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Riots and social capital in urban India

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Abstract: This paper explores the relationship between household exposure to riots and social capital in urban India using a panel dataset collected by the authors in the state of Maharashtra. The analysis applies a random–effect model with lagged covariates to estimate the exogenous effect of riots on social capital. Households living in neighborhoods prone to riots are more likely to invest in bridging social capital by joining community organizations but reduce face–to–face contact with neighbors. These effects are driven largely by levels of neighborhood social fragmentation in riot-prone neighborhoods. In these neighborhoods, the salience of social identity is also reduced as individuals attempt to reach out across social divisions. We interpret these results as indicating that households instrumentally use bridging forms of social capital as an insurance against potential future communal violence in socially fragmented contexts where conflicting social groups live alongside each other.

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1 Introduction

Riots and violent protests have been on the rise in the last two decades, causing deaths, injuries and serious economic damage in many parts of the world. Just between 2017 and 2018, the number of riots worldwide increased by almost 25 percent [Kishi and Pavlik, 2019]. These levels of civic upheaval are likely to have profound effects on societies, economies and political processes. However, even though riots have preoccupied scholars for several decades, this literature has largely focused on understanding the causes of riots [Brass, 1997, Wilkinson, 2004, DiPasquale and Glaeser, 1998, Horowitz, 2001, Petersen, 2002]. Although a few studies have examined the economic costs of riots [Collins and Margo, 2007], analyses of the social consequences of riots and the mechanisms that might shape them remain scarce.

These consequences are likely to be particularly pronounced in densely populated (often informal) urban settlements made up of diverse social groups where a melting pot of civilizations live alongside each other in extremely stressful situations. Riots are by and large an urban phenomenon [DiPasquale and Glaeser, 1998, Horowitz, 2001, Wilkinson, 2004],[1] and recent high rates of urbanization have resulted in increased proximity between different social groups. According to the United Nations, over one billion people across the world live in such conditions.[2] This number is estimated to double by 2030 [UN–Habitat, 2003]. The effects of civic violence on these communities and neighborhoods is likely to be considerable.

This paper studies the effects of exposure to riots that occur in urban neighborhoods affect household social capital, and what mechanisms may explain this relationship. The paper focuses on the Indian state of Maharashtra, and is based on a unique longitudinal household–level survey collected by the authors in riot and non–riot affected neighborhoods located in urban (largely informal) areas across Maharashtra. To the best of our knowledge, this is one of the first studies on the relationship between civic unrest and social capital in informal urban settlements.

[1] Though some riots may expand into rural areas, as illustrated in examples analyzed in Horowitz [2001].

[2] `https://unstats.un.org/sdgs/report/2019/goal-11/`

The social capital effects of urban riots are apriori unclear. Since Horowitz [2000, 2001], there has been an implicit assumption in the literature that civic violence has adverse effects on social relations. Riots that emerge between ethnic, religious or other cultural groups tend to foment further resentment between groups and reinforce in–group biases [Petersen, 2002]. However, research in civil war contexts has revealed a positive relationship between individual exposure to violence and forms of civic engagement and social cooperation, including participation in community organizations [Bellows and Miguel, 2009], voting [Blattman, 2009] and pro–social behavior [Gilligan et al., 2014, Voors et al., 2012]. More recent research has qualified that these positive effects may be limited to those among the same social groups [Bauer et al., 2014, 2016]. These studies have focused on postwar contexts, and there has been to date limited systematic understanding of how different dimensions of social capital may change in socially and politically unstable areas outside these extremely violent contexts.

Empirically, identifying the effect of riots on social outcomes is a challenging task because standard regression estimates may be affected by reverse causality and omitted variable biases. In the case of India, there is reason to believe that social capital at the neighborhood level may shape the likelihood of riots emerging in specific areas [Varshney, 2002]. At the same time, economic shocks, such as price rises, urban planning processes, such as the demolition of slum areas, and political processes, such as elections, may affect the onset and intensity of riots and levels of social capital simultaneously in given neighborhoods. In order to address these endogeneity concerns, this study makes use of a random–effect model with lagged covariates (exploiting the longitudinal nature of the data). We measure social capital in terms of bridging and bonding social capital [Putnam et al., 1994a]. Measures of bridging social capital include household participation in civic organizations. Bonding social capital is illustrated by levels of trust in neighbors and participation in face–to–face discussions with neighbors.

As a novel contribution, we investigate also the mediating factors that may shape the relationship between riot exposure and household social capital. Given the ethnic dimension of most riots in India, we hypothesize that the effect of riot exposure on social capital is shaped by levels of social diversity and the salience of individual identities in each given neighborhood. Social diversity is measured using indices of social fractionalization and polarization of religious and caste groups. The salience of identity is measured through vignettes included in the survey. This methodology allows us to elicit true behavioral responses by asking respondents to react to several scenarios designed to measure trust and cooperation where we randomly change the social identity of the characters in order to emulate exchanges between different religious and caste groups.

The main results show that households in neighborhoods exposed to riots in 2010 are more likely to join neighborhood organizations in 2012, but less likely to participate in face–to–face discussions. There is no direct effect of riot exposure on how households trust their neighbors. We interpret these results as indicating that exposure to riots leads to households favoring forms of bridging social capital, possibly as an insurance against future riots and their adverse effects. This effect is driven by highly fragmented, riot–prone neighborhoods, where households build networks with other social groups by joining local community organizations. Bonding social capital is reduced in riot–prone and fractionalized neighborhoods, most likely due to suspicion and reduced lack of trust in neighbors. We find, in addition, evidence for a fading in the salience of social identities — which is usually very strong in all aspects of life in India — in neighborhoods prone to riots. Taken together, these findings suggest that in contexts of informal and violence–prone urban settlements, where different social groups are forced to live in close physical proximity, households tend to invest in between–group interactions and behave in ways that bridge across social divisions, even when experiencing reduced levels of trust and confidence in neighbors. This interpretation reflects an instrumental use of social capital in co–ethnic communities where the threat of violence is high.

This paper is related to at least three bodies of literature. The first is the literature on ethnic riots [Horowitz, 2001], including a large literature on India [Wilkinson, 2004], which to date has offered only limited understanding of the consequences of riots. We show that riots have substantial impacts on social capital. We show also that social fragmentation plays an important role in explaining this relationship, whilst individual identity loses salience in riot–prone neighborhoods, despite the importance of caste and religious divisions in India. The second is a smaller body of research on the effect of violence on social capital in contexts of civil war (reviewed in Bauer et al. [2016]). The paper extends this literature to analyze the role of low–intensity violence (in the form of riots). A similar analysis is done in Hager et al. [2019], who focus on one riot that took place between two ethnic groups in the city of Osh in Kyrgyzstan. Our paper examines exposure of households to riots across time using a representative survey of informal settlements in a country (India) where riots are endemic to social, economic and political life. Finally, we contribute to the literature on the provision of public goods in ethnically diverse societies. Several studies have shown that collective action that sustains the provision of public goods is more challenging in heterogeneous societies [Alesina and La Ferrara, 2005, Vigdor, 2004, Alesina et al., 1999, Alesina and La Ferrara, 2000, Miguel and Gugerty, 2005, Habyarimana et al., 2007]. We show that the threat of violence in heterogeneous communities may facilitate some forms of collective action, as these can be used as ways of bridging across social divides and as insurance against the adverse impact of civic violence.

2 Theoretical Discussion

The literature on the effects of violence on social behavior has relied largely on evolution models of social cooperation where the threat of violence favors within–group cooperation at the expense of between–group cooperation, which may in turn lead to hostility towards others outside the immediate social group [Bowles and Gintis, 2011]. Recent research from civil war contexts has revealed a positive relationship between exposure to armed violence and forms of civic engagement and cooperation [Bauer et al., 2014, Bellows and Miguel, 2009, Blattman, 2009, Gilligan et al., 2014, Voors et al., 2012], particularly among those from the same community [Bauer et al., 2014, 2016]. Thus, based on the civil war literature, we would expect riots to increase ‘bonding’ social capital (which would strengthen within–group cooperation by encouraging social norms that keep the group together), while reducing ‘bridging’ social capital across opposing groups.

These predictions may not hold in contexts outside civil wars. Extreme poverty and lack of economic opportunity have forced Indians — and many other people in other developing countries — across different religious, caste and cultural groups out of rural areas and into the cities, in search of a more prosperous life. What they find is often unplanned infrastructure, lack of basic living conditions and close proximity between new migrants who must live side–by–side under extremely challenging circumstances [Mazumdar, 1987, Deaton and Dreze, 2002]. In these contexts barriers to choosing where to live are very high, even between groups that traditionally oppose each other. It is not therefore a surprise that violence is endemic in slum areas in India and elsewhere.

Under these complex social arrangements, the effects of urban violence on social capital are theoretically ambiguous. The literature on civil wars explains a positive effect between war victimization and social capital based on theories of post—traumatic growth [Tedeschi and Calhoun, 2004], whereby victimized people find strength in adversity and come together to overcome previous trauma. This mechanism may arise also in riot-–prone areas when, under the threat of violence, close social proximity between different ethnic, religious or cultural groups may lead to tolerance rather than hostility [Côté et al., 2015]. For instance, in India, historical trade exchanges between Hindu and Muslims living in the same communities have reduced the likelihood of ethnic animosity [Jha, 2013]. According to the widely studied social contact theory, proximity between social groups, like that observed in urban slums, and shared experiences (like for instance riots) may promote tolerance and reduce social distances [Allport et al., 1954] — see also review of latest evidence in Paluck et al. [2019]. Both post-traumatic growth and social contact theories predict an increase in social capital as a result of riot exposure

However, competition between social groups implies that forced direct proximity between heterogeneous social groups, due to increased urbanization or migration flows, may trigger ethnic animosities and possibly conflict [Forbes, 1997, Caselli and Coleman, 2013]. Ethnic violence will, in turn, destroy further the social fabric of affected communities, particularly in those communities where rival groups (for instance, Muslims and Hindus in the case of India) live in close proximity [Horowitz, 2001]. Thus, social competition theories predict a reduction in social capital among riot-exposed communities. However, relations between rival groups in contexts of violence may depend on the nature of this violence, particularly on whether this is indiscriminate (targeting everyone in a community randomly) or selective (targeting specific individuals and households due to idiosyncratic characteristics) [Kalyvas, 2006]. Although riots may affect some people indiscriminately, there is strong evidence of selective targeting in urban riots in general [Horowitz, 2001]. Selective violence has also been found in Maharashtra where specific slum dwellers are targeted by rioters [Gupte et al., 2014]. Therefore, households living in close proximity to those that may become their assailants when a religion or caste—based riot breaks out may want to minimize their exposure to being a target of violence. Like with other forms of coping strategies under adverse economic conditions [Fafchamps and Gubert, 2007], social relations and forms of social cooperation that bridge across social divides may become a valuable investment for households living under unstable socio-–political conditions. This instrumental use of social capital has been documented in other areas, such as accessing jobs and social networks [Portes, 1998]. Co–ethnic civic associations, in particular, may be useful sources of information [Caria and Fafchamps, 2019], including about factors that may trigger the next riot, like for instance rumors and warnings that tend to circulate during riot preparations [Horowitz, 2001]. Access to such information is crucial in ensuring that households protect lives and property before a riot erupts. Under these circumstances of social/ethnic competition and uncertainty (due to the threat of violence), exposure to riots may reverse the previous result and lead to higher levels of social capital — at the very least of social capital that can be used instrumentally to avoid exposure to future riots.

