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Storms, floods, landslides and elections in India's growing metropolises: Hotbeds for political protest?

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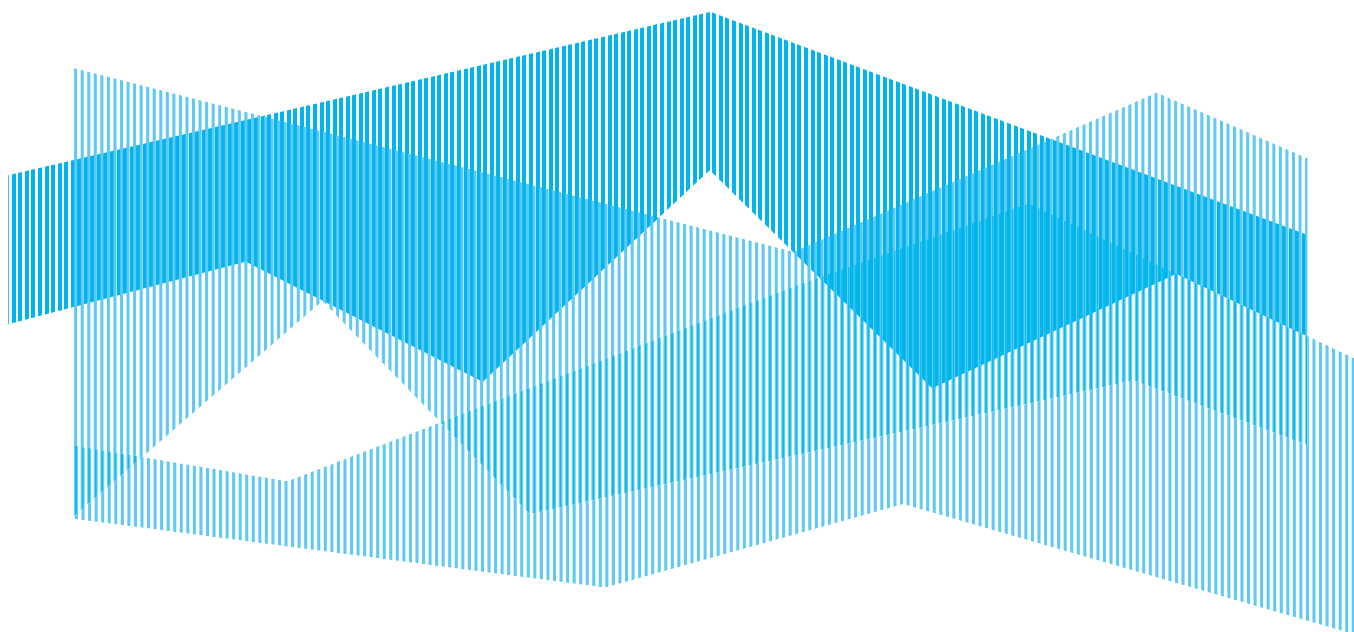
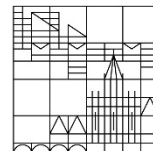
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Storms, Floods, Landslides and Elections in India's Growing Metropolises: Hotbeds for Political Protest?

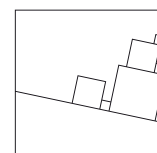
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Storms, floods, landslides and elections in India's growing metropolises: Hotbeds for political protest?

Viktoria Jansesberger

Abstract

Do sudden weather disasters in cities of the Global South increase the likelihood of anti-government protests? In cities of the Global South, floods, storms, and landslides strain already fragile infrastructure, often leading to destruction and hardship. While urban residents occasionally protest in response to such dire conditions, they often do not. Thus, this paper addresses the question of when this is more likely to occur. I argue that sudden destructive weather events spark anti-government protests if they coincide with upcoming elections as organizing protests can serve as a strategy by political actors to gain attention and mobilize voters. Given the increased public attention, citizens might furthermore consider it a good time to voice their dissatisfaction. I test this hypothesis using novel self-compiled protest data on 19 Indian metropolises (2000-2019). Quantitative regression analyses on samples pre-processed with Coarsened Exact Matching and insights from illustrative examples yield robust support for the argument.

Introduction

The manifold consequences of climate change pose significant challenges to citizens in many regions worldwide. One of the most destructive outcomes of global warming is the heightened probability of severe episodes of extreme weather, such as sudden anomalies in precipitation and windspeed (IPCC, 2023, 2021). More vulnerable populations, such as those in the Global South, may face particular difficulties in coping with such destructive events. In cases where societies struggle to prepare for extreme weather conditions, storms and spikes in precipitation often result in immense destruction and considerable hardship (Buurman et al., 2017; Salvador et al., 2016; Strömberg, 2007).

As grievances and discontent play pivotal roles as drivers of societal upheaval, numerous studies have explored whether and under what conditions disastrous weather events cause or exacerbate unrest (Koubi, 2019; Von Uexkull and Buhaug, 2021). To date, much emphasis has been placed on how extreme weather and deviations in rainfall impact agricultural livelihoods. Consequently, many studies focus on why and when weather-related disasters give rise to unrest in rural areas, such as communal disputes between herders and farmers or insurgent activities in remote areas (Bagozzi et al., 2017; Buhaug et al., 2021; Döring, 2020; Gleick, 2014; Koren and Bagozzi, 2017; Van Weezel, 2019; Von Uexkull et al., 2016). Nevertheless, only a limited number of studies have investigated the repercussions of destructive weather extremes in urban areas (see Plänitz, 2020; Yeeles, 2015). Hence, there still exists relatively little research concerning how weather anomalies influence the types of societal unrest most typical for urban areas, such as protests, leaving a notable knowledge gap regarding how disastrous weather affects more widespread forms of collective action.

Between October and December 2005, the Indian megacity of Chennai was hit by torrential rains resulting in widespread flooding. A few weeks into the disaster, affected citizens began taking to the streets to protest against the state government. While Chennai residents did not

blame the authorities for the abnormal spike in precipitation, they were outraged by the mismanagement of the situation. During the demonstrations, flood victims emphasized the severe impact of floods on their living conditions and the substantial losses they incurred (The Hindu, 2005). Yet, what upset them most was how these hardships were addressed by governing authorities. Protestors described flood relief as being delayed, insufficient, and unfair. Anger boiled over when the chaotic distribution of limited aid resulted in riots, during which several people died. Demonstrators, led by an alliance of opposition parties, held the state administration responsible for this tragedy and accused them of poor disaster preparedness and response (Hindustan Times, 2005a, 2005b). Complaints and accusations regarding how the state government handled the flood disaster highlight the high risk of disappointing citizens faced by political actors in the wake of destructive weather events.

Undoubtedly, sudden weather disasters can easily exacerbate grievances. Nevertheless, little is known about when these extreme weather events spark protests. Destructive storms and floods are not uncommon in many cities in the Global South, nor is a lack of relief supplies (Baker, 2012; Pelling, 2003). Yet, despite the prevalence of severe grievances, protests often do not occur, raising the question of *when exactly* disaster-related grievances lead to anti-government mobilization. According to UN projections, the percentage of the global population living in cities will have increased to 60% by 2030 (United Nations, 2018). Much of this growth is taking place in low-income states in Africa and Asia, where episodes of extreme weather often coincide with overstrained infrastructure (Dorward and Fox, 2022; Fox and Bell, 2016). Given the growing importance of metropolitan areas in the Global South, addressing the conditions under which weather disasters increase the likelihood of political unrest in these regions is of significant scientific and societal relevance.

Research on protest reveals that all discontent, regardless of its severity, must be mobilized (Chenoweth and Ulfelder, 2017; Kriesi, 2011; Tarrow, 1994). Existing studies on extreme

weather and protest (e.g., Gizelis et al., 2021; Ide et al., 2021a, 2021b; Petrova, 2021) primarily provide insights into a) where and for whom grievances associated with extreme weather should be particularly grave, and b) where and for which groups mobilization potential should be highest. However, these studies hardly consider political events that might create “windows of opportunity,” thereby increasing the incentives for political actors to identify issues related to extreme weather-induced hardships and mobilize around them (Fröhlich, 2016).

I argue that sudden weather disasters are most likely to trigger spark protests in the months preceding elections, particularly at the level of government responsible for disaster management. Destructive floods and storms often reveal the extent to which political authorities mismanage resources, underinvest in infrastructure, and are ill-prepared for emergencies (Buurman et al., 2017; Plänitz, 2019; Strömberg, 2007). Politicians seek to garner support from voters and persuade them to choose their party over their political rivals in the run-up to elections (Birch et al., 2020; Harish and Little, 2017; Salehyan and Linebarger, 2015; Thomson et al., 2021). Particularly for opposition parties, the deficiencies of the incumbent administration in disaster preparedness and response should be a welcome topic. Organizing protests against governmental disaster management might offer an opportunity to garner votes. Furthermore, citizens affected by disasters may be more receptive to participating in protests in the pre-election period. Arguably, political actors concerned about their election results should be more attentive to citizens’ demands (Bunce and Wolchik, 2011; Little et al., 2015; Thomson et al., 2021).

