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Abstract

This study employs unique household data collected in cyclone-affected communities in Bangladesh to uncover the impact of religious fractionalisation on victimization to crime after the disaster. The identification strategy relies on two natures of the study area: 1) the religious composition is stable; and 2) the pre-disaster socio-economic status of households is uncorrelated with religious fractionalisation and disaster damage, after controlling for the observed characteristics. The findings suggest that following a natural disaster, households in disaster-affected and religiously fractionalised communities are more likely to be victims than those in non-fractionalised communities. This is caused by the misallocation of disaster reliefs in fractionalised communities.

JEL Classification: O12; Z12; K42

Keywords: crime, religious fractionalisation, natural disaster, Bangladesh

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1. Introduction

Natural disasters cause multifaceted damages to affected communities, including the persistent effects on health status and education. Increases in crimes such as theft and rape are also serious issues (Harper and Frailing 2010). Individuals affected by disasters suffer from a decline in income and difficulties in smoothing consumption. The probability of crime detection also decreases in the affected areas. These incentives to commit crime aggravate crime incidences in both developed and developing countries. For example, in the month after Hurricane Katrina, the burglary rate increased by 402.9% compared to the month before the disaster event (Frailing and Harper, 2010). However, it is also claimed that disasters may give rise to altruism, and norms of reciprocity that reduce or stabilize crimes (Barsky et al. 2006; Fischer 1998; Fritz 1961; Quarantelli 1994; Rodriguez et al. 2006; Goltz 1984). Since the post-disaster crimes cause the delay of post-disaster rehabilitation (Aldrich, 2012), it is important for policymakers to understand under which situations disasters trigger the crimes.

Nevertheless, rigorous quantitative analyses on the post-disaster crime are scarce. Exceptionally, Bignon et al. (2016) and Mehlum et al. (2006) analyse the impact of disaster shocks on increasing property crime by using historical data on Europe. Miguel (2005) finds that disasters increase homicide of unproductive household members in Tanzania. Miguel et al. (2004) also show the positive association between the rainfall shock and civil conflicts. Collier and Hoeffler (2004) present that man-made disasters such as civil wars increase homicide. On the contrary, Cassar et al. (2011) show that experiencing natural disasters foster social trust. Siegel et al. (1999) and Zahran et al. (2009) examine the disaster impact on crimes and find mixed results. While these studies are insightful, they do not discuss the heterogeneity of a disaster effect across the communities, despite the observed variation in the crime rate across the affected regions. As Glaeser et al. (1996) claim, the most intriguing aspect of crime is its astoundingly high variance across time and space. This study aims at addressing this question.

One likely explanation for the heterogeneous effect is grounded in the ethnic and religious fractionalisation of the community.[1] Fractionalisation aggravates the governance (Mauro, 1995; La Porta et al., 1999; Alesina et al., 2003), economic inequality (Kelly, 2000; Bénabou, 2005; Alesina et al., 2016; Dev et al., 2016), and riots/conflicts (Montalvo and Reynal-Querol, 2005; Field et al., 2008; Esteban et al., 2012). Fractionalisation also affects the spending on productive public goods (Alesina et al., 1999). Social sanction cannot be imposed effectively in such communities (Miguel and Gugerty, 2005). Furthermore, fractionalisation leads to the decline in social preference (Bouckaert and Dhaene, 2004; Charness and Gneezy, 2008) and social capital (Alesina and La Ferrara, 2000, 2002). Criminologists also claim that fractionalisation is a driver of social disorganisation (Shaw and McKay, 1942; Kornhauser, 1978; Sampson, 1987).[2] These effects potentially exacerbate the risk of post-disaster crimes. Consistently, there is evidence that the communities with lower social capital suffer from severer disaster damages and the delay of post-disaster rehabilitation (Aldrich and Meyer 2015, Dynes 2006, Klinenberg 2003, Nakagawa and Shaw 2004, Tse et al. 2013). However, to the best of my knowledge, there is no empirical study arguing that fractionalisation is a driver of post-disaster crime.[3]

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[1] In this paper, a community is defined as religiously fractionalised when it consists of multiple religious groups.

[2] See Alesina and La Ferrara (2005) for a further review.

[3] Alternatively, the peer effects may also explain the disparity of crime rate across the

This study bridges the gap in the literature by conducting two closely related analyses. First, the study evaluates the impact of religious fractionalisation on the risk of crime victimisation after a cyclone in rural Bangladesh. Second, it disentangles four channels through which religious fractionalisation increases post-disaster crimes: the misallocation of disaster reliefs, inefficient risk-sharing arrangement, high income inequality, and political tension. There are particular insights to be gained from analysing the context of rural Bangladesh; Bangladesh is a disaster-prone country and is marked by a history of significant religious tension, which remains today (Alexander et al., 2016).

This study employs a unique household survey data collected after cyclone Aila, which struck south-western Bangladesh in May 2009. The data were collected from 427 households in 24 communities, of which 11 consist of multiple religions. In quantifying the post-disaster crime incidence, this study examines property and violent crimes occurred during the 18 months after the cyclone attack. Specifically, I employ the crime victimisation data at the household level in order to mitigate the under-reporting problem. The use of household-level data rather than regional-level data has two advantages: first, it enables us to identify who particularly suffers from victimisation in fractionalised communities; and second, it allows us to disentangle the underlying mechanism.

The identification strategy of this study relies on two natures of the study area.[4] First, the religious composition is stable over the decades. Second, the socio-economic

affected areas. However, there is no consensus on whether the peer effect in crime indeed exists; while some empirical studies have found evidence on significant peer effects (Glaeser et al., 1996; Zenou, 2003; Bayer et al., 2009), others have not (Ludwig and Kling, 2007; Dahl and DellaVigna, 2009).

[4] This strategy is similar with Miguel and Gugerty (2005) and Egel (2013).

status of households in the pre-cyclone period is uncorrelated with the religious fractionalisation and disaster damage at the community level, after controlling for the observed characteristics. Exploiting these natures, this study analyses the impact of interaction between religious fractionalisation and cyclone damage at the community level on the post-disaster victimisation at the household level.

The result shows that the impact of cyclone damage on the victimisation risk is significantly larger in religiously fractionalised communities. In particular, the socio-economically vulnerable households, such as religious minorities and the landless, are more likely to be victimised in fractionalised communities. I also find supporting evidence that the high victimisation risk is driven by the misallocation of disaster reliefs in fractionalised communities. However, the results do not support the effect of the remaining three channels.

The contribution of this study to the literature is two-fold. First, households in developing countries use various risk-coping strategies to smooth their consumption against negative shocks. In particular, poor households face no choice but to take costly strategies that may lead to the decline in their short- and long-term livelihood. Such strategies include the reduction of human capital investment (Jacoby and Skoufias, 1997), engagement in risk-taking behaviour, including theft (Fafchamps and Minten, 2006; Robinson and Yeh, 2011), dissaving of productive assets (Rosenzweig and Wolpin, 1993; Hoddinott, 2006; Sultana and Mallick 2015), dependency on moneylenders (Shoji, 2008; 2012), natural resource extraction (Takasaki et al., 2004; McSweeney, 2005), and the reduction of intra-household resource allocation to unproductive members (Behrman and Deolalikar, 1990; Rose, 1999; Miguel, 2005; Shoji, 2010). The finding of the present study that the households commit crimes as a consumption smoothing device is in line with these studies. Second, it has been argued that the ethnic/religious fractionalisation of communities has a negative effect on the formation of social capital because of the difficulties in coordination among the community members (Alesina and La Ferrara, 2000). However, this study provides an alternative explanation that poor governance and misallocation of disaster reliefs in fractionalised communities trigger crimes, and this may, in turn, decrease social capital.

The remainder of the paper is structured as follows. Section 2 illustrates the relationship between religious fractionalisation and post-disaster crime. Sections 3 and 4 describe the study site and dataset, respectively. Section 5 evaluates the impact of religious fractionalisation on crime victimisation, and Section 6 uncovers the underlying mechanisms. Finally, Section 7 concludes the study.

2. Conceptual framework

This section illustrates how the post-disaster situation triggers crime and this is particularly exacerbated in fractionalised communities. Becker's (1968) seminal paper predicts that one's willingness to commit crime increases with the payoff from illegal activity, while it decreases with the probability of crime detection, severity of punishment, and income from legal sources. Two factors are primarily responsible for increased crime incidences during disasters: first, people lose their income and have difficulty in finding alternative income-earning opportunities. It is also difficult to cope with the income loss by using risk-sharing arrangement and sales of assets. Second, the probability of crime detection could become low during the emergency situation. Thus, natural disasters tempt even those who do not normally violate the law to commit crime.

This situation could be particularly aggravated in fractionalised communities at least through four channels. Although I explain each channel separately below, they are not mutually exclusive. First, the local governance may be exacerbated during the disasters, and this problem may be particularly severe in fractionalised communities. Therefore, the disaster-affected households in such communities may not be able to benefit from the disaster relief as much as those in non-fractionalised communities.[5] In fact, Mahmud and Prowse (2012) find that the allocation of relief programs suffered from corruption during Cyclone Aila in Bangladesh. If this is the case, the households which are severely affected by the disaster but cannot receive the relief are likely to experience transient poverty. This potentially tempts them to commit crime to smooth consumption (Fafchamps and Minten, 2006; Cameron and Shah, 2014).

Second, efficient risk sharing is difficult to be achieved in fractionalised communities, given the limited availability of social sanction (Miguel and Gugerty, 2005) and lower altruism (Bouckaert and Dhaene, 2004; Charness and Gneezy, 2008).[6] Therefore, while the household consumption in non-fractionalised communities, where efficient risk sharing can be achieved, is affected only by the covariate component (community-level) of disaster shock, those in fractionalized communities cannot cope with the idiosyncratic (household-level) shock and therefore suffer from both covariate and idiosyncratic shocks. Therefore, the incentive to commit crime during disasters becomes particularly higher in fractionalised communities.

The third channel is through the increased income inequality. A person's religion predicts his/her occupation in rural Bangladesh, implying high income

[5] The governance is significantly associated with the targeting accuracy of reliefs in developing countries (Coady et al., 2004).

[6] Existing studies on risk sharing show that the arrangement is likely to be inefficient if the potential sanction against the deviation from the arrangement is lower (Ligon et al., 2002) and if individuals are self-interested (Foster and Rosenzweig, 2001).

inequality in religiously fractionalised communities (Ahmed, 2005). The inequality across religious groups is expected to become even larger during disasters, since poorer households are usually more vulnerable to disaster risks. As theoretically presented by Becker (1968) and Kornhauser (1978), and empirically tested by many researchers, economic inequality aggravates crime (Fajnzylber et al., 2002; Barslund et al., 2007; Gibson and Kim, 2008).

Finally, religious fractionalisation may also trigger crime if it is associated with the heterogeneity of supporting political parties. Esteban and Ray (2011) and Esteban et al. (2012) argue that such heterogeneity is a cause of conflict in the community. Political tension may become particularly severe during disasters when the resources are scarce (Miguel et al., 2004).

3. Study Site

3.1. Religious fractionalisation

The study site is Satkhira District in south-western Bangladesh. This country experienced two historical events in the mid-twentieth century. In 1947, two regions in India with a large population of Muslims were partitioned as West Pakistan (later Pakistan) and East Pakistan (later Bangladesh). This triggered violent attacks, such as looting and rape, against religious minorities in both the countries: Hindus in East Pakistan and Muslims in India. The situation was further exacerbated after the Indo-Pakistan war began and the Pakistani government enacted the Enemy Property Act in 1965. The act declared that all interests of the enemy in firms, companies, lands and buildings located in Pakistan were to be seized by the government. Furthermore, the government designated Hindus as enemies of the state. This discriminatory legislation was used selectively to seize Hindu-owned property.

