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Households amid Urban Riots: The Economic Consequences of Civil Violence in India

Jaideep Gupte[1], Patricia Justino[1], and Jean-Pierre Tranchant[1]

Abstract

This article analyzes the determinants of household riot victimization, based on a unique survey collected in Maharashtra, India. We adopt a multilevel framework that allows neighborhood and district effects to randomly influence household victimization. We find that economically vulnerable households, households living close to unsafe areas, and shop owners are more prone to suffer from riots. Households report lower levels of victimization if they live further from police stations, exhibit higher levels of trust, are able to rely on outside help in times of need and accumulate savings. The results show, however, a double-edge effect of income: wealthier households are better able to cope with the adverse effects of riots, but also have more to lose from riots and are more exposed to opportunistic violence and looting. We find further that affluent neighborhoods and neighborhoods where caste fragmentation is high report higher levels of victimization. Neighborhoods with stronger social interactions experience lower levels of victimization.

Keywords

riots, India, urban, conflict

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This article presents the results of a new study on the micro-foundations of rioting in India. The main objective of this article is to identify empirically the determinants of riot victimization at the household level within a multilevel framework that takes into consideration how the dynamics of rioting play out at the neighborhood and district levels. The analysis is based on a unique data set collected by the authors from March to May 2010 in the state of Maharashtra, which has experienced some of the highest rates of communal violence in India since the early 1980s. To the best of our knowledge, this is one of the first studies to empirically analyze the determinants of household victimization in the context of communal riots.[1]

While much has been written about riots in India, there is very limited understanding of how individuals and their families experience communal violence. Episodes of rioting are commonplace in India and their causes are addressed in a large and well-established literature (e.g., Tambiah 1996; Brass 1997; Varshney 2002; Wilkinson 2004). Much of this literature has focused on the analysis of the causes of riots at the national, state, and city levels.[2] This literature is more limited in accounting for the consequences of riots and explaining how, within the same communities, different people may experience riots in different ways. There is some literature on the individual experiences of violence in India (for instance, Chatterji and Mehta 2007). This literature is, however, based on small-sample case studies that do not necessarily allow for systematic aggregation of individual experiences of violence to be made. Using a unique household survey conducted in the state of Maharashtra, we are able to document the extent of household victimization in areas endemically affected by riots and uncover its main determinants. 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 our household sample is clustered within neighborhoods and districts across Maharashtra.

The article is organized as follows: The second section introduces the Maharashtra Household Longitudinal Survey on Civil Violence and Welfare (MHLS), which provides the basis for the empirical study. In the third section, we review the existing literature on riots in India in order to derive testable hypotheses on the determinants of riot victimization among households and neighborhoods. The econometric analysis of the determinants of riot victimization is discussed in the fourth section. The fifth section presents our conclusions.

The Maharashtra Household Longitudinal Study on Civil Violence and Welfare

Data Set and Sampling Design

From March to May 2010, the authors conducted a unique household survey across the Indian state of Maharashtra with the objective of obtaining fine-grained data on social, economic, and political processes associated with the persistence of communal violence, and its consequences on individuals, households, and neighborhoods.

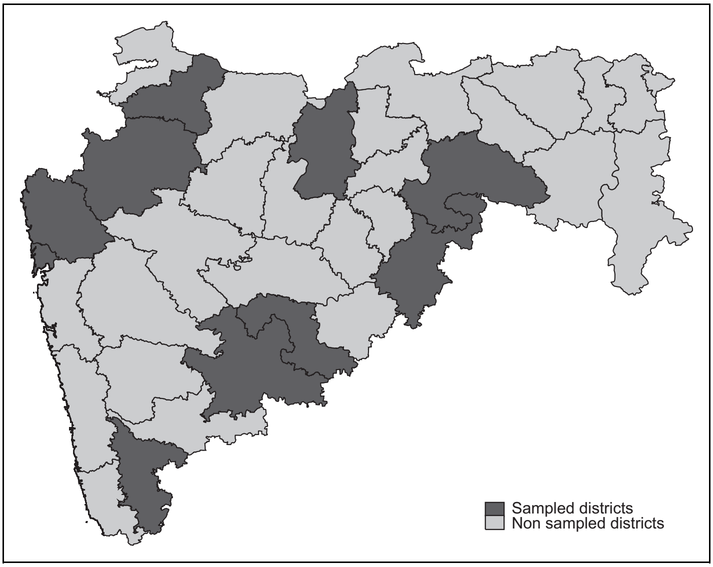

Figure 1. Sampled districts in the Maharashtra longitudinal survey of civil violence and welfare.

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 adopted 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 to 2008, contain information on the number of communal riots for each district. The data set reports 75 communal riots in 2006, 74 in 2007, and 186 in 2008 in Maharashtra. We discounted these data progressively by an order of one-sixth, so that six riots in 2003 equated to one 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, while simultaneously allowing us to capture the short- and medium-term effects 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 (fewer 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 sociocultural divisions in the sample. Our final selection included three districts in each of the medium- and low-rioting clusters, and four in the high-rioting cluster. Figure 1 displays the location of sampled districts within the state, and Table 1 lists the number of sites within each sampled towns and districts.

Table 1. Localization of the Forty-five Neighborhoods in the Maharashtra Longitudinal Household Survey (MHLS).

District	Town	Number of neighborhoods	Randomization level[a]
Buldhana	Buldhana City	2	City
Buldhana	Jalgaon/Jamod	2	City
Buldhana	Khamgaon	1	City
Dhule	Dhule City	5	Areas of interest
Kolhapur	Ichalkaranji	1	City
Kolhapur	Haathkangde	1	City
Nanded	Nanded City	5	Areas of interest
Nashik	Malegaon	5	City
Osmanabad	Osmanabad City	5	City
Sangli	Miraj	3	Areas of interest
Mumbai	Mumbai	5	Areas of interest
Thane	Thane City	5	Areas of interest
Yavatmal	Pusad	3	City
Yavatmal	Digras	2	City

[a]The randomization level refers to the sampling frame used to select neighborhoods. "City" means that neighborhoods were randomly selected from the whole range of voting booths in the city. "Areas of interest" indicates that the neighborhoods were randomly selected from a narrower range of voting booths corresponding to urban areas of interest.

