigger interreligious riots in India. If there is a systematic tendency that this happens, and these festivals happen in seasons where disasters are more frequent, this may potentially cause a spurious relation between disasters and violence. In order to control for this – and any other season-dependent spuriousness – all analyses are also tested without the cold season (December-March), the pre-monsoon (April-May), the monsoon (June-August) and the post-monsoon (September-November).

5. RESULTS

Figure 2: Distribution of Hindu-Muslim riots before and after disasters

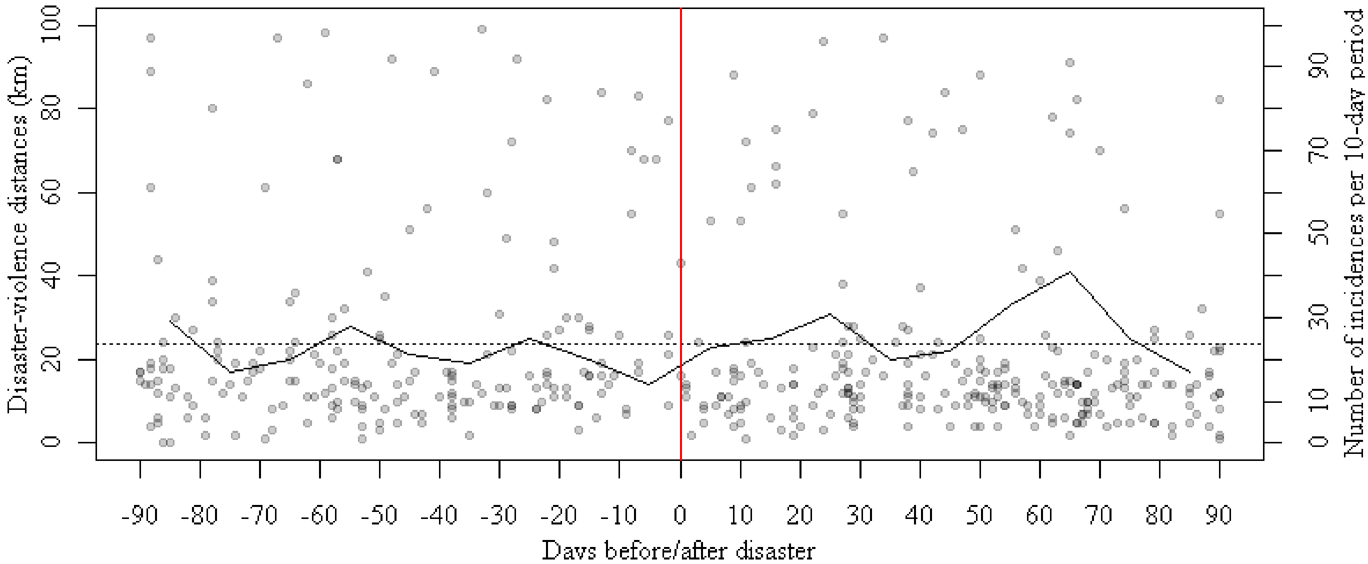


Figure 2 illustrates the distribution of Hindu-Muslim riots that happened 100 km or less from a disaster area, before and after natural disasters. The vertical red line indicates the time of disaster onset for each of the 118 disasters analyzed in this study. The area to the left of this line is the last 90 days before the disasters, while the area on the right-hand side is the corresponding period after. As indicated on the left x-axis, the lower in the figure the grey dots which symbolize riots are, the closer they are to the disaster area in question. Darker colors on the dots indicate space/time-distance overlap between riots. Finally, the trend line indicates the number of riots for each 10-day period, while the horizontal dotted line indicates the mean frequency for the entire period (23.9 incidences).

The clustering of points at short geographical distances suggests a tendency that disasters and riots happen in the same areas. This does, however, not necessarily indicate any direct relation between them. Rather, two factors are likely to be driving this tendency. First, the disasters are coded as polygons, so riots occurring within them are measured with very short distances[4],

