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Natural disasters and domestic violence?: A study of the 2015 Nepal earthquake

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Abstract

This study estimates the impact of exposure to the 2015 Nepal Earthquake on intimate partner violence with two rounds of Demographic and Health Surveys data. Using differences-in-differences estimation, we find that exposure to the earthquake lead to a statistically and economically significant increase in intimate partner violence in the urban areas but not in the rural areas. This is possibly due to an increase in the stress felt by the earthquake victims. We also offer some evidence that the impact heterogeneity between the urban and rural areas is attributable to the differences in the reconstruction processes and assistance provided.

Keywords: Earthquake, Stress, Intimate partner violence, Difference-in-differences, Gender

JEL codes: J12, J16, Q54

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1 Introduction

Intimate partner violence (IPV) [1] has become a public health crisis that is prevalent across the world on a massive scale. In 48 population-based surveys from around the world, 10 to 69 percent of women reported being physically assaulted by an intimate male partner at some point in their lives (Krug et al., 2002). This form of domestic violence constitutes a major public health challenge as it is associated with worsened physical, reproductive, and mental health of victims (Trevillion et al., 2012; World Health Organization, 2005; Fischbach and Herbert, 1997) among several other negative consequences. Using a quasi-experimental approach, this study analyzes the impact of the 2015 Gorkha earthquake in Nepal on IPV. We provide evidence that the Gorkha earthquake led to a significant increase in IPV in the urban areas but not in the rural areas. We hypothesize that the increase in IPV was due to increased psychosocial and economic stress caused by the earthquake, which was exacerbated in the urban areas due to the reconstruction policies and processes that complicated and delayed reconstruction process in the urban areas. We provide a set of empirical evidence that is consistent with this hypothesis.

This paper contributes to several strands of literature relating to IPV and the impact of natural disasters. Firstly, this study contributes to the vast literature on IPV, a topic that has been studied in economics, public health, psychiatry, psychology, and sociology among others. Besides its impact on the health of victims, there is also evidence of adverse long-term economic impacts of IPV on employment, annual work hours, job turnover, job performance and productivity of victims in the workplace (Tolman and Wang, 2005; Staggs and Riger, 2005; Swanberg et al., 2005). It has also been shown that IPV experiences among women significantly decrease their confidence in negotiating condom use with a partner, putting them at higher risk of HIV infection (Swan and O'Connell, 2012). The negative consequences of intimate partner violence extend beyond the immediate victims and have negative consequences on children as well. A review article by Holt et al. (2008) finds that children and adolescents living with domestic violence are at increased risk of experiencing emotional, physical, and sexual abuse, of developing emotional and behavioral problems, and of increased exposure to the presence of other adversities in their lives.

[1] IPV refers to any behaviour within an intimate relationship that causes physical, psychological, or sexual harm to those in the relationship according to the World Health Organization (WHO). See, `https://apps.who.int/violence-info/intimate-partner-violence/` accessed on June 16, 2021

Researchers, and economists in particular, have examined factors that affect domestic violence such as women's (un)employment and other economic opportunities (Anderberg et al., 2016; Aizer, 2010; Bulte and Lensink, 2019; Farmer and Tiefenthaler, 1997; Macmillan and Gartner, 1999), marital endowment (Menon, 2020), and policies against perpetrators (Aizer and Bó, 2009; Aizer, 2011; Iyengar, 2009, 2019; Chin and Cunningham, 2019). Economists have also explored the IPV impacts of programs that alter the bargaining power of women in the household such as cash transfers (Heath et al., 2020; Hidrobo and Fernald, 2013; Hidrobo et al., 2016) and gender and entrepreneurship training (Bulte and Lensink, 2019). However, how natural disasters affect IPV incidence has been understudied by economists.

Natural disasters such as earthquakes, volcano eruptions, floods, droughts, and storms cause loss or damage of human lives and properties every year and are an important topic to study on their own. In 2019, there were 396 natural disaster events recorded with 11,755 deaths, over 95 million people affected, and USD 130 billion in economic losses across the world (UCLouvain et al., 2020). These figures would arguably understate the true overall impacts of natural disasters on humanity since what natural disasters destroy is not limited to human lives or properties and could include family relations, among others. We study an earthquake as opposed to other natural disaster events since earthquakes are responsible for a large proportion of deaths caused by natural disasters. For instance, there have been 8 million deaths since 1900 due to natural disaster events such as earthquakes, floods, storms, volcano eruptions and bushfires, and out of these, about 30% deaths were caused due to earthquakes. Hence, earthquakes constitute a major threat to human life (Landgraf and Officer, 2016).

Secondly, this study contributes to the body of economics literature on the impact of natural disasters in general and earthquakes in particular. This literature examined different aspects of natural disaster impacts. For example, a number of studies have estimated the macroeconomic impacts of natural disasters (Barone and Mocetti, 2014; Cavallo and Noy, 2010; Cavallo et al., 2013; Cuaresma et al., 2010; Felbermayr and Gröschl, 2014; Raddatz, 2007; Shabnam, 2014; Skidmore and Toya, 2002). Most studies report a short-run decline in GDP, but the direction of the long-run impact varies across studies. This lack of consensus may be attributed to a variety of economic and sociopolitical conditions prevailing at the time of disaster. Consistent with this, several studies have found that developing countries are more vulnerable to disasters of similar magnitude than developed countries (Toya and Skidmore, 2007; Loayza et al., 2012; Kahn, 2005; Noy, 2009). The differences in the impact may also arise from differences in coping strategies across different levels of welfare as found in Sawada and Shimizutani (2008) and Van den Berg (2010). A number of studies have also explored the impacts of natural disasters on time preferences (Callen, 2015; Cassar et al., 2017) and risk attitudes (Hanaoka et al., 2018; Cameron and Shah, 2015; Cassar et al., 2017; Eckel et al., 2009), and the direction of the impact is mixed across studies. Other studies such as Takasaki (2017) and Paudel and Ryu (2018) indicate that natural disasters affect the schooling of different demographic groups differently. There are also studies that examine firm-level outcomes of natural disasters (De Mel et al., 2012; Hosono et al., 2016; Leiter et al., 2009) and cross-country association of natural disasters with civil conflicts (Brancati, 2007) and international relief (Strömberg, 2007). Theoretical literature relevant to natural disasters primarily focused on the implications for economic growth (Akao and Sakamoto, 2018; Hallegatte and Dumas, 2009; Ikefuji and Horii, 2012). The current study differs from these studies as we focus on IPV, an outcome to which little attention is paid in the economic analysis of natural disasters.