Subsequently, the Liberation War broke out in 1971 and Bangladesh attained independence from Pakistan. The government of Bangladesh also enacted the discriminatory legislation in 1972, namely the Vested Property Act. The target of confiscation in this act included not only Hindus but also the Muslim supporters of West Pakistani regime, further exacerbating the violent attacks in Bangladesh.

These violent attacks influenced the religious composition of Satkhira District. During the two partitions, approximately 20 million Muslims and Hindus have crossed the India-Bangladesh border, and a similar number were internally displaced within the national borders in order to shelter themselves from the violent attacks (Alexander et al., 2016). The displaced people in Bangladesh and the refugees from India mainly settled down in the regions close to the national borders such as Satkhira (Tsubota 2016). Due to the influx of forced migrants, the proportion of Muslims in Satkhira increased from 58.6% in 1951 to 74.0% in 1974 (Figure 1). Furthermore, the religious composition had changed even at the village level, since a part of the confiscated lands were leased to Muslims.

Despite the substantial change in the religious composition during the chaotic period, the region has been relatively stable over the recent decades: the Muslims accounted for 78% of the total population in 1991 and 81% in 2011. However, even though Muslims and Hindus live next to each other, the minorities still continue to perceive and experience discrimination from Muslims, and are sometimes victims of crimes even today (Alexander et al., 2016).

[Figure 1]

3.2. Incidence of crime

Bangladesh is prone to crime because of ineffective law enforcement, and the crime rate of Sakhira was the 18^{th} worst of the 64 districts (Faruk and Khatun, 2008). Crime incidences in Bangladesh have two features. First, criminals tend to commit crime against their peers in their community. Faruk and Khatun (2008) report that 64% of the crimes occurred between family members, relatives, friends, and neighbours in the same community, and the incidences between strangers accounted for only 22%.

Second, although the criminals commit crime for monetary gains, the socio-economically vulnerable individuals, such as the poor and non-Muslims, are more likely to be victimised. Crimes against the poor are not necessarily counter-intuitive or inconsistent with Becker (1968). First, it could be too risky to commit crime against wealthy individuals because they are connected with the village leader and law enforcement authority, raising the probability of detection. Second, they may also invest into crime-preventing technologies such as fencing around the home. Third, as argued in the literature of victimology, those who are socially and geographically close to criminals are likely to be victimised (Cook, 1986).

3.3. Cyclone Aila

Since Satkhira District is located in a river-delta plain, it is vulnerable to floods and cyclones. In particular, this district was severely affected by cyclone Aila on 25 May 2009. It was a category 1 cyclonic storm with the highest wind speed being as 100km per hour. The water was approximately 10-12 feet above normal height (Mallick and

Vogt 2012). It killed 190 and affected four million people in the country.[7]

The cyclonic storm caused significant economic loss, destroying around 300,000 acres of cropland and killing over one million livestock (Mallick and Vogt 2012). 650,000 houses were destroyed fully or patially, causing a significant amount of repairment costs. Furthermore, a survey by Mallick et al. (2011) presents that 80% of workers lost their jobs and 40% changed their occupation. They also report the breakout of water-borne diseases, such as dysentery, cholera, diarrheal diseases, skin diseases and fever.

In the face of these hardships, the affected people took various coping strategies, such as selling out own resources and changing occupation (Sultana and Mallick 2015). The government also provided them with Tk 3-5000 of cash and 20 kg of rice. However, the situation did not recover quickly, since the damaged infrastructure had not been reconstructed long. It appears from previous studies and my field interview that even two years after the cyclone attack, the land looked wasted in large areas (Mallick and Vogt 2012 p.224). The distribution of cash/food relief was also corrupted (Mahmud and Prowse 2012). Since the households with lower income have lower quality homes, they were affected more severely by the cyclones, and recovered more slowly (Mallick and Vogt 2015).

There was an increase in robberies and violence after the cyclone (Azad and Khan 2015, Saha 2015). According to the field interview by the author, the stolen items mainly include small assets such as poultry and household utensils. As described in Section 4 with summary statistics, around 40% and 20% of the survey households experienced victimisation of property and violent crimes after the cyclone, respectively.

[7] EM-DAT, accessed on 07 March 2017, http://www.emdat.be/disaster_list/index.html

4. Dataset

I conducted a unique household survey in Satkhira District during December 2010, by employing the multistage stratified random sampling methodology. In the first stage, three *upazila* (sub-districts) of Kaliganj, Shamnagar, and Ashashoni were selected based on their economic status, the intensity of cyclone damage, and crime incidences. In the second stage, I randomly sampled two *unions* from each sub-district.[8] In the next stage, four villages from each union and one *para* (cluster) from each village were selected randomly. In these *para*, the survey team created a list of all households. According to the list, the size of a *para* ranges from 27 to 189 households in the survey area and the average size is 67.1. This paper considers *para* as a unit of community. Finally, 18 households were randomly chosen from each *para* based on the list. Since five households were unavailable for the survey, I obtained 427 of 432 sample households from 24 *para*. The total sample size and studied villages in this study is comparable or larger than the other quantitative and qualitative studies on Cyclone Aila, such as Mallick and Vogt (2012; 2014), Saha (2015), Mahmud and Prowse (2012), Sultana and Mallick (2015) and Mallick et al. (2011). Appendix Table A1 employs the Population and Housing Census 2011 (Bangladesh Bureau of Statistics 2014) to compare the socio-economic characteristics between the surveyed and not surveyed villages in Satkhira. It appears that there is no significant difference in demographics, industrial structure, and access to infrastructure, although a significant difference is observed in the material of housings. This supports the representativeness of the survey areas.

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[8] A union is an administrative unit in Bangladesh. Each union includes multiple villages.

The questionnaire consists of 13 modules: (1) the experience of post-cyclone crime victimisation; (2) self-reported cyclone damage; (3) evacuation behaviour; (4) geographical characteristics; (5) bilateral relationships among the survey households; (6) demographic characteristics and time allocation; (7) self-reported social capital; (8) asset holdings and savings; (9) disaster relief provided by the government and NGOs; (10) membership of microfinance institutions; (11) consumption; (12) labour and non-labour incomes; and (13) experience of unanticipated shocks (floods, pest, asset loss, and so forth). Although the survey was conducted only once in December 2010, the retrospective data on pre- and post-cyclone periods were collected regarding modules (7) to (13).

The definition of post-disaster crime differs across studies depending on the context of the studies. Barsky et al. (2006) focuses on the theft of luxury goods unnecessary for survival, such as TV, while Siegel et al. (1999) and Zahran et al. (2009) cover a wider category of property crimes. The measures in this study take unity if the household experienced victimization of any types of property and violent crimes during the 18 months after the cyclone attack, respectively.

This study employs the height of inundation at the residence as an exogenous determinant of cyclone damage to the residence and the other assets. Higher level of inundation indicates more severe asset loss and repairing costs of residence, and thus higher incentive to commit crime. A preferable feature of using this variable rather than a more direct measure, such as the value of asset loss, is the measurement accuracy. Although it is a self-reported variable, the survey respondents could observe the height accurately by checking out the eroded wall of their housing. In addition, since the mark of erosion on the wall remained even at the time of household survey, the enumerators could also confirm the level.

This study computes four indices of religious fractionalisation with this dataset: the number of religious groups in the *para* (Egel, 2013), an indicator of multiple religions, the proportion of households which does not constitute the religious majority of the community (Miguel and Gugerty, 2005), and the index proposed by Taylor and Hudson (1972) to analyse the ethno-linguistic fractionalisation. Therefore, this index is often referred to as the ELF index. This study applies this to the context of religious fractionalization. The ELF index is defined as $1 - \sum_r (\text{Proportion of religion } r)^2$, indicating the probability that two people randomly drawn from the population are from distinct religions.[9] Table A2 in Online Appendix lists the religious composition and fractionalisation indices of the sample communities. It appears that 11 of 24 *para* consist of multiple religious groups, and the four indices are positively correlated (Table A3).

Figure 2 depicts the respondents' timing of settlement in the current community. It appears that most survey households settled down between the 1947 partition and the 1971 Liberation War. This pattern is similar regardless of their religion and fractionalisation of community, except for the distinction that non-fractionalised Hindu communities have resided earlier. This is consistent with the argument in Section 3.1 that the population of the study area is largely influenced by refugees and displaced individuals.

[9] Montalvo and Reynal-Querol (2005) suggest the use of polarisation rather than fractionalisation indices. However, since the samples include only four religious groups, the polarisation index is strongly correlated with the ELF index. Therefore, this study cannot differentiate between the polarisation and fractionalisation effects. Hence, although the use of polarisation index does not change the empirical result qualitatively, is not reported in the paper.

Table 1 compares the household characteristics relative to the religious fractionalisation and severity of cyclone damage. Panel A shows that 30–45% and 14–27% of the households experienced victimisation with regard to property and violent crimes after the cyclone, respectively. The remaining variables are used in Section 6 to disentangle the underlying mechanisms. They show that the households in severely affected and religiously fractionalised communities trust the local government less. Among the affected communities, those in fractionalised communities are less likely to receive the relief from the government. Panel B of the table presents the geographic and pre-cyclone socio-economic characteristics across the four columns. It appears that economic inequality is larger, cyclone damage is smaller, and asset holdings are higher in fractionalised communities. These distinctions are potentially associated with the victimisation risk, suggesting the importance of controlling for them in the empirical analysis (Fafchamps and Minten, 2006; Barslund et al., 2007; Öster and Agell, 2007; Fougère et al., 2009).

[Figure 2]

[Table 1]

5. The Impact of Religious Fractionalisation on Post-Disaster Crime

5.1. Estimation Model

This section estimates the impact of religious fractionalisation on post-disaster crime. Given that the underlying mechanism of post-disaster crimes is based on the behavioural patterns of criminals (Section 2), it should be straightforward to investigate the determinants of crimes committed by the survey respondents. However, since the data on crime incidence generally suffer from the under-reporting bias, this study rather uses the households' experience of crime victimisation, by following Gaviria and Pagés (2002), Barslund et al. (2007), Gibson and Kim (2008), and Cameron and Shah (2014). Exploiting the fact that a large proportion of crimes occur between the peers living in the same community (Faruk and Khatun, 2008), my testable hypothesis is that the probability of victimisation is expected to be higher in the severely affected and religiously fractionalised communities. Section 5.2 argues the validity of the assumption regarding the criminals and victims residing in the same para more carefully.

Since my dataset does not include data on pre-disaster crime victimisation, this study examines the cross-sectional variation of disaster damage and controls for potential determinants of pre-disaster victimisation. Specifically, the following single probit model is estimated:

$$\begin{aligned} \mathrm{V}_{hi} = 1[\beta_0 + \beta_1 Damage80_h + \beta_2 Damage80_h \times Frac_h + \beta_3 Frac_h \\ + \beta_4 Damage50_h + \beta_5 Damage_{hi} + X_{hi}\gamma + \varepsilon_{hi} > 0] \end{aligned} \quad (1)$$

where V_{hi} takes unity if household i in *para h* is victimised after the cyclone, and zero otherwise. $Damage_{hi}$ denotes the height of inundation (feet) at the residence of household i. $Damage80_h$ and $Damage50_h$ are the 80th percentile and the median of $Damage_{hi}$ in *para h*, respectively. These variables capture the extent of cyclone damage to neighbour households. $Frac_h$ denotes the index of religious fractionalisation. Finally, X_{hi} includes the timing of settlement, asset holdings, religion, demographics, geographic characteristics, and the standard deviation of the value of landholdings across the survey households in *para h*. This study employs clustered standard errors to address the correlation of residuals within a *para*.