In summary, existing theoretical frameworks predict that riot exposure may reduce social capital if it breaks the social fabric of local neighborhoods by increasing in–

group biases and out–group prejudices, or it may increase social capital if it promotes empathy and tolerance across social groups and among individuals of different cultural and social backgrounds or if investments in social capital are seen as a useful instrument of social insurance against riot threats. Which of these theoretical approaches may prevail will depend on the balance achieved in the social composition and social preferences that characterize each community. Traditionally, the literature has focused on two important dimensions of social composition: levels of community social diversity and how attitudes towards others are shaped by social identities.

Social diversity. It is generally postulated that homogeneous groups achieve higher levels of social capital because the costs of coordination and cooperation are lower among these groups [Alesina and La Ferrara, 2000]. The levels of social heterogeneity that characterize densely populated urban settlements have generally been found to reduce group cooperation and the effectiveness of public good provision [Alesina and La Ferrara, 2005, Miguel and Gugerty, 2005, Bardhan, 2005]. Group heterogeneity has also been found to reduce participation in community groups, although this matters less for groups that require low levels of daily direct contact [Alesina and La Ferrara, 2000]. Large levels of social diversity in riot–prone contexts may in addition reduce social capital when violence pits neighbor against neighbor. Kalyvas [2006] discusses how suspicion, mistrust and fear hinders social relations between community members in contexts of civil war. Nunn and Wantchekon [2011] describe how individuals tried to protect themselves against the slave trade by denouncing others in their communities, leading to long–lasting forms of mistrust. Horowitz [2001, p. 11] documents how ethnic riots spread “bitterness and suspicion and aloofness”. In the case of India, Hindu–Muslim riots are pervasive and more often than not result in deepening the social distances between the two religious groups [Varshney, 2002, Wilkinson, 2004].

However, under stressful conditions, households in heterogeneous communities may want to find ways of coping and insuring themselves against future shocks — such as riot exposure. This is particularly true when households are not able to sort themselves easily into homogeneous groups. Although segregation is common in large urban areas, physical proximity and lack of infrastructure may force people into social proximity, particularly in unplanned slum areas. Even though people from the same religion or caste may form small homogeneous clusters, living in slums will still imply close proximity to other social groups, unless the household is able to move out of the slum altogether [Jaffrelot, 2006, Spater, 2019].

We hypothesize that this instrumental dimension of social capital is central to socially diverse informal urban settlements where rival social groups must live side–by–side under stressful situations. Under the close threat of ethnic violence, inter–group co-operation in heterogeneous communities becomes a survival strategy. The empirical analysis in Section 6.1 will test this hypothesis by determining empirically the net effect of potentially negative or positive impacts of social diversity on social capital in riot–prone neighborhoods in Maharashtra.

Social identity. In addition to group factors, individual social preferences and prejudices may also shape the relationship between riot exposure and social capital. Based on seminal studies by Tajfel et al. [1971] and Tajfel [1978], a large literature has shown that shared identities shape individual decisions in several areas of life, including who to marry, who to exchange goods with and how to vote [Akerlof and Kranton, 2000, Hoff and Pandey, 2006, Chen and Li, 2009, Afridi et al., 2015]. In India, religious and caste identities are central to all aspects of life [Iyer, 2016]. There is also substantial evidence that social capital investments are shaped by shared identities when individuals show prejudice against and aversion to mixing with others from different backgrounds [Alesina and La Ferrara, 2000]. In riot–prone contexts, shared identities may reduce social interactions between groups when they reinforce in–group biases. For instance, Beber et al. [2014] show that Northern Sudanese individuals exposed to an ethnic riot in Khartoum were more likely to support independence of South Sudan because they were unwilling to continue living alongside Southern Sudanese co–citizens. In Israel [Canetti-Nisim et al., 2008] and in the USA [Huddy et al., 2005, Davis and Silver, 2004], the threat of terrorism has resulted in negative stereotyping of Muslim groups. In all these cases, exposure to violence or the threat of violence increased in–group bias through increased prejudice towards those of different social identity.

On the other hand, it is possible that in politically unstable areas individuals may exhibit larger level of empathy towards other groups. Corno et al. [2019] show evidence for this mechanism in the case of an inter–racial policy in South Africa that promoted room sharing across black and white university students in order to break stereotypes in post–apartheid South Africa. Individuals may want also to reach out across identity divides to prevent further violence, as studies have shown in the case of Israelis living close to areas targeted by Palestinian attacks who support the two–state solution [Gould and Klor, 2010] and Chechen rebels under the threat of Russian forces that refrain from retaliation [Lyall, 2009]. In these cases, shared identities become less salient in social and economic exchanges and political attitudes because the threat of being targeted by ethnic violence is high. We hypothesize that in the case of slums in India, where rival groups live in close proximity, the salience of shared identities may be reduced in ways that will allow individuals to reach across social divides. We test this hypothesis empirically in Section 6.2. First, we turn to the discussion of the data and the estimation of the direct effect of riot exposure on social capital.

3 Data and variables: the Maharashtra Household Longitudinal Survey on Civil Violence and Welfare (MHLS)

India has registered historically some of the highest numbers of riots and riot–related fatalities in the world [Kishi and Pavlik, 2019], which have been particularly endemic to informal urban settlements [Varshney, 2001, Wilkinson, 2005, 2004, Brass, 1997]. Almost 110 million people live in slum areas in India, and 11 million in Maharashtra (the highest in India). Riots have been a constant feature of life in urban Maharashtra in the last decades, with particular deadly years in 1970, 1984 and 1992–93, when major Hindu–Muslim riots broke out across the state [Varshney, 2002, Wilkinson, 2004], often fueled by competing political interests [Wilkinson, 2004] and often involving extremist groups such as the Shiv Sena, a Hindu nationalist political organization, which has been operating in Maharashtra since the 1960s [Horowitz, 2001]. In addition to these particularly violent years, riots break out nearly every year in Maharashtra (Figure A.1 in the online appendix).[3]

The empirical analysis in this paper is based on a panel dataset collected by the authors among 1,089 households interviewed in 2010 and 2012 in 45 urban neighborhoods in Maharashtra. This dataset was collected using a clustered sample approach that took into consideration the fact that riots are concentrated in certain areas across Maharashtra and are rare events (even if regular and persistent in many parts of the state) [Gupte et al., 2014]. We started by using district–level data from the Maharashtra police between 2003 and 2008 to identify three district categories: high rioting (5 or more riots per year), medium rioting (between 1.5 and 5 riots per year) and low rioting (less than 1.5 riots per year). We then selected within these categories districts that offered a good spread of administrative and socio–cultural divisions in the state, resulting in three districts in the medium and low rioting categories and four high rioting districts. This process is described in detail in Gupte et al. [2014].

In each of the ten districts, we collected information on the location of riot events in the 24 months prior to the collection of the first panel wave (2008–2010) using newspaper information (Figure A.1 in the online appendix). The aim of this work was to identify as precisely as possible urban areas where riots took place (our sites of interest). We then matched these sites to a list of voting–booths obtained from the Maharashtra Election Commission and randomly selected 45 neighborhoods. Coincidentally, though not surprisingly, these were all located in slum areas.

In the last stage of the sampling proceeding, we randomly selected households to be interviewed in the 45 neighborhoods. Given the lack of accurate census information

[3]This data was collected by the authors with the support of a Marathi speaking research assistant, who read through the Maharashtra edition of the Times of India and the leading Marathi news site, the Loksatta. Details are provided in Gupte et al. [2014]. In total, we coded 225 riots that took place from the 1st of January 2008 to the 1st of January 2012.

in slum areas, we selected households following a random walk strategy whereby each field team started walking from equidistant points in the perimeter of each neighborhoods towards the center, turning right at each junction and making sure that no alley was missed. This was an important aspect of the strategy to minimize missing the most vulnerable households. Households were randomly selected along the walk using a skip pattern (every 7th or 8th household in larger neighborhoods and every 4th or 5th in smaller neighborhoods). This was a time–consuming process due to the haphazard nature of dwellings in these contexts but resulted in one of the few available representative longitudinal surveys of slum populations in the world.

We went back to re–trace these households in 2012. To do this, we used cell phone numbers we had collected in 2010, as well as detailed maps of each neighborhood (including all dwellings and landmarks) hand drawn by a cartographer who was part of the enumeration team. Despite our best efforts and detailed planning, we were not able to find all households in the original sample. In total, 874 out of the original 1,089 households were traced, or 80.4 percent of the original sample.[4]

The MHLS questionnaire includes several questions on the exposure of households to riots (detailed in Gupte et al. [2014]), as well as a detailed module on social capital. We discuss below how we use the MHLS to measure our main variables of interest.

Riot Exposure. In India, a riot is officially defined as an assembly of more than five people who use violent means to achieve a common goal [Wilkinson, 2009], and fall within the categories defined in Horowitz [2001, p. 1] of “an intense, sudden, though not necessarily wholly unplanned, lethal attack by civilian members of one ethnic group on civilian members of another ethnic group”. The majority of riots in India are between Hindu and Muslim groups, although there have also been instances of riots between caste and migrant groups [Wilkinson, 2004]. While the definition of

[4] We noted in detail the reasons why each household could not be tracked. Eighty–one households were not found because they had since migrated. We were not able to find the original dwellings of 68 households because a particular slum in Mumbai was destroyed by a fire. In 65 households, no respondent was available after repeated visits. In 5 cases, the respondents refused to be re–interviewed. We discuss later in the paper that attrition did not introduce selection bias into our main results.

a riot in India is broad, there is severe under reporting of riots because policemen and politicians prefer to convey a peaceful and well–functioning society [Wilkinson, 2009]. Although we were able to collect sub–district level riot event data to construct the main sample, this information was not available at the neighborhood level. In the absence of such data, we measured household exposure to riots using a question that asks the respondent “In the last 12 months, have any of the following events occurred in your neighborhood?”. The events include riots, as well as modalities of violence commonly associated with riots such as stone pelting, public fights, bottle throwing, and tire burning. Twenty–three percent of respondents reported a riot taking place in their neighborhood in 2010 (Table A.1 in the online appendix). Self–reported data entails some challenges since such data can be under– or over– reported by households and could be correlated with household characteristics, including social capital. We address potential self–reporting biases in three ways. First, we control for household income as this variable may be correlated with the likelihood of a household being affected directly by the riot (for instance, through targeting by looters or because they live in makeshift houses that are easier to destroy) [DiPasquale and Glaeser, 1998, Gupte et al., 2014]. Second, our main empirical analysis relies on households being asked about a riot taking place in the neighborhood rather than the household experiencing the riot directly. This alleviates concerns about under–reporting among households that may be scared to admit their involvements in riots and about over–reporting among households that might be expecting compensation in return for their exposure to riots. Finally, we also accounted for the possibility that households may have conflicting views about the occurrence of a riot and where. This potential measurement error could occur because the household is genuinely confused or because some riots might have only affected parts of the neighborhood and thus specific households may have been unaware of the riot. In order to minimize this potential bias, we computed for each neighborhood the proportion of households who reported a riot in their neighborhood. By aggregating this variable, we are able to address some of these discrepancies and get a fuller picture that accounts for all responses. We then partitioned the sample into riot–affected and less affected sites based on whether at least 30% of respondents in a given site report a riot in their neighborhood.[5] While this might miss out on some information, it means in the paper we provide a conservative measure of riot exposure, rather than risk over–estimating the results.[6] Figure 1 plots the proportion for each neighborhood.