For each of the ten districts, we then collected information on the precise location of instances of rioting in the twenty-four months prior to fieldwork (2008 to 2010). We did this through a scan of print and online media, as well as key informant interviews conducted between December 2009 and March 2010 with city and state police of varying ranks and responsibilities. The aim of this exercise 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. Forty-five neighborhoods were then randomly selected from the list of voting-booth zones obtained from the Maharashtra Election Commission corresponding to our sites of interest. Each voting booth zone covers roughly 250 households. In spatial terms, this was equivalent to an area which our research team could walk the perimeter in approximately twenty minutes. It follows that neighborhoods in this study are very small units, which had two main advantages. First, it allowed us to generate reliable neighborhood-level variables by aggregating a relatively small number of individual answers. Second, it ensured sufficient variability in the degree of exposure to rioting 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 forty-five neighborhoods. Our field team began household interviews simultaneously from a set of starting points agreed a priori,[3] working their way inward in each neighborhood making sure that no alley, no matter how small, was missed by following a right-turn pattern at all junctions. Households were randomly selected through a skip pattern, which for larger neighborhoods was seven or eight households, while for smaller neighborhoods was four to five households. This ensured a sample of twenty-four to twenty-five households per neighborhood, corresponding to a sample of around 10 percent of all households in each neighborhood. This multistaged sampling framework resulted in a final sample of 1,089 households, spread across forty-five neighborhoods, in ten districts in Maharashtra.

Household Characteristics and Exposure to Rioting

The MHLS survey was in part designed to provide detailed information on household characteristics associated with exposure to violence. During the sampling stage of the project, it became apparent that most of the sites we identified as affected by riots were located in informal settlements (slums) or in low-income neighborhoods. Summary statistics of main household and neighborhood characteristics are provided in the Online Supplementary Material.

The MHLS questionnaire includes several questions aimed at capturing the exposure of households to various forms of violence. One of the important questions we asked was the following: in the last twelve months, have any of the following events occurred in your neighborhood? The events include riots (*dangali*), stone pelting, public fights, damages of buses or public property, burning of tires, throwing of bottles, police harassment, agitation related to strike (*bandh*), and violence during curfew. While some of these events may be considered as modalities of violence within the context of a riot (e.g., stone pelting or damages to property), they may also occur separately. Riots are the most common form of violence reported (Table 2): one in every five households reported at least one riot in their neighborhood. This is followed by public fights and stone pelting. Curfew follows closely (14 percent), indicating that the 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 violence are heavily concentrated in some neighborhoods. The median proportion of households reporting at least one public fight is 12 percent (8 percent 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 (reported in the last column of Table 2) in which the exposure to violence of household h living in neighborhood n is explained by a neighborhood-specific effect and a disturbance term.[4] The proportion of variance explained by the neighborhood random effect is 56 percent for riots, around 40 percent for curfews and stone pelting, and 29 percent for public fights. These results suggest that household exposure to riots needs to be understood within the wider neighborhood context. We return to this point in the empirical analysis in the fourth section.

Table 2. Household Exposure to Various Forms of Civil Violence.

Type of violence	Mean (*SE*)	Median per neighborhood	Max per neighborhood	Intra-neighborhood correlation
Riot	0.22 (0.41)	0.08	0.92	0.56
Stone pelting	0.18 (0.39)	0.08	0.8	0.44
Public fight	0.20 (0.40)	0.12	0.88	0.29
Curfew	0.14 (0.35)	0	0.72	0.39
Tire burning	0.08 (0.27)	0	0.62	0.25
Bandh	0.08 (0.27)	0.04	0.44	0.14
Bottle throwing	0.07 (0.25)	0	0.43	0.15
Damage to property	0.06 (0.24)	0	0.44	0.18
Police harassment	0.03 (0.16)	0	0.24	0.07

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

We captured levels of household victimization using the following question: in the past twenty-four months, did you or any member of the household experience a riot? Overall, 136 households report being victims of riots (12.5 percent of the sample). Among those 136 households, 26 suffered direct effects such as injuries and physical damage. These households declared that 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. The remaining households report more indirect effects, which may include loss of workdays, isolation due to curfew, and increase in insecurity and fear, among others.

Determinants of Riot Victimization in India

Communal violence, as ethnic riots are usually labeled in South Asian studies, refers to riots in which two communities (most often, but not always, Hindus and Muslims in the case of India) clash and engage in killing, maiming, looting, arson, and destruction. 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, the wave of violence in Gujarat in 2002 and the 1984 anti-Sikh riots in Delhi. Almost 40,000 people have been killed or injured in communal riots in India since Independence (Wilkinson 2004).

Interestingly, there is very limited literature on the impact of rioting in India on levels and patterns of victimization. The existing literature on causes of riots provides, however, helpful suggestions about potential correlates of victimization. We are able to hypothesize that at least three important factors may be associated with levels of violence victimization: presence of visible assets or wealth that may attract opportunistic violence, levels of social integration and civic engagement within neighborhoods, and group identity. In addition, our own sampling exercise discussed in the previous section showed us that, at least in Maharashtra, areas of recurrent and persistent rioting are areas of acute economic vulnerability.

Vulnerability to Opportunistic Violence

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 may be at greater risk because of direct targeting or opportunistic looting. Opportunistic looting and other criminal activities have been reported in many instances of communal violence, whereby individuals exploit the riot to settle scores, enrich themselves, or get rid of business rivals (Engineer 1991; Wilkinson 2004). Similar evidence has been provided in Kalyvas (2006) in contexts of civil wars.

In impoverished urban areas, visible assets are relatively uncommon but are also particularly exposed to onlookers. We consider as an indicator of visible wealth the share of the following variables in any given household in our sample reports owning: dish TV, car, scooter, motorcycle, air-conditioning device, and generator. All these assets are likely to be readily visible from the outside. In addition to visible assets, other possible attributes that may place households at risk of opportunistic violence or direct targeting include the size of the dwelling, the material with which it is built (concrete or brick rather than less permanent materials), and whether the household owns a shop.[5] The presence of visible assets may increase the likelihood of opportunistic violence depending on the relative safety of the area where the household lives. Therefore, we consider as additional indicators of potential exposure to opportunistic violence the (self-reported) presence of unsafe places in the proximity of households and the distance of the household to the local police station.

Social Integration and Civic Engagement

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 households are able to draw on strong integration within local social networks (Mitra and Ray

2014). 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 levels of social capital may 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 or their neighbors. Varshney (2002) has famously argued that the strength of civic life is one of the main factors preventing the outbreak of violence between Hindu and Muslim communities, while Jha (2013) has shown that Hindus and Muslims will coexist peacefully if they complement each other in terms of local productive activities. Taken together, these findings suggest that strong community ties may act as a protection against individual victimization.