The idea of controlling for $Damage_{hi}$, $Damag\ 80_h$, and $Damage50_h$ is as follows. Assuming the damage level to household i ($Damage_{hi}$) as constant, the damage to neighbour households has a positive effect on the victimisation risk of household i. In particular, the severity of damage to the worst affected neighbours ($Damage80_h$) should be associated with the victimisation risk more than moderately affected neighbours ($Damage50_h$). Therefore, this study controls for these three variables and investigates the heterogeneous effect of $Damage80_h$ across religious fractionalisation. In this estimation model, it is expected that $\beta_2 > 0$.

5.2. Identification Strategy

The estimation of Equation (1) relies on the following five conditions. First, the crime incidences or disaster damages do not enhance migration, and therefore do not affect the religious composition of the communities. Mallick and Vogt (2012) and Saha (2015) have found the increases in migration after Cyclone Aila from the severely affected regions, such as Samnagar and Assasuni upazila, to the urban regions, such as Satkhira Sadar upazila. However, I still consider that the migration was not accelerated enough to influence the religious composition for three reasons. First, Mallick and Vogt (2012, p226) claim that only male members of the household migrated, while females and children stayed in the village. Saha (2015) also argues the migration as a risk coping strategy, but the study sites include only three most severely affected villages which were non-randomly selected. On the contrary, this study uses the stratified random sampling to select 24 villages and Saha's study sites are not included. Second, if many households in the severely affected areas had indeed migrated to the urban areas, the population growth in Samnagar and Assasuni upazila should have been slower than the other upazila, and particularly Satkhira Sadar upazila should have experienced remarkable population growth. To test this, Appendix Table A4 reports the annual population growth between 2001-2011 in the first column and between 1981-2001 in the second column, respectively. The third column shows the difference between these periods. It appears that the population growth in Assasuni and Samnagar did not necessarily slow down from 1981-2001 to 2001-2011 compared to the other upazila. Satkhira Sadar did not experience the rapid population growth either. A similar pattern is observed when analyzing Muslims and non-Muslims separately. These findings do not fit the hypothesis. Finally, the Household Income and Expenditure Survey (HIES) 2010 – a nationally representative survey conducted in the next year of Cyclone Aila – shows that among the respondents who experienced negative shocks in 2009, such as disasters, only 2.42 % chose migration as a risk coping strategy (Bangladesh Bureau of Statistics 2011).

This stability is presumably because land transactions are not frequent in rural Bangladesh. The main ways of obtaining land are either as an inheritance or as dowry, making it difficult for rural households to obtain a land from those belonging to a different religion or to migrate to other villages.[10] In fact, Mallick et al. (2011) also explicitly mention that *as Bangladesh is already extremely densely settled, relocation of coastal people in inland region is not possible*. These findings suggest that the impact of migration on changes in the religious composition is limited.

The second condition is conditional independency of religious fractionalisation and cyclone damage to the community. Although it is not well known how the residents

[10] According to the survey by Ahmed (2005), only 11% of the rural households purchased land.

of religiously fractionalised communities were determined, I indirectly test the conditional independency by conducting a placebo test. Given the unavailability of data on pre-disaster victimisation, however, I regress four pre-disaster socio-economic status that are related with victimisation—household income, the size of risk-sharing network, trust in the local government, and general trust—on the independent variables of Equation (1).[11] The first three of the four variables are the determinants of pre-disaster victimisation, while the last one is a consequence of victimisation. Cook (1986) argues that both poor and wealthy individuals could be targeted as victims. He also claims that socially isolated individuals tend to be victimised. Furthermore, the poor governance of the local government leads to an ineffective law enforcement authority and thus higher victimisation risk. Since the benefit from the local government may differ across socio-economic status and religions within a community, this study investigates household i's trust in the local government rather than a direct indicator of governance. Finally, those facing higher victimisation risk should trust the others less. Thus, a positive or negative coefficient of interaction term in the equation of household income, and a negative coefficient in the equation of risk-sharing network size, trust in the local government, and general trust indicate the possibility of spurious correlation.

The results of the placebo test are reported in Table 2. It appears that after controlling for the observed characteristics, the socio-economic status in the pre-cyclone period are uncorrelated with religious fractionalisation and cyclone damage, supporting

[11] The data on risk-sharing network is obtained from the following question: *how many households in the village could you call for help if you are in need*? General trust is based on the subjective information elicited by the following question: *generally speaking, would you say that; (1) most people can be trusted; (2) you can't be too careful; or (3) no idea*. The indicator of general trust takes unity if the answer is (1) or (3), and zero otherwise. Trust in the local government is also elicited by a similar question.

the validity of my empirical strategy. This result is plausible in the context of Satkhira District. Since it is located in a river-delta plain, most communities are homogenous in terms of proximity to rivers (and hence the cyclone risk) and industrial structure. Furthermore, the path of each cyclone is randomly determined. Therefore, it is difficult to anticipate the severity of potential damage from Aila beforehand and choose the location of residence based on the risks. Regarding the conditional independency of religious fractionalisation, as documented in the previous sections, the religious composition of the study site was substantially influenced by the refugees and the internally displaced individuals. Presumably, such individuals who migrated to Satkhira during the chaotic periods could not systematically select the community in which they settled regardless of their socio-economic status and religion, because they were unfamiliar with the geographic and economic conditions of the area.

[Table 2]

Third, the use of fractionalisation and cyclone damage at the *para* level assumes that the criminals and victims reside in the same *para*. Although it is difficult to provide rigorous evidence to justify this assumption given the unavailability of information on the criminals, it could still be plausible because individuals should face limited mobility after the cyclone due to the severe inundation of road. In addition, Faruk and Khatun (2008) show that 71.8% of crime incidences in 2007 occurred in disaster-affected districts, and 64% of crimes were committed by peers. This suggests that post-disaster crimes occur between peers. However, there still is a remaining possibility that crimes were committed by the peers residing in the other para. This possibility may affect the interpretation of estimation result if the villagers in the religiously fractionalized and severely affected para have larger peer group outside the para. In order to test this, I exploit two variables at the pre-cyclone period: size of risk sharing network outside the village, and self-reported trust in the residents of the other villages. I regress these variables on the same independent variables as Equation (1). Unfortunately I cannot examine the social network in the other para of the same village due to the data unavailability. The result is reported in Table A5. It shows that the network size and trust are uncorrelated or correlated in the opposite direction with the religious fractionalization and cyclone damages, supporting the validity of identification strategy. In addition to this, I also address the potential concern regarding the crime incidences across *para* in Section 5.4 by employing an alternative dataset.

Fourth, $Damage80_h$, $Damage50_h$, and $Frac_h$, may be subject to the measurement error, because they are computed based on the data from the survey households rather than the entire population in the community. Nevertheless, the sampling methodology used in this study enables us to minimise the error. The height of inundation at home is highly correlated with the location of the house. Similarly, villagers of the same religion form sub-clusters and live close to each other. Therefore, the measurement error could be large if the survey households are coincidentally selected from particular areas in the *para* intensively. However, I sampled the survey households with equally-spaced intervals in each *para*.

Finally, the dataset needs to have enough variations in the religious fractionalisation and cyclone damage to estimate the treatment effect precisely. This issue may be crucial because although this study exploits the treatment variable at the community level, the survey was conducted in only 24 communities. However, as shown in Appendix Figure A1, presenting the histogram of $Damage80$ relative to religious fractionalisation, we can find a variation over the damage levels in both fractionalised and non-fractionalised communities. In addition, the analysis using small sample data could be sensitive to outliers, but Appendix Figure 2—depicting the correlation among $Damage80$, religious fractionalisation, and victimisation rate at the community level—shows that the data do not contain outliers. This study also addresses this concern by conducting various robustness checks, including the analysis using an alternative district-level dataset.

5.3. Benchmark Result

Table 3 presents the estimation results of Equation (1). The table shows different patterns between property and violent crimes. With regard to the property crime, the fractionalised communities without the disaster shock or the non-fractionalised communities experiencing a shock do not suffer from high crime incidence.[12] The crime incidence is significantly high only in the fractionalised and disaster-affected communities. Column 2 indicates that the impact of a one-foot increase in the height of inundation on increasing the victimisation risk is larger by 5.6 percentage point in the fractionalised communities. On the other hand, victimisation related to violent crime is weakly exacerbated by disaster shocks or religious fractionalisation on average. Furthermore, after controlling for the fractionalisation variables, one's religion does not predict the patterns of his/her victimisation risks.

Intriguingly, the level of cyclone damage to the household or asset holdings do not predict the propensity to be a victim. Although educated households are more likely to be victims of property crimes, the land holdings are not associated with victimisation,

[12] The coefficients of $Damage80$ are counter-intuitively negative, although statistically insignificant. However, the signs vary across specifications, as shown in Section 5.5.

and the coefficient of the value of grain storage is rather negative. Related with this, the victims of property crimes are fewer in *para* with higher asset inequality. Although these findings are different from the prediction of Becker (1968), they are in fact consistent with the statistics of Faruk and Khatun (2008) and argument in Section 3: those who are geographically and socio-economically close to potential criminals and those who cannot call for help to law enforcement authorities are more likely to be victimised. Consequently, the wealthy households are not necessarily targeted as victims of crime in rural Bangladesh. This study analyses this point more carefully in Section 5.6. With regard to the other control variables, the households living close to paved roads are more likely to be victims.

[Table 3]

5.4. Evidence from District-Level Data

A potential concern regarding the use of survey data is the small sample size of the community-level variables. In particular, the data may not show sufficient variations of the cyclone damage and religious fractionalisation, given that the sample communities were selected only from one district. Another issue is that the validity of the estimation model relies on the assumption that the criminal and victim reside in the same community.

In order to address these issues, this section employs an alternative dataset at the district level. Since the administrative data on crime rate usually face the problem of under-reporting, I use the data collected by Faruk and Khatun (2008). They surveyed 164,526 crime incidences that occurred in all Bangladeshi districts in the year 2007, based on police reports and four major daily newspapers.[13] Although there may exist some petty crimes that were not reported on the newspapers, I still believe that this is the most reliable statistics available. In 2007, when the data were collected, 39 of 64 districts were affected by a nation-wide flood since July until September. Hence, this study combines these data to test whether the crime rate was higher in the flood-affected and religiously fractionalised districts. Specifically, this study estimates the following OLS model:

$$Crime_d = \beta_0 + \beta_1 Flood_d + \beta_2 Flood_d \times Frac_d + \beta_3 Frac_d + \beta_4 Population_d + \varepsilon_d \tag{2}$$

where $Crime_d$ denotes the number of crime incidences per 100,000 people in district *d*. $Flood_d$ and $Frac_d$ represent the proportion of flood-affected areas (or affected population) and the religious fractionalisation index in district *d*, respectively. Finally, $Population_d$ denotes the total population of the district. The data on religious composition and population are collected from the 2001 population census (Bangladesh Bureau of Statistics, 2007), and those on flood damages are obtained from the Disaster Management Bureau (2007, pp.7). Table 4 presents the result. The coefficients of the interaction term are positive and significant for three of the four specifications, consistent with the result of Table 3.

[Table 4]

[13] This crime statistics includes eight types of crime: property crime (34.0%), organised crime (22.7%), hate crime (16.0%), violent crime (15.0%), innocent victimisation (11.0%), victimless crime (1.0%), public order crime (0.3%), and political crime (0.04%).

5.5. Further Robustness Checks

The first potential issue in the benchmark result is that the religious fractionalisation indices could be correlated with the proportion of non-Muslims in the community. Given the argument that non-Muslims tend to be victimised, the estimated coefficients of religious fractionalisation may simply capture the existence of non-Muslims. In order to test this, I additionally control for the proportion of non-Muslims and its interaction with $Damage80_h$. The result is presented in Table A6 in Online Appendix. The estimated effect of fractionalisation is still significant and the proportion of non-Muslims does not predict the patterns of victimisation risks.