Finally, this paper adds to the body of literature considering the impact of natural disasters on domestic violence. Most of the studies exploring this relationship have been from disciplines outside economics such as public health, psychiatry, psychology, and sociology. Many studies in these fields have found an association between exposure to natural disasters and increased violence against women (Harville et al., 2011; Schumacher et al., 2010; First et al., 2017; Fisher, 2010; Felten-Biermann, 2006; Parkinson et al., 2013; Horton, 2012). However, existing studies are predominantly based on qualitative evidence. Even when quantitative data are used, the analysis is often based on post-event surveys conducted only in affected areas with no credible comparison group. Some studies use police or administrative data, which may have some comparison groups, but they typically lack the characteristics of individuals or households and contain only a limited number of outcomes. Besides these issues, existing studies tend to be conducted in a developed country. As a result, there is a dearth of credible causal analysis of the impact of natural disasters on IPV, particularly in the developing world. The only notable exception we are aware of is Schwefer (2018), who finds that volcanic eruptions lead to an increase in IPV in Indonesia using a quasi-experimental approach. Similar to Schwefer (2018), we add to the body of literature on the impact of natural disasters on IPV by applying a quasi-experimental approach to the analysis of a disaster with data from a developing country. However, our paper make the following unique contributions: firstly, use nationally representative survey data to establish the causal connection between exposure to a natural disaster and the incidence of domestic violence, secondly, we provide evidence of considerable impact heterogeneity between urban and rural areas and explore possible reasons for the disparity and thirdly, in our setting, we highlight the importance of stress as a mechanism in explaining the increase in violence.

This paper is organized as follows. We provide some background information on the 2015 earthquake in Nepal in section 2 and describe data sources in section 3. Section 4 discusses the empirical methodology. Section 5 provides the main results, followed by some robustness checks in section 6. Section 7 explores the relevance of stress to our main finding. Section 8 discusses plausible explanations for the urban-rural disparity in the earthquake impact. Section 9 concludes.

2 The 2015 Gorkha earthquake

On April 25th, 2015, at 11:56 am local time, an intense earthquake of moment magnitude 7.8 struck Nepal. According to the United States Geological Survey (USGS), the epicenter of the earthquake was in Gorkha, about 80 kilometers northwest of Kathmandu. This earthquake occurred as the result of thrust faulting between the subducting India plate and the overriding Eurasia plate to the north. Hundreds of aftershocks followed this event, including one of magnitude 7.3 on May 12th, 2015 (Hayes et al., 2017).

As can be seen from the ShakeMap of this earthquake (USGS, 2017),[2] the felt intensity of the earthquake measured by the Modified Mercalli Intensity (MMI) tends to be stronger as one gets closer to the epicenter, even though the contour of the same intensity is not a concentric circle (See also Figure 1). The MMI scale ranges from 1 to 10 with larger numbers representing higher intensity. For example, intensity 6 represents "strong shaking," which would be felt by all and frighten many but cause little damage. Intensity 7 represents "very strong shaking", which would cause considerable damage to poorly built or badly designed structures. Intensity 8 represents "severe shaking," which would cause considerable damage to ordinary substantial buildings with partial collapse and great damage to poorly built structures. The maximum intensity felt for the 2015 Gorkha earthquake was 8.5.

Nearly 9,000 lives were lost, and around half a million houses were fully collapsed or damaged beyond repair. Another quarter million houses were partially damaged. The total value of disaster effects have been estimated at about USD 7 billion, which is about a third of Gross Domestic Product of Nepal in Fiscal Year (FY) 2013-14.[3] The earthquake was estimated to have pushed an additional 2.5 to 3.5 percent of the Nepalese population into poverty in 2015-16 (National Planning

[2]ShakeMap is a product of the USGS Earthquake Hazards Program in conjunction with the regional seismic networks and provides near-real-time maps of ground motion and shaking intensity following significant earthquakes.

[3]Fiscal year is based on the Nepali calendar and roughly corresponds to mid July to the following mid July.

Commission, 2015).

3 Data

3.1 Demographic and Health Survey

We use two rounds of the Nepal Demographic and Health Survey (DHS) conducted in 2011 and 2016, which are before and after the earthquake in 2015. The DHS data are repeated cross-sectional data that are nationally representative, and its sample was drawn in multiple stages[4]. For example, the rural clusters (wards) in DHS 2016 were randomly chosen in the first stage from the rural areas in each province, and then households were randomly chosen in each cluster. The sampling in the urban areas was similar except that the cluster unit in the urban areas was smaller because urban wards are large. The sampling of DHS 2011 was also similar (Ministry of Health and Population et al., 2011; Ministry of Health et al., 2017) .

The DHS data contain a wealth of information about the characteristics of individuals and households along with their geocoded cluster information. Most notably, both rounds of the DHS data include an extensive questionnaire administered to women on their experience of domestic violence.[5] The domestic violence module was administered to one random woman per household, only if privacy could be secured.[6] The DHS data contain four summary measures of violence: "less severe violence", "severe violence", "sexual violence", and "violence-related injuries".[7] These summary variables are based on two to four component questions about some specific forms of violence that the respondents have experienced from their husbands/partners, as detailed below:

- Less severe violence: (i) pushed, shook, or had something thrown, (ii) slapped, (iii) punched or hit by something harmful, or (iv) arm twisted or hair pulled.
- Severe violence: (i) kicked, (ii) strangled or burnt, or (iii) threatened with weapon.
- Sexual violence: (i) physically forced into unwanted sex or (ii) forced into other unwanted sexual acts.

[4] The eligible women response rates (i.e. respondents interviewed/eligible respondents) in DHS 2011 [2016] were 96.8% [97.9%] in urban areas and 98.6% [99.0%] in rural areas.

[5] Note that this module was only administered to women and not to men.

[6] Among the female respondents selected for the domestic violence module, the proportion of those who could not be interviewed due to privacy not being secured or other reasons is only 0.64 [0.15] percent in the urban areas and 0.29 [0.05] percent in the rural areas in 2011 [2016].

[7] The last item is labelled as "any listed actions" in the data, but we use "violence-related injuries" to be more descriptive.

- Violence-related injuries: actions leading to (i) bruises, (ii) eye injuries, sprains, dislocations, or burns, or (iii) wounds, broken bones, broken teeth, or other serious injuries.[8]

The summary variables take unity if the respondent has experienced any of the specific forms of violence. For instance, severe violence takes unity when the respondent has reported to have ever been kicked, strangled or burnt, or threatened with weapon. Using the respondents' experience on the first three summary variables (i.e., less severe violence, severe violence and sexual violence), we created an aggregate indicator, any physical violence, which is a dummy variable taking unity if any of the three summary variables takes unity. Violence-related injuries takes account of violence intensity since this variable takes unity only if violence has resulted in injuries. We also have information on "emotional violence," which is an aggregate measure that takes unity when the respondent has ever been (i) humiliated, (ii) threatened, or (iii) insulted by her husband/partner, but we use the experience of any physical violence as our main outcome of interest. This is because the experience of physical violence will give us a more objective measure of violence experience than the experience of emotional violence. That is, what is humiliating or insulting may greatly depend on the respondent, and the respondent's tendency to answer these questions may confound our regression results. We also prefer to use any physical violence over each of the three summary variables, because different respondents could recognize the same action by their husbands/partners as different forms of violence. Further, the aggregate measure also enables us to focus on the impact of the earthquake on violence overall instead of any specific form of violence. Nevertheless, we conduct a variety of robustness checks with respect to the choice of outcome measures.