The indicators we use to account for household integration 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 local civic life through membership in various local organizations.

Group Identity

One of the predominant form of riots in India is known as *jatiya dangali*, that is, communal riots. The term 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. The MHLS questionnaire includes questions on religious affiliations, caste, and language. We matched each caste with its corresponding status (scheduled castes, scheduled tribes, Other Backward Class, and forward castes others).[6] We also distinguish between native Marathi speakers and native speakers of other languages (predominantly Hindi and Urdu) in order to capture potential victimization of interstate migrants (Hansen 1996). At the community level, we computed fractionalization and polarization indexes of local castes (*jati*), larger caste grouping, and religious affiliations. The fractionalization index is given by $F_n^j = 1 - \sum_{j=1}^{j=J}\left(p_j^2\right)$, where j represents the identity line under study, J is the total number of categories within the identity line, n is the neighborhood, and p_j is the share of households with identity j in neighborhood n. Per the definition of Montalvo and Reynal-Querol (2005), the polarization index is given by $P_n^j = 4\sum_{j=1}^{j=J} p_j^2\left(1 - p_j\right)$.

Economic Vulnerability

We discussed earlier how households in possession of visible wealth or assets may be vulnerable to being targeted by rioters through direct attacks and looting.

However, households that are economically better off may also be in a stronger position to cope with the adverse effects of riots, because they may be able to move their resources elsewhere, flee areas of violence more easily, have access to larger safety nets or buy protection (Levitt 1999). Riots that result in physical damage, injuries, forgone income, or restricted access to markets and services are likely to affect the poor disproportionately. Curfews that follow severe riots may be particularly relevant because they restrict the access of households to work, markets, shops, and essential services. Again, the poor are likely to experience more acutely these adverse effects.[7]

Households with a secure stream of income, comfortable savings, and not reliant on informal arrangements to get by may be more apt to navigate through the period of rioting.

We use several indicators to capture economic vulnerability, notably monthly income per capita, possession of nonvisible assets, reliance on community assistance, capacity to use savings in case of need, and whether the household relies on daily wages. In addition, we make use of a subjective valuation of each household's welfare with respect to others in the neighborhood.

Econometric Analysis of Determinants of Victimization

Empirical Specification

We discussed in Household Characteristics and Exposure to Rioting subsection how exposure to violence is shaped by neighborhood effects. Therefore, we model the probability that a specific household is 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 use allows us to correct the estimations for the dependence of residuals that arise between households within neighborhoods and between neighborhoods within districts.

Any model with random effects requires that the unobservable components are uncorrelated with the covariates. In the context of a three-level model, this 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 that 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 parameterize the unobserved heterogeneity), the impossibility to explore the effects of contexts (which are key to our article), and to produce out-of-sample predictions (Gelman and Hill 2012). Mundlak (1978) and Chamberlain (1980) have developed an approach that allows us to avoid using fixed effects while ensuring that the random effects model is valid. This consists in approximating the unobservable heterogeneity at level L by 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

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

$$\zeta_{d}=\mu_{d}+\gamma_1\bar{x}_{d}+\ \gamma_2\bar{w}_{d}, \tag{3}$$

where y_{hnd} takes the value 1 if household h in neighborhood n in district d reports having been 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 $(\bar{x}_{nd})$ and the within-district means of neighborhood covariates $(\bar{w}_{d})$, respectively. Conditional on these means, the random intercept at each level $(\mu_{nd}$ and $\mu_{d})$ is assumed to be independent of the covariates $(x_{hnd}$ and $w_{nd})$. The Mundlak–Chamberlain approach is powerful, yet underused. 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 $(\bar{x}_{nd})$ and the random effect (Raudenbusch and Bryk 2002, 262). By controlling for the group means, we remove by construction the correlation between the level 1 covariates and the level 2 random effect and hence restore 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 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 nonnull, one needs to include them as additional covariates to restore the equivalence between fixed and random effects (see, e.g., Mundlak 1978; Snyders and Berkhof 2008).[9]

Level 1 Estimation Results

We begin by estimating a baseline model like in equation (1) without neighborhood-level predictors (w_{nd}) and without the within-neighborhood means (i.e., $\bar{x}_{hnd}$). The results are displayed in the first three columns of Table 3. We then introduce the contextual effects in columns (4) to (6).

Vulnerability to opportunistic violence: the coefficient associated with the distance of the household from the police station is negative and, in most specifications, significant at the 10 percent level. The point estimate is substantial based on column (2), ceteris paribus, an increase in distance from five to twenty minutes (the interquartile of the distribution of distance to the police station) translates into a reduction of 38 percent in the odds of victimization.[10] The presence of unsafe areas near the household is statistically significant (at the 1 percent level) and with the hypothesized positive sign. Its associated odds ratio is also very large: the odds of victimization for households that report living close to unsafe places is 2.8 times higher than for households that do not report the presence of unsafe places nearby (based on column 6). Households that own a shop are between 2.6 and 3.3 times more likely to report riot victimization than others, depending on the specification. The magnitudes of both the point estimate and the standard errors are very stable across specifications. The index of visible assets, the size of the house, and the other variables we expected to be associated with household vulnerability to opportunistic violence during riots do not appear significantly related to household victimization.[11]

The positive association between household victimization and living in the vicinity of unsafe areas is not surprising, given the many accounts in the literature on how riots follow predetermined paths and tend to take place in notorious areas such as markets and near temples (Brass 1997, 2003). This result may, therefore, be explained by the location of some households in the sample near some of these places.[12] The positive association we find between household victimization and the distance of the household from the police station is more notable, as it appears to intuitively describe a contradictory relationship between policing and the incidence of riots. This finding must, however, be interpreted in light of the complex relationships through which the Indian state is known to "govern" riots (Chatterji and Mehta 2007, 37). The maintenance of public order in India has historically been a manifestation of political interests (Wilkinson 2004), where in many occasions the occurrence of riots is often accompanied by the state's unwillingness to deploy the police to take preventative actions.[13] There are also several accounts of direct collusion of the police with rioters along ethnic groupings (Das 2004; Wilkinson 2004). Our results complement this literature by showing a direct association between closeness to police stations and household riot victimization.