The protests against the state government during the devastating floods in Chennai in 2005 support this argument. In India, states are the primary authorities responsible for disaster management. At the time of the floods, the upcoming elections to the state legislative assembly were only four months away. Opposition parties, notably the Democratic Progressive Alliance (DPA), actively organized anti-government protests, with numerous opposition politicians

participating in them (Hindustan Times, 2005b). They highlighted the unjust distribution of relief goods by the ruling party of Tamil Nadu, the Anna Dravida Munnetra Kazhagam (AIADMK), even accusing them of nepotism. The opposition parties collectively called for the formation of a relief distribution committee comprising representatives from political parties at both the district and state levels, suggesting that the incumbent government was inadequate for the task (Hindustan Times, 2005a).

The hypothesis that sudden weather disasters in urban areas in the Global South are most likely to trigger anti-government protests in the months leading up to elections primarily applies to democracies, where elections determine who holds power. India, as an emerging economy with one of the highest urbanization rates globally and the world's most populous democracy, constitutes an ideal case to test this hypothesis. Moreover, in comparison to Africa, Asia has been relatively understudied in the literature on climate change and conflict (Courtland et al., 2018; Hendrix, 2017). Thus, India is highly relevant for the study of the research question posed.

Nevertheless, the study of the influence of disastrous weather events on the overall likelihood of protests in the case of India has been hampered by limited data availability. Datasets covering low-intensity forms of societal unrest are either limited to very specific forms of contentious activities, such as electoral violence (Daxecker et al., 2019) or Hindu-Muslim riots (Wilkinson, 2006). The coverage of India in more general datasets is quite limited, either in terms of geographic scope (Thomson et al., 2022) or temporal range (Chenoweth et al., 2018; Raleigh et al., 2010).

To test the outlined hypothesis on India, and given the lack of available protest event data, I compiled a novel hand-coded dataset based on keyword searches of international news sites (Agence France Press, Associated Press, and BBC-Monitoring). This innovative dataset covers 19 major Indian metropolises over a 20-year period (2000-2019) and includes detailed

descriptions of over 400 anti-government protests, along with information about protest actors, demands, and locations.

The results of several logistic regression analyses, with city- and month-fixed effects, conducted on samples pre-processed with Coarsened Exact Matching (CEM) to address the potential endogeneity of disastrous events, provide empirical support for my argument. I observe a higher likelihood of anti-government protests occurring when disastrous weather events impact a city during the months leading up to state elections. However, I do not find similar results in non-pre-election periods, the months following state elections, or the months shortly before national elections. These findings remain robust across various model specifications.

In the following sections, I will first delve into what is already known about the relationship between extreme weather and societal unrest, with a particular focus on protest occurrence. Subsequently, I will clarify the significance of urban areas in the Global South in this context and why the trigger effect of extreme weather on protest is most likely to manifest when sudden weather disasters coincide with the pre-election periods for the political authority responsible for disaster management.

Literature review

Reflecting on the profound grievances that environmental degradation and disastrous weather events can potentially generate or exacerbate, a strand of literature examines whether and under what conditions these factors increase the likelihood of various forms of societal unrest (Koubi, 2019; Von Uexkull and Buhaug, 2021). Political unrest can manifest in a multitude of ways (Gurr, 1970), and previous research has explored the effects of disastrous weather events on many of these. However, some types of societal unrest have received more scholarly attention than others. Given that disastrous weather events can readily damage crops and livestock, much emphasis in this research has been placed on groups and regions reliant on agriculture (Bagozzi

et al., 2017; Koren and Bagozzi, 2017; Von Uexkull et al., 2016). Consequently, many studies have focused on forms of political unrest more commonly observed in rural areas, such as rebellions (Bergholt and Lujala, 2012; Buhaug et al., 2021; Devitt and Tol, 2012; Gleick, 2014; Selby et al., 2017; Slettebak, 2012; Wischnath and Buhaug, 2014) or communal conflicts (Döring, 2020; Fjelde and Von Uexkull, 2012; Petrova, 2022; Van Weezel, 2019). In contrast, forms of societal unrest based on relatively spontaneous mass mobilization and therefore more easily implementable in more urban areas have received less attention.

The imbalance in focus between densely and sparsely populated regions in the literature on climate change and conflict leads Plänitz (2019) to term this “urban neglect.” This imbalance has important implications for our understanding of the conditions under which extreme weather events lead to societal unrest. While various event types can be categorized as forms of unrest, protest, a typically urban phenomenon and, especially in democracies, considered a legitimate form of political participation, is fundamentally different from armed conflicts with rebels or communal disputes. Consequently, different factors influence how weather disasters affect the occurrence of these events. In recent years, several studies have attempted to address this research gap concerning urban areas.

The impact of destructive weather events on urban areas

Destructive weather events can have both direct and indirect effects on urban areas. On one hand, such events in rural areas can destroy harvests and livestock, endangering livelihoods that rely on agriculture. When agriculture becomes unprofitable, and no other sources of income are available, migration to urban centers in pursuit of employment may become an attractive option (Gizelis et al., 2021; Koubi et al., 2016). However, rapid urbanization, especially in low-income contexts, has been cited as a reason for increased levels of unrest. The uncontrolled influx of resource-poor individuals in need of housing and work can intensify competition for limited

resources, leading to discontent that may culminate in political unrest (Bhavnani and Lacina, 2015; Dorward and Fox, 2022; Koubi et al., 2021). To date, findings on the nexus between urbanization and unrest remain mixed and are found to depend on various socio-economic, political, and geographical factors (Buhaug and Urdal, 2013; Fox and Bell, 2016; Urdal and Hoelscher, 2012).

However, weather disasters may also directly affect cities, causing hardship for urban residents, especially in low-income states. While severe anomalies in precipitation, temperature, or windspeed always pose a threat, they manifest their full destructive potential when they impact vulnerable communities struggling to prepare for and adequately respond to such events (Buurman et al., 2017; Strömberg, 2007; Tennant and Gilmore, 2020). When storms, floods, or landslides strike unstable buildings and poor infrastructure, considerable devastation frequently ensues. In addition to material losses, injuries and fatalities are not uncommon. Moreover, damaged infrastructure often disrupts the water supply, impacting basic needs like sanitation and drinking water. (Döring, 2020; Gleick, 2014). Flooding in urban areas also increases the likelihood of waterborne diseases, such as cholera. Furthermore, existing societal issues like poverty, inequality, or deficiencies in government services may become more pronounced (Plänitz, 2019; Yeeles, 2015).

Cities as hubs for disaster-induced protests

Deprivation, political discontent, unsatisfactory living conditions, and perceived or actual injustices, all of which are common consequences of weather disasters impacting urban areas, are known to be frequent motivations for engaging in protest (Gurr, 1970). Nonetheless, numerous studies demonstrate that grievances alone are insufficient, and it is the interplay between grievances, resources, and mobilization that truly matters (Brady et al., 1995; Chenoweth and Ulfelder, 2017; Dalton et al., 2010; Meyer, 2004; Opp, 1988). Furthermore, a

significant level of organization is required to gather a group of individuals at a specific location to express their political demands. Democracies offer better opportunities for protest than autocracies, as participants have fewer reasons to fear repercussions (Asal and Brown, 2020; Hibbs, 1973; Tarrow, 1994). Protests may also be more viable in some regions than in others. Several reasons support the idea that cities foster protest occurrence and serve as the ideal setting for such types of unrest.

Firstly, potential mobilizing agencies for protests (e.g., political parties, trade unions, NGOs, and other civil society organizations) are predominantly concentrated in cities. (Thomson et al., 2022). If events causing dissatisfaction occur in cities, the likelihood of one of these political actors encouraging citizens to protest is much higher than in rural areas. The close proximity of city residents facilitates the organizational aspect required for protests. Proximity implies that urban dwellers can easily communicate their grievances and discontent. This ease of interaction makes the relatively spontaneous organization of a larger group of people more feasible (Buhaug and Urdal, 2013; Fox and Bell, 2016; Plänitz, 2019).

In addition, urban environments significantly enhance the visibility of contentious political activities. Major cities receive more media coverage than rural regions, and the extensive population in cities ensures that many citizens will notice a protest. Also, many government agencies have their headquarters in major cities. Thus, citizens in large urban centers can address their demands directly to the relevant authorities (Plänitz, 2020, 2019).

Hence, grievances induced by disasters, which often arise in cities, are likely to find a voice through protests there. Several scholars have begun to explore whether and under what conditions this is the case. Plänitz (2020) and Yeeles (2015) exclusively focus on cities in their studies and investigate whether precipitation extremes increase the likelihood of unrest in urban agglomerations. Furthermore, Ide et al. (2021a) and Ide et al. (2021b) exclusively focus on

explaining the occurrence of extreme weather-related protest events, which they find to be most common in places with higher population densities.

Most of the limited existing studies on the relationship between destructive weather events and protests theorize and test the circumstances under which disaster-induced grievances intensify, creating the ideal conditions for protest. Koubi et al. (2021) find that migrants affected by multiple environmental events are more inclined to join social movements advocating for their cause. Plänitz (2020) shows that urban flooding primarily ignites unrest in marginalized and less resilient neighborhoods. In line with this, Ide et al. (2021a) and Ide et al. (2021b) emphasize the prominent role of disaster impact in inciting protests triggered by destructive weather. Their findings suggest that severe droughts leading to prolonged water shortages or floods resulting in numerous fatalities and displaced people increase the likelihood of disaster-related protests. In addition, Ash and Obradovich (2020) and Ide et al. (2021a) suggest that pre-existing ethnic tensions can further amplify the risk of protests by disaster victims.