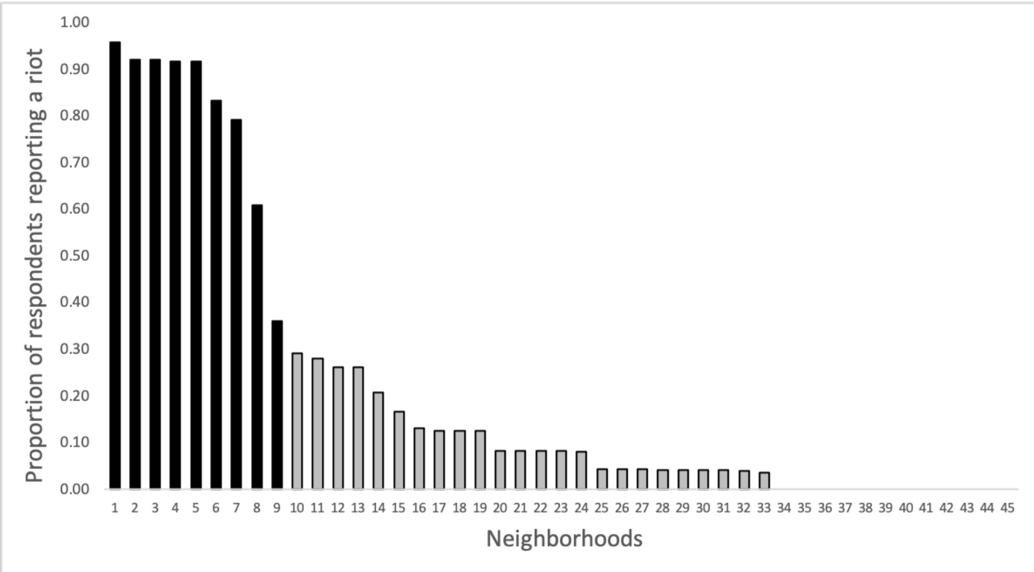

Figure 1: Proportion of self–reported riots in each neighborhood.

Social Capital. The definition of social capital often encompasses many indistinct concepts [Portes, 1998]. Despite this ambiguity, there seems to be a growing consensus that "social capital stands for the ability of actors to secure benefits by virtue of membership in social networks or other social structures" [Portes, 1998, p. 6]. Other concepts that have been added to the mix include social cooperation and norms of trust and reciprocity [Putnam et al., 1994a]. Given the variation in definitions, it make sense to understand social capital as a multi–faceted concept and

[5]This number was chosen as a cut–off point because this was the average number of households reporting a riot in neighborhoods where at least one household reported a riot. When including neighborhoods where no households reported a riot, the average is 23 percent (Table A.2 in the online appendix).

[6]As a robustness check we repeated the analysis using different cut–offs for the proportion of households reporting a riot. Within the range of 20% to 80% of households reporting a riot, the impact effect of rioting on social capital is largely similar to the results we report in the next section (Figure A.2 in the online appendix).

explore each dimension independently [Dasgupta and Serageldin, 2002, Grootaert and van Bastelaer, 2002]. We use three variables that represent different dimensions of social capital. The first is household participation in community organizations or groups, which measures bridging forms of civic association [Putnam, 2000, Varshney, 2002]. In our survey, 15.9 percent of respondents reported that they or a member of their household belong to a neighborhood group or organization. These include women's groups, political parties, gyms,[7] religious organizations, local *mohalla* committees, caste organizations, trade unions, student organizations, cooperatives, sport or cultural groups, youth organizations, farmer organizations, village organizations and others. Women's groups are the most common form of neighborhood organization (10.3 percent), which reflects the known importance of women's groups in slum areas in India,[8] and historically as part of the organization of peace committees in riot–prone situations [Katzenstein, 1989]. Other relevant organizations include political parties (2.2 percent of total respondents), gyms (1.9 percent) and religious organizations (1.5 percent). The second measure is self–reported trust towards neighbors, which asks whether the respondent would trust their neighbors to safe keep their money, a measure of pro–social preferences commonly used in the literature [Voors et al., 2012]. Just over 17 percent of respondents reported that they would be willing to trust their money or assets for safekeeping with their neighbors. The final measure is household participation in discussions, which captures face–to–face interactions between neighborhood members, and an important feature of communal life in India [Varshney, 2002]. Forty–two percent of households report participating in face–to–face discussions. All these are binary variables with value '1' when the respondent (most frequently the household head) reported that they belonged to a neighborhood organization, trusted their neighbors with their money or assets or participated in neighborhood discussions. Table A.3 in the online appendix shows how each of these variables was measured in the survey questionnaire, while summary statistics are provided in Table A.4. Table 1 disaggregates household measures

[7] This was included because gyms in many slum areas in Maharashtra are well–known recruitment grounds for the Shiv Sena.

[8] For several examples see `https://www.globalgiving.org/projects/self-reliance-and-resilience-in-slum-womens-groups/reports/`

of social capital across riot–prone and peaceful neighborhoods. Respondents who have at least one household member belonging to an organization are more likely to live in riot–prone neighborhoods. This difference is statistically significant. The other social capital variables move in the opposite direction: trust towards neighbors and participating in face–to–face discussions are significantly lower in riot affected neighborhoods.

	Mean		
Variable	**Riot**	**No riot**	**Diff.**
Household member belongs to an organization	0.27	0.14	0.12^{***}
	(0.03)	(0.01)	(0.03)
Trust towards neighbors	0.11	0.19	-0.07^{**}
	(0.02)	(0.02)	(0.03)
Household participates in community discussions	0.34	0.45	-0.1^{***}
	(0.04)	(0.02)	(0.02)

Source: MHLS 2012.
Standard errors in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Table 1: Differences in social capital variables separated by whether at least 30% of neighborhood reports a riot.

Control variables. We employ a range of respondent, household and neighborhood level controls summarized in Table A.2 in the online appendix and found to be important predictors of social capital [Glaeser et al., 2002, Alesina and La Ferrara, 2002]. These include the gender of the respondent as some studies have found that that women are less likely to trust others because they feel discriminated against [Alesina and La Ferrara, 2002]; age [Glaeser et al., 2002]; and house ownership, since home owners may have higher levels of social capital because of their long–term commitment to their community [DiPasquale and Glaeser, 1999, Glaeser et al., 2002]. Some studies have found income to be an important predictor of social capital [DiPasquale and Glaeser, 1999]. However, other studies have also shown how high social capital leads to higher levels of income [Narayan and Pritchett, 1999, Knack and Keefer, 1997], suggesting a potentially endogenous relationship between these two variables. We account for this by using lagged income levels and a random effects model, as we discuss below. We control, in addition, for various identity indicators that characterize the social composition of the community [Alesina and

La Ferrara, 2000]. Variables include whether the household is Muslim, whether their mother tongue is Marathi and whether the household belongs to the largest caste or religious group in the neighborhood. We also expect household size to play a significant role, because larger households may have more opportunity to engage in social capital. Finally, we collected neighborhood level indicators from the field site maps which illustrate the level of formal and informal institutions. These include the presence of a police station, a *chowk*,[9], a Hindu temple, a mosque, and a market.

4 Empirical strategy

As discussed in Section 2, the social composition of neighborhoods provides important contextual explanations for why riots emerge and their consequences. Neighborhood–level variables, such as local institutions and cultural characteristics, are thus likely to be important determinants of urban riots in Maharashtra. However, these variables are also key determinants of social capital [Putnam, 2000]. Therefore, including these variables as controls in a standard OLS estimation would introduce serious biases in the results. In order to alleviate this potential endogeneity bias, we estimate a random–effect model, which controls for neighborhood level unobserved heterogeneity.[10] Using random effects at the neighborhood level will control for any unobserved neighborhood level characteristics. Considering that the main variables of interest are at the neighborhood level, this will eliminate the interdependence of residuals between households caused by omitted variable bias. However, the random–effect models rely on a very strong assumption: that the random intercepts must be independent of the covariates. If this assumption does not hold, the estimation will yield biased results. This has made random–effect models unpopular, and most studies on the consequences of violent conflict rely on fixed–effect models instead. However, fixed effects would limit our analysis since we are interested in identifying specific

[9] A *chowk* is the area at an intersection of two roads, which usually serves as a small open market.

[10] In addition, we control for a range of neighborhood level variables as described earlier. Household level characteristics may also be confounding factors, and we include several household- level controls to correct for this, as discussed above.

neighborhood effects that would be wiped out in a fixed effects specification.

The assumption that the random intercepts must be independent of the covariates could fail if we suspect an interdependence between neighborhood institutions (the random intercept) and one or more of the covariates. Mundlak [1978] and Chamberlain [1984] have developed a useful tool to solve this problem by controlling for within–neighborhood means of the covariates. In order to do so, we estimate the following equation:

$$P[S_{i,n} = 1] = \Phi[\beta_1 X_i + \beta_2 R_n + \beta_3 Z_n + \delta_n + \epsilon_i] \tag{1}$$

where $P[S_{i,n} = 1]$ if household i in neighborhood n displays a given social capital, and $P[S_{i,n} = 0]$ otherwise. Φ is the probit function, or an inverse standard normal transformation of covariates. X_i denotes household level variables, R_n refers to neighborhood rioting, and Z_n includes a set of neighborhood characteristics. δ_n are the neighborhood level random effects. The Mundlak–Chamberlain decomposes δ_n into a function of the within–neighborhood means of the covariates X_i and random neighborhood level intercepts, as shown in equation 2.

$$\delta_n = \mu_n + \theta \bar{X}_n \tag{2}$$

Any dependence between the covariates and the neighborhood intercepts is captured by the set of within–neighborhood means of the covariates X_i. By controlling for the neighborhood level means of X_i, the intercept μ_n is considered to be independent of X_i. This ensures that the assumption required for a random–effects estimation is satisfied.