Second, religious fractionalisation is weakly but positively correlated with the community size (Table A2).[14] The coefficient of religious fractionalisation in Table 3 may capture the impact of community size. Thus, I additionally control for the community size and its interaction with $Damage80$. The result in Table A7 still presents the statistically significant impact of religious fractionalisation.

Third, the fractionalisation index may also be correlated with the distance to the India-Bangladesh border. The communities close to the border may be prone to crime because of smugglers and brokers of human trafficking. In my dataset, eight of 24 communities are located relatively close to the border. Therefore, I additionally control for the interaction between $Damage80_h$ and the indicator for the eight communities. The result does not change qualitatively (Table A8).

Fourth, given the unavailability of pre-disaster victimization data, I also

[14] The community size is significantly correlated with the number of religious groups (ρ=0.36, p-value=0.087), but not with the other three fractionalisation indices.

estimate Equation (1) with additionally controlling for four pre-cyclone variables which are used as dependent variables in the placebo test. Although these variables could be endogenous, it is still informative to know to what extent the estimation result changes in the alternative specification. The result is presented in Table A9 and does not change qualitatively.

Fifth, I also examine the relative importance of omitted variable bias driven by unobserved geographic characteristics and cyclone damage. Specifically, I estimate Equation (1) without controlling for height of inundation at home, duration of inundation on the paved road, a dummy if road to cyclone shelter is available, distance between home and local government office, and distance between home and paved road. The result is presented in Table A10. The coefficient of interest in this specification is smaller than the benchmark result. This implies that the estimated treatment effect would be even larger than that shown in Table 3 if the unobserved characteristics were fully controlled for.

Sixth, if the religious fractionalisation and cyclone damage increase the post-disaster crime and this has a negative impact on the social capital of the community, we may observe lower social capital in the severely affected and religiously fractionalised communities. Therefore, I also examine the impact on general trust in the post-disaster period. Again, I find supporting evidence (Table A11).

Seventh, in the benchmark estimation, the cyclone damage at the *para* level is characterised by the 80^{th} percentile (*Damage80*) and median height (*Damage50*) of inundation at home. I also estimate the model that uses the mean height of inundation. The result is reported in Table A12, and is shown to be robust.

Finally, the small sample size of the survey communities makes the estimation results sensitive to the outlier in the community-level variables. In order to address this issue, this study estimates Equation (1) by using OLS, which is less sensitive to the outlier than the probit model. In addition, this study analyses the interaction of binary treatment variables, namely the indicator of fractionalised community and a dummy variable indicating whether $Damage80_h$ is higher than the sample median (two feet). The results are reported in Table A13, and they do not differ from the benchmark specification qualitatively.

5.6. Who is Victimised in Fractionalised Communities?

So far, it has not been uncovered as to who is particularly victimised in the religiously fractionalised and severely affected communities. The victimisation risk could vary across religions and wealth. The historical background presented in Section 3 predicts that non-Muslims could be more likely to be victimized than Muslims. Wealthy households may face higher risk of victimization, given higher material payoff for the criminals in case of succeeding in the theft (Becker 1968). On the contrary, poor households cannot invest in the crime prevention technology, or do not have social network with the village authorities, such as the leader and police. This, in turn, increases the probability of succeeding in the theft, aggravating the victimization risk (Cook 1986). Thus, the impact of wealth is an empirical question. Therefore, this section compares the estimation results of Equation (1) between the subsamples of Muslims and non-Muslims (Table 5), and between landed and landless households (Table 6).

It is demonstrated from Tables 5 and 6 that the socio-economically vulnerable households, such as non-Muslims and landless households, are more likely to be victimised. While the impact on the property crime is comparable between the Muslims and non-Muslims in fractionalised and cyclone-affected communities, the Muslims in such communities tend to be targets of violent crime as well. For the landed households, the impact on property crime becomes insignificant for all specifications, but the impact for landless households remains large and statistically significant.

Why do the criminals not target landed households, even though the material payoff from stealing is higher? There are two potential explanations. First, landed households are connected with village leaders and police, and therefore, it is too risky to steal their properties. Second, they invest more to protect their properties, and therefore, the probability of succeeding in the crime is too low. My data fit the first explanation; land holding is positively and significantly correlated with the indicator of knowing the village leader personally (ρ=0.13, p-value=0.007). On the other hand, it is uncorrelated with the investment into crime prevention technology.[15]

[Table 5]

[Table 6]

6. Underlying Mechanisms of Post-Disaster Crime

This section disentangles four channels through which religious fractionalisation triggers the post-disaster crime.

6.1. Misallocation of disaster reliefs

[15] The survey households are considered to be connected with the village leader if they self-report that the relationship with the leader is relative, friend or neighbour. The investment into crime prevention technology is captured by three indicators, such as locking the door of residence (ρ=0.02, p-value=0.679) and livestock hut (ρ=-0.07, p-value=0.307), and watching livestock when feeding them (ρ=0.033, p-value=0.635).

In the context of Bangladesh, the Vulnerable Group Feeding (VGF) programme provides disaster-affected households with food. The survey data show that 40% of the households received the relief after the cyclone and the average amount is approximately Tk 2,100 which is equivalent to three weeks' worth of income in the study area. The beneficiaries of the relief programme are selected by the local committee members based on the severity of damage, income, land holding, gender of household head, and so forth. It may be the case that disasters make the local governance of the communities with religiously fractionalised committee members less effective than those with non-fractionalised members, and hence, the former may not be able to choose the relief beneficiaries properly.

The explanatory power of this channel is examined by conducting the following three tests: 1) whether the cyclone damage aggravates the local governance particularly in the religiously fractionalised communities; 2) whether the cyclone-affected households in religiously fractionalised communities are less likely to receive the disaster relief than those in non-fractionalised communities; and finally 3) whether the victimisation risk in fractionalised communities is particularly higher if a larger proportion of community members are severely affected by the cyclone but do not receive the relief.

First, I approximate the local governance by using the indicator of trust in the local government. I regress the first difference of this indicator before and after the cyclone on the control variables of Equation (1) with the ordered probit model.[16]

Regarding the second test, I estimate the following probit model to investigate

[16] Note that the trust in the local government in the pre-cyclone period is shown to be uncorrelated with fractionalisation or cyclone damage (Table 2).

the effect of inundation at home ($Damage_{hi}$) on the propensity for the household to receive disaster relief from the government, and how the effect differs between fractionalised and non-fractionalised communities:

$$\begin{aligned} Relief_{hi} = 1[\beta_0 + \beta_1 Damage_{hi} + \beta_2 Damage_{hi} \times Frac_h + \beta_3 Frac_h \\ + \beta_4 Damage80_{hi} + \beta_5 Damage50_{hi} + X_{hi}\gamma + \varepsilon_{hi} > 0] \end{aligned} \quad (3)$$

where $Relief_{hi}$ takes unity if household i in *para* h received relief from the government after the disaster, and zero otherwise. The height of inundation at home captures the eligibility for the household to receive the relief, and therefore, I test to what extent fractionalisation influences the propensity to receive the relief, given the equal level of eligibility. The smaller effect of inundation on the probability of receiving the relief in fractionalised than non-fractionalised communities is consistent with the hypothesis; i.e., $\beta_1 > 0$ and $\beta_2 < 0$.

Finally, in order to investigate whether the victimisation risk is indeed higher in the communities with severe misallocation of disaster relief, I compute the proportion of households in the community except household i, which are inundated more than the sample median (two feet) but did not receive the relief from the government, $Prop_{hi}$. Then, I additionally control for the proportion interacted with $Damage80_h \times Frac_h$ in Equation (1) as follows:

$$\begin{aligned} \mathrm{V}_{hi} = 1[\beta_0 + \beta_1 Damage80_h + (\beta_{20} + \beta_{21} Prop_{hi}) \times Damage80_h \times Frac_h \\ + \beta_3 Frac_h + \beta_4 Damage50_h + \beta_5 Damage_{hi} + X_{hi}\gamma + \varepsilon_{hi} > 0] \end{aligned} \quad (4)$$

If the crimes in the fractionalised communities are committed by the severely affected but uninsured individuals, we should observe $\beta_{20} = 0$ and $\beta_{21} > 0$. Although the proportion of affected and uninsured households is admittedly non-random, it is still insightful to show the correlation as suggestive evidence.

Tables 7–9 present the results. Overall, the results are consistent with the hypothesis, although the result in Table 7 is relatively unstable. In Table 7, the coefficients of interaction terms are negative for all specifications as expected, but the first and third columns are statistically insignificant. Regarding Table 8, the coefficients of inundation at home are significantly positive and the interaction terms are significantly negative for all specifications, supporting the hypothesis. Column 2 shows that while a one-foot increase in the inundation level significantly raises the propensity to receive government relief by 13.3 percentage point in the non-fractionalised communities, the corresponding figure for the fractionalised communities is -3.7 percentage point (0.133–0.170). The latter figure is statistically insignificantly different from zero. In addition, the coefficients of fractionalisation, β_3, are positive, implying a higher incidence of inclusion errors in the fractionalised communities. Non-inundated households in the fractionalised communities are 24.5 percentage point more likely to receive the relief than those in the non-fractionalised communities (Column 2). Furthermore, I also conduct the same estimation models using the subsamples of Muslims, non-Muslims, landed households, and landless households, and obtain qualitatively comparable results for all specifications; the cyclone-affected households in the fractionalised communities are excluded from the relief beneficiaries regardless of their religion and wealth.[17] Finally, Table 9 also supports the hypothesis. It appears that high victimisation risk in the fractionalised and severely affected communities is observed only when the proportion of affected but uninsured neighbour households is large.

[Table 7]

[Table 8]

[Table 9]

6.2. Inefficient Risk sharing

The frequent post-disaster crime in the fractionalised communities can also be driven by the inefficient risk-sharing arrangement. This study tests this channel by estimating a similar model to Equation (3). Here, the dependent variables are binary variables that indicate the receipt of informal assistance from neighbours, such as gifts and loans without interest. If the risk-sharing arrangement is inefficient and cannot pool the idiosyncratic shock in the fractionalised communities, we should observe $\beta_1 > 0$ and $\beta_2 < 0$. The results in Table 10, however, suggest that this channel is not likely to explain the high victimisation risk in fractionalised and severely affected communities.

[Table 10]

6.3. Increasing Income Inequality

The cyclone could have enlarged income inequality, particularly in the fractionalised communities, and this could be the driver of high victimisation risk in such

[17] The results are not reported in the paper, but are available from the corresponding author upon request.

communities. However, the data suggest that this is not likely. Before the cyclone, the standard deviation of monthly household income is larger in fractionalised communities (avg. = 3.43) than in non-fractionalised communities (avg. = 2.90). After the cyclone, however, it rather decreases in both communities and is smaller in the fractionalised communities (1.19 in non-fractionalised communities and 1.07 in fractionalised communities). The comparison based on the coefficient of variation does not differ qualitatively. This is inconsistent with the underlying assumption.

6.4. Political Tension

Finally, the channel through the increased political tension cannot fully explain the observed patterns of victimisation risk either. First, the riots for political purpose are often accompanied by violent attacks; however, as shown in Table 3, fractionalisation triggers only property crimes. Second, if some political tension exists before the cyclone, households in the fractionalised communities should exhibit lower trust in the local government in the pre-disaster period. The result from Table 2 is, however, counter to the prediction. Third, if the post-disaster crimes are driven by political tension, the landed households who are connected with the village leaders should be victimised. However, it is found that rather the landless are victimised (Table 6). Finally, this survey includes the question regarding the time allocation for political activities. It appears that less than 5% of the households spent time for political activities during 2009–2010, and it is correlated with neither the fractionalisation index, crime victimisation, or religion.[18]

[18] The statistics are not reported in the paper, but are available from the corresponding author upon request.