Nonetheless, it is well-established in protest research that discontent must be mobilized for riots and demonstrations to occur (Chenoweth and Ulfelder, 2017; Kriesi, 2011; McCarthy and Zald, 1977). When citizens, particularly disaster victims, are dissatisfied and angry, they are unlikely to spontaneously organize and stage a protest. Like all forms of collective action, protests require organization and preparation. Therefore, some societal or political entity is needed to gather those who share similar grievances and wish to voice them. Many studies on weather disasters and protests acknowledge the significance of mobilization, emphasizing that certain groups are more susceptible to mobilization, and that mobilization is more likely to occur in certain locations. Petrova (2021) and Koubi et al. (2021) highlight the role of migrant networks in the participation of citizens displaced by weather disasters in protests. Similarly, Nardulli et al. (2015) find that disaster victims who are members of a political association are more likely to initiate mass mobilization events.

While these studies identify the actors and regions prone to disaster-induced mobilization, none of them illuminate *when* this mobilization is most likely to occur. Consequently, it remains uncertain during which time periods the likelihood of protests increases when disaster strikes. Since most protests have political undertones, disaster-induced grievances are often framed as political failures. However, the incentives for political actors to do so may vary at different times. Hence, political events should play a major role. In the following section, I explain the reasons for my argument that sudden weather disasters in urban areas are most likely to trigger anti-government protests in pre-election and election periods.

Time to speak up: Elections as focal points for disaster-related grievances

Elections are pivotal political events, especially in democracies, as they determine who gains access to power and resources. Consequently, politicians must make every effort to persuade citizens to cast their votes in their favor. (Birch et al., 2020; Daxecker et al., 2019; Salehyan and Linebarger, 2015; Thomson et al., 2021).

Pre-election periods can potentially stimulate increased protest activity for several reasons. Political actors, especially opposition parties, may actively seek to organize protests to draw attention to current issues. This enables them to demonstrate how they would address issues more effectively than the incumbent (Robertson, 2010; Salehyan and Linebarger, 2015). Hence, protests during pre-election periods provide opposition politicians with a platform to convey their plans for improving the situation if elected. Furthermore, by organizing protests against governmental disaster management, opposition parties can convey solidarity with citizens when issues arise.

Under ordinary circumstances, it would require much greater effort to vote incumbent parties out of office. Therefore, pre-election periods are times when numerous issues may be raised

and politicized as political actors strive to capitalize on them (Birch et al., 2020; Harish and Little, 2017; Little et al., 2015; Tucker, 2007).

Simultaneously, citizens affected by disasters may have strong incentives to participate in such protests. From a citizen's perspective, pre-election periods might also appear as ideal times to air grievances through protests (Bunce and Wolchik, 2011; Little et al., 2015; Thomson et al., 2021). Thus, citizens may be unwilling to engage in such activities under ordinary circumstances. They are most likely to be inclined to invest their resources in protest participation when the prospects for success and the likelihood of protests leading to an improvement from the status quo are highest (Fröhlich, 2016). Pre-election periods may serve as windows of opportunity that increase the likelihood that grievances aired during protests will be taken seriously by political decision-makers. Political actors concerned about losing electoral support in upcoming elections are more likely to pay attention to citizens' concerns.

Hence, I posit that sudden weather disasters in urban areas are particularly prone to triggering protests in the months leading up to elections. While few individuals would directly blame political actors for exogenous weather shocks, the behavior of politicians can significantly contribute to making societies more resilient to weather hazards (Buurman et al., 2017; Döring, 2020; Salvador et al., 2016; Strömberg, 2007). Storms and floods do not necessarily result in destruction; however, they do when existing infrastructure cannot adequately cope with them (Plänitz, 2019).

I contend that, although sudden weather disasters are not uncommon in specific contexts, it is predominantly during pre-election and election periods that these grievances translate into protests. Politicians, particularly those not currently in office, will seize the opportunity to highlight how inadequate investments and policies have allowed such hazards to cause significant harm. Furthermore, citizens, aggrieved and distressed by the hardship they endure, may take the chance to take to the streets and voice their complaints publicly. The rationale is

that while, under ordinary circumstances, political decision-makers might not pay too much attention, they should become more responsive to their demands in pre-election periods to avoid alienating potential voters.

I emphasize that cities in the Global South are environments where sudden weather disasters often result in severe grievances. If these events occur shortly before elections for the political entities responsible for disaster management, these issues, especially the role of political mismanagement, will receive increased attention. Politicians seeking (re)election will capitalize on every available issue and may stage protests when they perceive this as an effective tool to position themselves as the best political option. In turn, disaster victims may use this opportunity to voice their grievances and participate in such contentious activities. Hence, I hypothesize that *if sudden weather disasters strike metropolises in the Global South during pre-election and election periods, involving the government level responsible for disaster management, the likelihood of anti-government protests will increase.*

Research design

Case selection

When considering which countries would constitute the ideal and most relevant cases to test this hypothesis, India emerges as of utmost relevance. India ranks among the top countries across various indices measuring vulnerability to weather disasters and exposure to adverse consequences of climate change. (Eckstein et al., 2020). Moreover, as an emerging economy in the Global South, it represents a prime location for the hazardous impacts of extreme weather to manifest. India is also one of the most pertinent cases regarding urbanity and urbanization (Jaysawal and Saha, 2014; Sadashivam and Tabassu, 2016), boasting the second-highest number of megacities worldwide (United Nations, 2018).

Furthermore, India stands as the world's largest democracy and, more recently, the most populous country globally. This underscores the significance of understanding the societal developments that sudden weather disasters may incite in the region. This is especially valuable because protest can be viewed as a form of political participation, making it particularly relevant to study protest dynamics in a democratic setting like India. By investigating the outlined research question in India, I also make an empirical contribution to the literature, as much of the findings on the links between climate and conflict originate from research conducted on African states (Courtland et al., 2018; Hendrix, 2017).

Method

To test my theoretical argument, I employ quantitative regression analyses. Event datasets that record incidents of protest offer appropriate ways to operationalize my dependent variable. To accurately capture the spatial and temporal dynamics as outlined, I conduct my analyses at the monthly level, with cities as the spatial units. Hence, the unit of analysis in all my models is city months.

Data

The above-mentioned limitations in data availability partly underlie the streetlight effect mentioned earlier. Empirically testing the outlined hypothesis using protest event data in India poses certain challenges. Focusing on the overall likelihood of protests disqualifies existing high-quality datasets that cover India but are restricted to specific, more violent event types, such as electoral violence (Daxecker et al., 2019) or Hindu-Muslim riots (Wilkinson, 2006). Furthermore, a spatially fine-grained analysis that allows for a comprehensive study of the localized effects of sudden weather disasters in urban areas requires high-resolution data on where demonstrations occurred. This requirement renders the usage of datasets without geo-

referenced events like CNTS (Banks, 2011) or the Mass Mobilization Data (Clark and Regan, 2016) unfeasible.

Two datasets that would meet the criteria in terms of data structure and the events they cover, the Social Conflict Analysis Database (Salehyan et al., 2012) and the Mass Mobilization in Autocracies Database (Weidmann and Rød, 2019), cannot be used due to limitations in geographical coverage. They are restricted to Latin America and Africa or autocratic states, respectively, which naturally excludes India. The Urban Social Disorder Dataset (Thomson et al., 2022) which includes India, is restricted to only three major cities, namely New Delhi, Mumbai, and Calcutta, not including other relevant areas. Although ACLED (Raleigh et al., 2010) covers the entirety of India, it only does so for the most recent years since 2016, which also applies to the Nonviolent and Violent Campaigns and Outcomes Dataset (Chenoweth et al., 2018).

Owing to the limited coverage provided by the datasets typically used for research on protest events, I compiled a novel dataset covering anti-government protests in 19 Indian metropolises over a 20-year period beginning in the year 2000. This was achieved through a keyword search in Lexis Nexis, identifying relevant newswire reports by Agence France Press, Associated Press, and BBC Monitoring. Additional details about the search string used can be found in Appendix A1. Subsequently, I conducted manual coding of information at the protest-event level. The methodology for collecting information and classifying events drew inspiration from the Urban Social Disorder Dataset (Thomson et al., 2022; Urdal and Hoelscher, 2012). In addition to the protest location, as well as start and end dates, I collected information on involved actors, targets, and protest issues. The complete codebook with detailed coding instructions is available in Appendix A2. Due to practical constraints, data collection was limited to the largest and most prominent Indian metropolises, chosen based on size and political significance. This resulted in a total of 19 metropolitan agglomerations in India,

including the ten largest cities and state capitals with more than one million inhabitants according to the UN World Cities Booklet 2018. An exhaustive list of the included cities is available in Appendix A3.

Variables

The dependent variable in this study is the occurrence of anti-government protests in specific city months, encompassing contentious incidents directed against local or national governments that convey a political message and transpire in public spaces (Schumaker, 1975). Protests may vary in terms of organization, and may range from relatively peaceful demonstrations to violent riots. While governments are the most frequent targets of such events, this is not exclusively the case. As shown in Appendix A4, a total of 522 riots and demonstrations were identified, with 431 directed against national or regional governments (see Appendix A5). To operationalize the occurrence of anti-government protests in a given month and metropolitan region, the number of riots and demonstrations against any government (state, regional, municipal) was counted and then recoded into a dichotomous variable. The main reason for recoding the count variable into a binary one is its skewed distribution. Only 3% of all city months have seen more than one anti-government protest event, and only 1% experienced more than two in a single month. Consequently, the variation between city months lies not so much in the number of protests but rather in whether a protest took place or not.