The second potential source of endogeneity bias results from the fact that social capital may be both a determinant and a consequence of violence. Neighborhoods with dense ties and high social capital could be targeted by rioters for political or economic reasons. Or, as discussed in Varshney [2001], neighborhoods with high levels of civic association may be less likely to be affected by riots. This potential reverse causality can yield a biased estimate of the effect of riots on social capital.

In order to deal with this potential bias, we make use of the longitudinal nature of the data and include in the regression the lag of all covariates by one time period. This ensures that the riots in 2010 ($t-1$) occur before the social capital observed in 2012 (t), which eliminates concerns for possible reverse causality.

The combination of lagged covariates, random effects, and neighborhood level effects gives us reasonable confidence that our estimates are the result of an exogenous relationship between riot exposure and social capital. By applying these strategies, we estimate the following equation:

$$P[S_{i,n,t} = 1] = \Phi[\beta_1 X_{i,(t-1)} + \beta_2 R_{n,(t-1)} + \beta_5 Z_{n,(t-1)} + \theta \bar{X}_{n,(t-1)} + \mu_n + \epsilon_i] \qquad (3)$$

where $P[S_{i,n,t} = 1]$ if household i in neighborhood n at time t displays a given social capital, and $P[S_{i,n,t} = 0]$ otherwise. The vector of regressors $X_{i(t-1)}$ includes the lags of various household characteristics that are likely to be correlated with riots and social capital, such as household size or income. As per the Mundlak–Chamberlain approach, $\bar{X}_{n,(t-1)}$ is a set of neighborhood averages of the household and respondent covariates. The variable $R_{n,(t-1)}$ takes the value 1 if the neighborhood was affected by a severe riot (if at least 30% of respondents in the area report a riot) and 0 otherwise. The vector of regressors $Z_{n,(t-1)}$ includes a set of lagged neighborhood characteristics, such as the presence of police station, temples, and a mosque in 2010. δ_n is a vector of neighborhood–specific random effects which absorbs the neighborhood time–invariant heterogeneity. All independent variables are summarized in Table A.2 in the online appendix. Standard errors are clustered at the neighborhood level, which allows us to relax the assumption that standard errors are independent of each other within a given neighborhood.

When reporting findings in the next section we report marginal effects for continuous independent variables and impact effects for binary independent variables, in order to ease interpretation.[11] The marginal effect is interpreted as the effect (in probabil-

[11] The marginal effect involves multiplying the estimated coefficient by the standard normal probability density function calculated at sample averages of the covariates. The impact effect is calculated as the difference in the cumulative distribution function when the binary variable equals 1

ity points) of an infinitesimally small change in a continuous independent variable on the probability of a given social capital occurring at the sample averages of specified covariates. The impact effect gives the probability point increase (or 1/100 percentage point increase) in the probability of a given social capital occurring when the binary independent variable is equal to one and at the sample averages of specified covariates.

5 Main results

Table 2 shows the impact and marginal effects of the estimates of equation 3. The equation is estimated for three dependent variables: membership of an organization (column 1), trust towards neighbors (column 2) and participation in face–to–face discussions (column 3).

Table 2: Effect of riot on social capital

	(1) Organization	(2) Trust	(3) Discussions
At least 30% of neighborhood witnessed a riot (d)	0.50***	-0.072	-0.19**
	(0.17)	(0.25)	(0.087)
Respondent age and sex in 2012			
Age of respondent	-0.0027	-0.0029	-0.0070**
	(0.0035)	(0.0037)	(0.0030)
Sex of respondent (1=Male) (d)	0.13	0.046	0.18*
	(0.13)	(0.099)	(0.093)
Household is Muslim (d)	-0.23	0.53**	0.26
	(0.20)	(0.24)	(0.18)
Household size	0.012	0.013	-0.0017
	(0.018)	(0.018)	(0.012)
Household rents house (0=Owns) (d)	0.038	0.29**	-0.094
	(0.16)	(0.13)	(0.12)
Log of monthly income per capita	-0.065	-0.0098	0.18***
	(0.082)	(0.081)	(0.064)
Mother tongue is Marathi (d)	0.0054	0.51***	0.26**

and 0, both calculated at sample averages.

	(0.15)	(0.17)	(0.13)
Hhd belongs to predominant religion/caste group (d)	-0.13	-0.034	0.15
	(0.13)	(0.12)	(0.098)
Lagged neighborhood level variables (2010)			
Police station in neighborhood (d)	-0.066	-0.033	0.063
	(0.18)	(0.11)	(0.099)
Chowk in neighborhood (d)	0.30	-0.23	0.13
	(0.21)	(0.19)	(0.11)
Hindu temple in neighborhood (d)	-0.44*	-0.11	0.041
	(0.24)	(0.23)	(0.12)
Mosque in neighborhood (d)	-0.035	-0.22	-0.17*
	(0.18)	(0.15)	(0.095)
Market in neighborhood (d)	0.051	0.17	-0.064
	(0.17)	(0.13)	(0.11)
Lagged neighborhood level averages			
Average respondent age	-0.0082	-0.031	0.0053
	(0.031)	(0.024)	(0.020)
Percentage of male respondents	-0.46	-0.73	-0.16
	(0.88)	(0.81)	(0.50)
% of Muslim households	-0.28	-0.83*	-0.46
	(0.63)	(0.43)	(0.40)
Average household size	0.077	0.053	0.010
	(0.083)	(0.093)	(0.047)
% of hhds who are tenants	-0.99	-0.82	1.48*
	(1.14)	(0.75)	(0.79)
Average monthly income per capita	0.13	0.32*	-0.13
	(0.24)	(0.19)	(0.16)
% of Marathi speakers	0.22	-0.92**	-0.82**
	(0.68)	(0.41)	(0.42)
Observations	853	853	853
Degrees of freedom	21.000	21.000	21.000
Chi-squared	97.799	71.500	181.845
Prob > chi2	0.000	0.000	0.000
Number of clusters	45.000	45.000	45.000

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Membership in organizations: Column (1) shows that in riot–prone neighborhoods (where at least 30 percent of the respondents in that neighborhood reported a riot), the respondent and their household members are 50 percentage points more likely to be part of a group or organization. None of the other respondent, household or neighborhood level covariates, except the presence of a Hindu temple in the neighborhood, produce significant effects on membership in community organizations.

Trust in neighbors: Riot exposure does not affect social trust, but Muslim and Marathi speaking households are, respectively, 53 and 51 percentage points more likely to trust their neighbors. In addition, households who rent (rather than own property) are 95 percentage points more likely to trust their neighbors. Neighborhoods that are older are less trusting. As the proportion of Muslims and/or Marathi speakers increase in a given neighborhood, trust towards neighbors decreases, suggesting that social heterogeneity (which we will investigate in more detail in the next section) may partly explain reduced levels of trust.

Participation in community discussions: Column (3) shows that households living in riot–prone neighborhoods are 19 percentage points *less* likely to participate in face–to–face discussions. Young male respondents are more likely to report that they, or a member of their household, participate in neighborhood discussions. Marathi speakers are 26 percentage points more likely to participate in discussions. Wealthier households are also more likely to join community discussions. The proportion of tenants (versus landowners) increases the likelihood of face–to–face discussions. A neighborhood with a high proportion of Marathi speakers has low participation in discussions.

Overall the results show that riot exposure in 2010 results in higher levels of household participation in community organizations in 2012, but in lower levels of trust (albeit not statistically significant) and reduced engagement in face–to–face community discussions. Therefore, households exposed to riots increase bridging forms of social capital but experience a reduction in bonding social capital. These results support the argument of social competition under uncertainty discussed in Section

2: under the threat of violence, households might invest in building networks with other social groups by joining local organizations since neighborhood organizations may facilitate access to valuable information, as well as the coordination of collective action against adverse events (such as riots) [Verba et al., 1993].

At the same time, riot–affected neighborhoods experience a reduction in trust between neighbors, who are also less likely to contribute to face–to–face community discussions. This is not surprising given that riots in India have largely an ethnic dimension, often pitching different religious and caste groups against each other — groups that are found living side–by–side in slum areas. These results suggest that in contexts of informal urban settlements, where different social groups must live in close physical proximity, households may invest in between–group interaction mechanisms (like joining community organizations), even when experiencing reduced levels of trust and willingness to engage in face–to–face interactions.

One concern with the findings above is the extent to which they may be affected by possible selection bias. This is because changes in household and neighborhood composition may lead to either an over– or under–estimation of the results. If, for instance, households with less social capital left riot–affected neighborhoods between survey rounds, then the results above could well be due to selective migration. As we discussed in Section 3, we were able to find 80.4 percent of the original sample in 2012. This attrition rate compares favorably to other panels [Lee, 2003], particularly since it is reasonable to expect high levels of population movements in slum areas. Nonetheless, this attrition rate may raise concerns about selection bias if those who dropped out of the sample are significantly different to those who have remained. To test this potential bias, Table A.5 in the online appendix compares the 2010 socio–economic characteristics of those who were located in 2012 and those we were not able to re–survey. This serves as a simple check of parallel trends. We note that households who dropped out of the sample are less likely to have reported a riot and lived in neighborhoods where households were less likely to report a riot. We also observe that households from less fractionalized and polarized neighborhoods were more likely to drop out of the panel. In the analysis above, we controlled for these variables. In addition, we corrected for potential selection bias using a Heckman two stage regression as a robustness check and found results to remain largely similar. The added Heckman selection term was also insignificant. These results are reported in Tables A.6 and A.7 in the online appendix and suggest that the results above are unlikely to be biased due to attrition and resulting selection.[12]

6 Mediating factors

Following the discussion in Section 2, we analyze here how the effects identified in the previous section might be conditional on the social diversity of neighborhoods and the salience of individual identities.

6.1 Social diversity of neighborhoods

As discussed in Section 2, diverse neighborhoods could be less resilient to the effects of riot exposure than more homogeneous neighborhoods because neighbors in the latter areas might be more willing to come together in the face of adversity. Alternatively, social diversity may be a source of social cooperation when different groups understand that peace is essential to their living together or shared adversity may bring them together. Social capital may also be seen as a form of insurance, bridging across social divides. We measure the social composition of neighborhood along two dimensions: levels of fractionalization and levels of polarization. We focus on two social groups relevant in the Indian context: religion and caste.[13] In our sam-

[12]The first stage is a probit model which predicts selection into the second wave of the survey. The regressors are the same as in the main analysis, with the addition of a set of variables likely to affect attrition: fear of traveling to the nearest town alone, fear of walking alone in the neighborhood, poor amenities in the neighborhood, feelings of safety among female household members in neighborhood during the day and night, and reporting that the household would like to move if possible. For the second stage, we run the same regression as equation 3, but include the inverse–Mills ratio as one of the covariates. The coefficient for the inverse–Mills ratio is not significant in all specifications except at a low level of significance for the dependent variable of participating in community discussions.

