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Households amidst urban riots: The economic consequences of civil violence in India[1]

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Abstract: The objective of this paper is to uncover the determinants of riot victimization in India. The analysis is based on a unique survey collected by the authors in March-May 2010 in Maharashtra. We adopt a multilevel framework that allows neighborhood and district effects to randomly influence household victimization. The main results are that households that (i) are economically vulnerable, (ii) live in the vicinity of a crime-prone area, and (iii) are not able to rely on community support are considerably more prone to suffer from riots than other households. All else equal, income per capita increases victimization, presumably through an opportunity cost mechanism. We find further that relatively affluent neighborhoods and those characterized by large caste fragmentation are more riot-prone than disfranchised and homogeneous ones. Victimization is more common in neighborhoods with weaker social interactions, but some evidence suggests that weak social interactions may also be a consequence of rioting.

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1 Introduction

The World Bank (2011) has recently estimated that one in four people in the world (1.5 billion) live in countries affected by conflict, fragility and high levels of criminal activity. Yet the literature on violent conflict mostly focuses on civil wars, while other forms of violence remain largely under-researched. Although civil wars have represented a serious constraint to development and political stability in recent decades, many countries are affected by local conflicts and forms of social unrest that result in considerable economic, social and political costs, sometimes more so than larger-scale armed conflicts (Barron, Kaiser & Pradhan 2004, Collins & Margo 2004*a*, Collins & Margo 2004*b*, Deininger 2003, Klinken 2007, Murshed & Tadjoeddin 2009, Wilkinson 2004, Wilkinson 2005). Persistent forms of civil unrest have also often constituted the initial stages for more violent conflicts.[1] Existing literature offers, however, remarkable limited understanding on the dynamics of non-war forms of violence.

This paper addresses this gap in the literature. The paper presents the results of a new study on the micro-foundations of civil violence in India. The main objective of the paper is to identify empirically the determinants of riot victimization at the household level within a multilevel framework that takes into consideration how civil violence dynamics plays out at the neighborhood and district levels. The analysis is based on a unique dataset collected by the authors in March-May 2010 in the state of Maharashtra, which has experienced some of the highest rates of civil violence in India since the early 1980s. To the best of our knowledge this is the first study to empirically analyze the foundations of civil violence in India from a bottom-up perspective. To that purpose, the study identifies and analyzes important links between individual and household experiences of violence and wider neighborhood and district dynamics through the use of multilevel models.

While much has been written about riots in India, there is very limited understanding of the relationship between endemic rioting and individual forms of economic, social, political and physical vulnerability. Episodes of rioting are commonplace in India and their causes are addressed in a large and well established literature (Tambiah 1996, Brass 1997, Varshney 2002, Wilkinson 2004). Much of this literature analyses different factors (at national, state and city levels) that may account for the emergence of riots in India in particular locations and at particular points in time. The literature fails, however, to explain how within the same communities different people experience riots in different ways, and how these important variations in turn may affect the outbreak, organization and persistence of civil violence across neighborhoods and cities in India. There is some literature on the individual experiences of violence in India (for instance Chatterji & Mehta 2007). This literature is, however, based on small sample case studies, that fail to account for the fact that individual experiences of violence are very much linked to wider political, social and economic dynamics at the neighborhood, city, district and even state and country levels. Using an original household survey in the state of Maharashtra, we are able to document the extent of victimization, its profile and some of its consequences. Importantly, we are able to do so by inserting the micro level into wider neighborhood and district contexts thanks to the particular way in which the household sample is clustered within neighborhoods and districts across Maharashtra.

The paper is organized as follows. Section 2 below provides background information on communal violence in India in general and across the state of Maharashtra more specifically. Section 2 also introduces the Maharashtra Longitudinal Survey on Civil Violence and Welfare (MHLS), which provides the basis for the empirical study.[2] In section 3 we review the existing literature on rioting in India in order to derive possible testable hypotheses on the determinants of riot exposure among households, neighborhoods and districts. The econometric analysis of the determinants of riot victimization are presented and discussed in section 4. We start by presenting the results of a set of simple bivariate analyses, before introducing the results of more complex multilevel models where the linkages between micro and neighborhood and district levels are explored. Section 5 summarizes the main conclusions of the paper.

2 Maharashtra Longitudinal Study on Civil Violence and Welfare

2.1 Dataset and sampling design

In March-May 2010, the authors implemented a unique household survey across Maharashtra with the objective of obtaining fine-grained data on social, economic and political processes associated with the persistence of civil violence, and its consequences on individuals, households and neighborhoods.

Given the high concentration of rioting in certain areas in Maharashtra and the fact that riots are (despite constant and regular) a rare event in such a large state, we followed a clustered sample approach. To assess the prevalence of rioting within the state, we used district-level data from the Maharashtra Police on *Jatiya Dangali* which captures 'significant' riots reported at the police station level for which a First Information Report was filed with a magistrate. These data, spanning the period 2003-2008, contains information on the number of communal riots for each district. The dataset reports 75 communal riots in 2006, 74 in 2007 and 186 in 2008 in Maharashtra.

We discounted this data progressively by an order of 1/6th, so that 6 riots in 2003 equated to 1 riot in 2008. This was done in order to give a greater weight to more recent riots, thereby ensuring a good recall by those interviewed and allowing us to capture short and medium term impacts of violence. The average of the discounted data was ordered and clustered into three categories of districts: high rioting district (5 or more riots per district per year), medium rioting district (more than 1.5 and less than 5 riots per district per year) and low rioting district (less than 1.5 riots per district per year). We took into account the geographical spread of the state by choosing districts that represented all administrative regions and socio-cultural division in the sample. Our final selection included three districts in each of the medium and low clusters, and four in the high cluster. Figure 1 displays the location of sampled districts within the state.

For each of the ten districts, we then collected information on the precise location of instances of civil violence in the 24 months prior to fieldwork (2008-2010). We did this through a scan of print and online media, as well as key informant interviews. Our aim in doing so was to identify urban areas where violence took place (our sites of interest) within which to sample neighborhoods. In some instances, we were able to narrow down these urban areas to particular neighborhoods. In others, the information we were able to gather was less specific and we could not identify sites of interest below the town level.

Overall, 45 neighborhoods were then randomly selected from the list of voting-booths zones corresponding to our sites of interest. Each voting booth zone covers roughly 200 households, which equates to approximately 1000 individuals of voting age. In spatial terms, this was equivalent to an area which our research team could walk the perimeter in approximately twenty minutes.[3] It follows that neighborhoods in this study are very small units. The fact that neighborhoods are small even relative to our sites of interest had two main advantages: firstly, it allowed us to generate reliable neighborhood-level variables by aggregating a relatively small number of individual answers, and secondly, it ensured sufficient variability in the degree of exposure to civil violence across neighborhoods while reducing the risk that we missed relevant neighborhoods altogether.

The last stage of our sampling strategy consisted in randomly selecting households to be interviewed in each of our 45 sites/neighborhoods. Our field team began household interviews simultaneously from all starting points, working their way inwards. Household were randomly selected through a skip pattern, which for larger neighborhoods was 7 or 8 households, while for smaller neighborhoods was 4 to 5 households in order to ensure a sample of 24 to 25 households per neighborhood. This corresponded to a sample of around 10 per cent of all households in each neighborhood. Through this multi-staged sampling framework, we obtained a final sample of 1089 households, spread across forty-five neighborhoods, in ten districts in Maharashtra.

2.2 Descriptive statistics

The questionnaire administered to the respondents was in part meant to inform us on household characteristics associated with exposure to violence. To this end, the questionnaire included modules on income and consumption, access to services and amenities, the extent of civil violence in the neighborhood, and the experience of household members with acts of violence amongst others. We also gathered data on community relations and trust, with a special emphasis on relations with police and officials. Summary statistics are provided in table 1.

As became apparent during the sampling stage of the project, most of the sites affected by civil violence were slums/low income neighborhoods. An array of vulnerability indicators stemming from the survey confirms this. The median monthly income of the sample is 5,000 rupees (around 95$) while the median household hosts 5 members. Because our sample is made of predominantly low-income urban areas in every district, the sub-state variations in terms of income are much lower than representative district figures.

The two most common occupations are pupils/students (30 per cent) and housewives (25 per cent), that is, people not in the labor force. Amongst the active population in the sample, the main occupations are daily wage earners (22 per cent of the labor force), followed by service officers (10.2 per cent), manual laborers (9.6 per cent) and shop owners (7.6 per cent). Petty traders and businessmen constitute more than five per cent of the labor force. The predominance of casual laborers, together with the extremely high level of unemployment we found among the active population (13 per cent), low access to water and low levels of asset ownership are obvious signs that households in the sample are economically vulnerable in a very acute way.