The primary independent variable is the occurrence of sudden weather disasters (storms, floods, and landslides). The International Disaster Database (EM-DAT) (CRED, 2022) records natural disasters leading to loss of life or impacting a larger populace. By utilizing the Geocoded Disaster Locations Dataset (referred to as GDIS) created by Rosvold and Buhaug (2020), which provides precise coordinates for events recorded in EM-DAT, I can determine which city was subjected to a sudden weather disaster in a certain month.

The most significant moderating factor in my proposed hypothesis is the proximity of elections at the level of government responsible for disaster management. In India, the primary responsibility for disaster management rests with the states, although the central government provides financial and logistical support if required. The specific provisions are outlined in the National Disaster Management Plan (UNDP, 2012). Furthermore, many matters related to sanitation and water supply fall under the purview of municipal corporations (The Constitution of India, 1992). Municipal corporations are the democratically elected local governance bodies in India below the state level (Kishore, 2022). They exist in municipalities with more than 1 million inhabitants, as is the case for each of the cities in my sample. Hence, I anticipate that the hypothesized effect of sudden weather disasters on protests will predominantly occur in the months leading up to state elections.

Elections for the state legislative assembly, known as the “*Vidhan Sabha*,” occur at different times in different states, typically at five-year intervals. In cases where a state government fails or cannot be formed, early elections may be called, resulting in shorter intervals (Gilmartin and Moog, 2012; Kishore, 2022). I identified the months in which elections for one of these legislative bodies occurred and considered a relevant pre-election period spanning nine months before and during these elections. While there is no universally agreed-upon definition of what constitutes a pre-election period, for the purposes of this research question, I argue that a slightly longer time interval beyond the immediate months preceding the elections is relevant. This extended period allows for the consideration that issues related to disasters may be strategically adopted by opposition parties in preparation for the upcoming or ongoing election campaign against the ruling parties. Such a strategy is most effective for opposition parties when there is still time for voters to adjust their opinions and voting choices in their favor. However, to ensure the robustness of my results, I also created a dummy variable encompassing months falling within a six-month window before state elections.

Nation-wide general elections for the “*Lok Sabha*,” the lower house of India’s bicameral parliament, are held every five years, though not necessarily concurrently with state elections. To confirm that the hypothesized protest-enhancing effect is specific to approaching elections at the level of government responsible for disaster management and not applicable to pre-election periods in general, I likewise constructed a binary variable indicating periods (nine-month window) leading up to national elections. Furthermore, I repeated this process for the months leading up to municipal corporation elections, which follow varying schedules depending on the specific city (Kishore, 2022).

Although all the cities in the sample are large, they vary in size. To account for this variation, I utilized city population data from the United Nations and the Indian census, interpolating for years with no available data. As mentioned earlier, state capacity and economic development often vary among sub-national regions. To account for this variation below the country level, I incorporated the Subnational Human Development Index (SHDI) which measures the average life expectancy, education level, and standard of living for each region (Kummu et al., 2018). Additionally, not all cities in the sample are state capitals. To control for the possibility of higher protest frequency in state capitals due to the concentration of vital political institutions (Buhaug and Urdal, 2013; Thomson et al., 2022), I included a binary variable to indicate whether a city is a state capital or not. An overview of the descriptive statistics for each of the variables is presented in Table I.

Table I: Descriptive statistics

	Obs.	Min	Max	Mean	Std. Dev.
DV:					
Anti-government protest event (dichotomous variable)	4560	0	1	0.095	0.293
IV:					
Sudden weather disaster (dichotomous variable)	4560	0	1	0.089	0.285
Moderating factor:					
Pre-election and election period (dichotomous variable)	4560	0	1	0.101	0.301
State elections (6-month period)					
Pre-election and election period (dichotomous variable)	4560	0	1	0.147	0.354
State elections (9-month period)					
Controls:					
Pre-election and election period (dichotomous variable)	4560	0	1	0.167	0.373
General elections (9-month period)					

Pre-election and election period (dichotomous variable) Municipal elections (9-month period)	4560	0	1	0.136	0.343
Population	4560	617300.2	30200000	5634634	5710179
Subnational Human Development Index	4560	0.433	0.782	0.602	0.072
State capital (dichotomous variable)	4560	0	1	0.842	0.365

Empirical findings

Due to the dichotomous nature of the dependent variable, I employ logistic regression analyses to test my hypothesis. To ensure that I only measure within-city variance, I include city-fixed effects in all my models. This allows me to assess whether protest likelihood within the same city is higher after a sudden weather disaster has occurred in the months leading up to a state election. To account for potential seasonal effects, I also introduce month-fixed effects in each of the models. Following Carter and Signorino (2010), I include the time elapsed since the last anti-government protest event in a city, along with its squared and cubed version as control variables.

Given the prevalent endogeneity concerns, I pre-process my samples using CEM (Iacus et al., 2012). The distribution of weather disasters typically does not occur randomly but depends on various societal, economic, and political circumstances. The CEM process involves identifying variables on which treated and untreated observations in the sample systematically differ. For each treated observation, in this case, city months affected by a sudden weather disaster, the CEM algorithm seeks a statistical twin—an observation that closely resembles the respective treated observation but has not been affected by a disaster. Subsequently, it trims the sample by discarding untreated observations that significantly deviate from any treated observation. This approach aims to achieve a better balance within the sample between treated and untreated observations.

There is some debate on the best way to implement matching techniques when the hypothesis being tested includes a conditional factor, in this case, the proximity to (state) elections (Iacus et al., 2019). I follow the approach suggested by Carey et al. (2022) and divide my samples

based on the hypothesized conditioning factor, applying matching to each of the sub-samples before conducting my quantitative analyses. In the initial step, I divide my observations into months falling within a nine-month period before state elections (pre-election and election period) and months that do not. Imbalance checks in Appendices A6 and Appendix A7 reveal that both sub-samples—those comprising pre-election periods and those comprising non-election periods—are highly imbalanced concerning sub-national HDI and population size. This is expected since disasters are more frequent in vulnerable, less-developed regions. Furthermore, with more people residing in an area, the likelihood of casualties, injuries, or displacements during disastrous events increases. Thus, I perform matching on these two variables, substantially enhancing balance in both (see Appendices A6 and A7). For example, the imbalance measure L1 decreased from 0.49 to 0.29 in the pre-election period sample.

The results in Model 1 indicate that the occurrence of a disastrous weather event in a city shortly before state elections significantly increases the likelihood of anti-government protests. The probability of a protest occurring during the pre-state election period increases by approximately 1.1% when a sudden weather disaster strikes. Conversely, in Model 2, which displays the results of an analysis of non-pre-state election periods only, such a protest-enhancing effect is not observed. Although the number of observations is much higher in this analysis, as most of the time, state elections are not approaching, the effect of sudden weather disasters is statistically insignificant. These findings align with my theoretical expectations. This effect remains robust across different model specifications. In Models 3 and 4, I vary the definition of what constitutes a pre-election period and use a six-month window before state elections as the cut-off point. The respective balance and matching statistics are included in Appendices A8 and A9. In Model 3, the probability of protest occurrence in the six months leading up to state elections increases by approximately 1.6 % when a weather disaster affects the respective city month. The effect of sudden weather disaster occurrence remains

insignificant during non-pre-state election periods, irrespective of the specific operationalization used.

Table II: Logistic regression results with city- and month-fixed effects for the relationship between sudden weather disaster occurrence and anti-government protests, using sub-samples pre-processed with CEM (Coarsened Exact Matching)

Dependent variable: Anti-government protest event

	M1 Pre-election periods (State – 9 months window)	M2 Non-election (State – 9 months window)	M3 Pre-election periods (State – 6 months window)	M4 Non-election (State – 6 months window)
Sudden weather disaster	1.871** (0.776)	0.0788 (0.241)	2.653* (1.380)	0.0878 (0.232)
Population	2.57e-06*** (9.20e-07)	-3.23e-08 (1.12e-07)	3.94e-06 (3.42e-06)	6.82e-09 (1.31e-07)
Subnational Human Development Index	-62.91*** (20.53)	-9.223*** (2.566)	-102.0 (65.10)	-9.850*** (2.542)
State capital	47.75** (24.00)	5.045*** (1.482)	45.75 (2,639)	5.202*** (1.698)
Constant	-9.507 (24.17)	1.603 (1.321)	16.38 (2,639)	1.358 (1.284)
City FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Time since last anti-government protest event & polynomials	Yes	Yes	Yes	Yes
Observations	314	3,273	131	3,629
Log Likelihood	-54.173081	-724.55418	-24.758231	-774.74173
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table III presents several sensitivity and placebo tests. Adhering to econometric research recommendations (Angrist and Pischke, 2008), I re-estimate the primary model (M1) using a linear regression model and city- and month-fixed effects instead of a logistic one. Once again, I observed a significant positive relationship between sudden weather disaster occurrence and anti-government protests in pre-state election periods. To determine whether this effect is unique to the periods shortly *before* elections at the level of government responsible for disaster management, I re-estimate my analysis using a sample of months within a six-month window *after* state elections (M6). There, I do not observe a significant protest-enhancing effect of sudden destructive weather events. The same holds when only including pre-general election periods, i.e., the months leading up to nationwide elections (Model 7). These findings align with my hypothesis and are consistent with the theoretical argument.