[13]While the *jati* (which corresponds to the narrow definition of a sub–caste) is also a relevant social group in India, this would have created 98 separate groups in our sample and neighborhoods would still show similarly high levels of fractionalization. Therefore, we have estimated results for

ple, 54 percent of respondents are Hindus, 39 percent of respondents are Muslims and the rest are either Christians or Buddhists. The Indian government's Mandal commission (1978) classified existing sub–castes according to certain socio–economic indicators, leading to four broad categories of the Hindu caste system: Scheduled Tribes (ST), Scheduled Caste (SC), Other Backward Castes (OBC) and other (or Forward Castes). 6.51 percent of the sample is ST, 14.59 percent SC, 34.96 percent OBC and 43.94 percent are 'other'.

Considering the social composition of each neighborhood along both religion and caste group simultaneously will lead to multicollinearity because they are highly correlated. For this reason, we have combined religion and caste affiliations by considering Muslims (formally outside of the caste system) as an additional category to the Hindu caste system. This approach has been taken by scholars who have studied social diversity and heterogeneity in India [Banerjee and Somanathan, 2007]. According to this categorization, 4.97 percent of the sample is ST, 11.19 percent SC, 16.59 percent OBC, 26.91 percent 'other caste', and 40.34 percent Muslim. This categorization is a slight simplification because, in reality, the caste system has adapted to apply to Indian Muslims. However, the social implications of this categorization are minimal and this strategy helps avoiding larger issues around multicollinearity. We measure within each neighborhood levels of polarization and fractionalization along caste and religious dimensions, using the following indices developed by Esteban and Ray [2008]:

$$F = \sum_i n_i(1 - n_i) = 1 - \sum_i n_i^2$$

$$P = \sum_i n_i^2(1 - n_i)$$

F refers to social fractionalization and P is social polarization. n_i is the share of the population in each neighborhood belonging to each social group i (ST, SC, OBC, other caste and Muslim). F can be interpreted as the probability that two

the main caste categories only.

individuals from a given neighborhood belong to different social groups. The higher that F is, the more fractionalized the neighborhood is. P measures the dominance of a certain social group in the neighborhood, with higher values indicating higher levels of polarization.[14] Both indices range between zero and one. High values of F indicate a large number of small social groups that are evenly represented, and high values of P indicates a more even distribution of the population between few groups (in the case of P=1, the population would be split equally between two groups).

Table A.2 in the online appendix provides summary statistics of these measures. In our sample, fractionalization ranges between zero (all households in neighborhood belong to the same social group) and 0.78. The average fractionalization is 0.53. This means that, on average, there is a 53 percent chance that two households picked at random are from different social groups. Polarization ranges from zero (all households belong to the same social group) to 0.93. On average, a neighborhood has a polarization index of 0.68, which is considerably high.

In order to investigate how levels of fractionalization and polarization shape the relationship between riot exposure and social capital measures, we interacted the neighborhood experience of a riot with these two measures, as represented in the following equation:

$$\begin{aligned} P[S_{i,n,t} = 1] = \Phi[&\beta_1 X_{i,(t-1)} + \beta_2 R_{n,(t-1)} + \beta_3 D_{n,(t-1)} + \beta_4 Z_{n,(t-1)} \\ &+\beta_5 [R_{n,(t-1)} \times D_{n,(t-1)}] + \theta \bar{X}_{n,(t-1)} + \mu_n + \epsilon_i] \end{aligned} \tag{4}$$

The variable $D_{n,(t-1)}$ indicates the social diversity of the neighborhood n, measured by either polarization or fractionalization of the social group. To avoid multicollinearity, polarization and fractionalization will be modeled in two separate regressions. Equation 4 is similar to equation 3, with the addition of an augmented interaction term between exposure to violence and pre–existing social diversity. Equation 4 estimates (β_5), which can be interpreted as the effect of riots on social capital conditional

[14]The polarization index can account for parameters such as inter–group distance and group identity (see Esteban and Ray [2008]), but this is difficult to measure in India and is highly subjective.

on the social composition of the neighborhood. Table A.8 in the online appendix shows the results of estimating equation 4 for three dependent variables: membership in an organization (columns 1 and 2), trust towards neighbors (columns 3 and 4) and participation in discussions (columns 5 and 6). Columns (1), (3) and (5) interact the riot variable with social fractionalization and columns (2), (4) and (6) interact the riot variable with social polarization for each of the dependent variables.

It is important to keep in mind that β_5 does not represent an impact effect. Interpreting interaction terms in a non–linear framework such as a probit estimator is not straightforward, especially for continuous conditional variables. Therefore, we illustrate the main marginal/impact effects graphically in figures 2 to 6.

(a) fractionalization (b) polarization

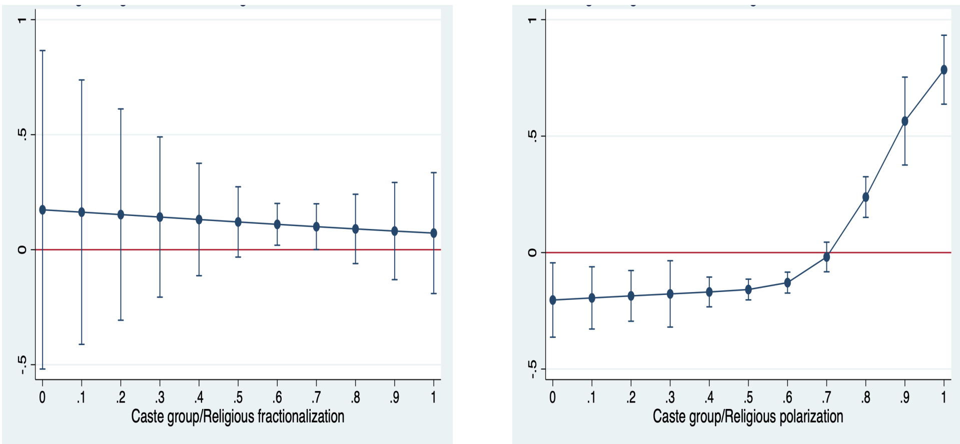

Figure 2: Impact effects of riot exposure on belonging to an organization conditional on:

Membership in organizations: Figure 3a shows a positive effect (of around 10 percentage points) of riot exposure on the probability of being part of a civic group or organization when social group fractionalization is between 0.6 and 0.7. Conditional on polarization, the figure also shows that in non-–polarized neighborhoods riot exposure reduces the probability of belonging to an organization by 20.3 percentage points. As polarization increases this effect becomes smaller. In

(a) fractionalization (b) polarization

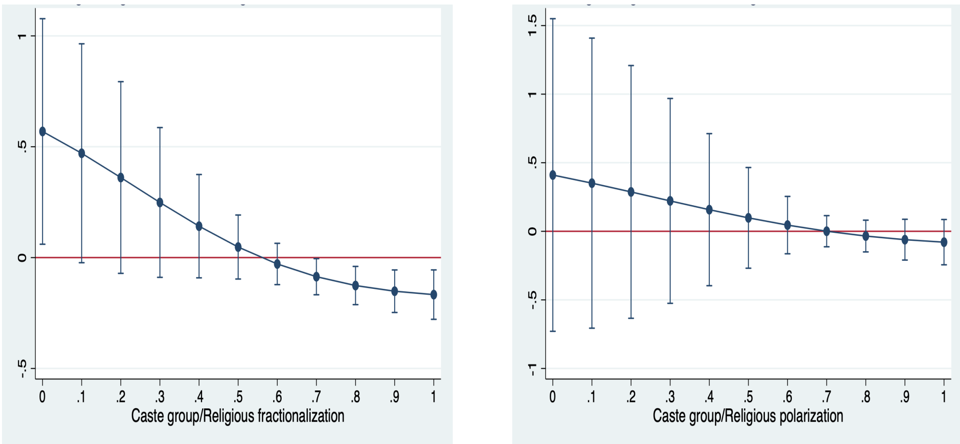

Figure 4: Impact effects of riot exposure on trust in neighbors conditional on:

(a) fractionalization (b) polarization

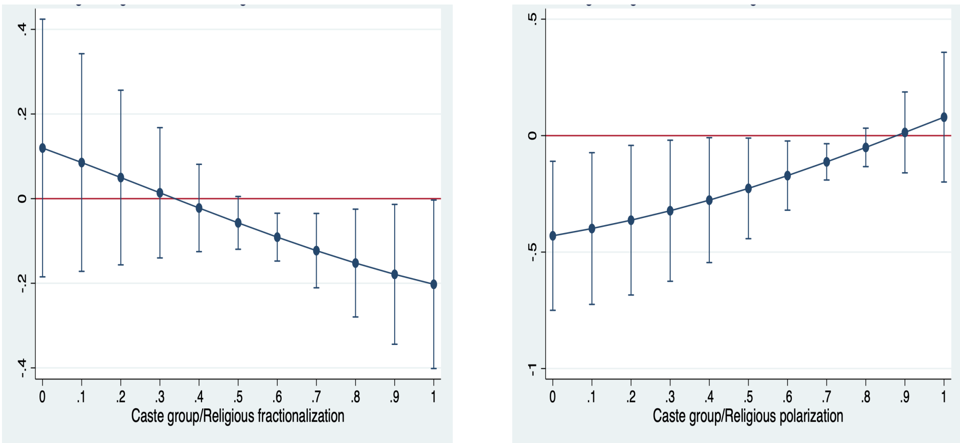

Figure 6: Impact effects of riot exposure on participating in discussions conditional on:

highly polarized neighborhoods there is a positive effect of riot exposure on the probability of membership of local organizations, which reaches a maximum increase of 78.5 percentage points. While both of these conditional effects are measured at the extreme conditions of polarization that are unlikely to exist in most neighborhoods, an important mechanism is revealed: social diversity can shape the effect of riot exposure on membership in organizations, creating a positive relationship in polarized or fractionalized neighborhoods.

Trust in neighbors: Figure 5a shows that in less fractionalized neighborhoods riot exposure has a positive effect on social trust. There is a maximum increase of 56.8 percentage points in these neighborhoods. In highly fractionalized neighborhoods (when the index is greater than 0.7), the effect of riot becomes significant and negative: riot exposure reduces social trust by around 8.6 to 16.7 percentage points. The impact effect of riot exposure on the probability of trusting neighbors conditional on polarization is never significantly different than zero.

Participation in community discussions: Figure 7a shows that in neighborhoods where fractionalization is 0.4 and lower, exposure to riots increases participation in community discussions, but not in statistically significant way. When fractionalization is above 0.4, there is a significantly negative effect of riot exposure on the probability of participating in a community discussion, ranging from -9.1 percentage points to -20.2 percentage points in completely fractionalized neighborhoods. Figure 7b shows that the effect of riots on the probability of participating in community discussions ranges from a negative effect in non–polarized neighborhoods, to a positive (but insignificant) effect in polarized neighborhoods. When polarization is lower than 0.7, the impact effect ranges from a 43 to 11.2 percentage point reduction, reducing when polarization increases.