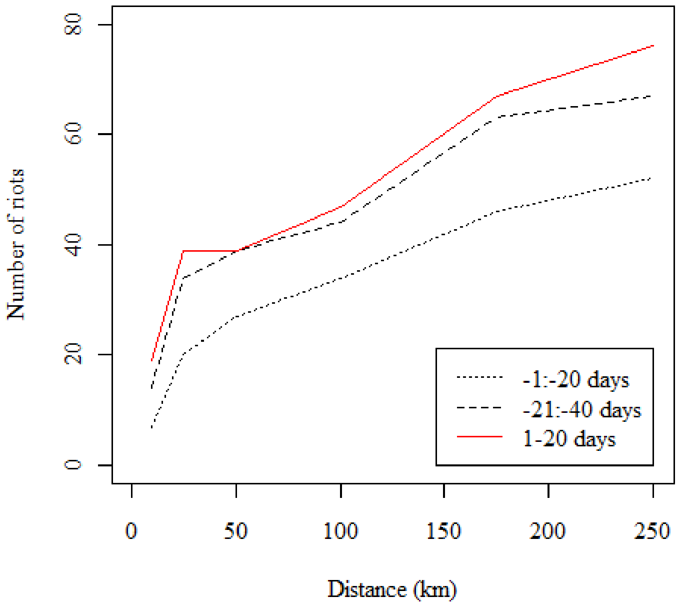
[4] The distances are not quite zero as they were measured from control points inside, near the edge of the polygons rather than the polygon edge itself.

thereby yielding a higher share of short-distance riots. Second, riots and disasters have a commonality in that both are more likely to happen in densely populated areas. This makes them likely to occur in the same areas, irrespective of whether disasters contribute to triggering riots.

As illustrated by the trend line, the number of riots is somewhat higher after disasters than before. However, the perhaps most noteworthy feature is perhaps the relative absence of riots near the disaster areas immediately *before* the disasters. As the riots cluster near the disaster-affected areas, the mean frequency per 10-day period is not much affected by restricting the maximum geographical distance analyzed to 30 km: it drops from 23.9 to 20. However, during the last 10 days before disasters only eight riots happen within 30 km. The first periods after disasters, on the other hand, are at or slightly above the mean.

As have been mentioned, climate-related natural disasters often – but not always – offer a certain forewarning, notably through weather forecasts. The drop in riot frequency in areas that are about to be hit by such disasters suggest that a certain sense of reverse causality may be at play here: either by gradual manifestation (for example rising temperatures signaling a heat wave or heavy precipitation before a flood) or actual warning, the disasters seem to affect the risk of riots before their actual onsets. In order to assess whether disasters contribute to triggering riots, this must be taken into account in the analysis, as a comparison of the immediate post-disaster periods to the immediate pre-disaster periods is likely to be interpreted as an increase in riot risk when it actually is a return to normal rates. Figure 3 illustrates the number of riots at different distances from the disaster areas, within 20 days before and after disasters, as well as 21-40 days before the disasters. The trend line for the first 20 days before disasters stands clearly out with fewer riots, while there are minor differences between the post-disaster and lagged pre-disaster trend lines. This strengthens the suspicion that looming climate-related disasters contribute to reducing the likelihood of Hindu-Muslim riots.

Figure 3. Number of Hindu-Muslim riots before and after disasters



Below, a more formal test of the difference in likelihood of observing riots before and after disasters is presented. A positive sign indicates a higher frequency after disasters than before. Values that are significant at the 5% level are marked with bold characters, while values that fall within the 10% level are marked with italics.

Table 1: T-values for difference in frequencies of Hindu-Muslim riots before and after disasters

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0-25 Km	**3.281 (p=0.001),** n=6/23	**2.556 (p=0.011),** n=20/39	**3.057 (p=0.002),** n=37/67	**2.617 (p=0.009),** n=69/102	**3.473 (p=0.001),** n=142/204	**3.131 (p=0.002),** n=213/280	*1.831 (p=0.067),* n=288/332	-0.665 (p=0.506), n=596/574
0-50	**2.744 (p=0.006),** n=8/23	1.502 (p=0.133), n=27/39	**1.965 (p=0.05),** n=49/70	*1.845 (p=0.065),* n=83/108	**2.608 (p=0.009),** n=167/217	**2.3 (p=0.021),** n=250/303	0.85 (p=0.395), n=337/359	**-2.465 (p=0.014),** n=722/633
0-100	*1.917 (p=0.055),* n=14/26	1.459 (p=0.145), n=34/47	*1.882 (p=0.06),* n=59/81	*1.821 (p=0.069),* n=99/126	**2.47 (p=0.014),** n=193/244	**2.525 (p=0.012),** n=287/350	1.287 (p=0.198), n=382/418	**-2.384 (p=0.017),** n=824/731
0-175	*1.679 (p=0.093),* n=24/37	**1.992 (p=0.046),** n=46/67	*1.722 (p=0.085),* n=87/111	**2.003 (p=0.045),** n=138/173	**2.978 (p=0.003),** n=270/343	**3.27 (p=0.001),** n=391/487	**2.214 (p=0.027),** n=502/574	**-1.962 (p=0.05),** n=1115/1025
0-250	**2.408 (p=0.016),** n=25/45	**2.135 (p=0.033),** n=52/76	*1.838 (p=0.066),* n=96/123	**2.382 (p=0.017),** n=151/195	**3.417 (p=0.001),** n=300/389	**3.973 (p<0.001),** n=432/556	**2.876 (p=0.004),** n=563/663	*-1.729 (p=0.084),* n=1268/1183