Social integration and civic engagement: the results in Table 3 show that trust toward neighbors is associated with a 41 to 48 percent reduction in the odds of victimization (depending on the specification), an impact significant at the 10 percent level. Trust in police is not statistically significant. Households that

Table 3. Coefficients of a Three-level Logit with Neighborhood and District Random Effects.

	Household riot victimization					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Level 1 variables						
Visible assets index	−0.817	−0.227	0.016	−0.093	−0.160	
	(0.862)	(0.783)	(0.771)	(0.786)	(0.776)	
Distance to police station	−0.030	−0.035*	−0.042**	−0.057***	−0.044**	−0.013
	(0.019)	(0.019)	(0.019)	(0.021)	(0.019)	(0.014)
Size of house (m^2)	0.001	0.001	0.001	0.001	0.001	
	(0.001)	(0.0001)	(0.001)	(0.001)	(0.001)	
Permanent materials	−0.365	−0.284	−0.283	−0.383	−0.391	
	(0.321)	(0.311)	(0.310)	(0.323)	(0.315)	
Presence of unsafe place	1.552***	1.575***	1.685***	1.814***	1.896***	1.036***
	(0.426)	(0.427)	(0.430)	(0.461)	(0.446)	(0.350)
Shop owner	1.176**	1.159**	1.178**	1.186**	1.206**	0.973**
	(0.564)	(0.555)	(0.543)	(0.576)	(0.551)	(0.420)
Trust police	0.545	0.529	0.453	0.423	0.380	
	(0.340)	(0.339)	(0.338)	(0.351)	(0.340)	
Trust neighbors	−0.608*	−0.598*	−0.534*	−0.648**	−0.585*	−0.523**
	(0.315)	(0.314)	(0.311)	(0.326)	(0.318)	(0.260)
Community help	−1.425**	−1.372**	−1.244**	−1.149**	−1.211**	−1.282***
	(0.569)	(0.567)	(0.558)	(0.570)	(0.564)	(0.485)
Civic life	1.222***	1.263***				
	(0.390)	(0.388)				
Women's group			1.240**	1.425***	1.485***	1.040**
			(0.530)	(0.556)	(0.522)	(0.466)
Years in house	−0.007	−0.006	−0.007	−0.008	−0.004	
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	
Muslim	0.670	0.716	0.756	0.569	0.886	
	(0.565)	(0.563)	(0.566)	(0.621)	(0.562)	
Marathi	1.128**	1.145**	1.151**	1.070*	1.118**	0.452*
	(0.529)	(0.526)	(0.528)	(0.569)	(0.542)	(0.275)
OBC	0.348	0.363	0.418	0.632	0.379	
	(0.426)	(0.424)	(0.426)	(0.434)	(0.411)	
Forward caste	0.277	0.299	0.380	0.627	0.505	
	(0.435)	(0.436)	(0.436)	(0.449)	(0.429)	
Daily wage earning	0.584					
	(0.390)					
Can use savings	−0.981***	0.941***	−0.943***	−1.090***	−1.144***	−0.920***
	(0.317)	(0.316)	(0.319)	(0.331)	(0.327)	(0.258)
Nonvisible assets index	1.336					
	(1.118)					
Income per capita	0.0001	0.0002*	0.0002*	0.0002	0.0002*	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

(continued)

Table 3. (continued)

	Household riot victimization					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Subjective welfare		−0.089	−0.100	−0.123	−0.096	
		(0.134)	(0.134)	(0.139)	(0.133)	
Level 2 variables						
Jati fractionalization				0.363		
				(7.652)		
Caste fractionalization				16.234**	10.531***	7.226***
				(7.557)	(2.915)	(2.485)
Religious fractionalization				−0.364		
				(2.041)		
Presence of temple				0.486		
				(0.894)		
Presence of market				−0.648		
				(0.903)		
Presence of chowk				0.039		
				(0.794)		
Presence of police				−1.728		
				(1.166)		
Size of house (m^2)				0.003		
				(0.011)		
Permanent materials				−2.481		
				(3.187)		
Visible assets index				1.001	−0.772	
				(8.599)	(3.105)	
Shop owner				0.213		
				(9.303)		
Trust neighbors				−1.196	−2.128	
				(3.455)	(1.768)	
Community help				−12.604*	−12.943***	−9.704***
				(6.466)	(4.067)	(3.091)
Muslim				1.830		
				(2.625)		
Marathi				1.751		
				(3.296)		
OBC				−2.632		
				(4.460)		
Forward caste				1.010		
				(3.589)		
Can use savings				6.543**	6.639***	6.076***
				(3.039)	(2.151)	(1.605)
Income per capita				0.001		
				(0.001)		

(continued)

Table 3. (continued)

	Household riot victimization					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Variance of neighborhood effects	0.547	0.589	0.678	0.000	0.000	0.091
	(0.422)	(0.439)	(0.469)	(0.000)	(0.000)	(0.165)
Variance of district effects	3.836	3.781	3.585	3.424	5.319	4.132
	(2.220)	(2.196)	(2.104)	(2.622)	(3.328)	(2.332)
LR test p value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	756	756	756	756	756	944

Note: OBC = other backward classes; LR = likelihood ratio test.
Standard errors in parentheses. ***p < .01. **p < .05. ***p < .1.

are able to rely on the assistance of the community in case of need are between 68 and 76 percent less likely to report victimization (the effect is always significant, at 5 or 1 percent). These results are in line with our expectations outlined in the third section.

Interestingly, the results in Table 3 show that household participation in civic organizations, such as neighborhood organizations, political parties, trade unions and women's self-help groups, among others, is positively and statistically significantly associated with victimization. The odds of victimization of a household engaged in local organizations are three and a half times higher than those of households not involved in local civic life. This is a very large and counterintuitive effect as previous literature, Varshney (2002) in particular, has shown strong and compelling evidence for the role of local associations and organizations in the prevention of communal violence.[14] We have, therefore, investigated this result further by disaggregating its various components in order to see whether the result may be driven by any particular type of organization. These data show that of the 147 households in the sample for which at least one member is involved in local organizations 68 belong to women self-help groups (46 percent). Political parties are the second-largest group, including 27 households only. This disaggregation suggests that the positive association between participation in local civic associations and victimization is being driven by levels of participation in women's self-help groups. In column (3), we have replaced our former variable representing engagement in civic life by a variable that includes only household membership in self-help groups (membership in other groups is coded as zero). The coefficient associated with the self-help group variable is remarkably similar (1.240 in column 3) to the coefficient associated with any form of membership (1.263 in column 2). We have also found that membership in other type of organizations is unrelated to victimization.[15] These facts suggest that members of self-help groups are more likely to report victimization during riots. We believe that this result indicates a link between high levels of economic vulnerability and victimization (as reported, for instance, in Scacco [2012]). Households that take part in self-help groups are considerably more likely than others to depend on daily wage work for their main earnings (37 percent against 19 percent), a clear indicator of vulnerability. This interpretation is also in line with the findings we report subsequently on the association between economic vulnerability and household victimization.