Taken together, the results above suggest that social fractionalization and polarization have the potential to increase membership of organizations in riot–affected neighborhoods. Social trust and face–to–face discussions are reduced in riot–affected neighborhoods that are also highly socially fragmented. These results again reinforce our previous interpretation: households may be more likely to invest in bridging social capital and building networks with individuals and households from other social groups (by joining local community organizations) in communities that are more fragmented, and thus where the expectation of future riots may be highest. Households thus appear to invest in social capital in an instrumental way, possibly to mitigate future exposure.

Alternative explanations derived from social contact and post-traumatic growth theories may include more emotional and psychological factors, in that those living in riot–prone areas may join organizations as a way of seeking emotional support and solidarity from others that share similar experiences [Jennings, 1999]. However, the second set of results — that bonding social capital is reduced in riot–prone, fractionalized neighborhoods — suggests that the instrumental explanation may be more accurate. Psychological arguments would lead to us observing also a positive effect of riots on more bonding forms of social capital. However, the data show that households in riot–prone fractionalized neighborhoods are *less likely* to trust their neighbors and *less likely* to engage in face–to–face interactions.

We have tested the instrumentalization hypothesis further by disaggregating participation in community organizations according to whether the organization can be classified as co–ethnic (it includes members across all religions and castes) or not (it admits only members of one religion or caste). The underlying hypothesis is that interpretations aligned to social contact or post-traumatic growth theories would predict no statistically significance differences in participation across these categories of organizations. However, is the instrumental interpretation of social capital (predicted by theories of social competition under uncertainty) is correct, we should see stronger results among co-ethnic organizations. Table 3 shows that the main results we discussed above are strongly driven by co–ethnic organizations, which lends credibility to the argument that joining these organizations may be a means to bridge across social divides even if trust and confidence in neighbors may have been negatively affected.

Table 3: Effect of riot on belonging to a diverse group or organization

	(1) Diverse organization	(2) Non-diverse organization
At least 30% of neighborhood witnessed a riot (d)	0.53***	0.42
	(0.18)	(0.75)

Respondent age and sex in 2012	Yes	Yes
Lagged respondent and household variables (2010)	Yes	Yes
Lagged neighborhood level variables (2010)	Yes	Yes
Lagged neighborhood means of covariates	Yes	Yes
Observations	853	853
Degrees of freedom	21.000	21.000
Chi-squared	120.799	67.141
Prob > chi2	0.000	0.000
Number of clusters	45.000	45.000

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

There are compelling reasons why bonding social capital may be reduced in riot–prone neighborhoods. It is possible that people are suspicious of others in the aftermath of riots and thus try to minimize daily face–to–face exchanges. Increase in suspicion against close neighbors has been reported in other riot instances [Hager et al., 2019] and in civil war contexts [Kalyvas, 2006, Cassar et al., 2013]. It is also possible that the reduction in face–to–face interactions may reflect discontent with others in the neighborhood and even punishment and ostracizing of neighbors that may be blamed for prior exposure to riots [Petersen, 2002]. Both explanations are difficult to disentangle with the data we have available but the results estimated above appear to support more strongly the suspicion explanation given the large reduction in trust in neighbors reported by households in riot–prone and highly fragmented neighborhoods (recall that the effect of riot exposure on trust was not statistically significant in the overall sample).

We also tested whether the results above are due to social composition or may reflect relative social status of minority versus majority groups (Table 4). Studies have shown that group preferences, for instance about taxation [Xin Li, 2010] or cultural outcomes [Bisin and Verdier, 2001], may be shaped by whether the group is a minority or a majority group. In the case of India, Gupta et al. [2018] found that minority status is associated with positive in–group bias in social trust. We tested whether minority/majority status might affect the impact of riot exposure on social capital and found no statistically significant effects, suggesting that the social diversity effects above are not driven by relative social status but solely by the levels of social fragmentation and polarization that characterize different riot–exposed neighborhoods.

Table 4: Effect of riot interacted with belonging to major caste/religious group on social capital

	(1) Organization	(2) Trust	(3) Discussions
At least 30% of neighborhood witnessed a riot	0.41*	-0.35	-0.29
	(0.21)	(0.28)	(0.24)
At least %30 witnessed riot × Household belongs to majority group	0.16	0.45	0.16
	(0.25)	(0.36)	(0.34)
Hhd belongs to predominant religion/caste group	-0.18	-0.14	0.10
	(0.17)	(0.13)	(0.10)
Respondent age and sex in 2012	Yes	Yes	Yes
Lagged respondent and household variables (2010)	Yes	Yes	Yes
Lagged neighborhood level variables (2010)	Yes	Yes	Yes
Lagged neighborhood means of covariates	Yes	Yes	Yes
Observations	853	853	853
Degrees of freedom	22.000	22.000	22.000
Chi-squared	97.388	94.944	228.312
Prob > chi2	0.000	0.000	0.000
Number of clusters	45.000	45.000	45.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2 Salience of individual identity

Social identity has been widely documented as dominating social, economic and political processes and decision–making in India, with different religious and caste groups exhibiting strong in–group biases [Gupta et al., 2018]. Almost all major riots experienced in India since partition have been marked by divisions in social identity, particularly between Hindus and Muslims [Horowitz, 2001, Wilkinson, 2004]. We therefore expect social identity to be an important factor in shaping the relationship between riot exposure and social capital in Maharashtra.

To investigate the effects of riot exposure on the salience of shared identities, we used a series of vignettes in the second wave of MHLS. Vignettes are "short stories about hypothetical characters in specified circumstances, to whose situation the interviewee is invited to respond" [Finch, 1987, p. 105]. The use of vignettes in surveys provides a useful research method to investigate respondents' beliefs, attitudes and judgments [Atzmüller and Steiner, 2010, Finch, 1987, Nock and Rossi, 1982, Seekings, 2008], and by randomizing certain aspects of the context, it is possible to identify significant variables that explain certain beliefs.

While we could have directly asked the respondents for their opinions and attitudes towards people of the same or different identity, this strategy is unlikely to have elicited honest responses to such sensitive topics in Indian society. This could be due to social desirability biases, whereby respondents may want to impress the interviewers and respond in a way that they think will be socially approved of. Alternatively, normative factors that influence judgment may be subconscious so that the respondent is not aware of them [Alexander and Becker, 1978]. Vignettes may allow researchers to observe more accurate attitudes and beliefs by calculating average acceptance changes to apriori defined scenarios when key factors in the scenario are changed in a random way.

In our study, respondents were asked if they would be willing to give some money (3,000 *Rupees* or around 40 USD) to a person living in their neighborhood, for a given reason. In order to study the salience of identities in household choices, we randomized the name of the person living in the neighborhood. The person asking for the money was named in different versions of the vignette as *Yadav*, *Hanif* or *Deshpande*.[15] *Yadav* is a name typical to Hindus from OBC caste category, *Hanif*

[15] We also randomized the reason for the money request between repaying a loan, bribing a local goon or buying a festive saree. In this paper, we pool these three reasons for request of money

is a Muslim name and *Deshpande* is typical Hindu upper caste name.[16] For each respondent, we created a variable taking the value 1 if the identity of the respondent matches the identity of the person in the vignette and 0 otherwise.

We first tested whether the random assignment of the vignette characters created three groups from the sample that are roughly the same. Often studies have relied on a simple balance test of treatment and control groups to ensure random assignment, but in the case of three groups this is slightly more cumbersome and makes inference difficult. We tested first for differences in any of the covariates used in the analysis between *Deshpande* and *Hanif*, *Deshpande* and *Yadav*, and *Hanif* and *Yadav*. This resulted in 66 tests (22 covariates for each of these 3 combinations). Of these 66 tests, 9 showed a statistically significant difference in covariates. This is a reasonable result given the large number of tests. In addition, we regressed each of these covariates[17] on the character assignment, and then tested the joint significance of character assignment.[18] The results of these orthogonality tests are shown in Table A.9 in the online appendix, which shows that character assignment is only a significant predictor of belonging to the majority caste or religious group, again a reasonable result. Finally, we regressed each character assignment on all the covariates and tested for joint significance of the covariates.[19] These were found not to be significant predictors. These tests strongly indicate that the character assignment is random, providing an exogenous source of variation in the subsequent analysis. The dependent variable of interest is willingness to give money, which is equal to one if the respondent has said that they would be happy to offer money to the character in the vignette. We regress the willingness to give money on whether there is a shared identity between the vignette character and the respondent. We include the

together, as this dimension is not central to the research questions being addressed in the paper.

[16]Dalits, or untouchables, are excluded from this analysis as they cannot identify with these identities to the same extent as the other groups.

[17]For continuous variables we use a neighborhood fixed effects OLS estimation, and for binary variables a neighborhood fixed effect logit estimation.

[18]The p–value of the F–statistic is recorded for continuous variables, whereas the p–value of the Chi–squared is recorded for binary variables.

[19]This is using a neighborhood fixed effect logit estimation, and joint significance is tested using a Chi–squared distribution.

same household and neighborhood level covariates (including neighborhood means of household covariates) as in the analysis above. In addition, we include a variable indicating the character randomly assigned to the respondent:

$$\begin{aligned} P[G_{i,n,t} = 1] = \Phi[&\alpha_1 SI_{i,(t-1)} + \alpha_2 C_{i,(t-1)} + \beta_1 X_{i,(t-1)} \\ &+\beta_2 Z_{n,(t-1)} + \theta \bar{X}_{n,(t-1)} + \mu_n + \epsilon_i] \end{aligned} \tag{5}$$

This model also uses the probit function, Φ, the inverse standard normal transformation of covariates. $P[G_{i,n,t} = 1]$ is the probability of giving money to the character in the vignette, and $SI_{i,(t-1)}$ is a binary indicator taking the value 1 if there is a shared identity between the respondent and the character in the vignette, and 0 otherwise. $C_{i,(t-1)}$ is a set of two binary variables representing the character assignment (the variable indicating *Yadav* was omitted and acts as the base for comparison). $X_{i,(t-1)}$ are household characteristics, $Z_{n,(t-1)}$ neighborhood level characteristics, and $\bar{X}_{n,(t-1)}$ are the neighborhood level means of respondent and household characteristics.

Column (1) in Table 5 shows that a shared identity with the character in the vignette makes the respondent 24 percentage points more likely to give money to this character. We then explore whether the salience of shared identities is affected by riot exposure, by estimating the following equation:

$$\begin{aligned} P[G_{i,n,t} = 1] = \Phi[&\beta_1 R_{n,(t-1)} + \beta_2 [R_{n,(t-1)} \times SI_{i,(t-1)}] + \alpha_1 SI_{i,(t-1)} + \alpha_2 C_{i,(t-1)} \\ &+\beta_3 X_{i,(t-1)} + \beta_4 Z_{n,(t-1)} + \theta \bar{X}_{n,(t-1)} + \mu_n + \epsilon_i] \end{aligned} \tag{6}$$

In equation 6 the term of $R_{n,(t-1)} \times SI_{i,(t-1)}$ captures the interaction between riot exposure and shared identity. β_1 is the effect of riot exposure, and β_2 is the effect of riot exposure when the respondent shares the same identity as the character in the vignette.