The DHS data contain information on whether violence had ever been experienced and its frequency if it had been experienced in the last one year. Because the DHS 2016 data was collected between June 2016 and January 2017, 14–21 months had already passed since the earthquake at the time of data collection. Hence, if we consider only violence within the last year, we miss out on the violence that happened in the immediate aftermath of the earthquake but not in the last one year. Due to this, our main dependant variable of interest is whether any physical violence has *ever* been experienced by the respondent. We will, however, consider violence experienced in the last one year and provide further justification for using "ever experienced violence," instead of violence experienced in the last one year, as our main dependent variable of interest. Besides these variables collected from the female questionnaire, we also use data from the DHS male questionnaire to study

[8] The three component questions under violence related injuries are asked only to those who answered yes to any of the component questions under less sever violence, severe violence, and sexual violence. The indicator for violence-related injuries takes zero for those who did not answer these component questions.

men's occupational status and substance use in the aftermath of the earthquake.

Since our analysis is based on repeated cross-sectional data, the population that our sample represents should be comparable between the two survey rounds. Hence, we define a region as "urban" in the 2016 DHS using its status in 2011 according to the Nepal 2011 Census[9] to maintain uniformity and comparability of the definition of the urban areas between the two survey rounds. It should be noted that the number of designated urban municipalities increased drastically from 58 in 2011 to 217 in 2015 as a result of the substantial revision of the definitions of the urban and rural areas, implying nearly doubling of urban population between 2011 and 2015. However, the adequacy of the new definition of urban areas has been called into question (Bakrania, 2015; Devkota, 2018; Timsina et al., 2020; Chapagain, 2018). Thus, we choose to use the 2011 definition rather than the 2016 definition.

3.2 ShakeMap and treatment definition

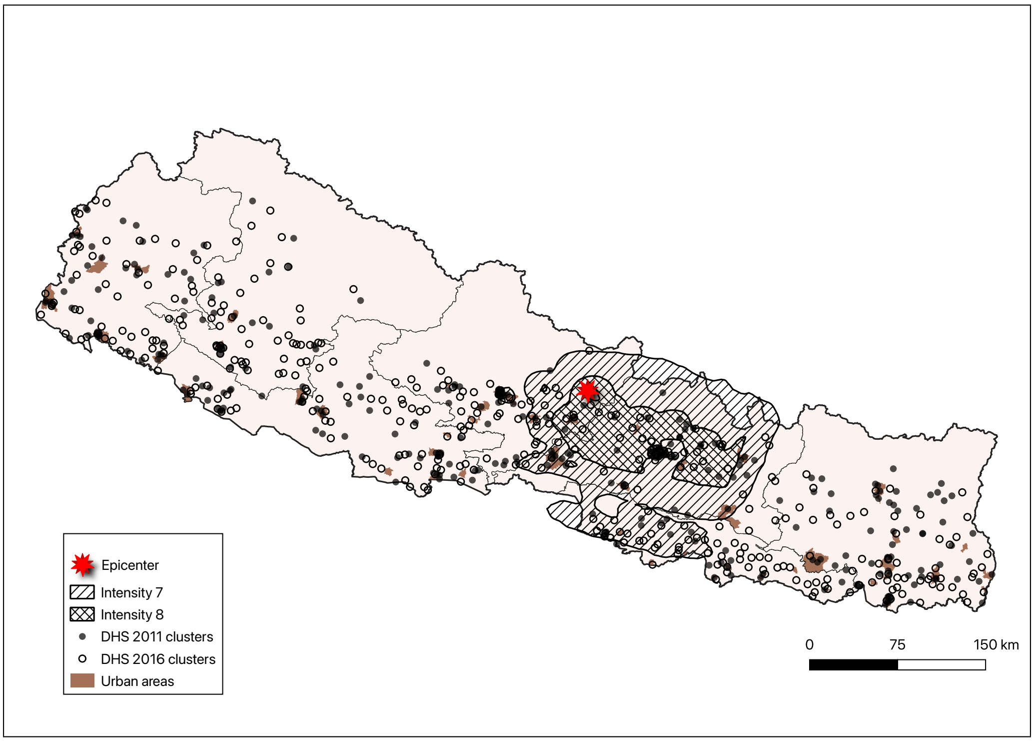
We use the ShakeMap for the Gorkha earthquake—obtained from the USGS website as a shapefile (USGS, 2017)—for the data on the earthquake intensity in MMI experienced in different areas in Nepal. Using a Geographic Information System (GIS), we overlay the ShakeMap with the locations of DHS clusters. We then identify the earthquake intensity felt by a given household based on its location. Figure 1 shows a map of Nepal with filled and empty circles respectively representing the locations of 2011 and 2016 DHS clusters, and hatched and heavily hatched regions respectively representing the areas that experienced intensity 7 and intensity 8 on the MMI scale. Brown areas represent the urban areas based on the 2011 definition.

While a very small area in Nepal faced the maximum intensity of 8.5, no DHS respondents were present in this area. We define the treatment indicator Treat_i as a binary variable taking unity if individual i was living in an area which faced intensity 7 or 8, and zero otherwise. We use these two intensity levels to define treatment since many buildings in Nepal would be considerably or greatly damaged at these levels. As shown in Figure A4 in Appendix E, the local polynomial smoothed plots of the deaths and damaged houses per capita against average MMI at the district level shows that the most of the earthquake impacts occurred at intensities 7 and above.[10] Our treatment areas also correspond well with the areas that were reported to have witnessed most significant damages in properties (National Planning Commission, 2015; Khazai et al., 2015). Further, Table A7 indicates that intensity 7 and above is the most relevant definition of treatment in our context.

[9] `http://dataforall.org/dashboard/nepalcensus/` accessed on June 25, 2020.

[10] For all figures and tables presented in Appendix E, additional explanations are provided in Appendix E

Figure 1: DHS clusters mapped to earthquake intensities



Hereafter, we will refer to the area hit hard by the earthquake with intensity 7 and above as the "treatment" area, and the rest of Nepal as the "comparison" area. For most of the paper, this treatment definition will be used, but at times, if the impact is only limited to the regions hit hardest by the earthquake, we conduct additional analyses using intensity 8 and 7 as separate treatments. Since the earthquake occurred in 2015, we will also use the terms "pre-treatment" and "post-treatment" periods to refer to the periods before and after the earthquake, respectively. The 2011 and 2016 DHS data come from pre- and post-treatment periods, respectively.

The summary statistics for the treatment and comparison areas in 2011 [2016] are reported, respectively, in columns (1) and (2) [columns (4) and (5)] of Table 1 and their difference in column (3) [column (6)] of the same table. We find that there are significant differences in the distribution of covariates between the comparison and treatment areas in both 2011 and 2016. These differences could bias our results and thus we will control for these covariates in our regressions. Furthermore, even when the earthquake has no impact on IPV and the distribution of covariates is constant between 2011 and 2016 in each of the treatment and comparison areas, the presence of covariate-dependent time trend could create a spurious change in IPV in the treatment area relative to the comparison area. Hence, we verify that our results are not driven by a covariate-dependent time trend in the robustness checks discussed subsequently.