Table 1 summarizes the t- and p-values derived from testing whether the probability of observing Hindu-Muslim riots within specified time-distance frames *before* disasters are different from the probability within similar frames *after* disasters. It is worth noticing is that for almost all the time-distance combinations tested there are more riots in the periods after disasters than the periods before (indicated by positive t-values). This also applies, although to a more limited extent to Table 2, where a 20-day lag is imposed on the pre-disaster comparison periods.

Table 2. T-values for difference in frequencies of Hindu-Muslim riots before and after disasters, using a 20-day lag on the pre-disaster distributions.

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0-25 Km	0.988 (p=0.324), n=17/23	0.607 (p=0.544), n=34/39	*1.74 (p=0.082),* n=49/67	1.292 (p=0.196), n=85/102	**2.815 (p=0.005),** n=153/204	*1.682 (p=0.093),* n=243/280	**1.961 (p=0.05),** n=285/332	-1.112 (p=0.266), n=611/574
0-50	0.152 (p=0.879), n=22/23	0 (p=1), n=39/39	1.274 (p=0.203), n=56/70	0.711 (p=0.477), n=98/108	**2.061 (p=0.039),** n=177/217	1.059 (p=0.289), n=278/303	0.929 (p=0.353), n=335/359	**-2.945 (p=0.003),** n=740/633
0-100	0.142 (p=0.887), n=25/26	0.318 (p=0.75), n=44/47	1.341 (p=0.18), n=65/81	0.851 (p=0.395), n=113/126	**2.014 (p=0.044),** n=202/244	1.414 (p=0.157), n=314/350	1.47 (p=0.141), n=377/418	**-2.904 (p=0.004),** n=845/731
0-175	-0.458 (p=0.647), n=41/37	0.354 (p=0.723), n=63/67	1.347 (p=0.178), n=92/111	0.551 (p=0.582), n=163/173	**2.72 (p=0.007),** n=276/343	**2.315 (p=0.021),** n=418/487	**2.533 (p=0.011),** n=492/574	**-2.43 (p=0.015),** n=1137/1025
0-250	0.107 (p=0.915), n=44/45	0.758 (p=0.448), n=67/76	1.623 (p=0.105), n=99/123	0.622 (p=0.534), n=183/195	**3.214 (p=0.001),** n=305/389	**2.902 (p=0.004),** n=464/556	**3.086 (p=0.002),** n=556/663	**-2.226 (p=0.026),** n=1293/1183

In order to avoid the reverse causality-problem, the results in Table 2 are calculated using a 20-day lag on the pre-disaster periods (e.g. the period covering the period -1 to -10 days (before disaster) is replaced with -21 to -30). This substantially weakens the results relative to Table 1. The effect is, as would be expected if reverse causality is present, strongest at the shortest timeframes. For the longer time periods, notably 90 days and more, the lag period constitutes a smaller share, so they are less affected. It should also be kept in mind that the number of observations in the upper left area is substantially lower than in the lower right area since the time-distance search areas are smaller. It is therefore, for mathematical reasons, more difficult to achieve statistically significant results in the upper left area.

5.1 Robustness tests

The results have been subjected to three main sets of robustness tests: exclusion of observations based on gross cell product, population size and seasons (see appendix for detailed results). For the two former, the tests were conducted by comparing the overall results to results where the upper or lower quartiles were excluded. Excluding single seasons (cold season, pre-monsoon, monsoon and post-monsoon) was also tested. For population size and economy, the statistical significance of the results is generally weakened, as would be expected when a quarter of the observations are removed from the sample, but no major changes in the overall tendencies were observed.