Group identity: neither caste nor religion variables seem to display a significant relationship with victimization. Marathi-speaking households are almost 60 percent more likely than non-Marathi households to report being affected by a riot (column 6).[16] This finding appears to challenge dominant discourses about communal violence in India based on religious divisions.[17] Our results seem to reflect more instrumentalist arguments (for instance, Brass 1997, 2003; Wilkinson 2004) based on the view that people during riots are driven by concerns about potential economic and political incentives rather than pure religious of caste-based ideology. We find some limited evidence that language may be associated with household victimization. However, in light of lack of any other empirical support for the role of identity markers in explaining patterns of victimization, we interpret this result as potentially reflecting the fact that majorities tend to feel that they are worse off than minorities, as discussed in Tambiah (1996).

Economic vulnerability: consistent with the hypotheses discussed in the third section, the results in Table 3 show that the odds of victimization for households that can use savings in times of needs are 60 percent lower than for households that are not able to access this kind of financial security. Relying on daily wages or having fewer assets does not affect the likelihood of household victimization. We find, in addition, that higher levels of income per capita, as hypothesized earlier, are associated with increased odds of victimization. The odds ratio of a change in income equal to the interquartile of the income distribution (around 1,000 rupees) is 1.22. Moreover, these results are driven by actual income levels and are not dependent on how households perceive their own relative wealth (column 2). This suggests that households with higher incomes are more likely to report being affected by riots, whereas households with high levels of savings report reduced odds of victimization. In addition, households that belong to self-help groups as discussed previously are more likely to suffer from the riots. Taken together, these results suggest that more economically vulnerable households (without savings and part of self-help groups) are more likely to suffer from riots. Similar associations among poverty, low incomes, economic vulnerability, and violence have been reported in the literature at the macro level (see, e.g., Miguel, Satyanath, and Sergenti 2004; Bohlken and Sergenti 2010). Two implicit mechanisms underlie this literature. The first is that economic vulnerability is associated with higher levels

> of violence because it encourages poorer and more disenfranchised segments of the population to participate in acts of violence. The second mechanism is that poorer countries and regions will have less capacity to prevent the organization of criminal networks. Our results suggest an additional mechanism: economic vulnerability is associated with household victimization because these households are unable to cope with the adverse effects of violence.

We find, however, a nonlinear effect of income: households with higher incomes are also more likely to report being victims of riots. Better-off households may be able to better cope with the adverse effects of riots (particularly those able to save), but may also have more to lose when riots take place (for instance, curfews may prevent them from continue trading or other activities), and may be more exposed to the possibility of opportunistic violence and looting. This reflects some of the findings in the literature on the micro-level dynamics of civil wars, which has suggested the presence of a nonlinear impact of armed violence on economic welfare (Bundervoet 2009; Justino 2009; Justino and Verwimp 2013; Verwimp 2005).

We note that in the specifications presented in columns (1) through (3) in Table 3, the estimated variances of the random effects remain stable around 0.6 for the neighborhood effects and 3.7 for the district effects. The validity of the multilevel approach with respect to a simple logit is justified by the results of the *likelihood ratio* (LR) test, which signals that the variances of the random effects are nonnull with a p value smaller than .001. We discuss the results regarding the contextual effects subsequently.

Level 2 Contextual Effects

In column (4) of Table 3, we include neighborhood-level covariates as an application of the Mundlak–Chamberlain approach. Variables included are fractionalization indices for *jati*, caste and religion, presence of specific landmarks (temple, chowk,[18] and market) and the within-neighborhood means of household covariates.[19] The model is overparametrized, which is not surprising considering the number of neighborhoods in the sample (forty-five) 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 stability of the estimates provides strong evidence that the results discussed previously are consistent and that the use of a random effects estimator is the most appropriate modeling choice.

Three level 2 variables are statistically significant: the index of caste fractionalization, and the mean at the neighborhood level of household savings capacity and community help. The caste fractionalization variable exhibits a very large coefficient (16.2). The index of fractionalization rises by about seven percentage points between the 25th and the 75th percentile of its distribution. The estimations show that an increase of this magnitude in the caste fractionalization index would triple the odds of victimization. This result suggests that although caste (and religious) identity is not associated with the odds of victimization at the household level, neighborhoods that are more fragmented along caste lines are more likely to report higher levels of household victimization. The effect is large and seems to concur with Hansen's (1999) argument that caste and religious identities may operate as collective rather than as individual identities. The result may also reflect the fact that the prevention of riots and the mitigation of the effects of rioting are public goods created (in part) by interactions between people in the neighborhood. In heterogeneous neighborhoods, this is likely to be more difficult to achieve. This argument has been put forward in a large body of literature on ethnic divisions and public good provision (e.g., Alesina and La Ferrara 2000; Miguel and Gugerty 2005), including the role of caste fractionalization in public good provision in India (Banerjee, Iyer, and Somanathan 2005). Taken together with the findings on household distance from police stations discussed previously, this result seems to suggest that victimization levels are higher is neighborhoods characterized by larger caste fractionalization due to a potential lack in riot prevention or mitigation measures in those neighborhoods.

The coefficient on the strength of community assistance is large (−9.7 in our preferred specification, column 6) and is significant at 1 percent. Quantitatively, this means that if we compare a household living in a neighborhood where just 4 percent of people can rely on help from the community (this corresponds to the first quartile), to a completely similar household living in a neighborhood where 21 percent can rely on community help (the third quartile), the former has 80 percent more chance to be affected by a riot. This result is in line with the results discussed previously for the level 1 variables: households that are able to rely on help from other neighbors in times of need are less likely to report being victims of riots, and neighborhoods with a larger share of these households are also less likely to experience riots. Such a contextual effect provides some evidence that the quality of social interactions at the macro level matters when explaining the determinants of household victimization. This finding is consistent with the argument of Varshney (2002) in terms of the importance of "everyday forms of engagement" in preventing the outbreak of communal violence in India.