2.3 Exposure to civil violence and victimization

Our questionnaire included several questions to capture the exposure of households to various forms of civil violence. We will describe first the results of the module in which households self-report the number of events of civil violence that happened in their neighborhood in the last year. The question asked was: *In the last 12 months, have any of the following events occurred in your neighborhood?* The different events include: riots (*danga*), stone-pelting, public fights, damages of buses or public property, burning of tires, throwing of bottles, police harassment, agitation related to a *bandh* (strike) and violence during curfew. Whilst some of these events may be considered as modalities of violence within the context of a riot (as stone-pelting or damages to property for example), they may also occur in the absence of it. As described in table 2, the most common forms of civil violence are riots: one in every five households reported at least one riot in their neighborhood, then public fights and stone-pelting. Curfew follows closely (14%) indicating that a majority of riots in the sample were severe enough to induce the state to resort to this coercive means of restoring law and order.

As is evident from table 2, most forms of civil violence are heavily concentrated in some neighborhoods. The median proportion of households reporting at least one public fight is 14% (8% for riot or stone pelting), well below the average proportion of exposed households. Evidence of neighborhood effects is further demonstrated by the analysis of variance of a fully unconditional random effect model in which the exposition to violence of household h living in neighborhood n is explained by a neighborhood specific effect and a disturbance term. The proportion of variance explained by the neighborhood random effect is 55% for riots, around 40% for curfews and stone pelting and 28% for public fights. These results suggest that household exposure to riots must be understood within the wider neighborhood context. We return to this point in the empirical analysis below.

We have captured levels of victimization using the following question: *In the past 24 months, did you or any member of the household experience a riot?* The question was asked after similar questions probing whether the household experienced negative events such as illness, flood or lost employment. In so doing, we are quite confident that our variable reflects actual impact on the household as opposed to signaling the simple presence of violence in the neighborhood. The fact that victimization rate is twice as low as the proportion of respondents declaring a riot occurred is also reassuring.

Overall, 136 households were victim of riots, which corresponds to 12.5% of the sample. Out of these 136 households, 26 suffered directly.[4] This minority of households declared they needed extra money to cope with the riot, either because of damages done to their house or shops or because of medical treatment of injuries.

3 Riot victimization in India: conceptual framework and determinants

Communal violence, as riots are usually labeled in South Asian studies, refers to riots in which two communities (most often Hindus and Muslims in the case of India) clash and engage in killing, maiming, looting, arson and destruction (Gupte 2012).[5] The single most important episode of communal violence in India took place during the partition of the erstwhile British Empire in which millions of Hindus, Sikhs and Muslims were killed or forced to move across the newly created border. Other notorious examples were the series of riots across Indian states after the destruction of the Ayodhya mosque in 1992, and the wave of violence in Gujarat in 2002.

In this paper, we use the term civil violence rather than communal violence to account for the fact that violence does not involve neatly defined communities (caste divisions play a great role for instance), as well as to emphasize that we will pay close attention to routine, smaller bouts of violence (Gupte 2012). The forms of civil violence of particular importance to our study are rioting and its closely related modalities including looting, ransacking, stone pelting and arson, and also, vigilantism, thuggery, gang violence and extortion.

Interestingly, there is very limited literature on the impact of civil violence in India on levels and types of victimization. Most of the literature has concentrated on explaining the outbreak of communal violence, with much less emphasis on the persistence of this violence across communities and cities in India, affecting specific social, economic and political groups. However, this literature provides some pointers regarding potential correlates of victimization. We are able to hypothesize that at least three main factors may be associated with levels of violence victimization: the presence of visible assets or resources that may attract opportunistic violence and increase physical vulnerability, the levels of integration within local communities and group identity. In addition, our own sampling exercise discussed in the previous section showed us that in Maharashtra areas of recurrent and persistent violence are also areas of acute economic vulnerability. We discuss these factors in more detail below and describe the indicators we will use for each one in our empirical analysis in section 5.

3.1 Physical insecurity

It is a well known fact that looting, arson and destruction of private and public property are among the main modalities of riots (Tambiah 2005). Even though the crowd may have originally gathered peacefully, it is easy for criminal elements to infiltrate it or merely exploit the confusion caused by the gathering. Some of these activities may be for personal gain. We hypothesize that households displaying visible assets are at greater risk either because of direct targeting or opportunistic looting. Opportunistic looting has been reported in many instances of civil violence whereby individuals exploit the riot to settle scores, enrich themselves or get rid of business rivals (Engineer 1991, Wilkinson 2004).

In the context of impoverished urban areas, visible assets are relatively uncommon. We consider as an indicator of visible wealth the share of following variables any given household owns: presence of a dish TV, car/scooter/motorcycle, air conditioning device, and generator. All these assets are readily visible from the outside, particularly in single storied shacks, tenements or houses, and signal potential riches inside the dwelling. In addition to visible assets, the size of the house and the material in which it is built (concrete/brick or in a building, as opposed to less permanent materials) and whether the household owns a shop are other possible attributes that put households at risk. It is worth noting that the material of the dwellings is a two-faceted indicator: on the one hand houses made of permanent materials may signal wealth and attract looters, but on the other hand houses made of non-permanent materials are easier to plunder. The presence of visible assets may increase physical vulnerability depending on the relative safety of the area where the household lives. We will consider as an indicator of physical vulnerability the existence of unsafe places in the proximity of households, as reported by households themselves, and the distance to the police station.

3.2 Insertion within local community

In low income areas of India there are few means available to households to protect themselves. Physical protection is likely to be more effective when household benefit from strong integration within local social networks (Mitra & Ray 2010). Social networks convey information about upcoming trouble and allow people to take steps to protect their family and assets (Tambiah 1996). Once the riot starts, households with high level of social capital will be able to receive aid from the community (e.g. food). In addition, households that know their local police and other important actors in the community are likely to be protected as their houses and people will be watched by police, their neighbors and so forth. Varshney (2002) has famously argued that the strength of civic life is the main factor that dampens the outbreak of violence between Hindu and Muslim communities, whereas Jha (2008) shows that the two groups will peacefully coexist if they complement each other in terms of local productive activities, and competition and inequalities between the two groups are kept low.

The indicators we use to account for household insertion within local networks include: the number of years a given household has lived in its current dwelling, whether respondents trust their neighbors and the local police, whether they normally ask for community support in times of need, and whether they are engaged in civil life through membership in various organizations.

3.3 Identity markers

Riots are known in India as *jatiya dangali*, i.e. ethnic riots, a term that conveys the idea that violence occurs between identifiable groups.

The hierarchical structure of our data offers a unique possibility to model identity markers at the household *and* neighborhood levels. We will thus be able to ascertain whether the potential victimization effect of any marker operates at the macro level (neighborhoods with specific distributions of caste, language and religion are more prone to rioting) or at the micro level (within neighborhoods, households with specific identity markers are prone to be affected) or at both at the same time. The Maharashtra questionnaire included questions on religious affiliations, caste (*jati*) and language. We matched each *jati* with its corresponding status (ST, SC, OBC, others) in the state of Maharashtra[6], and we use the latter as our household caste variable. As for language, we will distinguish between native Marathi speakers and native speakers of other tongues (predominantly Hindi and Urdu) as a means to capture the migration issue (Maharashtrians v non-Maharashtrians) that cuts across religious affiliations and has proven important in political violence dynamics in the state (Hansen 1996, Hansen 2000). At the community level, we computed fractionalization and polarization indexes of *jati*, larger caste grouping and religious affiliations. The fractionalization index is given by $F_n^j = 1 - \sum_{j=1}^{j=J} (p_j^2)$ where j represents the identity line under study, J the total number of categories within the identity line, n the neighborhood and p_j the share of households with identity j in neighborhood n. Per the definition of Montalvo & Reynal-Querol (2005) the polarization index is given by $P_n^j = 4 \sum_{j=1}^{j=J} p_j^2 (1 - p_j)$.