The main trends hold when removing each of the seasons from the dataset, but the levels of significance are diminished – with one exception. When the pre-monsoon period (April and May) is removed, the results are strengthened substantially. In the period analyzed, six disasters happened in April and 15 in May. Both months experienced 55 riots.

One interesting tendency in the data is how all time periods except 1-360 days (and 1-180 days when the post-monsoon season is excluded) consistently experience more riots after than before disasters. The difference is, however, rarely large enough to reach statistical significance. Further, when comparing the first 360 days after each disaster to a similar period before (with or without a lagged pre-disaster period), the post-disaster periods consistently display fewer riots than the pre-disaster periods. This suggests that to the extent natural disasters contribute to increasing the likelihood of Hindu-Muslim riots, the effect is short-lived and relatively weak.

6. CONCLUDING REMARKS

This study has tested the proposition that climate-related natural disasters are likely to increase the risk of interethnic violence in India by comparing the rates of Hindu-Muslim riots in or near disaster-affected areas before and after natural disasters. At first glance, climate-related natural disasters appear to be increasing the likelihood of Hindu-Muslim riots in India. However, the analysis reveals that this finding is caused not by unusually many riots after disasters, but rather unusually few immediately *before*. This may be explained by that people who might otherwise participate in riots may prefer to spend their time preparing or evacuating when the weather forecast has announced that a natural hazard is approaching.

The findings do indicate a tendency of more Hindu-Muslim riots after disasters than in similar periods before. One commonality for all tested specifications is, however, that although the risk of riots seems to rise somewhat in the short run, the first full year after a disaster tends to experience fewer riots than the same area experienced the year before. Thus, to the extent (if any) that climate-related natural disasters in India contribute to increasing the likelihood of Hindu-Muslim riots, the effect is weak and short-lived.

One implication of disaster sociology's claim of unity during and immediately after disasters due to the shared fate and challenges is that the risk of violence should drop and then revert to normal (or even higher) rates as the situation returns to normal. The environmental security perspective, on the other hand, seems to expect a general increase in the risk of violence during times of adversity. The finding of a weak tendency of more riots in the first months after climate-related natural disasters and then a drop in the rates in the longer term does not really support any of the two approaches. Even if climate-related natural disasters in India during the period analyzed have had some effect on the 'push' and 'pull'-factors that contribute to shaping the likelihood of interethnic violence such as Hindu-Muslim riots, the effect is not large enough to make post-disaster riot rates really stand out from other periods.

APPENDIX: RESULTS AND ROBUSTNESS TESTS.

All tables except the first employ a 20-day lag on the pre-disaster distributions.

Table 1: All observations, without lag

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0- 25 Km	**3.281** **(p=0.001),** n=6/23	**2.556** **(p=0.011),** n=20/39	**3.057** **(p=0.002),** n=37/67	**2.617** **(p=0.009),** n=69/102	**3.473** **(p=0.001),** n=142/204	**3.131** **(p=0.002),** n=213/280	*1.831* *(p=0.067),* n=288/332	-0.665 (p=0.506), n=596/574
0- 50	**2.744** **(p=0.006),** n=8/23	1.502 (p=0.133), n=27/39	**1.965** **(p=0.05),** n=49/70	*1.845* *(p=0.065),* n=83/108	**2.608** **(p=0.009),** n=167/217	**2.3** **(p=0.021),** n=250/303	0.85 (p=0.395), n=337/359	**-2.465** **(p=0.014),** n=722/633
0- 100	*1.917* *(p=0.055),* n=14/26	1.459 (p=0.145), n=34/47	*1.882* *(p=0.06),* n=59/81	*1.821* *(p=0.069),* n=99/126	**2.47** **(p=0.014),** n=193/244	**2.525** **(p=0.012),** n=287/350	1.287 (p=0.198), n=382/418	**-2.384** **(p=0.017),** n=824/731
0- 175	*1.679* *(p=0.093),* n=24/37	**1.992** **(p=0.046),** n=46/67	*1.722* *(p=0.085),* n=87/111	**2.003** **(p=0.045),** n=138/173	**2.978** **(p=0.003),** n=270/343	**3.27** **(p=0.001),** n=391/487	**2.214** **(p=0.027),** n=502/574	**-1.962** **(p=0.05),** n=1115/1025
0- 250	**2.408** **(p=0.016),** n=25/45	**2.135** **(p=0.033),** n=52/76	*1.838* *(p=0.066),* n=96/123	**2.382** **(p=0.017),** n=151/195	**3.417** **(p=0.001),** n=300/389	**3.973** **(p<0.001),** n=432/556	**2.876** **(p=0.004),** n=563/663	*-1.729* *(p=0.084),* n=1268/1183