7. Conclusions

Using household-level and district-level datasets of Bangladesh, I showed that religious fractionalisation significantly aggravates the victimisation risk of post-disaster crime. In particular, the non-Muslims and landless households in the fractionalised communities are more likely to be victimised. Further analyses provide supporting evidence that the high victimisation risk is driven by poor targeting accuracy of disaster relief programmes; severely affected but uninsured households commit crime to smooth their consumption.

In allocating the disaster relief to the affected individuals accurately, good governance is essential (Coady et al., 2004). Many researchers have claimed that good governance mitigates human loss (Kahn, 2005; Meng et al., 2015), reduces poverty (Fafchamps, 2003), and facilitates socio-ecological resilience (Adger et al., 2005) during and after disasters. In addition to these, this study suggests the importance of local governance in controlling the post-disaster crimes.

Two policy implications can be derived from these arguments. First, in fractionalised communities, the disaster relief programmes based on self-selection targeting such as Food/Cash For Work may be recommended, since the targeting accuracy of these programmes is less likely to be affected by the local governance. Second, since the affected households commit crime to smooth consumption, development of formal insurance institutions for covariate disaster shock could be helpful to control crime. However, these suggestions must be interpreted with caution, since they hinge on the validity of my identification strategy and the small sample dataset.

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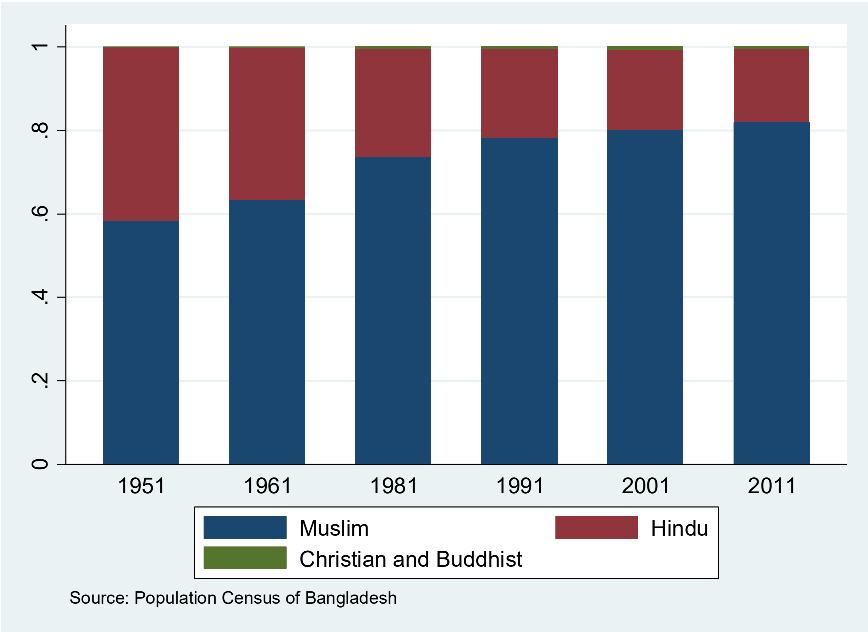

Note: the 1974 census does not report the religious composition of Satkhira district.
Figure 1: Religious Composition of Satkhira District: 1951–2011

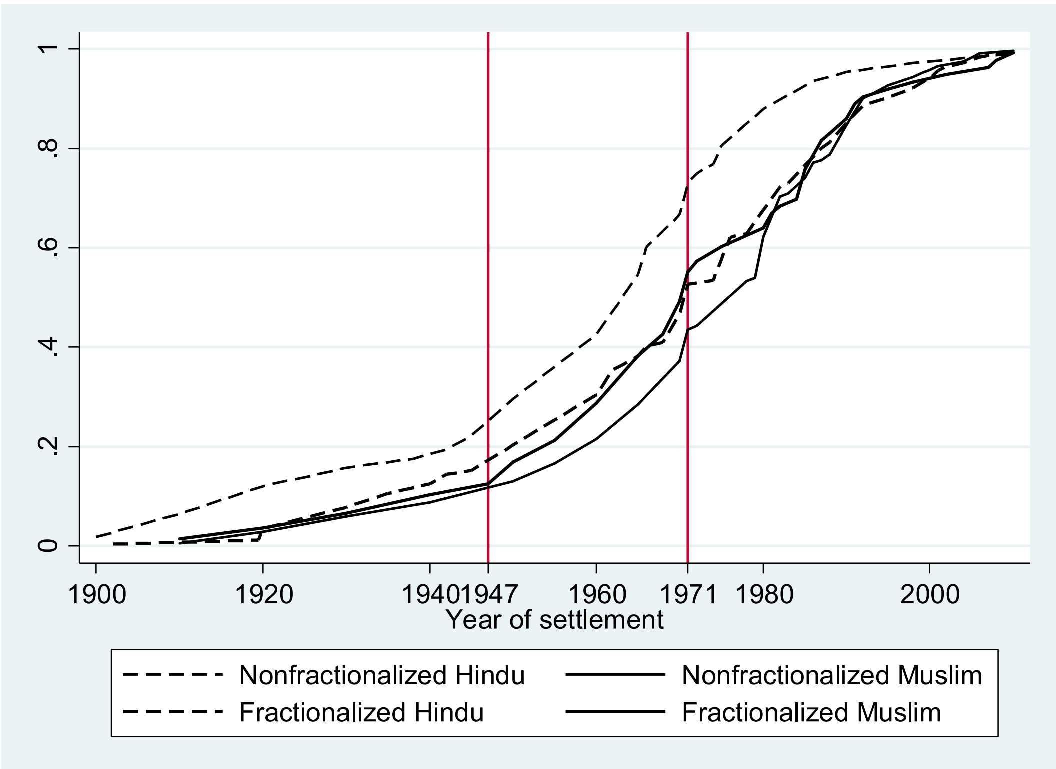

Figure 2: Cumulative Distribution Function of Year of Settlement

Table 1: Summary Statistics Relative to Religious Fractionalisation and Cyclone Damage

Multiple religious groups in the *para*?	Yes								No				
At least 20% of residences were inundated?	Yes (1)		No (2)			Yes (3)			No (4)			
	Mean	S.D.	Mean	S.D.		Mean	S.D.		Mean	S.D.	
Panel A: Dependent Variables											
1 if victim of property crime after the cyclone	0.45		0.44			0.30		***	0.44		
1 if victim of violence crime after the cyclone	0.27		0.26			0.14		***	0.17		
1 if trust the local government after the cyclone	0.75		0.98		***	0.89		***	0.81		
1 if recipient of disaster relief	0.27		0.26			0.60		***	0.17		
The amount of relief if recipient (Tk)	1521	3473	1660	2766	---	2496	2428	---	1416	2018	---
1 if recipient of interest-free informal loans	0.11		0.13			0.13			0.09		
The amount of loans if recipient (Tk)	782	3623	107	401	---	679	2063	---	2222	6666	---
1 if recipient of gift/remittance	0.08		0.04			0.05			0.02		
The amount of gift/remittance if recipient (Tk)	442	2267	0.00	0.00	---	339	1929	---	0.00	0.00	---
Panel B: Independent Variables											
Cyclone Damages											
Height of inundation at home (ft)	1.72	1.74	0.06	0.30	***	2.84	1.30	***	0.19	0.62	***
Duration of inundation on the paved road (month)	0.38	1.01	0.00	0.00	***	0.60	1.75		0.08	0.25	**
1 if road to cyclone shelter is available	0.43		0.44			0.29		***	0.59		**
Geographic Characteristics											
Distance between home and local government office (km)	2.61	1.80	2.72	1.89		3.65	3.16	***	1.94	1.06	**
Distance between home and paved road (km)	0.55	0.71	0.39	0.29		0.75	1.23	*	0.27	0.60	**
Demographics											
Household size	4.10	1.46	4.37	1.74		4.46	1.62	**	4.20	1.35	
Proportion of males aged 15 or over	0.38	0.19	0.36	0.19		0.35	0.16		0.36	0.15	
Age of head	43.67	13.20	46.54	12.94		44.22	13.29		41.39	12.92	
Schooling years of head	4.67	3.99	4.70	3.66		4.16	3.67		3.96	3.77	
Female head	0.06		0.07			0.03			0.06		
Socio-Economic Characteristics											
Muslim	0.32		0.43			0.69		***	1.00		***
Hindu	0.55		0.57			0.31		***	0.00		***
Christian	0.01		0.00			0.00			0.00		
Buddhist	0.12		0.00		***	0.00		***	0.00		***
Year of settlement in the current residence	1970	21.33	1963	23.33	**	1968	22.57		1971	19.73	
Standard deviation of land assets within *para* (10^6 Tk)	0.27	0.23	0.46	0.30	***	0.12	0.14	***	0.36	0.27	**
Value of land assets (10^6 Tk)	0.19	0.38	0.23	0.55		0.07	0.20	***	0.11	0.44	
Value of livestock assets (Tk^3)	13.91	52.85	15.61	18.53		4.03	9.88	**	8.82	30.11	
Value of grain stock assets (Tk^3)	1.12	3.24	1.72	3.98		0.21	0.97	***	1.08	3.00	
Value of deposit (Tk^3)	4.61	18.93	6.27	16.21		2.80	6.78		2.32	4.79	
1 if own cell phone	0.31		0.48		**	0.36			0.15		**
Obs. (Households/Communities)	142/8		54/3			177/10			54/3		

The mean difference from Column (1) is reported. * p<0.1. ** p<0.05. *** p<0.01. --- not tested.

Table 2: Placebo Test

	Pre-Cyclone Household Income				Pre-Cyclone Risk Sharing Network			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.195	-0.014	-0.057	0.018	-0.749	0.091	0.297	-0.206
	(0.287)	(0.251)	(0.293)	(0.271)	(0.918)	(0.694)	(0.667)	(0.687)
× Number of religions in the *para*	0.181				0.542			
	(0.109)				(0.322)			
×1 if multiple religions		0.163				0.469		
		(0.148)				(0.401)		
×1 – (proportion of majority in the *para*)			1.853				2.237	
			(1.639)				(4.760)	
×ELF index				0.534				2.871
				(0.707)				(1.813)
Number of religions in the *para*	-0.591*				0.090			
	(0.317)				(1.217)			
1 if multiple religions		-0.505				-0.690		
		(0.404)				(1.309)		
1 – (proportion of majority in the *para*)			-4.321				-5.708	
			(2.874)				(7.002)	
ELF index				-1.915				-3.017
				(1.396)				(3.961)
Median height of inundation	-0.369*	-0.348	-0.341	-0.404*	0.374	-0.035	-0.265	0.274
	(0.214)	(0.221)	(0.245)	(0.212)	(0.991)	(0.938)	(0.950)	(0.971)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 2: Continued

	Pre-Cyclone Trust in Local Government				Pre-Cyclone General Trust			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
80th percentile of height of inundation	-0.031	-0.039	-0.025	-0.041	0.016	0.039*	0.034	0.030
	(0.037)	(0.031)	(0.035)	(0.032)	(0.032)	(0.020)	(0.024)	(0.021)
× Number of religions in the *para*	-0.010				0.025			
	(0.020)				(0.020)			
×1 if multiple religions		-0.017				0.031		
		(0.021)				(0.020)		
×1 – (proportion of majority in the *para*)			-0.287				0.086	
			(0.206)				(0.179)	
×ELF index				-0.068				0.088
				(0.098)				(0.073)
Number of religions in the *para*	0.069				-0.020			
	(0.051)				(0.054)			
1 if multiple religions		0.087				-0.028		
		(0.063)				(0.065)		
1 – (proportion of majority in the *para*)			0.686*				0.215	
			(0.416)				(0.333)	
ELF index				0.318				0.090
				(0.223)				(0.152)
Median height of inundation	0.056	0.056	0.048	0.063	-0.005	-0.005	0.021	0.019
	(0.036)	(0.040)	(0.046)	(0.042)	(0.024)	(0.026)	(0.028)	(0.025)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	406	406	406	406

The marginal effects at the mean are reported. Clustered standard errors are in parentheses. * $p<0.1$. ** $p<0.05$. *** $p<0.01$.