3.4 Economic vulnerability

Economic vulnerability refers to the households' capacity to withstand adverse shocks. As mentioned earlier, riots are very disruptive for households that directly suffered from damages. However the majority of victims in our sample does not suffer from injuries or damaged houses but instead from the indirect consequences of riots. Curfews are of particular importance. Severe riots are associated with curfews, sometimes for an extended period of time. Curfews make it difficult or impossible to buy food, other first necessities, and medicines, or secure access to doctors as well as getting to work. Yet the welfare impact of curfews have not been a subject of analysis.[7] A notable exception is provided by Paul Brass (2006*a*) who writes: *"[in the slum areas of a city in India] in the summer months of hellish heat and humidity, where often large families comprising three generations of persons live in* *tiny flats without running water or toilets, with minimal stocks of food, curfew is invariably a dire experience easily turned into a catastrophe. This is especially the case for daily wage-earners who have to feed large families from their income, who have no monetary reserves whatsoever, and who face hunger within two days and potential starvation when curfew is imposed for weeks, as it often is, with minimal hours when movement outside one's house is allowed for the purpose of obtaining necessities.".*

Even when a curfew is not enforced, riots have the potential to temporarily disrupt the functioning of markets and communities. It is our assumption that those most vulnerable to changes in their economic conditions are more prone to acutely suffer from any disturbances, not matter how short-lived, brought by rioting. Those with a secure stream of income, comfortable savings and who are not reliant on informal arrangements to get by are conversely apt to navigate through the conflict insofar as they are not directly affected.

We will use several indicators to capture economic vulnerability: monthly income per capita, possession of non-visible assets, reliance on community's assistance, capacity to use savings in case of need and whether the household relies on daily wages. In addition, we will make use of a subjective valuation of each household's welfare with respect to others in the neighborhood. Income per capita is also an indicator of the monetary opportunity cost incurred by households if the riot and ensuing curfew keep them away from work for an extended period of time. Those with high income are not likely to experience the same level of hardship as that experienced by the poor, but in contrast may experience higher levels of foregone revenue.

4 Econometric analysis of determinants of victimization

We start by exploring the determinants of exposure to riots in Maharashtra through a set of naive bivariate analyses. These reveal simple correlations between victimization and the above hypothesized predictors, but lay down some ideas about the degree with which victims and non-victims differ in these characteristics.

4.1 Bivariate analysis

Table 3 displays whether predictors of physical vulnerability, insertion within local networks and economic vulnerability differ between victims and non-victims. This provides a first insight as to whether and which categories of household-level factors and neighborhood characteristics are relevant to explain household victimization. Covariates of identity lines will be dealt with later.

Several variables of physical insecurity are significantly correlated with household victimization: the index of visible assets, the size of the dwelling and the reported presence of an unsafe place in the area. All correlations exhibit the expected signs. Other predictors of physical vulnerability do not appear to significantly relate with victimization.

Are victims of riots less inserted in local networks and less likely to trust their neighbors or the police? According to the correlations displayed in table 3 the answer is a clear (and counter-intuitive) no: households that reported to have been affected by a riot do trust their local police significantly more and exhibit a higher rate of civic engagement than non-victims. There is no significant correlation between victimization and trust toward neighbors.

The evidence on the role of economic vulnerability on victimization is equally contradictory to our hypotheses: victims tend to resort less to community help in case of need, their income per capita is 400 rupees higher than non-victims and they enjoy an extra 1.5 hours of running water per day with respect to non-victims. The only contrast is the average access to electricity which is lower by one hour per day for victims.

Correlations results for identity markers are shown in table 4. We can see that among victims, the share of Hindus is significantly larger than within non-victims (by about 16 percentage points) whilst the converse is true for Muslims. There is no correlation between Buddhist affiliation and victimization. The same lack of relation appears for broad caste groupings. In contrast, Marathi speakers constitute 67% of the victims but only 47% of non-victims, a sizable and statistically significant difference. Does that mean that Hindu households are more prone to suffer from riots than their Muslim neighbors? Are native Marathi-speakers more at risk than native Hindi or Urdu speakers? Or do these results signal that predominantly Hindu (or Marathi) neighborhoods are more frequently hit by civil violence than predominantly Muslim (or non-Marathi) ones? We cannot at this stage answer these questions without falling prey to the *atomistic fallacy* which would consist in using the household-level correlations to inform on correlations at the neighborhood level. The lower part of table 4 provides a crude way to bring in neighborhood effects into consideration and overcome the atomistic fallacy. The sample has been restricted to the 8 neighborhoods wherein at least 50% of the respondents reported themselves as victims (84 out of the 136 victims live in these 8 neighborhoods). One can see that now the correlation between religious affiliations and victimization vanishes while that between Marathi and victimization, although reduced in magnitude, remains significant at the 5% level.

The upshot of this exercise is to show that household victimization relates to many household-level predictors, thereby confirming that within riot-affected neighborhoods, patterns of victimization exist. The sign of correlations is however the opposite to what we hypothesized. Yet the above analysis is unable to disentangle household and community effects. Insofar as riots are localized events, it might be for instance that income does not operate at the household level but at higher level. In other words, more affluent households may be more likely to be affected not because they are richer than their neighbors, but because riots are more common in affluent neighborhoods. We now turn to a multivariate and multilevel analysis to properly account for such effects.

4.2 Multivariate analysis of victimization

4.2.1 Empirical specification

We model the probability to be affected by a riot using a three-level logit model with random intercepts representing unobservable heterogeneity at both neighborhood and district levels. The hierarchical structure of our data is such that households are nested within neighborhoods which themselves are nested within districts. We will refer to level 1 as the household level, level 2 as the neighborhood level and level 3 as the district level. The multilevel modeling we propose allows us to correct the estimations for the dependence of residuals that arise between households within neighborhoods, and between neighborhoods within districts. Furthermore, these source of dependences of residuals are not a mere source of problem to the econometric exercise, but are in and of themselves important elements of the analysis. The questions we ask are the following: what are the respective contributions of neighborhood and district effects to household victimization? How do they vary once household and neighborhood covariates are introduced? Do some variables exert a different effect at the household and neighborhood levels? A multilevel model is a good way to address these questions while correctly accounting for the hierarchical structure of the data in the estimations. For sake of clarification, we will refer from now on to our empirical model as a three-level random-intercepts model. Alternative definitions include random-effect model, a mixed model or a hierarchical non-linear model. The difference between these terms is just semantic as all describe a model that features both fixed parameters to be estimated and random effects which can not be directly estimated (but can be predicted).

Any model with random effects requires that the unobservable components are uncorrelated with the covariates. In the context of a three-level model it means that the random effects associated with both neighborhood and district levels are uncorrelated with the covariates. This assumption does not hold if there exist omitted factors at level 2 or 3 which are correlated with level 1 covariates. Such a situation is very likely in most applications so that researchers usually prefer to use a fixed effect (or within) estimator whose consistency does not hinge on this assumption. However, the fixed effect estimator comes at the cost of increased variance of the coefficients (since they fully parametrize the unobserved heterogeneity), the impossibility to explore the effects of contexts - which are key to our paper, and to produce out-of-sample predictions (Gelman & Hill 2012). Fortunately, the Mundlak-Chamberlain approach allows us to avoid using fixed effects while ensuring that the random effects model is valid (Mundlak 1978, Chamberlain 1980). The approach advocated by Mundlak and Chamberlain consists in approximating the unobservable heterogeneity at level L by the means of covariates at level L-1. The three-level logit model with random intercepts can then be written as

$$logitPr(y_{hnd} = 1|x_{hnd}, \zeta_{nd}, \zeta_d) = \beta_1 x_{hnd} + \beta_2 W_{nd} + \zeta_{nd} + \zeta_d + e_{hnd} \tag{1}$$

with

$$\zeta_{nd} = \mu_{nd} + \theta \overline{x}_{nd} \tag{2}$$

$$\zeta_d = \mu_d + \gamma_1 \overline{x}_d + \gamma_2 \overline{w}_d \tag{3}$$

where y_{hnd} takes the value 1 if household h in neighborhood n in district d reports it was affected directly or indirectly by a riot. To simplify the notation, x_{hnd} represents the vector of household-level covariates and w_{nd} denotes the set of neighborhood-level variables. The random intercepts at the neighborhood level, ζ_{nd}, and district level, ζ_d, are assumed to be a function of the within-neighborhood means of household covariates ($\overline{x}_{nd}$) and the within-district means of neighborhood covariates ($\overline{w}_d$), respectively. Conditional on these means, the random intercept at each level (μ_{nd} and μ_d) is assumed independent of the covariates (x_{hnd} and w_{nd}). The Mundlak-Chamberlain approach to random effect estimations is a potent yet underused one. By partitioning the unobserved heterogeneity into within and between components, it considerably weakens the assumption that random effects must be uncorrelated with the covariates. The correlation between a level L random effect (e.g. ζ_{nd}) and a level L-1 covariate (e.g. x_{hnd}) must operate through the covariance between the group mean ($\overline{x}_{nd}$) and the random effect (Raudenbusch & Bryk 2002, p. 262). By controlling for the group means one removes by construction the correlation between the level 1 covariates and the level 2 random effect and hence restores the validity of the random effect estimation (Mundlak 1978). The coefficients associated with the group means (θ, γ_1 and γ_2) are interpreted as contextual effects, which are the difference between the within and between effects of a given variable.[8] It is worth noting that the Hausman test which is abundantly used in the literature to choose between fixed and random effects is fundamentally a test that θ, γ_1 and γ_2 are equal to zero. In that case, contextual effects are absent and both estimators are equivalent. If contextual effects are statistically non-null, one needs to include them as additional covariates to restore the equivalence between fixed and random effects (see e.g. Mundlak 1978, Rabe-Hesketh & Skrondal 2012, Fielding 2004, Snyders & Berkhof 2008).