Interestingly, I observed a positive effect of sudden weather disasters significant at the 10% level in the lead-up to municipal corporation elections. This could be explained by the fact that urban water and sanitation management falls under the purview of these urban governance bodies. Floods, storms, and landslides often impact water and sewage infrastructure, leading to the perception that municipal corporation administrations are at least partially responsible for addressing the local effects of sudden weather disasters. Appendices A10 to A12 contain the imbalance and matching statistics of the samples on which Models M5 to M8 are estimated.

Table III: OLS and logistic regression results with city- and month-fixed effects for the relationship between sudden weather disaster occurrence and anti-government protest, using sub-samples pre-processed with CEM (Coarsened Exact Matching)

Dependent variable: Anti-government protest event

	M5 Pre-election periods (State – 9 months window) OLS	M6 Post-election (State – 6 months window)	M7 Pre-election periods (General – 9 months window)	M8 Pre-election periods (Municipal – 9 months window)
Sudden weather disaster	0.0635** (0.0305)	-1.499 (1.622)	1.439 (1.034)	3.701* (1.971)
Population	9.17e-08*** (2.65e-08)	6.92e-07 (8.53e-07)	1.03e-05* (5.63e-06)	-5.50e-07 (3.76e-06)
Subnational Human Development Index	-2.080*** (0.546)	-30.80* (16.60)	-130.1* (68.13)	-124.8* (65.17)
State capital	0.421*** (0.131)	-3.725 (11.03)	-355.1 (343.9)	<i>omitted</i>
Constant	0.714*** (0.231)	8.878 (6.156)	36.86* (19.79)	92.31** (41.20)
City FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Time since last anti- government protest event & polynomials	Yes	Yes	Yes	Yes
Observations	493	180	181	115
Log Likelihood		-39.009585	-38.217505	-27.344193
R ²	0.356			
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

To further validate my hypothesis, I conducted additional robustness checks without pre-processing the samples with CEM, as shown in Appendix A13. Logistic regression models with fixed effects were employed. The analysis was performed on a sub-sample consisting only of the months within the nine-month window leading up to state elections and on a full sample, estimating an interaction effect between disaster occurrence and proximity to state elections. The results corroborate my hypothesis, demonstrating, as in Model 1, a significant effect of

weather disasters in triggering protests when state elections are approaching. Addressing concerns about potential bias from multiple fixed effects, I conducted a multilevel analysis in Appendix A14. Furthermore, conditional logistic regressions were run in Appendix A15. Regardless of the various model specifications used, the results remained consistent, offering robust support for the theoretical argument presented in this paper.

Plausibility checks – illustrative examples

In addition to quantitative analyses that provide empirical support for my theoretical argument, I conducted plausibility checks by examining illustrative examples. One central expectation underlying my argument is that grievances arising from sudden weather disasters are severe and salient enough for politicians to address them in their election campaigns. Numerous reports on recent election campaigns in Indian metropolises corroborate this claim. In preparation for the 2019 elections, for instance, the BJP launched a “Save Hyderabad” campaign to protest the inability of Telangana governing parties to address recurring floods in Hyderabad (The Times of India, 2017). Leading up to the 2021 Kerala state legislative assembly elections, the problems stemming from sea erosion and increased vulnerability to floods were considered “key challenges for candidates from all fronts in Kochi” (The Times of India, 2021).

Another crucial aspect of the argument is that political parties actively organize protests to draw attention to how governing authorities have failed to prevent and address disaster-induced hardships. Several examples from Indian cities illustrate how parties use disastrous weather events to highlight the shortcomings of incumbent political actors. In 2004, Bihar was struck by devastating floods, and the situation escalated when afflicted citizens tried to forcibly obtain limited relief goods, leading to police firing on rioters (The Times of India, 2004a). In the days following this incident, a coalition of opposition parties organized several protests and even called for a general strike in Patna. Left-wing parties, all in the opposition, emphasized the state

government's mismanagement of the situation and its consistent lack of preparedness for such disasters. They openly and repeatedly discouraged citizens from re-electing the state government in the upcoming elections. "The state government failed to solve the perennial problem of floods and when victims demanded relief, they were showered with bullets by cops," said the general secretary of the Communist Party of India. (AFP, 2004; The Times of India, 2004b). These events, occurring less than six months before the next Bihar state legislative assembly elections, underscore how opposition parties may capitalize on political discontent arising from sudden weather disasters to actively mobilize against incumbent parties and use protests to gain visibility.

Incidents such as the sit-in protest led by the mayor of Bhopal, the capital of the Indian state Madhya Pradesh, in a waterlogged area of the city, highlight how even prominent politicians utilize disastrous events to underscore their political views on various issues. Alok Sharma, the mayor of the state capital, attributed his agitation to the state government's inaction regarding the prevalent issue of urban flooding in Bhopal. He emphasized that with upcoming state elections, this problem deserved more attention (PTI, 2013). Similar dynamics unfolded when a series of cyclones and floods struck the capital city of Odisha (Bhubaneswar) a few months before the 2014 state elections. Despite promised aid, it did not arrive to the extent expected (Hindustan Times, 2013). Consequently, protests erupted in more than 18 flood-affected districts of Bhubaneswar, with numerous politicians running for election participating in them (The Telegraph, 2013). They seized the opportunity to highlight that the insufficient quantity of relief goods and compensation payments was not their fault, illustrating how parties preparing for impending elections use protests to point out deficiencies of other political actors. Local observers of the scenarios support my argument that protests by parties against governmental mishandling of disastrous weather events are most pronounced in pre-election periods. For example, protests by the National Congress Party in Mumbai against water mismanagement by the ruling Bharatiya Janata Party were characterized in several newspaper

articles as being in “poll mode” and were described as the kick-off for their electoral campaign (Hindustan Times, 2018).

While the anecdotal evidence in the previous few paragraphs underscores the plausibility of the first part of my argument, the following examples illustrate how citizens leverage the public attention surrounding elections to advocate for their cause and voice their grievances. Upset about the “apathy” of the administration in handling the flash floods in Pune in 2019, slum dwellers staged protests that included blocking major roads (Hindustan Times, 2019a). Moreover, residents of some of the worst-hit districts called for a boycott of the state elections on October 21st to protest the lack of assistance from the local government (Hindustan Times, 2019b). Also, before the 2020 West Bengal state assembly elections, angry protestors threatened not to cast their votes because even one year after Cyclone Amphan, the destroyed tube wells had not been fixed. An agitated demonstrator told journalists, “Why should we vote? If the administration cannot meet our basic needs like water, there is no purpose in taking part in the poll process. We have made it clear” (The Telegraph, 2021).

Another aspect that warrants more in-depth examples is the timeframe within which such protests can be expected to occur. Several examples suggest that this effect may manifest not only immediately before elections but also a considerable time in advance. For instance, protests against corruption in the distribution of Cyclone Amphan funds occurred approximately 12 months before the next state elections in West Bengal (The Free Press Journal, 2020). Insiders commented that these protests were aimed at delineating the “battle lines” between the BJP and TMC parties for the upcoming state elections in the following year. Similarly, the “Save Hyderabad” campaign, mentioned earlier, was launched about one year before the next elections (The Times of India, 2017). Interestingly, the media-effective, sit-down strike of the mayor of Bhopal, which, by his own accounts, was staged to raise awareness about problems with the current administration in a year when state elections were due,

occurred about six months before the next elections (The Times of India, 2018). In summary, these anecdotal examples increase confidence that parties often incorporate disaster-induced grievances in their electoral campaign early on and stage protests around this issue even when several months remain before the elections.

To address potential questions about whether my theory is only applicable to India, I would like to briefly mention a recent example from another emerging economy. Shortly before the most recent state elections were held in the Mexican province of Oaxaca, Hurricane Agatha devastated large areas of the state and caused considerable damage in the state capital (NF News, 2022a). Desperate citizens, feeling abandoned by authorities, took to the streets and threatened to boycott the elections if relief did not arrive immediately. In some instances, protests escalated into riots during which polling stations were set ablaze and destroyed (NF News, 2022b).

Conclusion

This paper aims to address the question of when sudden disastrous weather events in metropolises in the Global South increase the likelihood of anti-government protests. For a considerable time, scholarly attention has predominantly focused on the adverse impacts of weather disasters on individuals whose livelihoods depend on successful harvests and healthy livestock. However, recent research has progressively shifted toward examining both the direct and indirect consequences of weather disasters on urban areas. Consequently, there has been a growing body of literature dedicated to discerning the conditions under which destructive weather events may lead to societal unrest within densely populated areas.

Undeniably, storms, floods, and landslides can have extremely adverse impacts in urban areas. This holds true particularly for fast-growing, less resilient metropolises in the Global South. For example, if infrastructure is not designed to cope with such events, large-scale destruction may rapidly ensue. Arguably, such situations constitute ideal breeding grounds for political

discontent. Destructive weather disasters may reveal deficiencies in public investments or expose a lack of preparedness for emergency situations among political decision-makers. However, grievances must be effectively mobilized to incite collective action. Notably, in many rapidly growing metropolises in the Global South, residents are frequently confronted with disastrous weather events that cause hardship, yet actual protests remain relatively rare.

Existing studies that have addressed this dilemma, investigating the conditions under which weather disasters may incite anti-government protests, have primarily focused on the geographical and demographic aspects of grievances linked to these disasters. While these studies have illuminated where the potential for protests following destructive weather events might be most pronounced, they have left substantial gaps in our understanding of the temporal dimension of these protests. Specifically, they have not adequately addressed when grievances arising from sudden weather disasters are most likely to be mobilized.