Table 3: The Impact of Religious Fractionalisation on Post-Disaster Crime Victimisation

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.079	-0.049	-0.045	-0.045	-0.085	-0.063	-0.055	-0.059
	(0.055)	(0.042)	(0.046)	(0.046)	(0.063)	(0.050)	(0.050)	(0.046)
×Number of religions in the *para*	0.043**				0.023			
	(0.022)				(0.030)			
×1 if multiple religions		0.056***				0.025		
		(0.019)				(0.035)		
×1 – (proportion of majority in the *para*)			0.418**				0.488	
			(0.204)				(0.306)	
×ELF index				0.238**				0.235*
				(0.103)				(0.132)
Number of religions in the *para*	-0.030				0.048			
	(0.060)				(0.099)			
1 if multiple religions		0.003				0.086		
		(0.059)				(0.120)		
1 – (proportion of majority in the *para*)			-0.496				-1.043*	
			(0.309)				(0.582)	
ELF index				-0.283				-0.468
				(0.177)				(0.320)
Median height of inundation	-0.042	-0.026	-0.029	-0.037	0.010	0.017	-0.027	-0.020
	(0.051)	(0.044)	(0.051)	(0.051)	(0.061)	(0.063)	(0.064)	(0.059)
Height of inundation at home	0.011	0.010	0.009	0.010	0.011	0.010	0.011	0.012
	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)	(0.021)	(0.022)	(0.022)
Log (Year of settlement)	0.007	0.006	0.003	0.004	0.021	0.020	0.015	0.016
	(0.050)	(0.049)	(0.049)	(0.049)	(0.029)	(0.028)	(0.031)	(0.030)
Duration of inundation on the paved road (month)	-0.036	-0.033	-0.038	-0.036	0.009	0.012	0.007	0.008
	(0.027)	(0.026)	(0.029)	(0.028)	(0.014)	(0.013)	(0.012)	(0.012)
1 if road to cyclone shelter is available	-0.071	-0.073	-0.072	-0.072	-0.171**	-0.172**	-0.175**	-0.174**
	(0.060)	(0.060)	(0.060)	(0.060)	(0.071)	(0.071)	(0.072)	(0.072)
Distance between home and local government office (km)	0.002	0.001	0.003	0.003	0.007	0.005	0.006	0.006
	(0.013)	(0.013)	(0.013)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)
Distance between home and paved road (km)	-0.057*	-0.058*	-0.054	-0.059*	-0.035	-0.037	-0.038	-0.041
	(0.033)	(0.032)	(0.034)	(0.033)	(0.031)	(0.031)	(0.032)	(0.033)

Household size	-0.007	-0.007	-0.008	-0.008	-0.017	-0.017	-0.018	-0.018
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)
Proportion of males aged 15 or over	0.033	0.029	0.019	0.031	-0.092	-0.100	-0.086	-0.084
	(0.134)	(0.133)	(0.133)	(0.134)	(0.122)	(0.119)	(0.122)	(0.130)
Age of head	0.002	0.002	0.002	0.002	-0.001	-0.001	-0.001	-0.001
	(0.012)	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.008)	(0.008)
Age squared ($\times 10^3$)	-0.018	-0.017	-0.019	-0.015	0.026	0.023	0.017	0.020
	(0.128)	(0.128)	(0.128)	(0.128)	(0.083)	(0.082)	(0.083)	(0.083)
Schooling years of head	0.017**	0.017**	0.017**	0.017**	0.006	0.006	0.004	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)
Female head	0.075	0.077	0.061	0.067	-0.092	-0.100	-0.109	-0.106
	(0.110)	(0.110)	(0.113)	(0.112)	(0.081)	(0.079)	(0.082)	(0.082)
Hindu	-0.035	-0.057	-0.009	-0.014	0.028	0.013	0.091**	0.083*
	(0.054)	(0.055)	(0.057)	(0.055)	(0.057)	(0.061)	(0.046)	(0.048)
Buddhist/Christian	-0.159	-0.068	0.015	0.008	-0.037	0.068	0.122	0.139
	(0.143)	(0.080)	(0.076)	(0.078)	(0.150)	(0.112)	(0.107)	(0.100)
S.D. of land assets ($\times 10^6$)	-0.182*	-0.207**	-0.198**	-0.217**	-0.090	-0.118	-0.123	-0.117
	(0.101)	(0.104)	(0.101)	(0.104)	(0.178)	(0.176)	(0.183)	(0.178)
Value of land assets (10^6 Tk)	-0.047	-0.051	-0.038	-0.041	-0.071	-0.071	-0.055	-0.055
	(0.093)	(0.095)	(0.093)	(0.093)	(0.056)	(0.056)	(0.056)	(0.055)
Value of livestock assets (10^3 Tk)	-0.000	-0.000	-0.000	-0.000	-0.001	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Value of grain stock assets (10^3 Tk)	-0.015**	-0.016**	-0.016**	-0.016**	0.003	0.003	0.004	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Value of deposit (10^3 Tk)	0.004	0.004	0.003	0.003	-0.002	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
1 if own cell phone	-0.022	-0.020	-0.026	-0.023	-0.082	-0.081	-0.070	-0.070
	(0.068)	(0.068)	(0.068)	(0.068)	(0.070)	(0.071)	(0.069)	(0.070)
Constant	0.026	0.001	0.027	0.042	-0.094	-0.033	0.067	0.059
	(0.322)	(0.294)	(0.305)	(0.303)	(0.292)	(0.261)	(0.264)	(0.267)
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported. Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 4: District-Level Analysis

	Crime Rate in 2007 (per 100,000)			
	(1)	(2)	(3)	(4)
Proportion of flood affected population	-1.303*	-1.452*		
	(0.669)	(0.772)		
×1 – (proportion of religious majority in the district)	8.836**			
	(4.125)			
×ELF index		5.917*		
		(3.195)		
Proportion of flood affected area			-0.550	-0.652
			(0.453)	(0.517)
×1 – (proportion of religious majority in the district)			4.494*	
			(2.507)	
×ELF index				3.229
				(2.107)
1 – (proportion of religious majority in the district)	-2.642		9.570	
	(63.973)		(63.886)	
ELF index		-4.719		6.809
		(62.176)		(61.574)
Population ($\times 10^6$)	7.892	7.818	8.177	8.165
	(7.743)	(7.585)	(7.567)	(7.433)
Constant	173.632***	174.521***	168.036***	167.858***
	(29.683)	(31.629)	(29.422)	(31.294)
Observations	64	64	64	64
R-squared	0.048	0.047	0.035	0.035

Robust standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 5: Heterogeneous Effects between Muslims and Non-Muslims

	Property Crime Victimization				Violent Crime Victimization			
Muslim Households	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.139*	-0.052	-0.061	-0.047	-0.017	-0.094**	-0.071*	-0.077*
	(0.071)	(0.060)	(0.059)	(0.055)	(0.082)	(0.043)	(0.041)	(0.039)
×Number of religions in the *para*	0.100**				-0.070			
	(0.045)				(0.058)			
×1 if multiple religions		0.115**				-0.057		
		(0.053)				(0.065)		
×1 – (proportion of majority in the *para*)			0.865***				-0.288	
			(0.287)				(0.334)	
×ELF index				0.462***				-0.149
				(0.166)				(0.189)
Number of religions in the *para*	-0.131				0.204*			
	(0.091)				(0.105)			
1 if multiple religions		-0.115				0.212**		
		(0.095)				(0.105)		
1 – (proportion of majority in the *para*)			-1.246**				0.585	
			(0.554)				(0.634)	
ELF index				-0.674**				0.352
				(0.300)				(0.354)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	245	245	245	245	245	245	245	245

	Property Crime Victimization				Violent Crime Victimization			
Non-Muslim Households	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
80th percentile of height of inundation	-0.460***	-0.714***	-0.140**	-0.375***	-0.109	-0.704***	-0.267***	-0.408***
	(0.171)	(0.159)	(0.070)	(0.135)	(0.162)	(0.229)	(0.047)	(0.083)
×Number of religions in the *para*	0.192**				0.067			
	(0.079)				(0.063)			
×1 if multiple religions		0.629***				0.715***		
		(0.116)				(0.221)		
×1 – (proportion of majority in the *para*)			0.733**				2.276***	
			(0.339)				(0.418)	
×ELF index				1.071***				1.554***
				(0.415)				(0.293)

Number of religions in the *para*	-0.452**				-0.085			
	(0.181)				(0.190)			
1 if multiple religions		-1.724***				-2.113***		
		(0.358)				(0.661)		
1 – (proportion of majority in the *para*)			-0.825				-5.107***	
			(0.890)				(0.921)	
ELF index				-2.108**				-3.809***
				(0.987)				(0.772)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	182	182	182	182	182	182	182	182

Marginal effects at the mean are reported.

Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 6: Heterogeneous Effects between Landless and Landed Households

	Property Crime Victimization				Violent Crime Victimization			
Landless Households	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.038	0.004	-0.004	-0.001	0.001	0.024	0.053	0.030
	(0.060)	(0.057)	(0.056)	(0.054)	(0.057)	(0.043)	(0.040)	(0.042)
×Number of religions in the *para*	0.046**				0.011			
	(0.022)				(0.025)			
×1 if multiple religions		0.065**				0.001		
		(0.025)				(0.032)		
×1 – (proportion of majority in the *para*)			0.602***				0.142	
			(0.218)				(0.323)	
×ELF index				0.305***				0.126
				(0.103)				(0.130)
Number of religions in the *para*	-0.116**				0.009			
	(0.050)				(0.073)			
1 if multiple religions		-0.151**				0.005		
		(0.062)				(0.111)		
1 – (proportion of majority in the *para*)			-1.297***				-0.773	
			(0.366)				(0.598)	
ELF index				-0.726***				-0.411
				(0.185)				(0.311)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	256	256	256	256	256	256	256	256
	Property Crime Victimization				Violent Crime Victimization			
Landed Households	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
80th percentile of height of inundation	-0.030	-0.040	-0.066	-0.058	-0.208**	-0.154**	-0.236***	-0.220***
	(0.078)	(0.049)	(0.055)	(0.055)	(0.081)	(0.071)	(0.065)	(0.077)
×Number of religions in the *para*	-0.012				0.052			
	(0.043)				(0.035)			
×1 if multiple religions		-0.018				0.049		
		(0.040)				(0.035)		
×1 – (proportion of majority in the *para*)			0.067				1.132***	
			(0.313)				(0.331)	
×ELF index				0.013				0.516***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				(0.178)				(0.174)
Number of religions in the *para*	0.191				0.116			
	(0.130)				(0.114)			
1 if multiple religions		0.262**				0.150		
		(0.115)				(0.124)		
1 – (proportion of majority in the *para*)			0.628				-1.387**	
			(0.509)				(0.622)	
ELF index				0.448				-0.608
				(0.318)				(0.401)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171	171	171	171	171	171	171	171

Marginal effects at the mean are reported.

Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 7: Fractionalisation and Disaster Effects on Changes in Trust in the Local Government

	ΔTrust in Local Government			
	(1)	(2)	(3)	(4)
80th percentile of height of inundation	-0.166	-0.372**	-0.354*	-0.322*
	(0.209)	(0.147)	(0.181)	(0.165)
× Number of religions in the *para*	-0.165			
	(0.102)			
×1 if multiple religions		-0.195**		
		(0.099)		
×1 – (proportion of majority in the *para*)			-1.104	
			(1.044)	
×ELF index				-0.670*
				(0.395)
Number of religions in the *para*	0.445			
	(0.365)			
1 if multiple religions		0.735**		
		(0.353)		
1 – (proportion of majority in the *para*)			2.870	
			(2.155)	
ELF index				1.626
				(1.131)
Median height of inundation	0.364**	0.444**	0.387*	0.358*
	(0.178)	(0.173)	(0.203)	(0.183)
Other independent variables	Yes	Yes	Yes	Yes
Observations	427	427	427	427

The dependent variable is the first difference of the indicator of trust in the local government.