The omission of higher levels variables is not the only concern in our empirical strategy. The absence of correlation between x_{hnd} and e_{hnd} remains crucial for the consistency of the estimations (and is independent of the choice between fixed and random effects). We will discuss the reliability of this identification assumption later in the paper.

The estimations are run with the *xtmelogit* command in stata with seven integration points at each level.

4.2.2 Results

We begin by estimating a model like in equation 1 without neighborhood-level predictors (w_{nd}) and without the within-neighborhood means (i.e. $\overline{x}_{hnd}$). The results are displayed in the first column of table 5. With neighborhood and districts effects now accounted for, we can see that the household-level variables behave very differently compared to the previous bivariate estimations. The coefficient associated with the variable of distance from the police station is surprisingly negative and significant at the 10% level. The point estimate is substantial: *ceteris paribus* an increase in distance from 5 to 20 minutes (which represents the inter-quartile of the distribution of distance to the police station) translates into a reduction of 40 % of the odds of victimization ($\exp 0.036 * 15 = 0.62$). The presence of a crime hotspot is the second variable of physical vulnerability that is significant in the estimation (at the 1% level), this one with the hypothesized positive sign. Its associated odds ratio of 5 is very large. The index of visible assets, the size of the house and the other predictors of physical vulnerability do not appear significantly related to household victimization.

Trust toward neighbors reduces the odds of victimization by 44% ($\exp -0.583$), an impact significant at the 10% level while trust toward the police is very imprecisely estimated. Further, households which can rely on the assistance of the community in case of need are 75% less likely to report a victimization status (with p-value<0.05). The numbers of years households spent in their current house do not play a role in explaining odds of victimization. The last variable of 'social capital', i.e. whether a household member is engaged in a CSO/political party/trade union or other group, is positively, and statistically significantly, related to victimization. The odds of victimization of a household engaged in civic life are three and a half times higher than households not involved. This is a very large and counter-intuitive effect. Our interpretation is that this variable reflects more economic vulnerability than social capital, a discussion we will elaborate on below.

Neither caste nor religion variables display a significant relationship with victimization, but Marathi households are almost three times more likely than non-Marathi to report being affected by a riot. These results are consistent with the preliminary finding of table 4. In terms of economic vulnerability, we find that the odds of victimization for households that can use savings in times of needs are 60% lower than for households without this kind of financial security. Relying on daily wages or having few non-visible assets do not affect the likelihood of victimization. Finally, income per capita, as hypothesized earlier, increases the odds of victimization presumably because of a higher opportunity cost. The odds ratio of a change in income equal to the inter-quartile of the income distribution (around 1000 rupees) is 1.22.

In column (2) we introduce a change in the indicators of economic vulnerability: daily earner and the index of non-visible assets are dropped and replaced by the variable of subjective welfare ranking. The latter displays the expected negative sign but fails to reach statistical significance. Following the surprising result on involvement in civic life, in column (3) we distinguished between membership in women self-help groups and membership in other groups. Out of the 148 households in the sample for which at least one member is involved in civic life, 86 belong to women self-help groups (58%). The second largest type of group is political party, with 27 households only. Based on the weight of self-help groups in the sample and on the idea that a membership in these organizations may be more related to economic vulnerability than to social interactions, we replace our former variable of engagement in civic life by a variable of membership in women self-help groups (membership in other groups is coded as zero). We can see that the coefficient associated with the women self-help group variable is larger (1.682) than the coefficient associated with any sort of membership (e.g. 1.26 in column 2). It means than the positive effect of the civic life variable was entirely driven by the membership in self-help groups, whereas membership in other type of structures is unrelated to victimization.[9] Households which take part in self-help groups are considerably poorer than average (970 rupees per month against 1445 for the others). This, together with the explicit economic function of these groups (such as saving and investing) explains why we interpret this variable as reflecting economic vulnerability rather than how well households are inserted in the local networks.

For all these three specifications, the estimated variances of the random effects remained stable: around 0.7 for the neighborhood effects and 3.7 for the district effects. The validity of the multilevel approach with respect to a simple logit is vindicated by the results of the LR test which signals that the variances of the random effects are non-null with a p-value inferior to 0.001. The importance of the random effect can be easily grasped through the median odds ratios (Rabe-Hesketh & Skrondal 2012, p. 533). The median odds ratio, which is easily derived from the estimated variance of the random effect, can be interpreted as follows: imagine we randomly choose two households with identical values of covariates, and that we then compute the odds ratio formed by comparing the household with the larger odds of victimization with the household with the lower odds. The difference between the two stem from the random effects as the households are otherwise similar. Given the estimated variances of random effects, we calculate that half of the time, such an odds ratio will exceed 6 when district random effects are considered and 2 when neighborhood effects are considered.

In column (4) we include neighborhood-level covariates as an application of the Mundlak-Chamberlain approach. Variables included are: fractionalization indexes for *jati*, caste and religion; presence of specific landmarks (temple, *chowk*[10] and market) and the within-neighborhood means of household covariates. As such the model is over-parametrized, which is not surprising considering the number of neighborhoods in the sample (45) and the number of level-2 variables included. The consequence is that the estimation of the variance for the neighborhood effects does not converge and is set to 0. A comparison of the estimates of level-1 covariates between column (4) and columns (1) to (3) reveals that they are remarkably stable. The only significant change concerns the estimated effect of OBC which increases from 0.5 to 0.7 and thus become significant at the 10% level. Fundamentally the stability of the estimates is evidence that the estimations are consistent and that the use of a random effects estimator is the most appropriate choice. Regarding level-2 variables two of them reach statistical significance: the index of caste fractionalization and the neighborhood means of savings capacity.[11] The former exhibits a seemingly massive coefficient of 17.9. Yet given that the index rises by less than three percentage point between the 25^{th} and 50^{th} percentile of its distribution, the corresponding impact on the odds of victimization is in fact limited to 1.7. The contextual effect of savings capacity is strongly positive: the odds ratio formed by comparing two households with the same capacity to use savings, one living in a neighborhood where 46% of households can use savings, and the other one in a neighborhood where 58% of households can do so, is as high as 2.29. The contextual effect of savings runs in opposite direction to the within effect. The latter has a protecting impact: within a given neighborhood, households with savings fare better, whereas, *ceteris paribus*, neighborhoods that are better-off (wherein a larger share of people can build savings) are more likely to experience riots than more economically disenfranchised neighborhoods.

In order to investigate further potential contextual effects, we need to reduce the dimensionality of the vector of level-2 covariates. The results of the Mundlak-Chamberlain approach in column (4) reassure us on the consistency of random effects estimations so that we can safely drop level-2 covariates. In column (5) we retain neighborhood means which correspond to potential contextual effects discussed above in the paper: these concern trust toward neighbors, visible assets/savings capacity/income per capita, and strength of community assistance. Each of these variable correspond to a broad category covering social insertion, physical vulnerability and economic vulnerability. We maintain caste fractionalization in the specification. In this more parsimonious specification the contextual effect of savings capacity is unchanged, the contextual effect of income per capita is positive and significant as well, and that of visible assets indistinguishable from zero. The contextual effect of trust towards neighbors remains statistically insignificant but that of the strength of community assistance becomes very precisely estimated. The point estimate is negative (-11.46) and significant at 1%. Quantitatively this means that if we compare a household living in a neighborhood where 25% of people can rely on help from the community to a completely similar household living in a neighborhood where the proportion of people who can rely on community help is 50%, the former has 60% more chance to be affected by a riot. Such a contextual effect provides evidence that the quality of social interactions at the macro-level matters considerably in explaining vulnerability to violence. This finding supports and strengthen the argumentative logic of Varshney (2002). Our multilevel framework allows us to measure both the within and the contextual impacts of social ties, something that macro-level studies cannot. As a result, we provide strong evidence that Varshney's point about social ties operating at the contextual level is credible, but that there is also an individual dimension to it, with households differentiated in their propensity to be affected by violence on the basis to their personal connections to the community.