I argue that major political events, particularly elections, play a pivotal role in determining the timing of such mobilization. In the months preceding an election, political actors have every incentive to highlight urgent issues and present their proposed solutions to voters. Opposition parties, in particular, are inclined to capitalize on dissatisfaction stemming from weather disasters. During this phase, opposition parties typically strive to highlight the shortcomings of the incumbent government and position themselves as the better alternative (Daxecker, 2020; Salehyan and Linebarger, 2015; Tucker, 2007). Consequently, sudden destructive weather events that expose deficiencies in disaster preparedness become opportune topics for opposition parties in campaign mode. Therefore, I anticipate that they will actively mobilize grievances induced by disasters if they occur shortly before an election.

When elections for the government level responsible for disaster management are imminent, opposition parties may organize protests to draw attention to the alleged mismanagement by the incumbent government and emphasize their superior competence in handling such crises.

Furthermore, citizens may be more inclined to voice their grievances publicly in pre-election periods, as politicians tend to be more attuned to voter concerns. In democracies, politicians are more concerned about what voters want as an election approaches since their election results and, consequently, their access to resources and power depend on it.

Drawing upon insights from the literature on electoral protests and electoral violence (Birch et al., 2020; Harish and Little, 2017; Salehyan and Linebarger, 2015; Thomson et al., 2021). I propose the hypothesis that sudden weather disasters in metropolises of the Global South are particularly likely to trigger anti-government protests if they occur during the months leading up to state elections.

I empirically test this hypothesis using a newly constructed dataset comprising protest events in 19 Indian metropolises spanning a 20-year period. My findings reveal a statistically significant increase in the likelihood of anti-government protests following sudden destructive weather disasters, such as storms, floods, and landslides, when they strike shortly before elections for the state legislative assembly. Importantly, this effect is not observed in non-election periods or in the lead-up to nationwide general elections. This pattern aligns with the Indian context, where the primary responsibility for disaster management lies with state governments. Additionally, my quantitative findings are supported by several illustrative case studies, such as the protests that followed the major floods in Chennai in 2005, highlighting how political parties sometimes stage protests in the run-up to elections to publicly denounce the politicians in charge for allowing disastrous weather events to result in chaos and suffering.

Finally, I would like to emphasize that the conclusion derived from my findings is not to abandon elections. On the contrary, protests are events through which citizens communicate their dissatisfaction and needs. Hence, protests can serve as starting points for improving an unsatisfactory situation. While protests offer a relatively constructive outlet for voicing discontent, all protests carry the risk of spiraling out of control, potentially leading to violent

conflict. I emphasize that understanding the periods in which grievances induced by disasters are most likely to lead to protests could provide valuable guidance to policymakers on when and where to focus their attention following sudden weather disasters.

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DATA AVAILABILITY STATEMENT

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

A1: Search string

headline(riot*) or headline(protest*) or headline(demonstra*) or headline(strik*)
orheadline(unrest*) or headline(turmoil*) or headline(disorder*) or headline(mobilization*) or
headline(rally*) orheadline(campaign*) or headline(picket*) and hlead(city name) or
hlead(alternative city name)

A2: Coding manual

The aim of this project is to collect information on protests and riots, including strikes.

Most important criteria:

1) The event must have taken place **within the respective city** (its outskirts & suburbs included)

AND the event must have been **of political nature**.

Within the respective city?

Events have to be coded if they happen in, on the outskirts, or near the city. If reports mention events in very specific locations such as squares or neighborhoods, or close to certain buildings or monuments, they should be included to this dataset. Events are generally included if the location was reported as having happened:

- *in the ‘suburbs’ or ‘outskirts’ of the city in question

- *near or in a central government building when coding a national capital

- *at a location that one is able to locate as being within the city (for instance a specific palace or monument).

An event is not coded if the location was reported as being ‘near’ or a certain distance ‘outside’ or ‘north/east/south/west of’ the city. When unsure, if an event-location belongs to a city’s outskirts or suburbs, include the event and code it.

Reports frequently include statements like “the incident took place 10 miles outside the city”. Whenever you read such a specification about how far away from a city something happened, exclude the event and do not code it. When reports mention a specific neighborhood and you

are not sure how far it is from the city, look at Google Maps. If it belongs to the contiguous built-up area of the city, code it. If it does not, exclude this event.

Of political nature?

The term ‘political’ is here understood to encompass social actions directed against a political target (broadly understood as including also different social or identity groups) and/or challenging political authority. ‘Political’ should be interpreted, in a broad sense of the word.

In concrete terms this means:

*the objective of the action/activity carried out was political

OR

*the target was a political actor or a political group

OR

*the event was designed to challenge political authority

The events in my dataset are separable from crime in that they are politically motivated, although that distinction sometimes is blurred. In some cases it is not possible to verify whether an event was of political or criminal character. In case of doubt an event should be classified as political. Also the term „political group“ should be interpreted very broadly. Identity groups like ethnic groups, or social groups like workers in a specific industry form a political group.

Events not to be considered in this dataset:

*Clashes between the police and gang members since this is arguably part of an ordinary process to uphold order and security, unless there is evidence to the contrary.

*Prison riots. This even applies if the rioters were mainly political prisoners aiming to make a political statement. BUT clashes between police and political groups, or politically motivated attacks on prisons from the outside are INCLUDED in this dataset.

*Public mass events which do not transport a concrete political message e.g.: a funeral of a politician is attended by a very high number people; many people are on the streets to see the inauguration of a new president, the celebration of an election outcome,...

*When police officers defend themselves (e.g., when getting attacked by criminals) and respond appropriately to a previous situation. When policemen just carry out their duty without abusing their power, this should not be considered repression.

*Looting after e.g., a natural disaster, as it has no clear target and is more of criminal nature.

One or many events?

Events may be rather complex. They may last over a longer period of time and change in intensity/level of escalation. There exist three main criteria to determine whether an event should be coded as one continuous or several discrete events. Events were coded as discrete events if (in decreasing order of importance):

*It was possible distinguish between different actors and targets

*Events took place in different locations

*Reported motives for the events were different As a rule of thumb, at least two of these criteria had to be met before an event was coded as a separate event.

However, if a report clearly identifies different actors and/or targets, events should be coded separately.

Furthermore, the time period within which a series of events happened determines whether events are coded as discrete.

If a series of events involving the same actors and targets happened within a short period of time, this would normally be coded as one event (e.g., several demonstrations within few days).

If it is known that the events were carried out by the same group, events that are not longer apart than 7 days, can be coded as one event. If events involving the same actors and targets are spaced by at least one week (seven days), they would normally be coded as different events.

Other times, a report will summarize a collection of events happening over a long time-period, such as a period of continuous demonstrations or riots lasting for several months. In the absence of information about each individual event these aggregated events are recorded as one long event. If events like demonstrations stretch over longer period (several weeks or even months), and sometimes escalate into riots, we code the events on a weekly basis. For every week (Monday to Sunday) we code the event at the highest level of escalation (even when the respective state of escalation only took place at one day). As long as the state of escalation remains the same, the event is coded as one long continuous event. When it escalates further or loses in intensity (e.g., from riot to demonstration), a new event starts with the beginning of this week.

If demonstrations take place every week (e.g., every Monday) they are coded as one continuous event. If the time period between the events grows longer (e.g., the weekly demonstrations pause for a few weeks) and the weekly events then start happening again, code a new event (even if the actors remain the same!).

Often strikes are accompanied by demonstrations. If the demonstrations remain at the same level of escalation as the strike (e.g., organized demonstration), both are coded as a single event.

If strike and demonstration differ in intensity (e.g., the strike remains peacefully, while the demonstration turns into a riot), code them as separate events.

Demonstrations often last over a whole day. Thereby they the location and the number of participants often changes (e.g., protestors march to a stadium, the number of participants grows steadily and doubles until they reach their destination). If the level of escalation remains the same, code it as one event. If the level of escalation is different (e.g., peaceful demonstration while they are marching but riots in the stadium), code the events as different events.

General rules:

- *Write the date of the event down in following format: MM, DD, Y/ Month, Day, Year

- *If events escalate always code the highest level of escalation. e.g.: a demonstration turns into a riot → riot. If you are unsure about how to classify an event, rather use the higher category.

- *Threats alone, without any concrete action following, should not be considered within the scope of this dataset.

- *Only code events that have actually taken place. Plans and announcements for an event are not enough to code an event.

- * In order to be able to encode an event, the information must be concrete. You will quite frequently encounter vague allegations, however, this is not enough. For being able to record an event, you have at least to be able to determine in which month an event took place and who the two most important actors were.

- * When insecure whether events should be considered a single event or coded as separate events, always code the events separately. This will give the researcher a better grasp of event-dynamics.

- *Nationwide events should be coded for the capital city, but not for secondary cities if they are not specifically mentioned. Nationwide events should usually be coded for capital cities even

if specific action is not reported for the capital city. The assumption is that nationwide events would almost certainly occur in the capital, as it is an important and often largest city.

*Information about an event in a city can also be retrieved from reports about other cities. An example: If a report originally downloaded for the coding of Mumbai mentions an incident in New Delhi you can use this information for the coding of New Delhi.

How do I recognize which event type?

Spontaneous Demonstration – 62

* Distinct, continuous, and uncoordinated peaceful action directed toward members of a distinct “other” group or government authorities. In this event, clear leadership or organization CANNOT be identified. This is what distinguishes it from an organized demonstration.