Table 2: All observations, 20-day lag

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0- 25 Km	0.988 (p=0.324), n=17/23	0.607 (p=0.544), n=34/39	*1.74* *(p=0.082),* n=49/67	1.292 (p=0.196), n=85/102	**2.815** **(p=0.005),** n=153/204	*1.682* *(p=0.093),* n=243/280	**1.961** **(p=0.05),** n=285/332	-1.112 (p=0.266), n=611/574
0- 50	0.152 (p=0.879), n=22/23	0 (p=1), n=39/39	1.274 (p=0.203), n=56/70	0.711 (p=0.477), n=98/108	**2.061** **(p=0.039),** n=177/217	1.059 (p=0.289), n=278/303	0.929 (p=0.353), n=335/359	**-2.945** **(p=0.003),** n=740/633
0- 100	0.142 (p=0.887), n=25/26	0.318 (p=0.75), n=44/47	1.341 (p=0.18), n=65/81	0.851 (p=0.395), n=113/126	**2.014** **(p=0.044),** n=202/244	1.414 (p=0.157), n=314/350	1.47 (p=0.141), n=377/418	**-2.904** **(p=0.004),** n=845/731
0- 175	-0.458 (p=0.647), n=41/37	0.354 (p=0.723), n=63/67	1.347 (p=0.178), n=92/111	0.551 (p=0.582), n=163/173	**2.72** **(p=0.007),** n=276/343	**2.315** **(p=0.021),** n=418/487	**2.533** **(p=0.011),** n=492/574	**-2.43** **(p=0.015),** n=1137/1025
0- 250	0.107 (p=0.915), n=44/45	0.758 (p=0.448), n=67/76	1.623 (p=0.105), n=99/123	0.622 (p=0.534), n=183/195	**3.214** **(p=0.001),** n=305/389	**2.902** **(p=0.004),** n=464/556	**3.086** **(p=0.002),** n=556/663	**-2.226** **(p=0.026),** n=1293/1183

Robustness tests:

Highest gross cell product quartile excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0- 25 Km	0.345 (p=0.73), n=17/19	0.402 (p=0.688), n=28/31	1.228 (p=0.22), n=37/48	0.611 (p=0.541), n=66/73	**2.076** **(p=0.038),** n=118/151	1.389 (p=0.165), n=187/214	*1.903* *(p=0.057),* n=213/253	-0.449 (p=0.653), n=447/434
0- 50	-0.322 (p=0.747), n=21/19	-0.128 (p=0.898), n=32/31	0.737 (p=0.461), n=43/50	0.082 (p=0.935), n=77/78	1.466 (p=0.143), n=138/163	0.719 (p=0.472), n=217/232	0.927 (p=0.354), n=254/275	**-1.998** **(p=0.046),** n=543/480
0- 100	-0.452 (p=0.651), n=24/21	0.117 (p=0.907), n=37/38	0.962 (p=0.336), n=50/60	0.522 (p=0.602), n=88/95	1.572 (p=0.116), n=159/188	0.976 (p=0.329), n=248/270	1.344 (p=0.179), n=290/323	**-2.021** **(p=0.043),** n=627/558
0- 175	-1.262 (p=0.207), n=37/27	-0.199 (p=0.842), n=52/50	0.748 (p=0.455), n=69/78	0.32 (p=0.749), n=121/126	**2.182** **(p=0.029),** n=212/259	*1.724* *(p=0.085),* n=323/368	**2.161** **(p=0.031),** n=373/434	*-1.701* *(p=0.089),* n=843/775
0- 250	-0.703 (p=0.482), n=40/34	0.188 (p=0.851), n=56/58	0.954 (p=0.34), n=74/86	0.481 (p=0.631), n=136/144	**2.704** **(p=0.007),** n=235/297	**2.264** **(p=0.024),** n=360/423	**2.743** **(p=0.006),** n=421/504	*-1.724* *(p=0.085),* n=968/894