Table 1: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Year	2011			2016		
Area	Comparison	Treatment	Diff	Comparison	Treatment	Diff
Urban	0.111	0.243	-0.131***	0.100	0.239	-0.139***
	(0.314)	(0.429)	(0.007)	(0.300)	(0.426)	(0.006)
Respondent's age	28.548	29.382	-0.833***	29.148	29.653	-0.505***
	(9.557)	(9.696)	(0.185)	(9.720)	(9.747)	(0.181)
Husband/Partner's age	35.480	36.347	-0.867***	35.747	36.744	-0.997***
	(9.983)	(9.843)	(0.223)	(9.749)	(9.668)	(0.208)
Respondent's education (years)	4.215	4.817	-0.603***	5.076	5.429	-0.353***
	(4.178)	(4.404)	(0.082)	(4.356)	(4.481)	(0.082)
Husband/Partner's education (years)	5.841	5.985	-0.144	6.454	6.799	-0.345***
	(3.936)	(4.139)	(0.088)	(3.859)	(3.942)	(0.083)
Number of children	1.935	1.864	0.071**	1.874	1.717	0.158***
	(1.785)	(1.777)	(0.034)	(1.667)	(1.621)	(0.031)
Hindu	0.871	0.775	0.097***	0.886	0.805	0.080***
	(0.335)	(0.418)	(0.007)	(0.318)	(0.396)	(0.006)
Buddhist	0.053	0.168	-0.115***	0.028	0.095	-0.067***
	(0.223)	(0.374)	(0.005)	(0.165)	(0.293)	(0.004)
Muslim	0.039	0.034	0.005	0.047	0.057	-0.011***
	(0.192)	(0.181)	(0.004)	(0.211)	(0.232)	(0.004)
Christian	0.016	0.021	-0.005*	0.020	0.041	-0.021***
	(0.125)	(0.142)	(0.003)	(0.140)	(0.197)	(0.003)
Wealth score	-0.409	0.137	-0.546***	-0.174	0.387	-0.561***
	(0.882)	(1.057)	(0.018)	(0.857)	(0.993)	(0.017)
Any physical violence	0.308	0.260	0.049***	0.236	0.262	-0.026*
	(0.462)	(0.439)	(0.017)	(0.425)	(0.440)	(0.015)
Observations	9,622	3,052	12,674	9,746	3,116	12,862

Columns (3) and (6) are based on the difference between the treatment and comparison observations. Urban is based on the 2011 definition. See Appendix A for the definition of wealth score. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

3.3 Other data sources

In addition to the above-mentioned data, we use survey data from the Inter Agency Common Feedback Project—a project funded by UK Aid—on the reconstruction experience of 2,100 people in 14 districts that were most affected by the earthquake.[11] The data, collected in May 2017, allow us to test how the reconstruction experience of the households affected by the earthquake varied between the urban and rural areas. We also use crime statistics obtained from the Annual Reports of the Office of the Attorney General (AROAG), Nepal and the Nepal Police to analyze the impact of the earthquake on crimes against women such as rape and attempted rape at the regional level. As elaborated below, this analysis also suggests that exposure to the earthquake lead to an increase in violence against women.

[11] `https://data.humdata.org/dataset/cfp-reconstruction-042017`, accessed on October 20,2020.

4 Empirical methodology

Our primary method of analysis is difference-in-differences (DiD), in which one difference is taken between the pre-treatment period in 2011 and post-treatment period in 2016, and the other difference is taken between the treatment area—the area hit hard by the earthquake with intensity 7 or above—and the comparison area—the rest of the country.[12] We add some covariates and estimate the following regression equation:

$$DV_{it} = \alpha + \beta \text{Treat}_i \times \text{Post}_t + \gamma \text{Treat}_i + \delta \text{Post}_t + \omega X_{it} + \lambda_{p(i)} + \epsilon_{it}, \tag{1}$$

where DV_{it} is an outcome indicator for domestic violence experienced by individual i in period t. Post_t is a dummy variable for the post-treatment period in 2016. X_{it} consists of control variables such as the age and education of the female respondent and her husband/partner, the number of children in the household, and the religion dummies. $\lambda_{p(i)}$ is the province-specific fixed effects, where $p(i)$ gives the province of residence for individual i. $\lambda_{p(i)}$ captures any province-specific unobserved time-invariant effects (e.g., local culture). The primary coefficient of interest is β on the interaction term Treat $\times$ Post, which identifies the causal impact of earthquake with intensity 7 or above. Standard errors in the regressions results reported in the main body of this paper are clustered at the level of the DHS clusters unless otherwise specified. All the specifications based on eq. (1) are weighted by DHS survey weights normalized to have the same aggregate weight each year.

It is worth noting that a few critical assumptions are made here to draw a meaningful causal inference from this analysis. First, the most important condition for estimating eq. (1) consistently is that the error term ϵ_{it} is uncorrelated with $\text{Treat}_i \times \text{Post}_t$. This condition would be violated if selective relocation between the treatment and comparison areas occurs during the period between the two survey rounds. This could happen, for example, if couples with more violent husbands in the comparison area systematically moved to the treatment area after the earthquake. To address this possibility, we will provide a set of evidence that our results are unlikely to be driven by this type of selective relocation.

Second, the time-specific effect (Post) in eq. (1) must have the same impact on the control outcomes (i.e., potential pre-treatment and post-treatment outcomes in the absence of earthquake) between the treatment and comparison areas. While we are unable to verify this directly from the

[12] Please note that for most of the analysis, we will consider intensity 7 and 8 combined as the "treatment" area. However, for some analysis when the impact is only limited to the most severely impacted areas, we conduct additional analyses in which we use intensity 7 and 8 as separate treatments.

DHS data, the analyses of crime statistics and stress-related outcomes discussed subsequently are consistent with the presence of a parallel pre-treatment trend in domestic violence between the treatment and comparison areas.

Third, eq. (1) implicitly assumes that there is no systematic difference in the impact of covariates on the potential outcomes between the treatment and comparison areas or between the pre-treatment and post-treatment periods. While this may not hold exactly in practice, the presence of the level-effect terms (i.e., Treat_i and Post_t) would mitigate the concern.

Fourth, the covariates may not include potential mediators, or those variables that are affected by the treatment and affect the outcome. Otherwise, our estimates will represent the direct effect after shutting off the indirect causal effects through the covariates. With this in mind, we chose to use such covariates that cannot be or are unlikely to be affected by the earthquake, including households' demographic characteristics and individuals' education and religion. We also address the third and fourth points by estimating models without covariates to verify that our results are robust with respect to the exclusion of the covariates.