* Since demonstrations usually require a certain amount of organization, planning and coordination, always code „60 - *Organized Demonstration*“ in case of doubt. Only use „62 - *Spontaneous Demonstration*“ if there is clear evidence that the demonstration is spontaneous and arose out of a situation.

* The term "largely peaceful" in the original USD-Codebook may be a little vague and sometimes confusing. Thus, interpret it very narrowly and use it as "completely peaceful". As soon as people start throwing stones, beating people, attacking policemen, breaking car windows, damaging infrastructure, ... it is no longer a demonstration, but a riot.

*Public event. →taking place in a public space e.g.: the streets, public places,... In it, individuals publicly commit themselves to the political message they want to convey.

Organized Demonstration – 60

*Distinct, continuous, and coordinated peaceful action directed toward members of a distinct “other” group or government authorities. In this event, clear leadership or organization(s) CAN be identified, this distinguishes it from a spontaneous demonstration. *The participants do NOT intend to cause physical injury and/or property damage, this is what distinguishes it from riots.

* The term "largely peaceful" in the original USD-Codebook may be a little vague and sometimes confusing. Thus, interpret it very narrowly and use it as "completely peaceful". As soon as people start throwing stones, beating people, attacking policemen, breaking car windows, damaging infrastructure, ... it is no longer a demonstration, but a riot.

In case of doubt, always use „50 – *Organized Violent Riot*“.

*Public event. →taking place in a public space e.g.: the streets, public places,... In it, individuals publicly commit themselves to the political message they want to convey.

*Peaceful strikes always belong this category. Strikes require coordination and planning, unless there is very convincing, clear evidence that the strike occurred spontaneously, it is always „60 – *Organized Demonstration*“. If strikes turn violent the appropriate category is „50 – *Organized Violent Riot*“.

Spontaneous Violent Riot – 51

*Distinct, continuous and violent action directed toward members of a distinct “other” group or government authorities.

*The participants intend to cause physical injury and/or property damage. In this event, clear leadership or organization(s) CANNOT be identified.

*There must be clear evidence that the violence - the "intention to cause physical injury and/or property damage" - was not planned but occurred spontaneously.

*IMPORTANT: A organized demonstration can never escalate into a spontaneous violent riot.

Only spontaneous demonstrations can turn into spontaneous violent riots.

In case of doubt code „50 – *Organized Violent Riot*“.

*Public event. →taking place in a public space e.g.: the streets, public places,... In it, individuals publicly commit themselves to the political message they want to convey.

*Examples for Spontaneous Violent Riots:

- When demonstrators of an originally peaceful spontaneous demonstration attack police forces.
- When participants of a/different spontaneous demonstration(s) clash and get into a fight with each other.

Organized Violent Riot – 50

*Distinct, continuous, coordinated, and violent action staged by members of a singular political or identity group and directed toward members of a distinct “other” group or government authorities.

*If demonstrators occupy/barricade buildings or roads, code organized violent riot. Although it might not involve the actual use of violence it definitely implies the threat of it.

*Strikes turned violent always belong in this category.

*Public event. →taking place in a public space e.g.: the streets, public places,... In it, individuals publicly commit themselves to the political message they want to convey.

*Examples for Organized Violent Riots:

- When demonstrators of an originally peaceful organized demonstrations attack police forces.
- When participants of a/different organized demonstration(s) clash and get into a fight with each other.

Variables

city_name	Name of the city in which the event occurred.
etype_no	number of the event-type 62, 60, 51, 50
etype_name	name of the event-type Spontaneous demonstration, organized demonstration, spontaneous riot, organized riot
bday	Records the day the event begins 1-31 Day of month the event begins 99 Not known
bmonth	Records the month during which the event begins 1-12 Month of year the event begins
byear	Records the year during which the event begins.
eday	Records the day the event ends 1-31 Day of month the event ends 99 Not known
emonth	Records the month during which the event ends 1-12 Month of year the event ends
eyear	Records the four-digit year during which the event ends. Always present.
actor1	Records the general political or identity group (i.e., actor) directly involved in the event. The information refers to who was directly involved on site and not just a target of the event.

actor2	<p>Records the second general political or identity group (i.e., actor) directly involved in the event.</p> <p>The information refers to who was directly involved on site and not just a target of the event.</p>
actor3	<p>Records the third general political or identity group (i.e., actor) directly involved in the event.</p> <p>The information refers to who was directly involved on site and not just a target of the event.</p>
target1	<p>Records the general political or identity group (i.e., target) directly targeted by the violence or protest that defines the event. This organization/person must not necessarily have been on site.</p>
target2	<p>Records the second political or identity group (i.e., target) directly targeted by the violence or protest that defines the event. This organization/person must not necessarily have been on site.</p>
agov_nat_d	<p>This variable is supposed to capture whether the event was directed against the national/central government.</p> <p>Code 0 if you do NOT think the action was directed against the national/central government. Code 1 if you think the action was directed against the national/central government. Code NA if you do not know.</p> <p>Government always refers to the government IN PLACE. After an election or after a coup this changes!</p>

agov_loc_d	<p>This variable is supposed to capture whether the event was directed against the local (regional or municipal) government. Code 0 if you do NOT think the action was directed against the local (regional or municipal) government. Code 1 if you think the action was directed against the local (regional or municipal) government. Code NA if you do not know.</p> <p>Government always refers to the government IN PLACE. After an election or after a coup this changes!</p>
agov_oth_d	<p>This variable is supposed to capture whether the event was directed against a government-related organization/institution (e.g., UN, pro-government journalists, police,).</p> <p>Code 0 if you do NOT think the action was directed against a government-related organization/institution. Code 1 if you think the action was directed against a government-related organization/institution. Code NA if you do not know.</p> <p>This refers to the government IN PLACE and might changer after an election or a coup.</p>
reactive_repression_d	<p>This variable is supposed to capture whether repression was employed in response to the protest or riot. Code 1 if governmental repression was employed, code 0 if this was not the case. When coding this variable, please keep in mind:</p>

	<p>*Simply because the police is involved in a protest or riot, the event is not automatically an incident of repression.</p> <p>*Repression often is not about the action carried out by the government, or groups acting in explicit support of the government, but about whether the action is the appropriate response to some previous incident. Generally, the use of violence very often is a hint towards repression. In case of doubt, we assume repression, unless the report clearly shows that the use of violence by the government was the proportionate response. It must be assumed that, the reporting already presents the government in a better light than it actually is.</p> <p><u>*Following activities are repression if they are carried out unlawfully and/or in response to peaceful demonstrations:</u></p> <ul style="list-style-type: none"> -severe assaults, -attacks -violent crackdowns -destruction of property -use of teargas -use of water cannons -arbitrary arrests → threat of violence in case of non-compliance -disproportionate police violence -harassment of journalists due to critical reporting
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	<p><u>*Following has to be considered outside of the scope of my dataset:</u></p> <p>-if police officers defend themselves and the use of violence or arrests are just the appropriate response to a previous action</p>
npart	<p>Records estimated total number of participants and people directly affected by the event according to the following scale. This is the sum of actors (participants of all sides) and targets (including the deaths listed in „nddeath“ as well as those wounded or otherwise affected). If the number of participants changes within a single event, use the highest number (e.g., an event has 50 participants in the morning and 2000 in the evening → code category 4)</p> <p>Code the number of participants according to following criteria:</p> <ul style="list-style-type: none"> 1 less than 10 2 10-100 3 101-1,000 4 1,001-10,000 5 10,001-100,000 6 100,001-1,000,000 7 over 1,000,000 9 Unknown, but probably very small number (less than 10) 10 Unknown, but probably small number (less than 100) 11 Unknown, but probably relatively small number (less than 1,000) 12 Unknown, but probably large number (less than 10,000)

	<p>13 Unknown, but probably very large number (less than 100,000)</p> <p>14 Unknown, but probably extremely large number (over 100,000)</p> <p>99 Unknown</p>
nddeath	<p>Records the best estimate of the number of persons killed in the event. If multiple estimates are given, use the number that is most frequently reported. If the exact number is not given, use estimates. Estimates in ranges are separated by a dash in increasing order, e.g. “100-800”. If the reported numbers are only a smaller sample of the total, this becomes the lowest possible estimate and is preceded with a “greater than” symbol (“>”). If the highest possible estimate is given, such as a combined estimate for multiple cities, precede with a “lower than” symbol (“<”).</p> <p>-99 = unknown (note the minus here)</p>
report_id1	<p>Records the id of the most important report that provided you with the necessary information for coding the event. The code consists of:</p> <p>1) The city_name</p> <p>2) The date of the report (MMDDYYYY)</p> <p>3) The number of the report. If there is only one report for this city on this date code 1. If there are two or three always code the number that is e.g. 2 if it is the second report for this city on this date</p>

	<p>The three id-elements are connected by a “_”</p> <p>Example of a report_id:</p> <p>Mumbai_01232001_1</p>
report_id2	<p>Records the id of the second report that provided you with the necessary information for coding the event. The code consists of:</p> <ol style="list-style-type: none"> 1) The city_name 2) The date of the report (MMDDYYYY) 3) The number of the report. If there is only one report for this city on this date code 1. If there are two or three always code the number that is e.g. 2 if it is the second report for this city on this date <p>The three id-elements are connected by a “_”</p> <p>Example of a report_id:</p> <p>Mumbai_01232001_1</p>
report_id3	<p>Records the id of third report that provided you with the necessary information for coding the event. The code consists of:</p> <ol style="list-style-type: none"> 1) The city_name 2) The date of the report (MMDDYYYY)