Table 5: Dependent Variable: Willingness to give

	(1) Riot	(2) Riot × Match
At least 30% of neighborhood witnessed a riot		-0.081

		(0.20)
At least %30 witnessed riot × Shared identity		-0.15
		(0.23)
Shared identity with vignette character	0.23**	0.26*
	(0.12)	(0.14)
Assigned *Hanif* as character	-0.16	-0.17
	(0.11)	(0.11)
Assigned *Deshpande* as character	-0.072	-0.083
	(0.099)	(0.097)
Respondent age and sex in 2012	Yes	Yes
Lagged respondent and household variables (2010)	Yes	Yes
Lagged neighborhood level variables (2010)	Yes	Yes
Lagged neighborhood means of covariates	Yes	Yes
Observations	852	852
Degrees of freedom	23.000	25.000
Chi-squared	94.986	177.255
Prob > chi2	0.000	0.000
Number of clusters	45.000	45.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Column (2) of Table 5 shows that the impact of shared identity on the willingness to give is driven by those who have not been affected by riots. Those who experience riots are not more likely to give money if their identity is shared with that in the vignette. This result may appear inconsequential but is of great significance in face of the enormous importance of social identities across all aspects of social, economic and political life in India. This comparison shows that experiencing a riot substantially reduces the salience of social identity, in inter-group exchanges in Maharashtra. This reinforces the argument that individuals from different social groups, forced to live side–by–side in slum areas, take actions to bridge across social divides to minimize the threat of future riots.

7 Conclusion

This study has explored the relationship between exposure to riots and social capital in informal urban settlements in India using a unique panel dataset. The results show that households living in neighborhoods that experienced a riot in 2010 are more likely to be members of groups and organizations, but less likely to join in face–to–face discussions with neighbors. Further analysis shows that this result in driven by social fragmentation: increased membership of organizations is greatest in fragmented neighborhoods.

We interpret these results as evidence for a precautionary mechanism adopted by competing co-ethnic groups living under uncertainty, whereby households insure themselves through investments in bridging social capital, even when riots lead to reductions in trust and confidence in neighbors. This result is further substantiated by a vignette analysis where we randomize pairing of social identities. We find that the salience of social identities — so important to life in India — disappears in riot–prone neighborhoods, where households may be trying to establish a systems of reciprocity.

Riots are an endemic feature of life in urban India and many other developing countries where urbanization is rising in unprecedented ways. Beyond the physical and economic losses suffered by those affected, trust and face–to–face relations can also be destroyed in such polarized, fragmented and violence–prone contexts. This analysis has shown that there is agency and thoughtful consideration in building some types of social capital, but this result raises a lot of new questions. Although it is widely accepted that bridging and associative forms of social capital are more relevant to peaceful inter–group relations than other more interpersonal relations [Putnam et al., 1994b, Varshney, 2002], how long can these associations be sustained in the absence of trust? Future research is needed to disentangle the complex ways in which different social groups relate when under the threat of violence, how new forms of urbanization may support or hinder such social interactions, what social, economic and political order may emerge from these processes and how this may expand into other areas of society as individuals graduate from slums into the formal economy, potentially bringing with them mistrust and fear into new relations, jobs and political decisions.

Appendix: Tables and figures

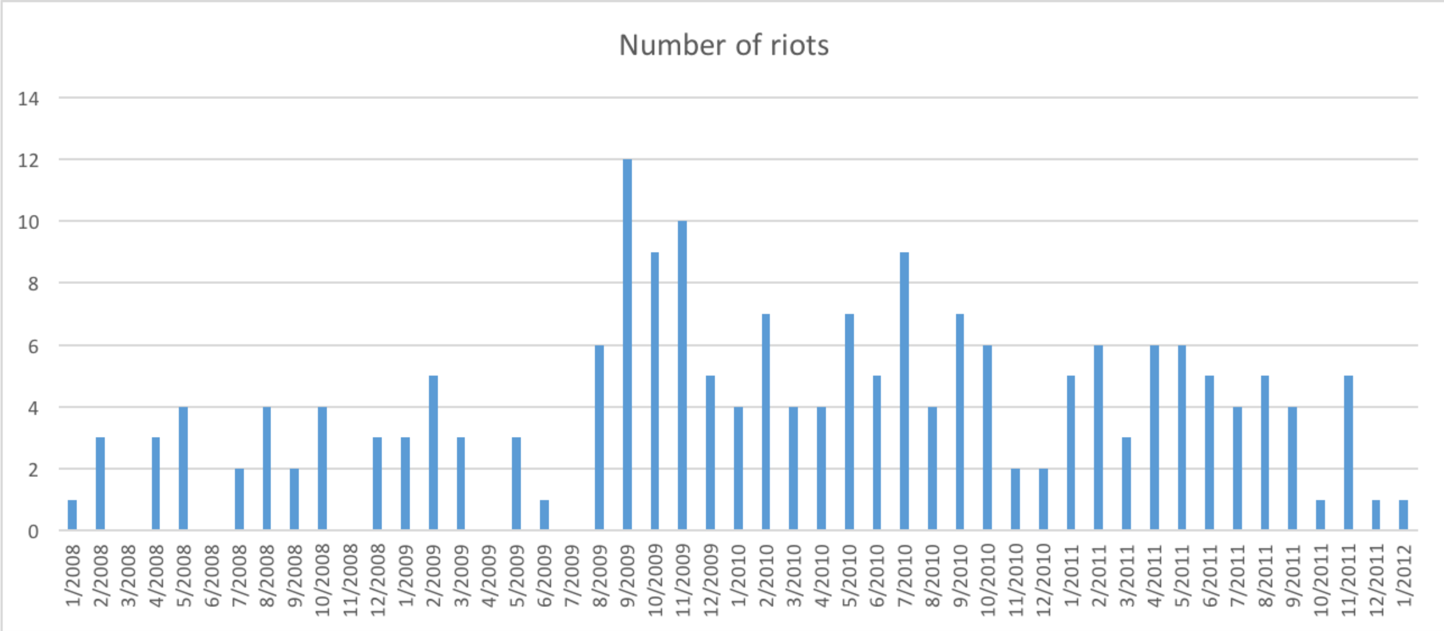

Figure A.1: Number of riots in Maharashtra per month, from January 2008 to January 2012.

Source: Prepared by the authors after scanning local newspapers.

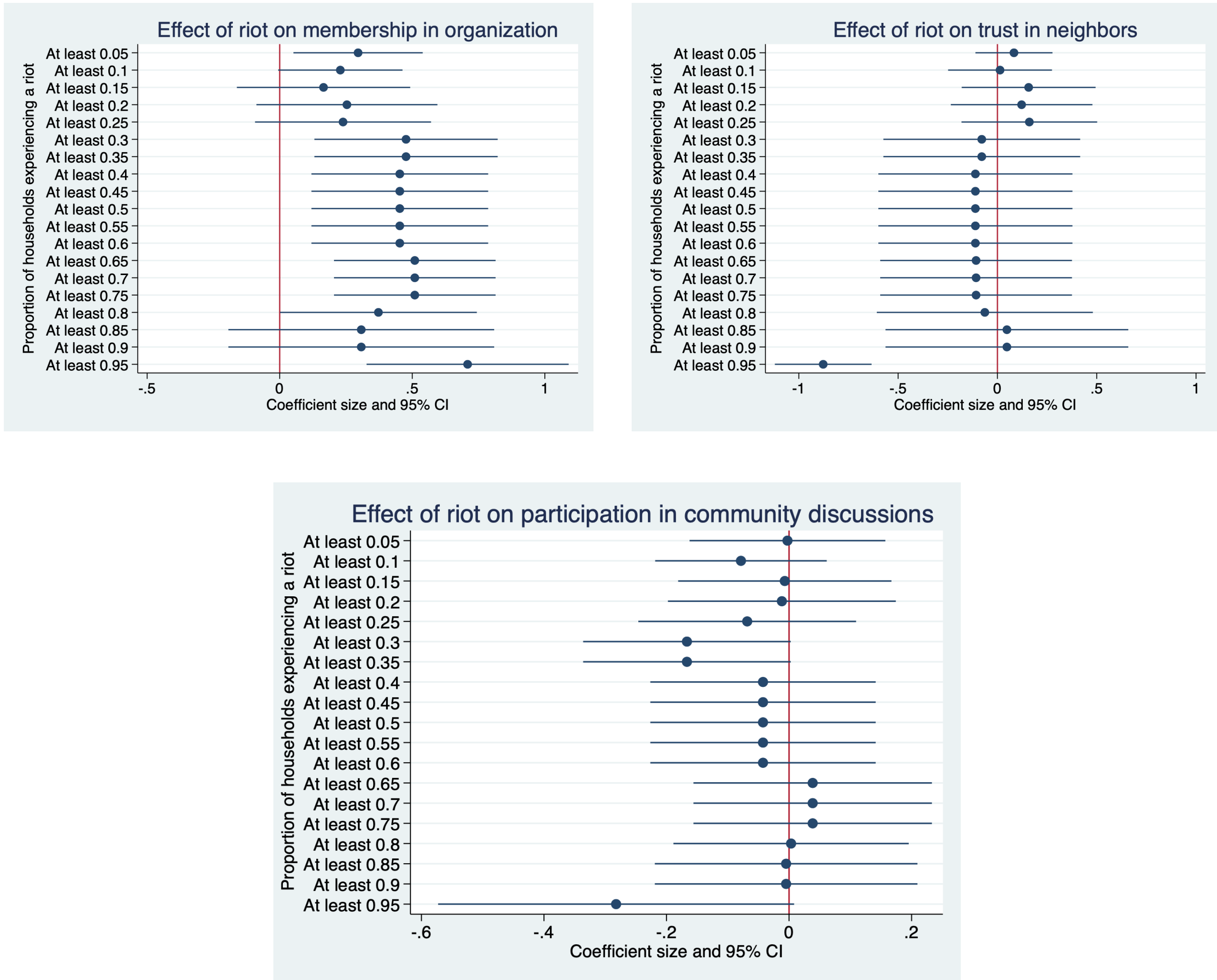

Figure A.2: Effect of riot exposure on social capital when using different cut–offs for neighborhood level riots

Table A.2: Summary statistics of independent variables in 2010.