Lowest gross cell product quartile excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0-25 Km	0.555 (p=0.579), n=14/17	0 (p=1), n=28/28	0.973 (p=0.331), n=41/50	0.894 (p=0.371), n=61/71	**2.152 (p=0.031),** n=108/141	0.811 (p=0.418), n=173/188	0.744 (p=0.457), n=206/221	-1.616 (p=0.106), n=448/402
0-50	0.177 (p=0.86), n=16/17	-0.266 (p=0.79), n=30/28	0.938 (p=0.348), n=43/52	0.507 (p=0.612), n=69/75	1.472 (p=0.141), n=125/149	0.304 (p=0.761), n=198/204	-0.185 (p=0.853), n=242/238	**-3.362 (p=0.001),** n=544/440
0-100	0.166 (p=0.868), n=18/19	-0.381 (p=0.703), n=33/30	0.683 (p=0.495), n=50/57	0.235 (p=0.814), n=81/84	1.256 (p=0.209), n=145/167	0.61 (p=0.542), n=224/237	0.471 (p=0.637), n=271/282	**-3.41 (p=0.001),** n=625/511
0-175	-0.521 (p=0.603), n=32/28	-0.411 (p=0.681), n=50/46	0.563 (p=0.574), n=75/82	-0.318 (p=0.751), n=128/123	*1.838 (p=0.066),* n=209/248	1.099 (p=0.272), n=315/343	1.157 (p=0.247), n=371/403	**-3.612 (p<0.001),** n=877/733
0-250	0.244 (p=0.807), n=33/35	0.098 (p=0.922), n=52/53	1 (p=0.317), n=79/92	0 (p=1), n=142/142	**2.307 (p=0.021),** n=231/283	1.508 (p=0.132), n=353/394	1.484 (p=0.138), n=422/466	**-3.241 (p=0.001),** n=985/847

Highest population quartile excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0-25 Km	0.836 (p=0.404), n=10/14	0.732 (p=0.464), n=22/27	*1.9 (p=0.058),* n=34/51	1.421 (p=0.156), n=59/75	**2.045 (p=0.041),** n=114/146	0.433 (p=0.665), n=176/184	0.891 (p=0.373), n=205/223	-1.551 (p=0.121), n=444/400
0-50	0 (p=1), n=14/14	0.139 (p=0.889), n=26/27	1.467 (p=0.142), n=40/54	0.915 (p=0.36), n=69/80	1.428 (p=0.153), n=134/158	0.151 (p=0.88), n=203/206	0.137 (p=0.891), n=245/248	**-3.03 (p=0.002),** n=542/448
0-100	-0.356 (p=0.722), n=17/15	0 (p=1), n=30/30	1.268 (p=0.205), n=47/60	0.69 (p=0.49), n=82/91	1.387 (p=0.165), n=153/178	0.604 (p=0.546), n=229/242	0.72 (p=0.472), n=275/292	**-2.988 (p=0.003),** n=619/519
0-175	-0.951 (p=0.342), n=31/24	-0.106 (p=0.916), n=46/45	1.23 (p=0.219), n=68/83	0.19 (p=0.849), n=125/128	**2.045 (p=0.041),** n=213/257	1.179 (p=0.238), n=313/343	1.482 (p=0.138), n=367/408	**-2.871 (p=0.004),** n=841/728
0-250	-0.386 (p=0.699), n=32/29	0.406 (p=0.685), n=47/51	1.496 (p=0.135), n=72/91	0.179 (p=0.858), n=141/144	**2.364 (p=0.018),** n=237/291	1.62 (p=0.105), n=351/395	*1.848 (p=0.065),* n=420/475	**-2.597 (p=0.009),** n=961/851

Lowest population quartile excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0-25 Km	0.9 (p=0.369), n=14/19	0.681 (p=0.496), n=26/31	1.333 (p=0.183), n=37/49	0.607 (p=0.544), n=67/74	*1.91 (p=0.056),* n=116/146	1.18 (p=0.238), n=190/213	1.172 (p=0.241), n=228/253	-1.313 (p=0.189), n=485/446
0-50	0.167 (p=0.867), n=18/19	0.13 (p=0.897), n=30/31	1.048 (p=0.295), n=42/52	0.164 (p=0.87), n=76/78	1.318 (p=0.188), n=133/155	0.675 (p=0.5), n=215/229	0.438 (p=0.661), n=263/273	**-2.858 (p=0.004),** n=580/488
0-100	0.312 (p=0.755), n=20/22	0.59 (p=0.555), n=34/39	1.437 (p=0.151), n=48/63	0.525 (p=0.6), n=87/94	1.341 (p=0.18), n=151/175	0.941 (p=0.347), n=243/264	0.978 (p=0.328), n=294/318	**-2.719 (p=0.007),** n=655/561
0-175	-0.376 (p=0.707), n=34/31	0.582 (p=0.561), n=51/57	1.267 (p=0.205), n=73/89	0.124 (p=0.901), n=130/132	*1.908 (p=0.056),* n=214/255	*1.935 (p=0.053),* n=327/378	**2.058 (p=0.04),** n=387/446	**-2.408 (p=0.016),** n=906/807
0-250	-0.12 (p=0.905), n=36/35	0.747 (p=0.455), n=54/62	1.293 (p=0.196), n=79/96	-0.119 (p=0.906), n=145/143	**2.037 (p=0.042),** n=235/281	**2.27 (p=0.023),** n=358/421	**2.271 (p=0.023),** n=432/501	**-2.57 (p=0.01),** n=1016/904