In the last column of the table we adopt the most parsimonious model in which we drop level-1 covariates which failed to have a significant effect. The results are mostly unaffected with the exception of the point estimate of caste fractionalization index which reduces in magnitude. The variance of the neighborhood effects is now correctly estimated, and appears not to be statistically different from zero. Once we account for the contextual effects of economic vulnerability (or lack thereof), community help and for the index of caste fractionalization, the random part of the neighborhood effect becomes insignificant.

4.2.3 Robustness tests

The results presented above are remarkably robust to a series of alternative specifications, which are shown in table 6. To save space we do not report the variance of the random effects and the p-value associated with the LR test. Neither are changed with respect to the previous specifications.

In column (1) we replicate our preferred specification that appears in column (6) of table 5 with one additional variable: the district mean of the caste fractionalization index, and without the index of visible assets which was insignificant. A comparison of these two estimations reveals that all the coefficients and associated standard errors remain remarkably stable. This is a direct result of the district-mean of caste fractionalization index to appear as indistinguishable from zero in the latter specification.

In column (2) and (3) we present the estimates obtained from a neighborhood fixed effects and a district fixed effects estimator, respectively.[12] Consistent with our previous endorsement of the validity of the random effects approach, the results of the two fixed effects estimations prove very close to the estimation with random effects. The only differences in the level-1 estimates introduced by the fixed effects are the lower precision of the estimated coefficient of presence of unsafe places (which nonetheless remains significant at the 10% and 5% levels for the neighborhood and district fixed effects, respectively) and the lower point estimate of the Muslim and Marathi coefficients in the specification with neighborhood fixed effects (but both variables remains indistinguishable from zero in any case). Among level-2 variables which are still identified with a district fixed effect estimator, a noticeable difference arises for trust toward neighbors for which the coefficient decreases from -1.7 to -2.6 and reaches significance at the 10% level.

In column (4) we revert back to the random effects specification but alter the sample so that Mumbai and Thane districts are excluded. Both districts stand out from the rest of the sample in that they are much more 'urban': for instance, 34% of sampled households in Mumbai and Thane districts live in a building, opposed to 8.2% in Sangli and Kolhapur, 7% in Dhule, and less than 5% in all other districts. They also exhibit much lower levels of trust toward neighbors and nearly non-existent community support (only 2 out of 143 households in Mumbai and Thane ask for community support in case of need, against more than 12% elsewhere in the sample). Yet, removing both districts from the estimation sample does not alter significantly the results. The only changes concern the presence of unsafe places, whose effect becomes smaller while remaining significant at the 5% level, and the neighborhood-mean of trust toward neighbors, whose effect is now larger in absolute value and becomes statistically significant (p-value<0.1).

The dependent variable we have thus far considered takes the value 1 for both direct and indirect victims of riots, and zero otherwise. Direct victims are defined as households which suffered injuries and/or physical damages as direct consequences of the violence; and we would want to test whether they differ from indirect victims in terms of the variables that put them at risk. Given that the sub-sample of direct victims is so small (n=26) we cannot resort to multinomial or ordinal modeling of victimization. Instead we recode in column (5) the dependent variable so that only indirect victims are compared to non-victims (observations for direct victims were set to missing). Large discrepancies between estimations with indirect victims only and estimations with all victims would be a sign that the use of the latter had been misguided. A comparison of columns (1) and (5) shows that the estimations are in fact qualitatively similar.

After having shown that our results are robust to the choice of estimator, sample and dependent variable we check in column (6) if the results suffer from response biases. Civil violence is a very sensitive topic in India, arguably creating a risk that respondents do not sincerely report riot and victimization to the enumerators. The situation is compounded when the interview takes place outside the house as more often than not a group of neighbors and passers-by gather around the respondents. Interviews in slum areas where houses are very small and the density of population is high were routinely done in such conditions. In column (6) we introduce as an additional covariate a categorical variable depicting the setting of the interview - it takes the value 1 if the respondent was alone, 2 if children were present, 3 if other adults were present and 4 if the spouse was present. A third of the interviews is coded as 1, a quarter as 2 and a fifth for each of 3 and 4. Another potential bias stems from the sex of the respondent. Two thirds of our respondents are female, thus if women (men) are more reluctant than men (women) to admit the presence of violence, the victimization variable would be subject to a non-random measurement error. One can see that when added alongside the other covariates in column (6), neither the setting of the interview, nor the sex of the respondent is a significant predictor of victimization.

Finally, in column (7) we drop the neighborhood-mean of trust toward neighbors which failed to reach statistical significance in most of the random effects estimations. The results show that the findings on the contextual effect of community support did not hinge on the presence of the level-2 variable of trust toward neighbors.

4.2.4 Endogeneity

We have seen that a correlation between the covariates and the random effects was unlikely to bias the results. However, endogeneity is still a problem if the covariates are correlated with the error term (e_{hnd}), an issue unrelated to the choice of random effects over fixed effects. The main cause of concern that such endogeneity is present is the plausibility of reverse causation in the estimations of tables 5 and 6. There are at least two channels through which reverse causation can operate: (i) riots and/or victimization increase the *feeling* of vulnerability among people affected, and (ii) riot and/or victimization increase *actual* vulnerabilities. The former hypothesizes that the experience of a traumatic event makes people more aware of potential risks (such as the presence of unsafe places) and their actual vulnerabilities. The latter points out that riots exert actual impacts on the very dimensions of vulnerability that are emphasized in the paper.

We do not have pre-riot data that could be used as controls, nor is there a credible and strong enough set of instruments available for each covariate we looked at. Yet, we can provide some indirect evidence that the results we presented so far have a causal value. To start with, most of the independent variables we used reflect behaviors as opposed to subjective valuations, which weaken the risk identified in point (i). For instance, for assessing economic vulnerability, we use membership in self-help groups and whether households *normally use savings in case of need* in our preferred specification. These are variables describing behaviors which are not subject to be affected by a change in perceptions due to a riot. The same applies to our most important variable for social capital: whether households normally ask for community support in case of need.[13] We believe that the risk of reverse causality due to a perception bias is acute for one important covariate: whether respondents report the presence of an unsafe place nearby. Experience of rioting is indeed likely to make respondents especially aware of all forms of physical insecurities they might not have fully internalized prior to it. To check whether this concern is justified, we run our preferred specification with an additional variable: whether the respondents report concerns about crime in their neighborhood. This variable is clearly excludable from the structural equation as concerns about crime should not impact victimization, as opposed to actual crime, which is approximated by and controlled for by variable on the presence of unsafe place in the area. The inclusion of the variable of concerns about crime does not change the results, and the coefficient associated with the additional variable is not statistically different from zero as can be seen from table 7 (column 1). The lack of influence of feeling about crime on victimization is comforting us that the results were not driven by point (i).

The second cause for concern about endogeneity is that riot and/or victimization may actually change vulnerabilities rather than the other way around. The focus on indirect victims greatly mitigates this concern regarding economic vulnerability. The overwhelming majority of victims in our sample did not report direct financial losses that would come from injuries or physical damages, and it is thus highly unlikely that the association between lack of savings and victimization is due to reverse causality.[14] In addition, the estimated effect of income per capita is positive which would suggest a very counter-intuitive impact of rioting if reverse causality was behind the result.