Fifth, the standard DiD analysis rests on the assumption that the earthquake had no impact on the comparison areas. However, given the magnitude of the damage the earthquake brought about to the Nepalese economy, it is conceivable that comparison areas may also be affected through the general equilibrium effect. While we do not have a compelling reason to believe that IPV is significantly affected by the general equilibrium effect, our results can be interpreted as the impact of the earthquake after netting off the general equilibrium effect that affects everyone equally.

In addition to the DiD analysis, we will also perform triple difference analysis using the family history of violence as the third dimension of difference to verify if the impact of exposure to the earthquake on the experience of violence varies with the family history of violence. This approach is inspired by a series of existing studies finding that there is an increased likelihood of experiencing IPV among those with a history of inter-parental violence (Bensley et al., 2003; Adjah and Agbemafle, 2016; Vung and Krantz, 2009; Karlsson et al., 2016) and that witnessing inter-parental violence would lead to a greater acceptance of violence in relationships (Vung and Krantz, 2009; Karlsson et al., 2016).[13] Specifically, we use the following triple-difference specification:

$$\begin{aligned}\text{DV}_{it} &= \alpha + \delta_1 \text{FamHis}_i + \delta_2 \text{Post}_t + \delta_3 \text{Treat}_i + \gamma_1 \text{Post}_t \times \text{FamHis}_i \\ &\quad + \gamma_2 \text{Treat}_i \times \text{FamHis}_i + \gamma_3 \text{Treat}_i \times \text{Post}_t \\ &\quad + \beta \text{Treat}_i \times \text{Post}_t \times \text{FamHis}_i + \omega X_{it} + \lambda_{p(i)} + \epsilon_{it}, \end{aligned} \tag{2}$$

where FamHis_i takes unity if a respondent reports that her father beat her mother and zero otherwise. Based on the above-mentioned studies, we conjecture that the impact of exposure to the earthquake on the experience of violence would be stronger among the subset of females who have a family history of violence. Our conjecture is indeed supported by our data as shown below.

5 Results

5.1 Main results

We begin with the baseline specification in eq. (1) without any controls or provincial fixed effects, where the outcome indicator is any physical violence as defined in section 3. As reported in column (1) of Table 2, the coefficient on the interaction term (Treat × Post) is positive, though it is insignificant. Next, we introduce province-specific fixed effects in column (2) and additional controls such as the age and education of the female respondent and her husband/partner, the number of children, and the religion dummies in column (3). The coefficient on Treat × Post is positive and significant in both columns (2) and (3). The point estimate reported in column (3) indicates that an exposure to intensity 7 or above tends to increase the likelihood of experiencing any physical violence by 8.9 percentage points. The magnitude of the coefficient on the interaction term is broadly consistent across the first three columns, showing that exposure to earthquake with intensity 7 or 8 is associated with an increase in any physical violence in Nepal as a whole.

Since one of the important losses that earthquake victims suffer is the damage or destruction of their properties, reconstruction of their dwellings and the way it was carried out could explain the severity of suffering from the earthquake. If this reconstruction, its process, and the policy governing it vary between the urban and rural areas, the impacts of the earthquake may also be very different between the urban and rural areas. We indeed find a set of evidence that is consistent with this possibility as elaborated below.

[13] Witnessing violence when one is young in general may affect the IPV at a later stage in life. See, for example, La Mattina (2017) on the impact of the 1994 Rwandan genocide on domestic violence.

Table 2: Impact of the earthquake on any physical violence

Dep var: Any physical violence	(1) All	(2) All	(3) All	(4) Urban	(5) Rural
Treat × Post	0.054	0.083**	0.089**	0.309***	0.025
	(0.043)	(0.040)	(0.038)	(0.065)	(0.042)
Treat	-0.030	-0.079	-0.067	-0.415***	-0.019
	(0.035)	(0.051)	(0.049)	(0.100)	(0.053)
Post	-0.057**	-0.077***	-0.073***	-0.146***	-0.047**
	(0.023)	(0.022)	(0.022)	(0.049)	(0.023)
Respondent's age			0.003*	0.006	0.002
			(0.002)	(0.004)	(0.002)
Number of children			0.009	0.038**	0.007
			(0.006)	(0.016)	(0.007)
Husband/Partner's age			-0.003**	-0.006*	-0.003*
			(0.001)	(0.003)	(0.001)
Respondent's education (years)			-0.007***	-0.003	-0.009***
			(0.002)	(0.005)	(0.002)
Husband/Partner's education (years)			-0.018***	-0.029***	-0.017***
			(0.002)	(0.006)	(0.002)
Hindu			0.023	-0.028	0.014
			(0.051)	(0.092)	(0.058)
Muslim			0.102	-0.029	0.111
			(0.083)	(0.138)	(0.100)
Christian			0.141**	-0.155	0.211***
			(0.070)	(0.133)	(0.077)
Buddhist			-0.057	-0.094	-0.060
			(0.053)	(0.101)	(0.060)
Observations	7,331	7,331	7,057	1,358	5,699
R^2	0.003	0.027	0.085	0.156	0.085
Controls	No	No	Yes	Yes	Yes
Province FE	No	Yes	Yes	Yes	Yes
Mean of dep var	0.261	0.261	0.261	0.263	0.261

Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

In order to explore the heterogeneity between the urban and rural areas, we repeat the regression in column (3) separately for the urban and rural subsamples, which are reported in columns (4) and (5), respectively. For the urban subsample, there is a statistically and economically significant increase in the likelihood of experiencing some form of physical violence by 30.9 percentage points in the treatment areas. On the other hand, the corresponding regression coefficient is statistically insignificant and close to zero in the rural subsample.[14]. Therefore, the positive and significant relationship between the earthquake exposure and experience of domestic violence in column (3) seems to be driven by the urban subsample. In what follows, we will continue to report the results

[14]Note though that the point estimates are sensitive to weighting. When we run unweighted regressions, the point estimate tends to be smaller (results available upon request). Nevertheless, the main conclusions remain the same

for the urban and rural subsamples separately. We consistently find that the impact of earthquake in the urban areas is more pronounced than that in the rural areas, and the reasons for this disparity between the urban and rural areas will be explored in section 8. This disparity between urban and rural areas holds even when we use an alternative specification where the treatment is disaggregated into intensity 7 and 8 as reported in Table A8 in Appendix E.[15] An important note here is that the violence seems to be driven by men more than women. When we consider a dummy variable for "female respondent beating her partner without him beating her first" as dependent variable, we find no evidence of an increase in violence driven by women both in the urban and rural areas (results available upon request).

Let us now explore whether some components of any physical violence are affected more than others by testing the same specification separately for different components of any physical violence. In columns (1), (3), and (5) of Table 3, we show the results for less severe violence, severe violence, and sexual violence, respectively, in the urban areas. In columns (2), (4), and (6), we show the corresponding results for the rural areas. We find that there is a positive and statistically significant relationship between exposure to the earthquake and experience of violence in the urban areas for all three components of any physical violence. The point estimates are quantitatively similar except that the increase in less severe violence seems to be larger than the rest. In contrast, none of the components shows a significant increase in the rural areas and point estimates are all very close to zero. As reported in columns (7) and (8), we find a similar urban-rural gap for violence-related injuries as well.