Winter (Dec-Mar) excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0- 25 Km	0.853 (p=0.394), n=16/21	-0.128 (p=0.898), n=33/32	0.213 (p=0.831), n=46/48	-0.417 (p=0.677), n=79/74	0.864 (p=0.388), n=133/147	1.112 (p=0.266), n=178/199	1.189 (p=0.235), n=202/226	-0.771 (p=0.441), n=438/416
0- 50	0.159 (p=0.873), n=20/21	-0.612 (p=0.54), n=37/32	-0.407 (p=0.684), n=52/48	-1.023 (p=0.306), n=90/77	0.293 (p=0.769), n=148/153	0.751 (p=0.453), n=198/213	0.559 (p=0.576), n=231/243	**-2.49** **(p=0.013),** n=530/453
0- 100	0.148 (p=0.883), n=23/24	-0.223 (p=0.823), n=42/40	-0.28 (p=0.779), n=60/57	-0.866 (p=0.387), n=104/92	0.163 (p=0.87), n=171/174	1.157 (p=0.247), n=225/250	1.077 (p=0.281), n=261/286	**-2.61** **(p=0.009),** n=608/521
0- 175	-0.483 (p=0.629), n=37/33	-0.093 (p=0.926), n=59/58	0 (p=1), n=83/83	-0.602 (p=0.547), n=145/135	1.602 (p=0.109), n=225/260	**2.797** **(p=0.005),** n=291/362	**2.896** **(p=0.004)**, n=328/406	**-2.526** **(p=0.012),** n=827/728
0- 250	0 (p=1), n=40/40	0.266 (p=0.79), n=63/66	0.149 (p=0.881), n=90/92	-0.509 (p=0.611), n=163/154	*1.895* *(p=0.058),* n=251/295	**3.082** **(p=0.002),** n=325/408	**3.344** **(p=0.001)**, n=368/464	**-2.532** **(p=0.011),** n=938/832

Pre-monsoon (Apr-May) excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0- 25 Km	1.166 (p=0.244), n=11/17	1.582 (p=0.114), n=20/31	**2.832** **(p=0.005),** n=32/58	**2.214** **(p=0.027),** n=66/93	**4.719** **(p<0.001),** n=115/195	**3.699** **(p<0.001),** n=188/264	**3.709** **(p<0.001),** n=225/308	-0.937 (p=0.349), n=522/493
0- 50	0.547 (p=0.585), n=14/17	1.103 (p=0.27), n=23/31	**2.467** **(p=0.014),** n=37/61	*1.852* *(p=0.064),* n=75/99	**4.083** **(p<0.001),** n=134/208	**3.134** **(p=0.002),** n=217/286	**2.697** **(p=0.007),** n=268/333	**-2.671** **(p=0.008),** n=632/542
0- 100	0.713 (p=0.476), n=14/18	*1.677* *(p=0.094),* n=24/37	**2.78** **(p=0.005),** n=41/70	**2.297** **(p=0.022),** n=83/115	**4.289** **(p<0.001),** n=150/233	**3.634** **(p<0.001),** n=243/329	**3.393** **(p=0.001),** n=299/387	**-2.471** **(p=0.013),** n=721/631
0- 175	0.581 (p=0.561), n=22/26	**2.388** **(p=0.017),** n=32/54	**3.433** **(p=0.001),** n=55/97	**2.945** **(p=0.003),** n=111/159	**5.702** **(p<0.001),** n=196/325	**4.741** **(p<0.001),** n=317/447	**4.681** **(p<0.001),** n=384/524	**-2.284** **(p=0.022),** n=964/867
0- 250	1.057 (p=0.291), n=25/33	**2.756** **(p=0.006),** n=35/62	**3.726** **(p<0.001),** n=60/108	**2.982** **(p=0.003),** n=128/180	**6.276** **(p<0.001),** n=218/369	**5.385** **(p<0.001),** n=352/509	**5.332** **(p<0.001),** n=435/606	**-2.179** **(p=0.029),** n=1094/995