The issue of reverse causality is particularly acute for the variable of community support. We held the view that socially isolated households find it difficult to withstand the effect of riots, while neighborhoods in which the extent of community support is weak either experience more riots (a la Varshney) and/or constitute unfavorable environments that make households vulnerable to the effects of riots. If we replicate our preferred estimation (column (6) of table 5) on the sub-sample of neighborhoods in which at least 50% of households reported a riot, the effect of community support at both the household level and the neighborhood level remain qualitatively similar (column (2), table 7). The fact that even within neighborhoods in which a major riot occurred, the contextual effect of community support remains significant, contradicts Varshney's results. Indeed it would predict an absence of effect as all these neighborhoods experienced a riot.[15] The existence of reverse causality would imply that victimized households become less likely to ask for community support and that the experience of riot in a neighborhood undermines the extent of solidarity networks. We believe that the first part of the argument is not very compelling: why would victimized households refrain from asking help to the community unless they feel their victimization is directly driven by the community letting them down? In that case, we are back to our initial argument that likelihood of victimization increases with social isolation. At the neighborhood level, it is very credible that riots may undermine the strength of social fabric, even more so in heterogeneous environments. In column (3) of table 7, we interact the neighborhood-mean of community support with caste fractionalization. We find that the effect of community support is maximal in homogeneous neighborhoods and become increasingly small with the index of caste fractionalization. The sign of the interactive term is consistent with a reverse causality where heterogeneous neighborhoods witness a drop in social networks after episodes of rioting. However, we do find that in homogeneous neighborhoods the contextual effect of community support remains negative and significant, while under the pure reverse causality hypothesis the coefficient should be zero. In other words, while we are confident that the level-1 causal effect of community support goes from lack of integration within local networks to victimization, there is strong evidence that the large contextual effect of community support is partly (but not fully) the result of reverse causality. Such potential consequences of rioting are of interest in their own right. To explore them would be beyond the scope of this paper but these consequences will be the object of future research by the authors...

5 Conclusion

Despite a large literature on civil violence in India, quantitative evidence on the effects of violence on populations and neighborhoods exposed to persistent forms of rioting is very limited. This paper analyzed empirically the determinants of riot victimization at the household level across the state of Maharashtra, where household effects were modeled in a multilevel framework, inserted within neighborhood and district dynamics. The analysis tested empirically four broad potential determinants of riot victimization identified in previous literature: the role of physical insecurity, identity markers, social capital and economic vulnerability. The empirical analysis adopted a multilevel framework allowing the integration of household effects within neighborhood and district effects, dependence of residuals between households and contextual effects.

The main results show that households that (i) are economically vulnerable, (ii) live in the vicinity of a crime-prone area, and (iii) are not able to rely on community support are considerably more prone to suffer from riots than other households. All else equal, income per capita increases victimization, presumably through an opportunity cost mechanism. We found further that relatively affluent neighborhoods and those characterized by large caste fragmentation are more riot-prone than disfranchised and homogeneous ones. We also found that victimization is more common in neighborhoods with weaker social interactions, but some evidence suggests that social interactions may be a consequence of rioting rather than its cause.

The paper aimed to contribute to a better understanding of the consequences of civil violence in India for those living in areas where violence is endemic and persistent. The results provide ample evidence for the destructive effects of riots and persistent forms of violence across many households in Maharashtra, emphasizing the need for the Government of India to focus more attention on the rise and persistence of communal violence in India. India's economic, social and political landscape has been changing dramatically since the early 1990s, when a large program of economic liberalization and de-regularization resulted in impressive increases in economic growth across the country. However, India's track record in terms of economic growth and economic internationalization has been accompanied by the persistence of pockets of poverty, rising inequalities in terms of political representation, income opportunities and social mobility and increased social and political tensions.

In particular, increased civil conflict, the rise of identity-based politics and inter-communal tensions poses a considerable challenge to India's future economic development processes and the survival of its long-held values of pluralism and social justice. This paper represented a first attempt at identifying and analyzing important micro-foundations of processes of violence victimization that continue to rise and persist across many communities, cities and states in India.

Notes

[1]El Salvador, Guatemala and Nicaragua, amongst others, constitute recent examples of countries where civil wars were preceded by civil protests and widespread rioting (see Brockett 1990, Seligson & McElhinny 1996, Wood 2003).

[2]The Maharashtra Longitudinal Survey on Civil Violence and Welfare (MHLS) is a unique panel dataset of households collected by the authors. The first wave - which we use in this paper - was collected in March-May 2010. The second wave was collected in March-May 2012 and is currently being processed, cleaned and analyzed.

[3]The delimitation information on the precise boundaries of these voting booths was obtained from the Maharashtra Election Commission.

[4]Direct victims are defined as households which suffered from injuries and/or physical damages from the violence.

[5]Not all riots involve Hindus and Muslims. For instance, there have been large-scale rioting between Hindus and Christians in Khandamal, in the state of Orissa in August 2008. Above 4000 houses were burnt and 38 people killed in the process. The term riot is also problematic as violence is usually organized and can in some instances be better described as pogroms (see Brass 1996, Brass 2006*b*).

[6]The government of India classifies people based on their caste status: ST refers to Scheduled Tribes, SC to Scheduled Castes, and OBC to Other Backward Castes.

[7]In his novel *Curfew in the City* high ranking police officer V.N.Rai (2005) vividly depicts the dramatic consequences of the curfew in a poor household hosting a pregnant woman.

[8]The within effect is given by the coefficient associated with the demeaned covariate $(x_{hnd} - \overline{x}_{nd})$ and the between effect with the cluster-mean covariate $\overline{x}_{nd}$. Had we chosen to cluster-mean the covariates, equation (1) would have yielded directly the within and between coefficients. Since we are not interested in between effects but rather in within and contextual effects we instead chose the specification shown in equation 1 (Rabe-Hesketh & Skrondal 2012, p. 158).

[9]Results not shown but available upon request.

[10]A *chowk* is a major crossroads.

[11]Polarization indexes have been tried as an alternative to fractionalization, but they never reached significance.

[12]The estimated standard errors are robust to a neighborhood cluster effect in column (2) and to a district cluster effect in column (3).

[13]The variable of trust toward neighbors is in contrast prone to perception bias, but it does play a much weaker role in the results than the variable of community support.

[14]Results with *indirect victims* as the dependent variable showed that this association was not driven by the small number of direct victims.

[15]Incidentally, all the other level-2 covariates lose statistical significance, as expected.

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Figure 1: Sampled Districts in the Maharashtra Longitudinal Survey of Civil Violence and Welfare

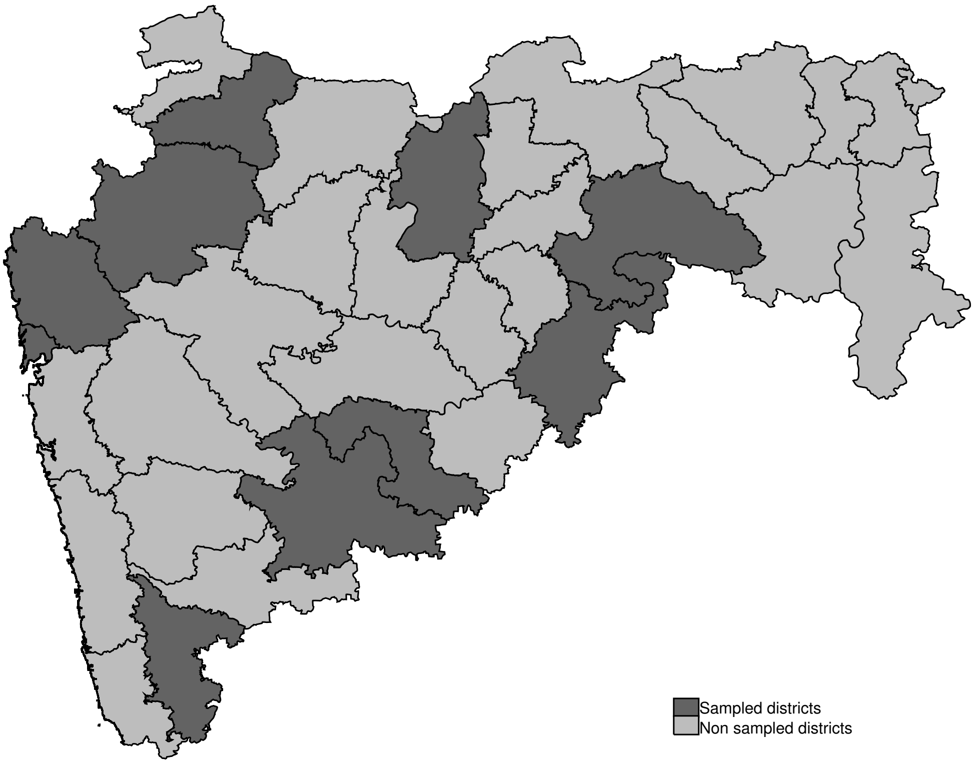

Table 1: Summary statistics

Variable	Mean	Std. Dev.	N
Index of visible assets	0.279	0.228	1089
Distance to police (minutes)	14.414	10.499	1084
Trust police	0.609	0.488	1089
Trust Neighbors	0.381	0.486	1089
Presence of unsafe place	0.106	0.308	971
Size of dwelling (Sq. Meters)	186.528	169.168	1086
Permanent materials	0.554	0.497	1089
Daily earnings	0.331	0.471	1089
Engaged in civic life	0.136	0.343	1089
Engaged in self-help group	0.057	0.232	1089
Years in house	17.716	14.185	1081
Can use savings	0.564	0.496	1086
Index of non-visible assets	0.44	0.201	1089
Shop owner	0.103	0.304	1089
Can rely on community's help	0.121	0.326	1085
Income per capita	1478.339	2475.324	1089
Hindu	0.537	0.499	1089
Muslim	0.393	0.489	1089
Buddhist	0.058	0.234	1089
Other religion	0.012	0.109	1089
Marathi	0.493	0.5	1089
ST	0.069	0.253	871
SC	0.147	0.354	871
OBC	0.355	0.479	871
Other caste	0.429	0.495	871
Temple in neighborhood	0.488	0.5	1089
Mosque in neighborhood	0.377	0.485	1089
Market in neighborhood	0.199	0.4	1089
Chowk in neighborhood	0.421	0.494	1089