The contextual effect of savings capacity is strongly positive: the odds ratio that results from comparing two households with the same capacity to use savings, one living in a neighborhood where 46 percent of households can use savings, and the other one in a neighborhood where 64 percent of households can do so, is 2.9. This contextual effect of savings runs in opposite direction to the within effect we reported in the previous section. The latter appears to have a protective impact: within a given neighborhood, households with savings are less likely to report victimization. However, ceteris paribus, neighborhoods wherein a larger share of people is able to build savings are more likely to have a higher number of riot victims than worse-off neighborhoods. We interpret this result as reflecting the double-edge effect of wealth-related variables as discussed earlier. These are relatively affluent neighborhoods where in general people tend to be better-off and are more able to cope with the adverse effects of riots. At the same time, these neighborhoods may be closer to obvious riot routes such as main roads en route to temples and markets (Brass 1997), may be likely to be more exposed to opportunistic looting, and may lose more in terms of local market interactions when for instance curfews are imposed.

It is not uncommon that the sign of a statistical relationship between two variables differ at the individual and aggregate levels (e.g., Schelling 1978). One advantage of using multilevel modeling, which can accommodate both effects at the same time, is precisely that it can distinguish between the within and between effects. In the case of the result on savings, our results show that while savings protect households within neighborhoods, collective levels of wealth seems to make the entire neighborhood more vulnerable to the consequences of rioting. In other words, poor households in relatively rich neighborhoods are the most affected by rioting.

In order to investigate further potential contextual effects, we have reduced the dimensionality of the vector of level 2 covariates (column 5). In this more parsimonious specification, the contextual effects of savings capacity and community's help are unchanged. We obtain similar results in column (6) where we drop level 1 covariates that failed to have a significant effect.

Robustness tests. The results presented previously are remarkably robust to a series of alternative specifications, which are shown in Table 4.[20] These include the replication of the results reported in Table 3 (1) using fixed effect models, (2) excluding the districts of Mumbai and Thane, (3) using alternative specifications of the dependent variable, and (4) correcting for potential response biases. We also discuss potential endogeneity issues in the data.

Fixed effect models: in columns (1) and (2), we estimate fixed effects models using a neighborhood-fixed effects and a district-fixed effects estimator, respectively.[21] Consistent with our previous discussion, the results in columns (1) and (2) show that the coefficients of the fixed effects estimators are very similar to those of the random effects estimators.

Exclusion of Mumbai and Thane: in column (3), we revert to the random effects specification but exclude the districts of Mumbai and Thane from the sample. Both stand out from the rest of the sample in that they are much more "urban." For instance, 34 percent of the sampled households in Mumbai and Thane districts live in a building, in contrast to 8.2 percent in Sangli and Kolhapur, 7 percent in Dhule, and less than 5 percent in all other districts. These two districts also exhibit much lower levels of trust toward neighbors. Removing both districts from the sample does not alter significantly the results.

Alternative specification of dependent variable: the dependent variable we have considered so far takes the value 1 for both households that experience riots directly (i.e., suffer direct injuries and damage) and households that report more indirect experiences of violence. It is, therefore, possible that the results we discussed earlier may be driven by particular types of victimization that we have not considered. Given the small size of the sample of households that suffered direct injuries or damage (twenty-six households), we are not able to use multinomial or ordinal models to estimate correlates of victimization across different types of victims. Instead, we recode in column (4) of Table 4 the dependent variable so that only indirect victims are compared to nonvictims. Observations for direct victims were set to missing. Large discrepancies between estimations with indirect victims would be a sign that we should not aggregate all types of victims in the specifications discussed in Table 3. A comparison of column (6) in Table 3 and column (4) in Table 4 shows that the coefficients are qualitatively similar.

Response biases: communal violence is a very sensitive topic in India, arguably creating a risk that respondents may underreport their experiences of violence and victimization. Underreporting may also be due to the fact that in some cases interviews were conducted outside the house, where groups of neighbors and passersby gathered around the respondents.[22] In order to be able to correct for these potential biases, we noted down during the surveys the circumstances under which each interview was conducted. In column (5) of Table 4, we introduce a categorical variable depicting the setting of the interview as an additional covariate. This variable takes the value 1 if the respondent was alone, 2 if children were present, and 3 if other adults were present; 43 percent of the interviews are coded as 1, 31 percent as 2, and 26 percent as 3. Another potential bias may stem from the sex of the respondent. Two-thirds of our respondents are female. If women (men) are more reluctant than men (women) to admit to exposure to violence, the victimization variable would be subject to a nonrandom measurement error. The estimates in column (5) show that when children were present, there is a higher likelihood of the respondent reporting victimization. Male respondents also seem more willing to declare victimization status. Both these effects are only marginally significant ($p < .10$), and the inclusion of these variables does not change the previous results.

Endogeneity: we discussed previously, how the correlation between the covariates and the random effects was unlikely to bias the results. We also discussed the robustness of the results to several potential measurement errors. However, results may still not be valid if covariates are correlated with the error term (e_{hnd}) due, for instance, to potential reverse causation. There are at least two channels through which reverse causation may operate. First, exposure to riots may increase the feeling of vulnerability among people affected, making those people more likely to report victimization, not because they were affected by the riots but rather because they feel more afraid and insecure. Second, exposure to riots may increase actual vulnerabilities. Therefore, more economically vulnerable people may not necessarily be more likely to be the victims of riots; rather, economic vulnerability may be caused by the riot itself. We are not able

Table 4. Determinants of Household Riot Victimization: Alternative Specifications.