5.2 Triple differences

We also employ a triple differences approach using eq. (2) to test whether the impact of exposure to the earthquake on the experience of violence varies with the family history of violence. To this end, we use a question in the DHS domestic violence module on whether the respondent's father ever beat her mother. In 2011 [2016], 17.7 [16.9] percent of the urban respondents reported a family history of violence, whereas the corresponding figure for the rural respondents was 16.8 [14.5] percent.

The results of this analysis are reported in Table 4. Columns (1) and (2) report the results for any physical violence for the urban and rural areas, respectively. In columns (3) to (8), we report

[15]In the urban areas, both intensity-7 and intensity-8 treatments were statistically significant and the former was more than twice as large as the latter. In Table A8, we also report the regression results for the urban and rural areas separately using the same specification as columns (2) and (3) of Table 2. Appendix E also provides other supplementary tables and figures with some additional explanations.

Table 3: Breakdown by the components of any physical violence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Less severe violence		Severe violence		Sexual violence		Violence-related injuries	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Treat × Post	0.258***	0.007	0.122***	0.002	0.152***	0.000	0.167***	0.019
	(0.061)	(0.039)	(0.044)	(0.024)	(0.044)	(0.026)	(0.048)	(0.022)
Treat	-0.354***	0.000	-0.125***	0.046*	-0.226***	0.041	-0.186***	0.005
	(0.086)	(0.047)	(0.042)	(0.026)	(0.076)	(0.028)	(0.053)	(0.026)
Post	-0.092**	-0.005	-0.024	-0.003	-0.102***	-0.071***	-0.062**	-0.023*
	(0.044)	(0.019)	(0.019)	(0.010)	(0.037)	(0.013)	(0.026)	(0.012)
Observations	1,358	5,699	1,358	5,699	1,358	5,699	1,358	5,699
R^2	0.135	0.093	0.076	0.042	0.086	0.046	0.080	0.033
Mean of dep var	0.215	0.226	0.0858	0.111	0.131	0.106	0.101	0.103

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

its components for the urban and rural areas separately. Columns (9) and (10) report the regression results for violence-related injuries. It is worth noting that the coefficient on the triple interaction term, Treat × Post × FamHis, is all positive both in the urban and rural areas. This indicates that women with a family history of inter-parental violence tend to have an increased likelihood of experiencing domestic violence due to exposure to the earthquake relative to women with no family history of inter-parental violence. Furthermore, the coefficient on the triple interaction term is statistically significant in the urban areas for every component of any physical violence except for sexual violence. In contrast, the corresponding coefficient in the rural areas is statistically insignificant and tends to be smaller in absolute value. Hence, the triple differences analysis corroborates our conjecture that a family history of violence augments the impact of earthquake on violence in the urban areas where such impact is sizable.

6 Robustness checks

6.1 Selective relocation of households

In this section, we conduct a number of robustness checks to address some potential concerns about the results presented in section 5. The first potential concern is selective relocation as discussed earlier. To address this issue, we use data on the amount of time in the current place of residence, which is available only in DHS 2016 (but not in DHS 2011). We omit about four percent of the households in DHS 2016 that have been in their current place of residence for less than two years, because they are the ones who may have moved due to the earthquake. Since the proportion of households that have moved in less than two years is small, it is not surprising that the results remain similar as shown in columns (1) and (2) of Table A9. It is also worth noting that internal displacement did take place and people started living in temporary shelters in the aftermath of the earthquake, but most displaced residents sought refuge close to their homes in open spaces (Khazai et al., 2015). Over time, the number of people living in temporary shelters dwindled, and there were approximately only 4,000 households in such temporary shelters about one year after the earthquake (International Organization for Migration, 2016). These pieces of evidence indicate that our results are unlikely to be driven by selective relocation of households.

6.2 Co-residence of couples

The second potential concern is the status of co-residence, which would affect the incidence of domestic violence. To underscore the relevance of this point, suppose that most women in the

Table 4: Triple differences analysis: Family history of violence

	(1) Any physical violence	(2)	(3) Less severe violence	(4)	(5) Severe violence	(6)	(7) Sexual violence	(8)	(9) Violence-related injuries	(10)
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Treat × Post × FamHis	0.311	0.157	0.354*	0.097	0.349**	0.006	0.105	0.127	0.424***	0.037
	(0.190)	(0.102)	(0.184)	(0.096)	(0.154)	(0.070)	(0.113)	(0.097)	(0.162)	(0.070)
Treat × Post	0.231***	-0.018	0.170***	-0.024	0.036	-0.007	0.128***	-0.027	0.071*	0.010
	(0.065)	(0.046)	(0.059)	(0.042)	(0.027)	(0.025)	(0.046)	(0.030)	(0.036)	(0.025)
Treat × FamHis	-0.123	-0.046	-0.182*	0.013	-0.093	-0.009	-0.098	-0.071	-0.081	-0.056
	(0.100)	(0.081)	(0.095)	(0.072)	(0.061)	(0.052)	(0.073)	(0.084)	(0.090)	(0.047)
Post × FamHis	-0.126	-0.012	-0.148	0.033	-0.039	-0.028	-0.085	-0.124***	-0.173**	-0.042
	(0.138)	(0.048)	(0.136)	(0.045)	(0.076)	(0.041)	(0.079)	(0.038)	(0.082)	(0.036)
Treat	-0.367***	0.004	-0.297***	0.008	-0.077**	0.056**	-0.207***	0.064*	-0.144***	0.013
	(0.103)	(0.054)	(0.087)	(0.048)	(0.033)	(0.027)	(0.077)	(0.033)	(0.049)	(0.029)
Post	-0.140***	-0.041*	-0.079*	-0.006	-0.023	0.004	-0.095**	-0.050***	-0.044	-0.016
	(0.052)	(0.023)	(0.045)	(0.020)	(0.019)	(0.011)	(0.039)	(0.014)	(0.027)	(0.013)
FamHis	0.280***	0.162***	0.333***	0.115***	0.096*	0.096***	0.121**	0.145***	0.172**	0.106***
	(0.061)	(0.033)	(0.065)	(0.030)	(0.055)	(0.032)	(0.057)	(0.033)	(0.071)	(0.027)
Observations	1,317	5,564	1,317	5,564	1,317	5,564	1,317	5,564	1,317	5,564
R^2	0.201	0.107	0.196	0.112	0.137	0.053	0.096	0.061	0.146	0.042
Mean of dep var	0.263	0.261	0.215	0.226	0.0858	0.111	0.131	0.106	0.101	0.103

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

urban areas live with their husbands/partners, whereas most women in the rural areas do not live with their husbands/partners because their husbands/partners work in the urban areas. Further, assume that women who are not living together with their husbands/partners are less likely to experience violence. Then, the difference in the impact of the earthquake on domestic violence between the urban and rural areas could be attributed to the difference in the status of co-residence, and our results could also be driven by a selective migration of the husband. This could happen, for example, if the type of husbands/partners that would become violent after the earthquake systematically migrate out of the household in the rural areas (but not in the urban areas). Note that the selective migration of husbands/partners cannot be adequately captured in the preceding analysis, since the location of residence is based on the location of female respondent in the DHS data.