Monsoon (Jun-Aug) excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0- 25 Km	0.836 (p=0.404), n=10/14	0.591 (p=0.554), n=22/26	*1.756* *(p=0.079),* n=31/46	1.3 (p=0.194), n=54/68	**2.963** **(p=0.003),** n=105/151	**2.005** **(p=0.045),** n=171/209	**2.545** **(p=0.011),** n=202/255	*-1.749* *(p=0.08),* n=473/422
0- 50	-0.188 (p=0.851), n=15/14	-0.139 (p=0.889), n=27/26	1.197 (p=0.232), n=38/49	0.43 (p=0.667), n=67/72	**1.973** **(p=0.048),** n=128/161	1.274 (p=0.203), n=202/228	1.33 (p=0.184), n=247/277	**-3.18** **(p=0.001),** n=570/469
0- 100	-0.346 (p=0.73), n=18/16	-0.256 (p=0.798), n=32/30	0.799 (p=0.424), n=47/55	0.079 (p=0.937), n=81/82	1.609 (p=0.108), n=151/180	1.359 (p=0.174), n=233/263	*1.721* *(p=0.085),* n=282/324	**-3.192** **(p=0.001),** n=659/549
0- 175	-0.969 (p=0.333), n=30/23	-0.644 (p=0.52), n=47/41	-0.085 (p=0.932), n=70/69	-1.473 (p=0.141), n=124/102	0.994 (p=0.32), n=216/237	1.2 (p=0.23), n=323/354	*1.728* *(p=0.084),* n=383/432	**-2.469** **(p=0.014),** n=881/781
0- 250	-0.644 (p=0.52), n=33/28	-0.51 (p=0.61), n=51/46	0 (p=1), n=76/76	-1.453 (p=0.146), n=138/115	1.557 (p=0.119), n=238/273	*1.81* *(p=0.07),* n=361/411	**2.322** **(p=0.02),** n=437/508	**-2.22** **(p=0.026),** n=1013/916

Post-monsoon (Sep-Nov) excluded

	1-10 Days	1-20	1-30	1-50	1-90	1-140	1-180	1-360
0-25 Km	0.555 (p=0.579), n=14/17	0.139 (p=0.89), n=27/28	1.215 (p=0.225), n=38/49	1.366 (p=0.172), n=56/71	0.889 (p=0.374), n=106/119	-1.299 (p=0.194), n=192/168	-0.936 (p=0.349), n=226/207	-0.327 (p=0.743), n=400/391
0-50	0 (p=1), n=17/17	-0.266 (p=0.79), n=30/28	1.159 (p=0.247), n=41/52	1.208 (p=0.227), n=62/76	0.513 (p=0.608), n=121/129	*-1.778 (p=0.075),* n=217/182	-1.614 (p=0.106), n=259/224	*-1.767 (p=0.077), n=488/435*
0-100	0 (p=1), n=20/20	0 (p=1), n=34/34	1.359 (p=0.174), n=47/61	1.435 (p=0.151), n=71/89	0.664 (p=0.507), n=134/145	-1.57 (p=0.116), n=241/208	-1.38 (p=0.168), n=289/257	*-1.719 (p=0.086), n=547/492*
0-175	-0.636 (p=0.525), n=34/29	-0.304 (p=0.761), n=51/48	1.307 (p=0.191), n=68/84	0.925 (p=0.355), n=109/123	0.807 (p=0.42), n=191/207	-1.01 (p=0.313), n=323/298	-0.776 (p=0.438), n=381/360	-1.061 (p=0.289), n=739/699
0-250	0 (p=1), n=34/34	0.195 (p=0.845), n=52/54	*1.727 (p=0.084),* n=71/93	1.005 (p=0.315), n=120/136	1.056 (p=0.291), n=208/230	-0.534 (p=0.593), n=354/340	-0.59 (p=0.555), n=428/411	-0.695 (p=0.487), n=834/806

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