Victims	All	All	All	Indirect	All	All	All
Sample	Full	Full	w/o Mumbai and Thane	Full	Full	Full	Most affected neighborhoods
	Neighborhood FE	District FE	Three levels RE	Three levels RE	Three levels RE	Three levels RE	Three levels RE
Estimator	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance to police station	−0.024	−0.013	−0.015	−0.023	−0.002	−0.014	−0.034
	(0.015)	(0.017)	(0.015)	(0.016)	(0.015)	(0.014)	(0.021)
Presence of unsafe place	0.982**	1.007*	0.780**	0.804**	1.300***	0.950***	0.357
	(0.496)	(0.529)	(0.366)	(0.387)	(0.426)	(0.357)	(0.561)
Shop owner	0.974***	0.949**	0.976**	0.982**	1.333***	0.980**	0.634
	(0.372)	(0.485)	(0.417)	(0.452)	(0.520)	(0.422)	(0.578)
Concerned by crime						0.387	
						(0.321)	
Trust neighbors	−0.453	−0.555*	−0.530**	−0.695**	−0.502*	−0.535**	−0.777**
	(0.342)	(0.326)	(0.261)	(0.285)	(0.297)	(0.261)	(0.369)
Community help	−1.192**	−1.262***	−1.275***	−1.534***	−1.452**	−1.342***	−1.768***
	(0.481)	(0.384)	(0.484)	(0.580)	(0.593)	(0.491)	(0.680)
Women's group	0.975***	1.083***	1.030**	1.139**	1.132**	1.010**	0.959
	(0.491)	(0.268)	(0.461)	(0.496)	(0.516)	(0.467)	(0.621)
Marathi	0.350	0.449	0.465	0.584*	0.357	0.434	0.645
	(0.319)	(0.380)	(0.287)	(0.308)	(0.315)	(0.278)	(0.436)
Can use savings	−0.889***	−0.926***	−0.955***	−0.739***	−0.745**	−0.901***	−0.685*
	(0.299)	(0.348)	(0.265)	(0.284)	(0.308)	(0.259)	(0.382)
Income per capita	0.0001	0.0002*	0.0002*	0.0002*	0.0001	0.0002**	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Level 2 covariates							
Caste fractionalization		7.056**	7.703***	6.579**	9.168***	7.353***	3.705
		(2.531)	(2.827)	(2.815)	(2.801)	(2.537)	(3.473)
Community help		−11.003***	−10.934***	−9.529***	−10.296***	−9.982***	−5.531
		(2.334)	(3.141)	(3.469)	(3.304)	(3.181)	(3.610)
Can use savings		5.629***	5.605***	6.668***	5.973***	6.158***	−0.998
		(1.435)	(1.621)	(1.854)	(1.559)	(1.637)	(4.026)
Children present					0.574*		
					(0.336)		
Other adults present					−0.295		
					(0.383)		
Male respondent					0.553*		
					(0.319)		
Observations	553	865	769	920	751	944	171

Note: FE = fixed effect; RE = random effect.
Standard errors in parentheses. ***p < .01. **p < .05. ***p < .1.

> to test directly for endogeneity or provide precise causal channels whereby riots may affect victimization. This is because it is nearly impossible to collect pre-riot data on household characteristics in areas affected by endemic rioting. We also do not think it is possible to construct a credible and strong enough set of instruments for each covariate of victimization we analyzed in the previous section. We provide subsequently, however, indirect evidence that the results we presented so far are not likely to be substantially driven by potential reverse causation.

Because we were aware of the potential for endogeneity in the estimates, we were very careful to ask questions about possible determinants of victimization in questionnaire modules that were separate to, and applied before, any questions about riots. The respondents were never told this was a survey about riot experiences (these questions were asked toward the end of the survey). Our main concern is with the result that households are more likely to be the victims of riots if they live near (self-reported) unsafe areas. This result may be due to increases in perceptions of insecurity rather than the nearness of unsafe areas per se. In order to test this further, we have included in column (6) of Table 4 a variable measuring related perceptions of insecurity, notably whether the respondents report concerns about crime in their neighborhood. If our result on the location of households near unsafe areas is being driven by heightened perceptions of insecurity due to riot exposure, we would expect these households to also report increased concerns with crime. This is not the case: the coefficient is positive but not statistically significant, and adding it to the regressions has no significant effects on other coefficients.

The second cause for concern about endogeneity is that exposure to riots may change economic vulnerability, rather than vulnerability being a determinant of victimization. The restriction of the results in Table 4 (column 4) to indirect victims goes some way toward mitigating this concern since most households reporting victimization in our sample did not report direct financial losses that would have resulted from injuries or physical damages. The issue of reverse causality may, however, still be present in variables measuring neighborhood support. The results discussed in the previous section showed that socially isolated households suffer more from riots, neighborhoods with weak support networks experience more riots, and households unable to resort to the help of neighbors in times of need are more likely to report being victimized. It is, however, possible that households most affected by the violence within their neighborhoods responded by withdrawing from existing social relations (especially if these households belong to local minority groups) or that neighborhood social interactions were in fact weakened by riots. In order to (at least partially) address this concern, we have restricted our sample to the most riot-affected neighborhoods (see column 7 in Table 4). These are neighborhoods in which at least 50 percent of households reported a riot.[23] We find that even in these neighborhoods the effect of community support at both the household and the neighborhood level remain large and, for the former, statistically significant. If riots caused people to withdraw from social networks of support, or social relations to become less strong, we should have observed no effect (or a high reduction of the effect) of community support on victimization. We observe instead an increase in the negative effect of trust in neighbors and community help on the likelihood of households reporting being victims of riots. However, the magnitude of the neighborhood variable representing community help decreases to 5.5, so that the effect is now just above the 10 percent level of statistical significance. Although we acknowledge that this test cannot replace a more rigorous causal identification strategy, these results suggest that it is unlikely that social isolation is being on the whole caused by the riots themselves. This exercise does not rule out the fact that reverse causation may also be the result of a positive effect of the riots on social relations, which has been reported in the literature on civil wars (for instance, Bellows and Miguel 2009; Blattman 2009). In that case, the results we discussed in the previous section are a lower bound estimate of the true association between community help and trust and the likelihood of household victimization.

Conclusion

Despite a large literature on communal violence in India, quantitative evidence on the effects of rioting on households and neighborhoods exposed to endemic violence is very limited. To the best of our knowledge, this is the first study to examine empirically the patterns of victimization among households and neighborhoods affected by riots in India.

The results discussed in the article show that households are more likely to report having been the victims of riots when they live in the vicinity of unsafe areas, own a shop, belong to self-help groups (which we interpret as indicating the level of economic vulnerability of the household), and report higher levels of income per capita. Households are less likely to report suffering from riots when they live farther from police stations, are more able to trust their neighbors, are able to rely on the help of neighbors in times of need, and are able to accumulate savings. Taken together, these results suggest that household riot victimization in Maharashtra is positively associated with economic vulnerability and weak social interactions. We also find an interesting double-edge effect of income: better-off households may be able to better cope with the adverse effects of riots (particularly those able to save) but may also have more to lose in terms of economic activities and be more exposed to the possibility of opportunistic violence and looting. At more aggregate levels of analysis, we find that relatively more affluent neighborhoods and with higher levels of caste fragmentation are more likely to include a larger number of riot victims, whereas neighborhoods with stronger social links between households are less likely to exhibit high levels of household victimization.