	<p>3) The number of the report. If there is only one report for this city on this date code 1. If there are two or three always code the number that is e.g. 2 if it is the second report for this city on this date</p> <p>The three id-elements are connected by a “_”</p> <p>Example of a report_id:</p> <p>Mumbai_01232001_1</p>
summary	<p>A summary description of the event. Usually, direct quotes from the news article, with three stars “***” indicating a break in the original text, and “...” indicating midsentence cutoffs.</p>
other_notes	<p>Do not feel obliged to code anything. Just note your general thoughts on the event. Especially if you are insecure about some aspects of your coding, for instance if you were undecided between two different event types, could not decide which actors to code,...</p>

A3: List of Indian cities included

	City	State
1	Ahmedabad	Gujarat
2	Bangalore	Karnataka
3	Bhopal	Madhya Pradesh
4	Bhubaneswar	Odisha
5	Chandigarh	
6	Chennai	Tamil Nadu
7	Delhi	
8	Hyderabad	Telangana
9	Jaipur	Rajasthan
10	Kolkata	West Bengal
11	Lucknow	Uttar Pradesh
12	Mumbai	Maharashtra
13	Patna	Bihar
14	Pune	Maharashtra
15	Raipur	Chhattisgarh
16	Ranchi	Jharkhand
17	Srinagar	Jammu and Kashmir
18	Surat	Gujarat
19	Thiruvananthapuram	Kerala

A4: Frequency of unrest events

Number of unrest events per city-month	Frequency	Percent
0	4038	88.55
1	332	7.28
2	119	2.61
3	42	0.92
4	20	0.44
5	4	0.09
6	4	0.09
7	0	0.00
8	0	0.00
9	1	0.02

A5: Frequency of anti-government protest events

Number of anti-government protest events per city-month	Frequency	Percent
0	4129	90.55
1	297	6.51
2	88	1.93
3	28	0.61
4	12	0.26
5	3	0.07
6	2	0.04
7	0	0.00
8	0	0.00
9	1	0.02

A6: CEM-Matching, sub-sample of pre-election periods (state – 9 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.49143693						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.16912	-6.7e+05	2.0e+05	5.1e+05	5.3e+05	-1.0e+06	-4.1e+06
Subnational Human Development Index	0.30804	-0.01058	0.032	-0.01	-0.004	-0.022	-0.068
Imbalance post-matching							
Multivariate L1 distance:	0.29115703						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.08075	-45629	2.0e+05	-5.6e+05	-8.4e+05	3.1e+05	34059
Subnational Human Development Index	0.11935	0.00013	0.032	0	0	0	-0.002

	0	1
All	608	63
Matched	432	63
Unmatched	176	0

A7: CEM-Matching, sub-sample of non-election periods (state – 9 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.37960442						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.15354	-1.3e+05	47045	3.3e+05	2.5e+05	62853	-9.4e+06
Subnational Human Development Index	0.20385	-0.02706	0	-0.036	-0.028	-0.039	-0.004
Imbalance post-matching							
Multivariate L1 distance:	0.19529634						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.03726	49045	47045	80474	1.3e+05	2.8e+05	-2.0e+06
Subnational Human Development Index	0.05669	-0.00053	0	-0.009	-0.002	0	-0.004

	0	1
All	3545	344
Matched	3297	344
Unmatched	248	0

A8: CEM-Matching, sub-sample of pre-election periods (state – 6 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.48427888						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.25097	-3.5e+05	4.5e+05	5.0e+05	8.2e+05	-7.8e+05	-4.1e+06
Subnational Human Development Index	0.2643	-0.00728	0.032	-0.01	-0.001	-0.022	-0.068
Imbalance post-matching							
Multivariate L1 distance:	0.17217076						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.07083	33105	4.5e+05	2993.6	2.4e+05	22268	34059
Subnational Human Development Index	0.09855	-0.00053	0.032	0	-0.001	0	-0.024

	0	1
All	418	42
Matched	274	42
Unmatched	144	0

A9: CEM-Matching, sub-sample of non-election periods (state – 6 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.36472465						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.15892	-2.0e+05	47045	3.6e+05	2.8e+05	-68667	-9.4e+06
Subnational Human Development Index	0.183	-0.02653	0	-0.034	-0.028	-0.039	-0.004
Imbalance post-matching							
Multivariate L1 distance:	0.18206432						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.04309	-35747	47045	34705	94670	-1.1e+05	-1.4e+05
Subnational Human Development Index	0.07241	-0.00084	0	-0.007	-0.001	0	-0.004

	0	1
All	3735	365
Matched	3493	365
Unmatched	242	0

A10: CEM-Matching, sub-sample of post-election periods (state – 6 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.40192308						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.10385	-5.6e+05	2.1e+05	-2.0e+05	1.2e+05	-7.8e+05	-2.1e+06
Subnational Human Development Index	0.24087	-0.00962	0	-0.01	-0.004	-0.033	-0.038
Imbalance post-matching							
Multivariate L1 distance:	0.23212974						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.03873	31565	2.1e+05	-4.1e+05	14335	-36540	-1.4e+05
Subnational Human Development Index	0.09559	-0.00148	0	0	0	0	0

	0	1
All	416	40
Matched	305	40
Unmatched	111	0

A11: CEM-Matching, sub-sample of pre-election periods (general – 9 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.56118227						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.21714	1.1e+05	1.1e+05	3.8e+05	-1.9e+05	2.7e+06	-8.4e+06
Subnational Human Development Index	0.3531	-0.04704	0	-0.05	-0.048	-0.062	-0.01
Imbalance post-matching							
Multivariate L1 distance:	0.09177164						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.07087	2.3e+05	1.1e+05	2.2e+05	5.5e+05	21458	1.4e+05
Subnational Human Development Index	2.1e-15	-0.00402	0	-0.002	-0.003	0	-0.01

	0	1
All	725	35
Matched	404	35
Unmatched	321	0

A12: CEM-Matching, sub-sample of pre-election periods (municipal – 9 months window)

Imbalance pre-matching							
Multivariate L1 distance:	0.49307692						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.28552	1.0e+05	1.2e+05	7.5e+05	6.0e+05	-3.3e+05	-8.4e+06
Subnational Human Development Index	0.30622	-0.03049	0	-0.02	-0.024	-0.055	-0.042
Imbalance post-matching							
Multivariate L1 distance:	0.10849466						
Univariate imbalance:							
	L1	mean	min	25%	50%	75%	max
Population	0.03382	16005	1.2e+05	51305	-2.3e05	5.4e+05	-85148
Subnational Human Development Index	0.07518	-0.00147	0	0	0	0	0

	0	1
All	572	50
Matched	403	50
Unmatched	169	0

A13: *Robustness check – logistic regression results on a non-pre-processed sample*

Dependent variable: *Anti-government protest event*

	MA1 Pre-election periods (State – 9 months window)	MA2
Sudden weather disaster	1.399** (0.550)	0.133 (0.240)
Pre-election period (state – 9 months window)		-0.228 (0.192)
Sudden weather disaster*pre-election period (state – 9 months window)		0.972* (0.527)
Population	6.06e-07*** (1.83e-07)	9.97e-08*** (3.26e-08)
Subnational Human Development Index	-22.96*** (6.314)	-11.81*** (1.864)
State capital	1.304 (6.651)	4.261*** (0.816)
Constant	1.858 (6.933)	2.241* (1.189)
City FE	Yes	Yes
Month FE	Yes	Yes
Time since last anti-government protest event & polynomials	Yes	Yes
Observations	486	4,302
Log Likelihood	-109.80065	-887.65656
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

A14: *Robustness check – Multilevel logistic regression results on a non-pre-processed sample*

Dependent variable: Anti-government protest event

	MA3 Pre-election periods (State – 9 months window)	MA4
Sudden weather disaster	1.266** (0.536)	0.124 (0.238)
Pre-election period (state – 9 months window)		-0.228 (0.192)
Sudden weather disaster*pre-election period (state – 9 months window)		1.004* (0.526)
Population	2.81e-07** (1.15e-07)	1.21e-07*** (3.07e-08)
Subnational Human Development Index	-12.46** (5.492)	-11.01*** (1.794)
State capital	0.113 (1.836)	1.874** (0.906)
Constant	1.382 (3.331)	1.196 (1.371)
Month FE	Yes	Yes
Time since last anti-government protest event & polynomials	Yes	Yes
Observations	668	4,541
Log Likelihood	-134.97296	-930.62802
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

A15: *Robustness check – conditional logistic regression results on a non-pre-processed sample*

Dependent variable: Anti-government protest event

	MA5 Pre-election periods (State – 9 months window)	MA6
Sudden weather disaster	1.323** (0.533)	0.132 (0.239)
Pre-election period (state – 9 months window)		-0.226 (0.192)
Sudden weather disaster*pre-election period (state – 9 months window)		0.965* (0.525)
Population	5.85e-07*** (1.79e-07)	9.92e-08*** (3.25e-08)
Subnational Human Development Index	-22.07*** (6.174)	-11.75*** (1.860)
State capital	<i>omitted</i>	<i>omitted</i>
City FE	Yes	Yes
Month FE	Yes	Yes
Time since last anti-government protest event & polynomials	Yes	Yes
Observations	486	4,302
Log Likelihood	-93.075368	-853.16935
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		