Continued on next page

Table 1 –*Continued from previous page*

Variable	Mean	Std. Dev.	N
Police station in neighborhood	0.111	0.314	1089
Caste fractionalization index	0.585	0.102	1089
Caste polarization index	0.834	0.089	1089
Religious fractionalization index	0.342	0.171	1089
Religious polarization index	0.613	0.279	1089
jati fractionalization index	0.828	0.068	1089
jati polarization index	0.494	0.117	1089
Hours of electricity	18.799	3.846	1089
Hours of running water	3.748	7.424	1089
Toilets in the house	0.568	0.496	1088
Community toilets	0.273	0.446	1088
Open defecation	0.159	0.366	1088

Table 2: Household exposure to various forms of civil violence

type of violence	Mean (standard error)	Median per neighborhood	Max per neighborhood	Intra-neighborhood correlation
Riot	0.22 (0.41)	0.08	0.92	0.55
Stone pelting	0.19 (0.39)	0.08	0.8	0.43
Public fight	0.21 (0.41)	0.14	0.88	0.28
Curfew	0.14 (0.35)	0	0.72	0.37
Tire burning	0.08 (0.28)	0.04	0.54	0.22
Bandh	0.08 (0.27)	0.04	0.44	0.13
Bottle throwing	0.07 (0.25)	0	0.14	0.14
Damage to property	0.06 (0.24)	0	0.44	0.17
Police harassment	0.03 (0.16)	0	0.21	0.06

Note: Exposure to each type of violence is defined as respondents reporting at least one occurrence.

Table 3: Characteristics associated with self-reported victimization by riots

variables	Mean (Standard deviation) Victim of riot: Yes	No	Ho: no difference in means [p-value]
Shop	0.098 (0.010)	0.140 (0.030)	0.042 (0.131)
Visible assets index[a]	0.352 (0.020)	0.269 (0.007)	0.083 (0.000)
Size house (Sq. meters)	251.494 (16.845)	177.228 (5.285)	74.266 (0.000)
Presence of unsafe place	0.228 (0.037)	0.088 (0.010)	0.141 (0.000)
Distance to police station (minutes)	15.066 (0.820)	14.321 (0.345)	0.746 (0.439)
Building	0.515 (0.043)	0.559 (0.016)	−0.045 (0.328)
Years in house	18.870 (1.263)	17.537 (0.459)	1.433 (0.272)
Trust local police	0.699 (0.039)	0.596 (0.345)	0.102 (0.022)
Member of local organization	0.228 (0.036)	0.123 (0.011)	0.105 (0.001)
Trust neighbors	0.368 (0.041)	0.383 (0.016)	−0.015 (0.730)
Use savings in case of need	0.507 (0.043)	0.572 (0.016)	−0.064 (0.158)
Ask for community in case of need	0.066 (0.021)	0.129 (0.011)	−0.062 (0.037)
Income per capita (Rs)[b]	1797 (200)	1365 (43)	432 (0.002)
Subjective welfare	4.044 (0.139)	4.149 (0.049)	−0.105 (0.453)
Non-visible assets index[c]	0.461 (0.017)	0.437 (0.007)	0.024 (0.186)
Hours of electricity per day	17.764 (0.352)	18.946 (0.122)	−1.182 (0.001)
Hours of running water per day	5.151 (0.723)	3.547 (0.235)	1.603 (0.018)
Daily earner	0.346 (0.041)	0.329 (0.015)	0.016 (0.709)

Note: *a*: the list of visible assets comprises phone, electric oven, computer, fridge, CD/DVD player, radio, TV, iron, mixer, kerosene stove, gas stove, washing machine, fan, furnitures and steel cupboard. *b*: we have excluded one household whose reported income per capita is 66,667 rupees, i.e. almost 70 times more than the median in the sample. Keeping this observation would bias the statistical tests. *c*: the list of non visible assets comprises cycle, scooter, car, air conditioner, inverter, and dish TV.

Table 4: Religious affiliations and victimization

	Mean (Standard deviation)		Ho: no difference in means [p-value]
	Victim of riot		
variables	Yes	No	
Full sample			
Hindu	0.676 (0.040)	0.517 (0.016)	0.159 (0.001)
Muslim	0.257 (0.038)	0.412 (0.016)	−0.155 (0.001)
Buddhist	0.059 (0.020)	0.058 (0.008)	0.001 (0.959)
ST	0.081 (0.027)	0.067 (0.009)	0.013 (0.619)
SC	0.121 (0.033)	0.150 (0.013)	−0.029 (0.443)
OBC	0.424 (0.050)	0.346 (0.017)	0.078 (0.125)
Marathi speaker	0.669 (0.040)	0.468 (0.016)	0.201 (0.000)
Severe rioting sites			
Hindu	0.774 (0.046)	0.734 (0.042)	0.040 (0.528)
Muslim	0.143 (0.038)	0.220 (0.040)	−0.077 (0.173)
Buddhist	0.083 (0.030)	0.046 (0.020)	0.037 (0.288)
ST	0.057 (0.032)	0.128 (0.036)	−0.071 (0.089)
SC	0.094 (0.041)	0.151 (0.039)	−0.057 (0.168)
OBC	0.491 (0.069)	0.349 (0.052)	0.142 (0.950)
Marathi speaker	0.821 (0.042)	0.697 (0.044)	0.124 (0.048)

Note: severe rioting site defined as a neighborhood in which at least 50% of the households reported a riot.

Table 5: Coefficients of a three-Level logit with neighborhood and district random effects

Dependent variable	Household riot victimization					
	(1)	(2)	(3)	(4)	(5)	(6)
Level-1 variables						
Visible assets index	0.150	0.487	0.768	0.537	0.514	
	(0.933)	(0.847)	(0.838)	(0.863)	(0.841)	
Distance to police station	−0.032*	−0.033*	−0.041**	−0.048**	−0.038**	−0.014**
	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.014)
Size of house (Sq. meters)	0.001	0.001	0.001	0.001	0.001	
	(0.001)	(0.0001)	(0.001)	(0.001)	(0.001)	
Permanent materials	−0.282	−0.309	−0.303	−0.407	−0.437	
	(0.318)	(0.311)	(0.313)	(0.327)	(0.318)	
Presence of unsafe place	1.614***	1.628***	1.753***	1.924***	1.984***	1.114***
	(0.428)	(0.430)	(0.437)	(0.465)	(0.452)	(0.355)
Shop owner	0.602	0.504	0.466	0.554	0.348	
	(0.452)	(0.443)	(0.439)	(0.458)	(0.440)	
Trust police	0.455	0.469	0.373	0.351	0.300	
	(0.337)	(0.338)	(0.341)	(0.353)	(0.344)	
Trust neighbors	−0.583*	−0.587*	−0.516*	−0.597*	−0.546*	−0.465*
	(0.314)	(0.313)	(0.311)	(0.324)	(0.315)	(0.256)
Community's help	−1.331**	−1.353**	−1.274***	−1.216**	−1.290**	−1.315***
	(0.560)	(0.568)	(0.566)	(0.580)	(0.577)	(0.479)
Civic life	1.270***	1.256***				
	(0.394)	(0.389)				
Women group			1.682***	1.772***	1.872***	1.253***
			(0.557)	(0.572)	(0.546)	(0.479)
Duration	−0.008	−0.007	−0.007	−0.010	−0.005	
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	
Muslim	0.713	0.744	0.798	0.554	0.954*	0.402
	(0.565)	(0.564)	(0.572)	(0.458)	(0.568)	(0.453)
Marathi	1.072**	1.085**	1.069**	1.100*	1.043*	0.615
	(0.528)	(0.527)	(0.533)	(0.579)	(0.540)	(0.428)
OBC	0.460	0.467	0.522	0.736*	0.473	
	(0.425)	(0.424)	(0.429)	(0.437)	(0.412)	
Higher caste	0.293	0.308	0.400	0.660	0.537	
	(0.439)	(0.439)	(0.442)	(0.454)	(0.432)	
Daily earner	0.406					
	(0.350)					
Use savings in case of need	−0.986***	0.967***	−1.000***	−1.113***	−1.155***	−0.873***
	(0.316)	(0.315)	(0.318)	(0.329)	(0.323)	(0.254)
Non visible assets index	0.231					
	(1.107)					
Income per capita	0.0002*	0.0002**	0.0002**	0.0003**	0.0003**	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Subjective welfare		−0.151	−0.167	−0.183	−0.167	
		(0.137)	(0.136)	(0.140)	(0.135)	