Variable	Mean	Std. Dev.	Min.	Max.	N
Household/Respondent level variables					
Report riot taking place in neighborhood	0.235	0.424	0	1	867
Age of respondent	39.13	13.34	15	90	874
Sex of respondent (1=Male)	0.375	0.484	0	1	874
Permanent house materials	0.527	0.5	0	1	867
Household is Muslim	0.386	0.487	0	1	867
Household size	6.562	3.369	1	26	867
Household rents house (0=Owns)	0.133	0.339	0	1	867
Log of monthly income per capita	6.841	0.75	4.711	11.027	854
Mother tongue is Marathi	0.509	0.5	0	1	867
Months lived in current house	18.984	14.282	0	65	859
There is an unsafe location nearby	0.099	0.299	0	1	867
Hhd belongs to predominant religion/caste group	0.621	0.486	0	1	867
Neighborhood level variables					
At least 30% of neighborhood report a riot	0.2	0.405	0	1	45
Proportion of households migrated by 2012	0.074	0.065	0	0.261	45
Police station in neighborhood	0.111	0.318	0	1	45
Chowk in neighborhood	0.4	0.495	0	1	45
Hindu temple in neighborhood	0.489	0.506	0	1	45
Mosque in neighborhood	0.378	0.49	0	1	45
Market in neighborhood	0.2	0.405	0	1	45
Caste group/Religious fractionalization	0.526	0.217	0	0.778	45
Caste group/Religious polarization	0.678	0.217	0	0.932	45
Religious polarization	0.613	0.282	0	1	45
Religious fractionalization	0.342	0.174	0	0.635	45
Caste group polarization	0.834	0.09	0.445	0.992	45
Caste group fractionalization	0.584	0.104	0.244	0.727	45
Caste polarization	0.496	0.118	0.281	0.806	45
Caste fractionalization	0.827	0.069	0.583	0.922	45

Source: MHLS 2010.

Table A.3: Description of social capital variables as found in MHLS 2012 questionnaire

Variable	**Description from questionnaire**
Household member belongs to an organization	Are you or any other household member a member of the following groups or organizations? (Political party; Trade union; Student organization; Farmer's organization; Cooperative; Sports/cultural organization; Gym; Women's group; Local *Mohalla* committee; Caste *Panchayat*/*Sabha*/association; Religious organizations; Youth organization; Village redressial committee; Other group or organization)
Trust towards neighbors	Would you trust your money or assets for safekeeping with your neighbors (Yes; No)
Household participates in community discussions	How common is it that you or a family member participates in a community discussion? (All the time; Sometimes; Never)

Table A.4: Summary statistics of social capital variables.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Household member belongs to an organization	0.159	0.366	0	1	1088
Trust towards neighbors	0.171	0.377	0	1	1087
Household participates in community discussions	0.421	0.494	0	1	1088

Source: MHLS 2012.

Table A.5: Differences of 2010 characteristics of tracked and not tracked households

	Mean		
Variable	**Tracked**	**Not tracked**	**Diff.**
Household member belongs to an organization	0.14	0.10	0.04
	(0.01)	(0.02)	(0.03)
Trust towards neighbors	0.4	0.29	0.11
	(0.02)	(0.03)	(0.04)
Report a riot taking place in neighborhood	0.24	0.16	0.07**
	(0.01)	(0.03)	(0.03)
At least 30% report a riot in neighborhood	]0.21	0.15	0.06*
	(0.01)	(0.02)	(0.03)
Caste group/Religious fractionalization	0.54	0.49	0.04***
	(0.01)	(0.02)	(0.02)
Caste group/Religious polarization	0.69	0.64	0.05***
	(0.01)	(0.02)	(0.02)
Age of respondent	34.05	32.7 7	1.27
	(0.35)	(0.69)	(0.79)
Sex of respondent (1=Male)	0.34	0.32	0.03
	(0.02)	(0.03)	(0.04)
Permanent house materials	0.53	0.66	−0.13***
	(0.02)	(0.03)	(0.04)
Household is Muslim	0.39	0.41	-0.03
	(0.02)	(0.03)	(0.04)
Household size	6.55	4.82	1.74***
	(0.11)	(0.13)	(0.24)
Household rents house (0=Owns)	0.14	0.41	−0.27***
	(0.01)	(0.03)	(0.03)
Log of monthly income per capita	6.84	7.19	−0.34***
	(0.03)	(0.05)	(0.06)
Mother tongue is Marathi	0.51	0.44	0.07*
	(0.02)	(0.03)	(0.04)
There is an unsafe location nearby	0.1	0.07	0.02
	(0.01)	(0.02)	(0.02)
Hhd belongs to predominant religion/caste group	0.62	0.65	−0.03
	(0.02)	(0.03)	(0.04)

Source: MHLS 2010 and 2012.

Standard errors in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Table A.6: Heckman first stage: Probit model

	(1) Selection into second wave
Afraid of going to nearest town out of fear of being mugged, attacked or abducted	0.11
	(0.10)
Afraid of going within current area out of fear of being mugged, attacked or abducted	-0.032
	(0.11)
Poor/unreliable amenities provision in neighborhood	-0.10
	(0.18)
No police station in area	0.14
	(0.27)
Respondent would like to move out of area	-0.34***
	(0.13)
Feel female members are safe at day	0.10
	(0.20)
Feel female members are safe at day	0.062
	(0.11)
Constant	4.33***
	(1.57)
Respondent and Household controls	Yes
neighborhood controls	Yes
Lagged neighborhood means of covariates	Yes
Observations	1071
Degrees of freedom	25.000
Chi-squared	215.919
Prob > chi2	0.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Heckman second stage: Effect of riot on social capital

	(1) Organization	(2) Trust	(3) Discussions
At least 30% of neighborhood witnessed a riot (d)	0.48***	-0.087	-0.16*
	(0.18)	(0.25)	(0.089)
Inverse Mills Ratio	-0.11	0.56	-0.70*
	(0.64)	(0.46)	(0.36)
Respondent and Household controls	Yes	Yes	Yes
neighborhood controls and means	Yes	Yes	Yes
Observations	853	853	853
Degrees of freedom	21.000	21.000	21.000
Chi-squared	92.547	75.773	105.186
Prob > chi2	0.000	0.000	0.000
Number of clusters	45.000	45.000	45.000

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Duration of riot in days	1.111	0.802	1	12	225
At least one civilian was injured	0.427	0.496	0	1	225
At least one civilian was killed	0.076	0.265	0	1	225
At least one policeman was injured	0.173	0.379	0	1	225
At least one policeman was killed	0	0	0	0	225
An arrest or charge was made	0.258	0.438	0	1	225
Number of charges	1.298	6.817	0	61	225
Number of arrests	11.924	71.503	0	1000	225
Police engaged in violence against civilians	0.249	0.433	0	1	225
A curfew was enforced due to the riot	0.089	0.285	0	1	225
The riot spread to neighboring towns/communities	0.044	0.207	0	1	225
There was a communal element to the riot	0.569	0.496	0	1	225
The riot initiated from a personal dispute	0.209	0.407	0	1	225
The riot was initiated by a rumor	0.027	0.161	0	1	225
The riot initiated from a protest	0.164	0.372	0	1	225
The riot initiated from a *Raasta roko*	0.058	0.234	0	1	225
The riot was initiated by a slum demolition (attempted or completed)	0.031	0.174	0	1	225
The riot was related to an election	0.089	0.285	0	1	225
The riot involved a *Bandh*	0.071	0.258	0	1	225
The riot caused physical damage to public or private property	0.262	0.441	0	1	225
Modality of Violence					
Stone throwing	0.511	0.501	0	1	225
Bottle throwing	0.027	0.161	0	1	225
Physical fight	0.271	0.446	0	1	225
Physical attack	0.067	0.25	0	1	225
Physical beating	0.062	0.242	0	1	225
Physical scuffle	0.04	0.196	0	1	225
Arson	0.084	0.279	0	1	225
Vandalism	0.08	0.272	0	1	225
Looting	0.013	0.115	0	1	225
Tire burning	0.004	0.067	0	1	225

Table A.1: Summary statistics of newspaper reported riot data

Source: Prepared by the authors after scanning local newspapers.

Table A.8: Effect of riot interacted with social diversity on social capital

	Organization		Trust		Discussions	
	(1)	(2)	(3)	(4)	(5)	(6)
	Frac	Pol	Frac	Pol	Frac	Pol
At least 30% of neighborhood witnessed	0.51	-6.43***	1.67*	1.13	0.32	-1.50
a riot	(0.96)	(1.50)	(0.88)	(1.71)	(0.42)	(1.08)
Caste group/Religious diversity	-0.66	-0.34	0.022	-0.48	-0.29	-0.23
	(0.48)	(0.44)	(0.48)	(0.36)	(0.37)	(0.27)
At least %30 witnessed riot ×	-0.15		-2.98**		-0.93	
Caste group/Religious fractionalization	(1.51)		(1.39)		(0.74)	
At least %30 witnessed riot ×		9.05***		-1.61		1.71
Caste group/Religious polarization		(1.95)		(2.34)		(1.43)
Respondent age and sex in 2012	Yes	Yes	Yes	Yes	Yes	Yes
Lagged respondent and household variables (2010)	Yes	Yes	Yes	Yes	Yes	Yes
Lagged neighborhood level variables (2010)	Yes	Yes	Yes	Yes	Yes	Yes
Lagged neighborhood means of covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	853	853	853	853	853	853
Degrees of freedom	23.000	23.000	23.000	23.000	23.000	23.000
Chi-squared	113.287	168.118	110.990	92.571	303.907	211.701
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Number of clusters	45.000	45.000	45.000	45.000	45.000	45.000

Standard errors in parentheses

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

Table A.9: Test of orthogonality of vignette character assignment

	Mean			Joint significance of *Deshpande* and *Hanif*
Characteristic	***Deshpande***	***Hanif***	***Yadev***	**Orthogonality test**
Main variables in analysis				
At least 30% of neighborhood witnessed a riot	0.17	0.24	0.23	–
Caste group/religious fractionalization	0.54	0.52	0.54	–
Caste group/religious polarization	0.69	0.68	0.69	–
Average household migrated in neighborhood	0.07	0.07	0.08	–
Respondent level variables 2012				
Age (2012)	39.05	39.33	38.27	0.525
Sex (2012)	0.38	0.31	0.35	0.277
Lagged respondent and household variables				
Age (2010)	33.68	34.89	33.75	0.277
Sex (2010)	0.37	0.31	0.36	0.384
Dwelling made of permanent material	0.51	0.55	0.51	0.502
Household is Muslim	0.39	0.39	0.39	0.851
Household size	6.5	6.9	6.3	0.14
Household rents (0=own)	0.12	0.13	0.15	0.547
Log per capita monthly income	6.82	6.82	6.88	0.804
Marathi mother tongue	0.49	0.51	0.52	0.909
Length of time in neighborhood	18.5	19.65	18.78	0.426
Unsafe location nearby	0.11	0.08	0.1	0.322
Household belongs to major social group	0.59	0.68	0.6	0.093*
neighborhood variables				
Police station in neighborhood	0.1	0.14	0.12	–
Chowk in neighborhood	0.43	0.48	0.42	–
Hindu temple in neighborhood	0.51	0.56	0.51	–
Mosque in neighborhood	0.39	0.48	0.38	–
Market in neighborhood	0.21	0.21	0.23	–

Orthogonality test: Joint significance of covariates on each character assignment	0.516	0.855	0.119

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

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