The coefficients of ordered probit model are reported. Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 8: Fractionalisation and Disaster Effects on the Misallocation of Disaster Relief

	Disaster Relief from the Government			
	(1)	(2)	(3)	(4)
Height of inundation at home	0.179***	0.133***	0.085***	0.111***
	(0.065)	(0.036)	(0.029)	(0.030)
×Number of religions in the *para*	-0.080*			
	(0.045)			
×1 if multiple religions		-0.170***		
		(0.049)		
×1 – (proportion of majority in the *para*)			-0.457***	
			(0.141)	
×ELF index				-0.450***
				(0.167)
Number of religions in the *para*	0.120			
	(0.079)			
1 if multiple religions		0.245***		
		(0.077)		
1 – (proportion of majority in the *para*)			0.964**	
			(0.440)	
ELF index				0.638***
				(0.243)
80th percentile of height of inundation	-0.085	-0.081	-0.103	-0.081
	(0.075)	(0.068)	(0.082)	(0.073)
Median height of inundation	0.156*	0.149*	0.191*	0.151*
	(0.081)	(0.080)	(0.098)	(0.089)
Other independent variables	Yes	Yes	Yes	Yes
Observations	427	427	427	427

Marginal effects at the mean are reported.

Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 9: The Proportion of Uninsured Neighbors and Post-Disaster Crime Victimisation

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.026	-0.040	-0.035	-0.028	-0.060	-0.066	-0.047	-0.057
	(0.055)	(0.043)	(0.045)	(0.047)	(0.068)	(0.052)	(0.049)	(0.050)
×Number of religions in the *para*	-0.023				-0.005			
	(0.030)				(0.042)			
×Number of religions in the *para*	0.066**				0.029			
×Proportion of affected but uninsured households	(0.027)				(0.022)			
×1 if multiple religions		0.028				0.032		
		(0.042)				(0.077)		
×1 if multiple religions		0.037				-0.010		
×Proportion of affected but uninsured households		(0.049)				(0.072)		
×1 – (proportion of majority in the *para*)			-0.235				0.099	
			(0.296)				(0.391)	
×1 – (proportion of majority in the *para*)			1.522**				0.872	
×Proportion of affected but uninsured households			(0.614)				(0.624)	
×ELF index				-0.014				0.211
				(0.175)				(0.249)
×ELF index				0.394*				0.037
×Proportion of affected but uninsured households				(0.227)				(0.240)
Number of religions in the *para*	0.043				0.080			
	(0.059)				(0.104)			
1 if multiple religions		0.014				0.083		
		(0.061)				(0.128)		
1 – (proportion of majority in the *para*)			-0.185				-0.835	
			(0.316)				(0.609)	
ELF index				-0.123				-0.452
				(0.187)				(0.362)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.

Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table 10: The Impact of Fractionalisation on the Efficiency of Risk Sharing

	Informal Loans without Interest				Gift/Remittance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Height of inundation at home	0.047	0.014	0.005	0.009	0.003	-0.001	-0.003	-0.001
	(0.035)	(0.019)	(0.021)	(0.018)	(0.011)	(0.006)	(0.005)	(0.006)
×Number of religions in the *para*	-0.032				-0.005			
	(0.024)				(0.006)			
×1 if multiple religions		-0.039				-0.008		
		(0.031)				(0.007)		
×1 – (proportion of majority in the *para*)			-0.091				-0.036	
			(0.130)				(0.029)	
×ELF index				-0.088				-0.032
				(0.100)				(0.025)
Number of religions in the *para*	0.053				0.026*			
	(0.051)				(0.014)			
1 if multiple religions		0.040				0.031		
		(0.067)				(0.019)		
1 – (proportion of majority in the *para*)			0.281				0.116	
			(0.252)				(0.080)	
ELF index				0.243				0.084
				(0.175)				(0.053)
80th percentile of height of inundation	-0.008	-0.002	-0.015	-0.015	0.001	0.003	0.003	0.004
	(0.030)	(0.031)	(0.033)	(0.031)	(0.010)	(0.010)	(0.011)	(0.011)
Median height of inundation	-0.023	-0.030	-0.004	-0.005	0.012	0.010	0.010	0.008
	(0.027)	(0.028)	(0.038)	(0.034)	(0.010)	(0.009)	(0.011)	(0.011)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	406	406	406	406	427	427	427	427

Marginal effects at the mean are reported.

Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

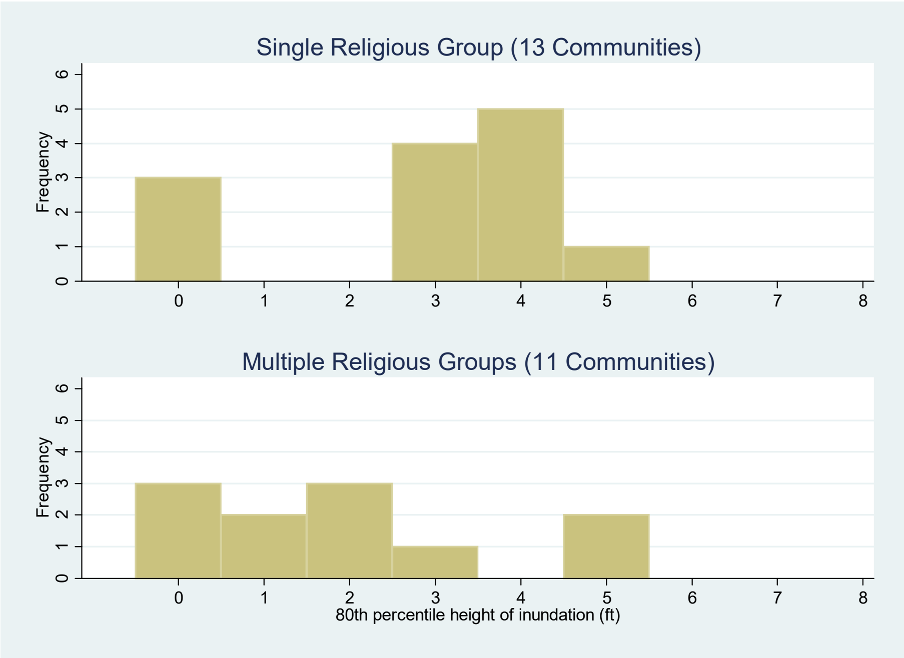

Figure A1: Cyclone Damage and Religious Fractionalisation across Communities

Figure A2: Correlation among the Height of Inundation, Religious Fractionalisation, and the Victimisation Rate at the Community Level

Table A1: Socio-Economic Characteristics of Surveyed and Not Surveyed Villages

	Not Surveyed		Surveyed		
	Mean	S.D.	Mean	S.D.	Difference
The number of households	299.47	310.85	271.43	173.99	
Household size	4.23	0.37	4.23	0.33	
Literacy rate	50.62	11.67	46.33	12.20	
Proportion of the employed (age>6)	0.36	0.09	0.36	0.07	
Agriculture	0.83	0.24	0.82	0.23	
Industry	0.03	0.08	0.02	0.05	
Service	0.14	0.22	0.15	0.21	
Proportion of the household work (age>6)	0.46	0.10	0.46	0.09	
% Pucca (high quality material) house	12.12	10.07	8.61	7.83	**
% access to sanitary toilet	60.62	31.80	66.98	26.00	
% access to tap water	4.29	16.67	5.07	12.02	
% access to electricity	33.30	20.89	29.93	19.32	
N	1,177		24		

Source: Computed from Population and Housing Census 2011. The villages in Satkhira Sadar Upazila are not included, since they are located in the urban areas and therefore not appropriate for the comparison group. * p<0.1. ** p<0.05. *** p<0.01.

Table A2: Religious Fractionalization in the Sample Communities

Para ID	Number of households	Proportion of Muslim	Hindu	Christian	Buddhism	Number of religions	1 – (% of majority)	ELF Index	Year of settlement Mean	S.D.
1	145	0.00	0.06	0.88	0.06	3	0.12	0.21	1983.6	16.4
2	189	0.71	0.18	0.12	0.00	3	0.29	0.49	1981.2	14.0
3	76	0.11	0.89	0.00	0.00	2	0.11	0.16	1967.9	24.7
4	146	0.00	1.00	0.00	0.00	1	0.00	0.00	1966.2	23.3
5	42	1.00	0.00	0.00	0.00	1	0.00	0.00	1981.5	10.7
6	30	0.06	0.94	0.00	0.00	2	0.06	0.20	1967.8	21.0
7	73	1.00	0.00	0.00	0.00	1	0.00	0.00	1977.1	19.9
8	68	0.67	0.33	0.00	0.00	2	0.33	0.36	1969.8	26.4
9	31	0.17	0.83	0.00	0.00	2	0.17	0.28	1960.0	25.7
10	50	0.06	0.94	0.00	0.00	2	0.06	0.13	1970.7	12.6
11	40	0.94	0.06	0.00	0.00	2	0.06	0.10	1962.7	19.7
12	56	0.22	0.78	0.00	0.00	2	0.22	0.38	1968.0	25.3
13	66	1.00	0.00	0.00	0.00	1	0.00	0.00	1967.8	19.5
14	27	1.00	0.00	0.00	0.00	1	0.00	0.00	1962.2	22.6
15	54	0.11	0.89	0.00	0.00	2	0.11	0.23	1958.4	24.9
16	35	0.78	0.22	0.00	0.00	2	0.22	0.37	1963.6	17.3
17	30	0.00	1.00	0.00	0.00	1	0.00	0.00	1954.8	22.3
18	38	1.00	0.00	0.00	0.00	1	0.00	0.00	1958.1	25.8
19	84	1.00	0.00	0.00	0.00	1	0.00	0.00	1972.1	20.2
20	40	1.00	0.00	0.00	0.00	1	0.00	0.00	1982.5	12.2
21	31	1.00	0.00	0.00	0.00	1	0.00	0.00	1969.6	17.5
22	57	0.00	1.00	0.00	0.00	1	0.00	0.00	1951.6	26.0
23	135	1.00	0.00	0.00	0.00	1	0.00	0.00	1972.1	21.8
24	67	1.00	0.00	0.00	0.00	1	0.00	0.00	1975.0	16.6
Mean (N=24)	67.1	0.58	0.38	0.04	0.00	1.54	0.07	0.12	1968.5	20.3

Table A3: Correlation across the Fractionalization Indices (N=24)

	Number of religions	1 if multiple religions	1 – (% of majority)
1 if multiple religions	0.914***		
1 – (% of majority)	0.776***	0.782***	
ELF Index	0.857***	0.857***	0.959***

* p<0.1. ** p<0.05. *** p<0.01.

Table A4: Population Growth across Upazila

	Total			Muslim			Non-Muslim		
	Population growth per year			Population growth per year			Population growth per year		
Name of Upazila	2001-2011	1981-2001	Difference	2001-2011	1981-2001	Difference	2001-2011	1981-2001	Difference
Assasuni	0.8%	0.6%	0.2%	1.0%	1.1%	-0.1%	0.1%	-0.6%	0.7%
Shyamnagar	0.1%	1.6%	-1.4%	0.4%	2.2%	-1.8%	-0.7%	0.0%	-0.7%
Debhata	0.5%	2.2%	-1.6%	1.0%	2.5%	-1.5%	-1.2%	1.1%	-2.3%
Kalaroa	0.7%	1.9%	-1.2%	0.7%	2.0%	-1.3%	0.4%	0.6%	-0.2%
Kaliganj	0.7%	1.2%	-0.5%	0.9%	1.7%	-0.7%	-0.4%	-0.5%	0.2%
Tala	0.2%	1.4%	-1.3%	0.4%	1.8%	-1.4%	-0.3%	0.7%	-1.0%
Satkhira Sadar	1.2%	2.6%	-1.4%	1.3%	2.9%	-1.5%	0.3%	1.3%	-1.0%

Source: Computed from Population and Housing Census 1981, 2001, and 2011.