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	(1)	(2)	(3)	(4)	(5)	(6)
Level-2 variables						
Jati fractionalization				−0.688 (8.371)		
Caste fractionalization				17.905** (8.580)	12.025*** (3.168)	6.761*** (2.323)
Religious fractionalization				1.218 (2.307)		
Presence of temple				0.141 (0.787)		
Presence of market				−1.096 (0.971)		
Presence of *chowk*				0.432 (1.006)		
Presence of police				−0.545 (1.201)		
Size of house (Sq. meters)				−0.005 (0.011)		
Permanent materials				−3.105 (3.172)		
Visible assets index				9.033 (8.606)	0.901 (3.427)	
Shop owner				−6.921 (7.188)		
Trust neighbors				−1.645 (3.029)	−2.198 (1.742)	−1.902 (1.472)
Community's help				−13.100 (8.472)	−11.463*** (4.027)	−9.554*** (2.892)
Muslim				1.083 (2.602)		
Marathi				0.128 (3.085)		
OBC				−0.289 (4.605)		
Higher caste				1.216 (3.873)		
Use savings				6.900** (3.230)	5.944*** (2.126)	6.823*** (1.655)
Income per capita					1.0001* (0.0001)	1.0001* (0.0001)
Constant	−4.237*** (1.091)	−3.554*** (1.060)	−3.439*** (1.058)	−15.648* (8.159)	−11.970*** (2.687)	−8.967*** (1.991)
Variance of neighborhood effects	0.708 (0.479)	0.673 (0.464)	0.801 (0.516)	0.000 (0.000)	0.000 (0.000)	0.036 (0.131)
Variance of						

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Table5– *Continued from last page*

	(1)	(2)	(3)	(4)	(5)	(6)
district effects	3.811 (2.238)	3.754 (2.201)	3.619 (2.147)	3.878 (3.119)	4.753 (3.084)	5.002 (2.826)
LR test p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	769	769	769	769	769	963

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

Table 6: Determinants of household riot victimization: alternative specifications

Dep. variable: Victims	All	All	All	All	Indirect	All	All
Sample	Full	Full	Full	w/o Mumbai & Thane	Full	Full	Full
Estimator	Three levels RE	Neighborhood FE	District FE	Three levels RE	Three levels RE	Three levels RE	Three levels RE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance to police station	-0.013	-0.023	-0.017	-0.019	-0.024	-0.016	-0.013
	(0.014)	(0.017)	(0.017)	(0.015)	(0.017)	(0.014)	(0.014)
Presence of unsafe place	1.105^{***}	1.021^{*}	1.109^{**}	0.865^{**}	0.885^{**}	1.167^{***}	1.033^{***}
	(0.354)	(0.550)	(0.550)	(0.374)	(0.393)	(0.364)	(0.350)
Trust neighbors	-0.467^{*}	-0.466	-0.459	-0.462^{*}	-0.643^{**}	-0.442^{*}	-0.534^{**}
	(0.256)	(0.329)	(0.391)	(0.258)	(0.282)	(0.258)	(0.255)
Community's help	-1.317^{***}	-1.215^{***}	-1.293^{***}	-1.305^{***}	-1.582^{***}	-1.215^{**}	-1.321^{***}
	(0.479)	(0.465)	(0.334)	(0.477)	(0.574)	(0.488)	(0.479)
Women group	1.239^{***}	1.237^{***}	1.286^{***}	1.232^{***}	1.355^{***}	1.340^{***}	1.318^{***}
	(0.479)	(0.441)	(0.287)	(0.477)	(0.511)	(0.480)	(0.479)
Muslim	0.412	0.166	0.396	0.270	0.280	0.373	
	(0.452)	(0.592)	(0.382)	(0.473)	(0.511)	(0.462)	
Marathi	0.623	0.350	0.584	0.487	0.644	0.592	
	(0.427)	(0.626)	(0.573)	(0.443)	(0.472)	(0.437)	
Use savings in case of need	-0.872^{***}	-0.846^{***}	-0.872^{**}	-0.900^{***}	-0.690^{**}	-0.895^{***}	-0.851^{***}
	(0.253)	(0.301)	(0.345)	(0.261)	(0.280)	(0.257)	(0.252)
Income per capita	0.0002^{**}	0.0002^{*}	0.0002^{*}	0.0002^{**}	0.0002^{**}	0.0002^{**}	0.0002^{**}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Level-2 covariates							
Caste fractionalization	6.517^{***}		6.838^{**}	7.539^{***}	6.425^{**}	6.561^{**}	7.180^{***}
	(2.324)		(3.225)	(2.686)	(2.774)	(2.381)	(2.545)
Trust neighbors	-1.716		-2.614^{*}	-2.799^{*}	-1.556	-1.883	
	(1.493)		(1.583)	(1.628)	(1.837)	(1.517)	
Community's help	-9.140^{***}		-10.887^{***}	-11.102^{***}	-9.234^{***}	-8.965^{***}	-9.267^{***}
	(2.925)		(1.381)	(3.069)	(3.460)	(2.995)	(3.244)
Use savings	6.690^{***}		6.995^{***}	7.207^{***}	7.469^{***}	6.874^{***}	6.312^{***}
	(1.653)		(1.550)	(1.835)	(2.049)	(1.691)	(1.675)
Children present						0.476	
						(0.325)	
Other adults present						0.221	
						(0.330)	
Spouse present						-0.378	
						(0.381)	
Female respondent						-0.164	
						(0.267)	
Level-3 variables							
Caste fractionalization	16.872^{***}						
	(15.763)						
Observations	963	564	877	777	939	963	963

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

Table 7: Determinants of household riot victimization: alternative specifications II

Estimator	Three-level random effects logit		
Sample	Full	Riot-affected Neighborhoods[a]	Full
	(1)	(2)	(3)
Level-1 covariates			
Distance to police station	-0.014 (0.014)	-0.036 (0.022)	-0.017 (0.014)
Presence of unsafe place	1.033^{***} (0.363)	0.267 (0.576)	1.130^{***} (0.354)
Concerned by crime	0.337 (0.319)		
Trust neighbors	-0.482^{*} (0.258)	-0.780^{**} (0.366)	-0.469^{*} (0.256)
Community help	-1.365^{***} (0.484)	-1.808^{***} (0.672)	-1.329^{***} (0.480)
Women group	1.227^{***} (0.478)	1.203^{*} (0.667)	1.251^{***} (0.480)
Muslim	0.373 (0.455)	0.840 (0.792)	0.389 (0.451)
Marathi	0.578 (0.429)	1.160 (0.744)	0.601 (0.426)
Use savings in case of need	-0.860^{***} (0.254)	-0.651^{*} (0.379)	-0.869^{***} (0.254)
Income per capita	0.0002^{**} (0.0001)	0.0001 (0.0001)	0.0002^{**} (0.0001)
Level-2 covariates			
Caste fractionalization	6.903^{***} (2.381)	4.393 (3.569)	1.837 (3.243)
Trust neighbors	-1.852 (1.517)	2.115 (3.565)	-1.991 (1.425)
Community help	-9.798^{***} (2.981)	-7.500^{*} (4.224)	-43.265^{**} (19.574)
Use savings	6.896^{***} (1.695)	-1.505 (4.065)	6.624^{***} (1.572)
Community help × Caste fractionalization			49.505^{*} (28.205)
Observations	963	174	174

a: districts in which at least 50% of respondents declared that a riot occurred in the neighborhood.
$***$: $p < 0.01$, $**$: $p < 0.05$, $***$: $p < 0.1$