To address the concerns arising from the fact that some couples are not living together, we limit our sample to females who are currently residing with their husbands/partners.[16] The share of rural couples not residing together was 33 [35] percent in 2011 [2016], which was higher than the corresponding figure of 27 [26] percent in the urban area, and the removal of these observations did not change the results much as can be seen from columns (3) and (4) of Table A9. Hence, our results are also unlikely to be driven by the changes in the co-residence of couples.

A related concern would be that the increase in violence is driven by a change in the marriage rates. For example, the earthquake may have increased marriage/cohabitation rates among those more susceptible to domestic violence, and this may have lead to an increase in IPV. In columns (1) and (2) of Table A10, we use a dummy variable for being married as the dependent variable. In columns (3) and (4), we interact the number of years since cohabitation with Treatment×Post and include it in the set of covariates. We find that the coefficient on this interaction term is small and insignificant both in the urban and rural areas. Hence, our results are not driven by the changes in the pattern of marriage or cohabitation.

6.3 Changes in the pattern of migration

The preceding analysis only addresses co-residence. However, migration of household members broadly may also matter. For example, IPV may decrease if there is someone in the household who tries to stop the violence. This is potentially an important point given that migration is

[16]The sample consists of women who said yes to the following question: "Is your husband/partner living with your or is he staying elsewhere?". This would include temporarily staying apart for work and other reasons, and does not necessarily imply a permanent separation.

common in Nepal.[17]

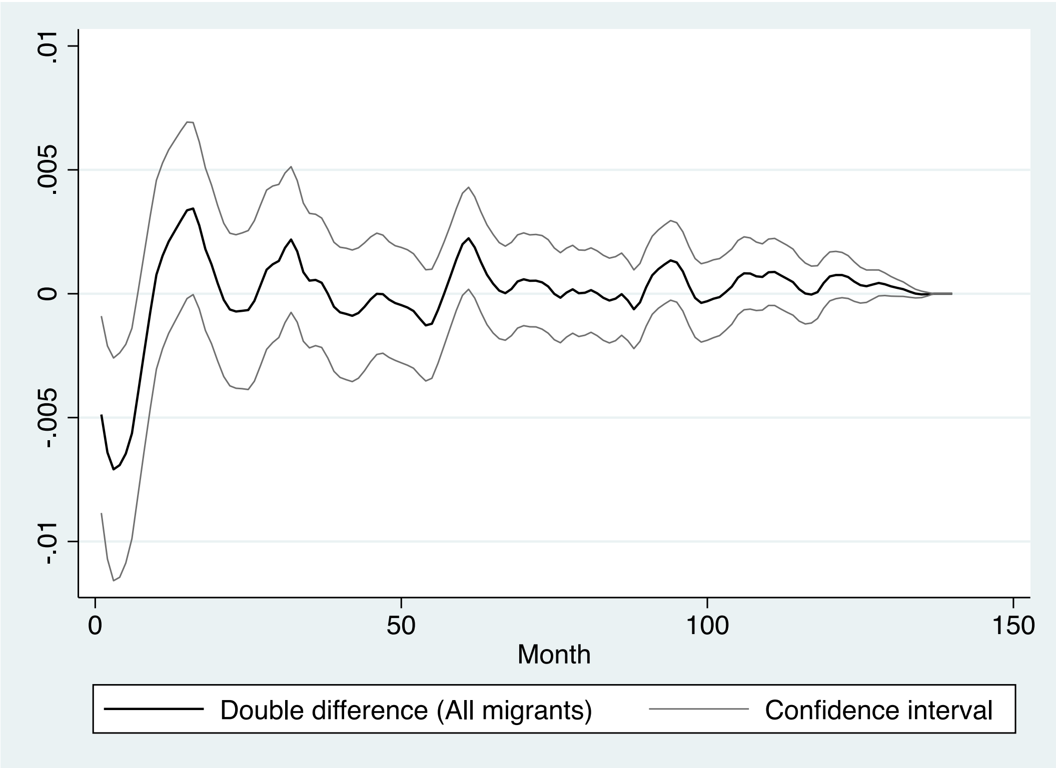
Hence, our third concern is that the earthquake may have changed the pattern of migration. For instance, it is possible that some potential migrants delayed or cancelled their plan to migrate because of the earthquake, and the presence of potential migrants in the household may affect the incidence of IPV. To understand the relevance of this concern, we examine the distribution of the number of months that have elapsed at the time of survey since a household member migrated. In Figure A5, we plot the kernel density estimates f_t^a of the months that have elapsed since a migrant moved away in area $a \in \{comparison, treat\}$ in year $t \in \{2011, 2016\}$. This question was asked only about those migrants who left the household in the past ten years, but the data include records of migrants who left the household slightly more than ten years ago. The densities do not appear to be very different in the four subsamples used to estimate f_t^a, except for the several months prior to the survey.

To see if our results are driven by the negative effect of earthquake on migration, we apply a difference-in-differences approach to the kernel density estimates. That is, we take the difference between 2011 and 2016 in the density difference between the treatment and comparison areas (i.e., $(f_{2016}^{treat} - f_{2016}^{comparison}) - (f_{2011}^{treat} - f_{2011}^{comparison}))$ and then plot it in Figure 2, together with their 95 percent confidence intervals under the assumption that errors across different density estimations are uncorrelated. Given that 14–21 months had elapsed between the earthquake and DHS data collection, this is the time period we will focus on to understand the impact of the earthquake on migration. Figure 2 shows that there was indeed a significant reduction in migration after the earthquake. To understand where this reduction comes from, we redid the same analysis separately by migrants' gender and for each of internal and external migrants. Even though the sample size for this analysis is small, there was a significant reduction in female internal migration in a period corresponding to the post-earthquake period. On the other hand, this was not the case for male internal migration or external migration. Hence, if migration had any impact on violence, it would be not because males cancelled migration but because potential female internal migrants—who would have migrated if the earthquake did not occur—did not migrate, which may have allowed violence to happen.

Since migration reduced after the earthquake, it would be useful to look at how this pattern varied between the urban and rural areas. We run a regression of the indicator for having a migrant (internal or external) in the household as the dependant variable separately for the urban and rural

[17]About 57 [46] percent of the households report that there is at least one household member who has migrated, about 29 [27] percent at least one external migrant, and about 37 [26] percent at least one internal migrant in 2011 [2016].