Appendix Table A5: Peers in the Other Villages at the Pre-Cyclone Period

	Risk Sharing Network in the Other Villages				Trust in the Residents of the Other Villages			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	0.516	0.559	0.347	0.202	0.035	0.029	-0.022	0.006
	(0.716)	(0.562)	(0.630)	(0.646)	(0.035)	(0.024)	(0.029)	(0.026)
× Number of religions in the *para*	-0.249				-0.009			
	(0.170)				(0.015)			
×1 if multiple religions		-0.281*				-0.003		
		(0.157)				(0.015)		
×1 – (proportion of majority in the *para*)			-0.369				0.224	
			(3.427)				(0.148)	
×ELF index				0.031				0.043
				(1.362)				(0.082)
Number of religions in the *para*	1.978				0.058			
	(1.439)				(0.059)			
1 if multiple religions		0.890				0.018		
		(1.319)				(0.052)		
1 – (proportion of majority in the *para*)			3.742				0.228	
			(5.468)				(0.228)	
ELF index				3.887				0.184
				(4.507)				(0.150)
Median height of inundation	0.186	-0.286	-0.072	0.165	-0.022	-0.033	0.036	0.001
	(0.975)	(0.832)	(1.092)	(1.115)	(0.039)	(0.035)	(0.041)	(0.041)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Columns (1) to (4) reports the OLS coefficients and Columns (5) to (8) reports the marginal effects at the mean, respectively. Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A6: Religious Fractionalization versus Proportion of Non-Muslim

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.137**	-0.052	-0.052	-0.063	-0.067	-0.062	-0.062	-0.072*
	(0.069)	(0.040)	(0.040)	(0.041)	(0.077)	(0.050)	(0.042)	(0.039)
×Number of religions in the *para*	0.099**				0.007			
	(0.050)				(0.056)			
×1 if multiple religions		0.132**				-0.001		
		(0.052)				(0.069)		
×1 – (proportion of majority in the *para*)			0.781***				0.913**	
			(0.287)				(0.437)	
×ELF index				0.651***				0.587**
				(0.224)				(0.264)
×Proportion of non-Muslim	-0.086	-0.104*	-0.065	-0.130**	0.023	0.034	-0.072	-0.110*
	(0.057)	(0.058)	(0.050)	(0.053)	(0.063)	(0.069)	(0.048)	(0.064)
Number of religions in the *para*	-0.154				0.075			
	(0.110)				(0.152)			
1 if multiple religions		-0.164				0.132		
		(0.129)				(0.190)		
1 – (proportion of majority in the *para*)			-1.210**				-1.930**	
			(0.539)				(0.877)	
ELF index				-1.118***				-1.240**
				(0.422)				(0.585)
Proportion of non-Muslim	0.178	0.206	0.202	0.357*	0.026	-0.018	0.351	0.442*
	(0.173)	(0.186)	(0.180)	(0.206)	(0.190)	(0.217)	(0.214)	(0.250)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A7: Religious Fractionalization versus Community Size

	Property Crime Victimization	Violent Crime Victimization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.022	0.012	0.022	0.025	-0.092	-0.081	-0.030	-0.044
	(0.060)	(0.057)	(0.060)	(0.064)	(0.066)	(0.057)	(0.062)	(0.061)
×Number of religions in the *para*	0.050***				0.026			
	(0.016)				(0.033)			
×1 if multiple religions		0.051***				0.029		
		(0.018)				(0.035)		
×1 – (proportion of majority in the *para*)			0.481**				0.455	
			(0.199)				(0.304)	
×ELF index				0.223**				0.226*
				(0.096)				(0.127)
×Community size	-0.001**	-0.001*	-0.001**	-0.001*	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Number of religions in the *para*	-0.057				0.031			
	(0.052)				(0.118)			
1 if multiple religions		-0.017				0.081		
		(0.054)				(0.120)		
1 – (proportion of majority in the *para*)			-0.753***				-1.125**	
			(0.214)				(0.559)	
ELF index				-0.372***				-0.542*
				(0.112)				(0.308)
Community size	0.002	0.001	0.002	0.002	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A8: Religious Fractionalization versus Proximity to India-Bangladesh Border

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.062	-0.033	-0.019	-0.021	-0.050	-0.026	-0.017	-0.018
	(0.056)	(0.044)	(0.042)	(0.046)	(0.069)	(0.057)	(0.049)	(0.055)
×Number of religions in the *para*	0.045**				0.032			
	(0.022)				(0.029)			
×1 if multiple religions		0.059***				0.039		
		(0.020)				(0.034)		
×1 – (proportion of majority in the *para*)			0.528**				0.780***	
			(0.242)				(0.300)	
×ELF index				0.255**				0.297**
				(0.103)				(0.145)
×1 if close to the border	-0.023	-0.015	-0.042	-0.030	0.029	0.036	-0.005	0.015
	(0.034)	(0.035)	(0.032)	(0.033)	(0.032)	(0.035)	(0.034)	(0.035)
Number of religions in the *para*	-0.039				0.038			
	(0.056)				(0.082)			
1 if multiple religions		-0.011				0.054		
		(0.059)				(0.108)		
1 – (proportion of majority in the *para*)			-0.570*				-1.100**	
			(0.299)				(0.561)	
ELF index				-0.295*				-0.426
				(0.164)				(0.323)
1 if close to the border	0.062	0.050	0.135	0.087	0.208**	0.187*	0.317***	0.242**
	(0.083)	(0.082)	(0.092)	(0.084)	(0.098)	(0.100)	(0.119)	(0.113)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A9: Estimation with Controlling for Pre-Cyclone Socio-Economic Status

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.087*	-0.054	-0.047	-0.051	-0.084	-0.058	-0.050	-0.056
	(0.053)	(0.042)	(0.043)	(0.045)	(0.061)	(0.048)	(0.047)	(0.045)
×Number of religions in the *para*	0.045**				0.027			
	(0.023)				(0.030)			
×1 if multiple religions		0.056***				0.029		
		(0.019)				(0.034)		
×1 – (proportion of majority in the *para*)			0.406**				0.519*	
			(0.194)				(0.300)	
×ELF index				0.246**				0.257*
				(0.100)				(0.131)
Number of religions in the *para*	-0.021				0.045			
	(0.062)				(0.093)			
1 if multiple religions		0.009				0.078		
		(0.061)				(0.114)		
1 – (proportion of majority in the *para*)			-0.478				-1.075*	
			(0.333)				(0.568)	
ELF index				-0.270				-0.481
				(0.185)				(0.315)
Pre-cyclone socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A10: Estimation without Controlling for Geographic Characteristics and Cyclone Damage

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80th percentile of height of inundation	-0.085*	-0.059*	-0.052	-0.052	-0.058	-0.045	-0.037	-0.039
	(0.050)	(0.036)	(0.041)	(0.041)	(0.070)	(0.057)	(0.054)	(0.052)
×Number of religions in the *para*	0.040*				0.015			
	(0.022)				(0.031)			
×1 if multiple religions		0.051***				0.013		
		(0.020)				(0.037)		
×1 – (proportion of majority in the *para*)			0.385**				0.434	
			(0.193)				(0.320)	
×ELF index				0.216**				0.192
				(0.103)				(0.141)
Number of religions in the *para*	-0.019				0.061			
	(0.061)				(0.101)			
1 if multiple religions		0.022				0.101		
		(0.061)				(0.129)		
1 – (proportion of majority in the *para*)			-0.439				-0.968	
			(0.307)				(0.628)	
ELF index				-0.247				-0.411
				(0.179)				(0.342)
Geographic characteristics	No	No	No	No	No	No	No	No
Cyclone damage	No	No	No	No	No	No	No	No
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A11: The Impact on General Trust

	Post-Cyclone General Trust			
	(1)	(2)	(3)	(4)
80th percentile of height of inundation	0.144*	-0.031	0.009	-0.007
	(0.079)	(0.062)	(0.061)	(0.063)
×Number of religions in the *para*	-0.167***			
	(0.043)			
×1 if multiple religions		-0.171***		
		(0.044)		
×1 – (proportion of majority in the *para*)			-1.692***	
			(0.334)	
×ELF index				-0.782***
				(0.168)
Number of religions in the *para*	0.193*			
	(0.112)			
1 if multiple religions		0.217*		
		(0.121)		
1 – (proportion of majority in the *para*)			2.495***	
			(0.732)	
ELF index				1.110***
				(0.395)
Other independent variables	Yes	Yes	Yes	Yes
Observations	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A12: Alternative Measure of Damages at the *Para* Level

	Property Crime Victimization				Violent Crime Victimization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean height of inundation	-0.152***	-0.094***	-0.095***	-0.098***	-0.152**	-0.098**	-0.127***	-0.121***
	(0.052)	(0.034)	(0.035)	(0.036)	(0.074)	(0.043)	(0.039)	(0.041)
×Number of religions in the *para*	0.057*				0.051			
	(0.030)				(0.046)			
×1 if multiple religions		0.077***				0.059		
		(0.026)				(0.051)		
×1 – (proportion of majority in the *para*)			0.576*				0.961***	
			(0.298)				(0.357)	
×ELF index				0.315**				0.427**
				(0.141)				(0.184)
Number of religions in the *para*	-0.021				0.007			
	(0.062)				(0.099)			
1 if multiple religions		0.006				0.031		
		(0.061)				(0.112)		
1 – (proportion of majority in the *para*)			-0.403				-1.297**	
			(0.345)				(0.579)	
ELF index				-0.216				-0.579*
				(0.183)				(0.335)
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427

Marginal effects at the mean are reported.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.

Table A13: Robustness to Outlier

	Property Crime Victimization					Violent Crime Victimization				
	OLS	OLS	OLS	OLS	Probit	OLS	OLS	OLS	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
80th percentile of height of inundation	-0.074	-0.050	-0.043	-0.044		-0.077	-0.060	-0.052	-0.054	
	(0.054)	(0.041)	(0.043)	(0.045)		(0.070)	(0.056)	(0.053)	(0.049)	
×Number of religions in the *para*	0.037*					0.020				
	(0.021)					(0.036)				
×1 if multiple religions		0.048**					0.021			
		(0.019)					(0.042)			
×1 – (proportion of majority in the *para*)			0.364*					0.510		
			(0.191)					(0.341)		
×ELF index				0.210**					0.236	
				(0.101)					(0.155)	
80th percentile of height of inundation $\geq$ 2 feet					0.148					0.349**
					(0.182)					(0.161)
×1 if multiple religions					0.204**					0.203*
					(0.091)					(0.119)
Number of religions in the *para*	-0.024					0.067				
	(0.060)					(0.115)				
1 if multiple religions		0.009			0.056		0.099			0.106
		(0.060)			(0.068)		(0.140)			(0.111)
1 – (proportion of majority in the *para*)			-0.450					-1.094		
			(0.308)					(0.664)		
ELF index				-0.261					-0.477	
				(0.178)					(0.383)	
Other independent variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	427	427	427	427	427	427	427	427

Columns (1) – (4), (6) – (9): coefficient, Columns (5), (10): marginal effects at the mean.
Clustered standard errors are in parentheses. * p<0.1. ** p<0.05. *** p<0.01.