The importance of economic factors in determining household riot victimization is noteworthy because these factors have been largely absent from the literature on riots in India, which for the most part has focused on political and social dynamics.

The nonlinear income result we find is, however, in line with findings in the civil war literature, which has found that victims of violence tend to be found among both the better-off and worse-off segments of the population (for instance, Verwimp 2005). This has not been explored in detail in the literature on riots and nonwar forms of political violence and is an interesting direction for future research.

Despite the importance of religious factors in most of the literature on riots in India (and the literature on ethnic riots more widely), we did not find an association between riot victimization and religious identity. This may well be because our definition of riots goes beyond the usual focus on Hindu–Muslim communal violence. We indeed found that Marathi speakers tend to be more likely to declare a victimization status, but the robustness of the result is somewhat questionable. We find strong evidence that caste fractionalization is associated with high levels of victimization at the neighborhood level. We have argued, however, that this result likely reflects a lack of capacity (or willingness) of state institutions to provide public goods in more heterogeneous neighborhoods. This interpretation is strengthened by the fact that we also found a robust negative association between household victimization and distance from police stations. We believe this is an important result showing how the police may not necessarily act to protect local populations in contexts of rioting. This complements the findings of Wilkinson (2004) on the role of the police and state institutions in selectively intervening to control communal rioting depending on electoral competition processes.

Our final set of results suggests that weak social neighborhood interactions and household social isolation are important determinants of household riot victimization. Varshney (2001, 2002) has argued that the strength of interethnic civic engagement is one of the key reasons why cities such as Lucknow, Kozhikode, and Surat have experienced lower levels of communal violence than other comparable cities such as Hyderabad, Aligarh, and Ahmadabad. We cannot directly compare our results with these. We show, however, that household integration in local social life (particularly the ability to draw on community help in times of need) acts as a protective shield against the adverse effects of riot exposure. In addition, households living in neighborhoods with stronger support networks are less likely to be affected by a riot. These results mirror some of the findings of Varshney (2001, 2002) about the importance of "everyday forms of engagement" in preventing the outbreak of riots. Our results suggest that everyday forms of social engagement act as important economic and physical security safety nets for households exposed to rioting. A large economics literature has shown how social networks are central to protecting the poor when they are affected by economic shocks (e.g., Townsend 1994). Similar mechanisms may also be at play in situations of endemic rioting, an issue that we intend to explore in more detail in future work.

These findings have also important policy implications. India's recent 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. The results discussed in the article suggest that rioting, which continues to rise and persist across many communities, cities, and states in India, may be deepening the economic, social, and physical vulnerability of those already unable to benefit from increases in economic growth.

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Notes

1. One exception is Scacco (2012), who has conducted a survey among perpetrators of riots in Nigeria in order to better understand why people participate in violent forms of civil unrest.
2. A few studies have focused on explaining the causes of communal riots at the neighborhood level. See Field et al. (2008) for an empirical analysis of riots in Ahmadabad, and Berenschot (2011) for an ethnographic study of violence in Gujarat after the 2002 events.
3. This usually consisted of five or six equidistant points around the perimeter and five or six starting points branching out from roughly the center of the site.
4. The working paper version of this article (Gupte, Justino, and Tranchant 2012) shows further evidence for the importance of neighborhood effects in shaping household determinants of victimization.

5. Houses made of permanent materials may signal wealth and attract looters, while houses made of nonpermanent materials are easier to plunder.
6. Scheduled castes (SC), scheduled tribes (ST), and other backward classes (OBC) are groups of historically disadvantaged people recognized in the Constitution of India.
7. In his novel *Curfew in the City*, Rai (2005) vividly depicts the dramatic consequences of the curfew in a poor household hosting a pregnant woman. See also Brass (2006).
8. The within effect is given by the coefficient associated with the demeaned covariate $(x_{hnd} - \bar{x}_{nd})$ and the between effect with the cluster-mean covariate $\bar{x}_{nd}$. 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 and Skrondal 2012, 158).
9. The estimations are run with the *xtmelogit* command in Stata with seven integration points at each level. Using the *lmer* command in R yields the same results. In all the subsequent estimations, we exclude one observation corresponding to a household with an income of Rs. 800,000, that is, almost US$13,000. The figure is correct (the household head is a very successful businessman) but is so out of line with the rest of the sample that we decided to exclude this observation so as not to bias the results.
10. By exponentiating the raw coefficients in Table 3, we obtain the odds ratio. The odds ratio associated with one additional minute needed to reach the police station is $e^{-0.035} = 0.97$, which indicates that every additional minute translates into a 3 percent reduction of the risk of victimization. The corresponding change in risk associated with a fifteen-minute increase is $e^{-0.035\times 15} = 0.59$, that is, a 40 percent reduction.
11. We also introduced the visible assets individually as covariates, but they remained statistically insignificant.
12. The results could also be explained by the fact that these are areas of high criminal activity. We test this result further in the next section but do not find support for this hypothesis.
13. Examples of this are also evident elsewhere in the world like, for example, during the civil wars and ethnic violence in Burundi and Rwanda, as described by Lemarchand (1996) and Straus (2006).
14. Jha (2013) provides evidence for a similar mechanism at play by showing a strong negative causal relation between riots and proximity to medieval trading ports across cities in India, which would have created strong institutions for interreligious trade and exchange.
15. Results not shown but available upon request.
16. This effect is, however, not very robust across the alternative specifications displayed in Table 4, on which we will return subsequently.
17. This debate is discussed in detail in Wilkinson (2005) and Jaffrelot (2011).
18. A *chowk* is a major crossroad.
19. We have also considered specifications with polarization instead of fractionalization indices, but none of them reached usual significance levels. Results are available upon request.

20. To save space, we do not report the variance of the random effects and the *p* value associated with the likelihood ratio test. Neither is changed with respect to the previous specifications
21. The estimated standard errors are robust to a neighborhood cluster effect in column (1) and to a district cluster effect in column (2).
22. This is a very common situation faced by surveys conducted in developing countries, including India. See Alderman, Das, and Rao (2013) for a discussion.
23. These neighborhoods are located in towns where the occurrence of large-scale riots is well documented. The research team was able to confirm in each of these sites the incidence of riots.

Supplemental Material

Online Supplementary Material is available from the authors or on the Journal of Conflict Resolution website at http://jcr.sagepub.com/supplemental.

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