Figure 2: Double difference in the kernel density of months since migrant moved away



Note: The graph above shows DiD in the kernel density estimates of the months since the migrant moved out of the household with 95% confidence intervals. Confidence interval is computed under the assumption that the four kernel density estimates presented in Figure A5 are uncorrelated.

areas. We then test the equality of coefficients of the DiD term across different regressions. We find no significant difference between the urban and rural areas in the likelihood of having a migrant—whether it is an internal migrant, external migrant, or any migrant. Therefore, while overall migration appears to have reduced in the aftermath of the earthquake, we have no reason to believe that the reduction significantly differed between the urban and rural areas. This means that the difference in the IPV impact between the urban and rural areas is not driven by the difference in the migration patterns between the urban and rural areas.

It is also possible that migrants at the time of the earthquake may have returned home before the 2016 survey. Unfortunately, we are unable to identify from the data who returned home after the earthquake and thus unable to address concern directly beyond the analysis of co-residence presented above. However, we conjecture that return migration is unlikely to be an important reason for the difference between the urban and rural areas, because the vast majority of migrants did not return home (Sijapati, 2015).

6.4 Changes in remittances

The fourth possibility is that the pattern of remittances may have been different between the urban and rural areas, and this could potentially explain our results to some extent. To see the relevance of this point, suppose that rural households are more likely to receive remittances or receive larger sums of remittances. Then, remittances would be more likely to alleviate the stress of rural victims of the earthquake than that of urban victims. This is an important possibility, because remittance flow is found to affect the IPV incidence elsewhere (Mitra et al., 2021).

However, we are unable to test this directly, since the DHS data do not contain information on remittances. Studies conducted just a few months after the earthquake indicate that remittance levels were similar to what they had been prior to the earthquake (Varughese and Barron, 2016a,b), even though remittances may have increased immediately after the earthquake (World Bank, 2016). Furthermore, even if we exclude households with at least one migrant member to remove the direct effect of remittances, the results remain similar qualitatively. Therefore, our results are unlikely to be driven by the change in the pattern of remittances.

6.5 Covariate-dependent time trend

The fifth potential concern is that there may be some covariate-dependent time trends that are different between the treatment and comparison areas. In the presence of covariate-dependent time trends, the differences in the distribution of covariates between the treatment and comparison areas would translate into different changes in the incidence of domestic violence. Hence, the results so far could be driven by the presence of covariate-dependent time trends and unbalanced distribution of covariates between the treatment and comparison areas. To address this concern, we combine DiD approach with kernel propensity-score matching (Blundell and Dias, 2009; Villa, 2016). In this method, the post-treatment observations in the treated areas are matched with each of post-treatment observations in the comparison areas, pre-treatment observations in the treatment areas, and pre-treatment observations in the comparison areas by some time-invariant covariates. The kernel density estimates of propensity scores were similar between the treatment and comparison areas regardless of the urban/rural classification and the year of observation (results available upon request). Further, the coefficient on Treat × Post in the matched DiD regression is positive and statistically significant in the urban area but it is insignificant in the rural area (Table A11).[18] Alternatively, we add an interaction term of each control variable with the post dummy to the baseline specification used in columns (4) and (5) of Table 2 to account for covariate-dependent time trend. As shown in Table A12, the coefficient on Treat×Post does not change significantly. Hence, our main finding remains unchanged even after allowing for the possibility of covariate-dependent time trend.

6.6 Violence in the last one year and other alternative outcomes

The finding that the impact of the earthquake on violence is likely to be temporary provides a justification for our use of ever experienced violence as the time frame we focus on. To further underscore this point, we now consider an alternative outcome in the DHS data, which asks the respondents whether violence was experienced in the last one year. We have so far chosen not to use this variable because well more than one year had already passed since the earthquake by the time of DHS data collection in 2016. Had we only considered the violence experienced in the last one year, we would have missed out on the violence that happened after the earthquake but prior to the last one year, or in the several months following the earthquake. If most of the violence happened during these few months immediately after the earthquake, we would find that the impact on violence when considering the last one year should be smaller. Indeed, based on the estimation of eq. (1), we find in Table A15 that the earthquake led to a significant increase in any physical violence experienced in the last one year in the urban areas. While there was also an increase in the rural areas, the increase was much smaller and only marginally significant. Using

[18] Additional details of the matched DiD regression are provided in Appendix E

alternative measures of violence—such as standardized violence measure based on Kling et al. (2007) and number of violence types—leads to the same conclusion. That is, there was a much larger increase in violence in the last one year in the urban areas than the rural areas. Further discussions on alternative outcomes are provided in Appendix section C.1.

We further examine whether the impact on violence declined over time by dividing the observations into two samples: those who were surveyed in the first half of the data collection period ("early sample") and those who were surveyed in the second half of the data collection period ("late sample") in each survey round. The results in Table A16 show that for each measure of violence, the coefficients on Treat $\times$ Post for the early sample are higher than that for the later sample and are statistically significant in the early sample when considering any violence and number of violence types in the last one year. These findings are consistent with the possibility that more violence happened in the months immediately after the earthquake but this impact subsided as the time passed.

6.7 Placebo test

To further boost the credibility of our results, we examine whether we obtained the estimated impact on IPV just by chance due to the particular realization of the epicenter location. To address this concern, we run a one-sided test, where we compare the actual impact estimate against the distribution of placebo estimates, or the estimates based on the placebo epicenters randomly drawn from the areas of Nepal that are not affected by the earthquake. The placebo test suggests that the impact of exposure to the earthquake on violence found above is not simply due to a chance location of the epicenter. Further details and additional discussions on the placebo test are provided in Appendix B.

Besides alternative outcomes measures discussed in the previous subsection, we also present additional robustness checks such as using violent crimes against women from administrative data, testing for pre-treatment parallel trends, changes-in-changes estimation, clustering standard errors at alternate geographic levels, and taking the distance from the epicentre as an alternative treatment. These robustness checks are presented in appendix section C.

7 Stress as a cause of violence

The analyses in the previous sections indicate that the earthquake increased IPV in urban Nepal, but it does not show why—the question we now turn to. Our hypothesis is that the earthquake increased psychosocial and economic distress, which in turn lead to increased violence against women. This hypothesis is broadly consistent with the findings from recent studies on the IPV impact of volcanic eruption (Schwefer, 2018) and COVID-related public health measures such as social distancing (Leslie and Wilson, 2020) and lockdown (Arenas-Arroyo et al., 2021).

Since we do not have data on a direct measure of stress such as cortisol levels, we explore the impacts on other intermediate outcomes that are likely to be closely related to psychosocial and economic distress—such as substance use, nutritional status of females and children, wealth, and occupational status. As with most of the previous results, we will conduct the analysis of each of these outcomes separately for the urban and rural areas to underscore the differential impact of the earthquake between the two areas. The possible reasons for this differential impact will be explored in section 8.

7.1 Male substance use

We first examine the impact of substance use among males. Several studies have found a positive association between stress or post-trauma stress disorder (PTSD) and substance use (Dixon et al., 2009; Vlahov et al., 2002; Stewart et al., 2004; Friedman, 2020). Other studies have directly linked exposure to natural disasters to an increase in PTSD and substance use (Cerdá et al., 2011; Vetter et al., 2008; Kishore et al., 2008). Therefore, if our hypothesis is correct, the earthquake is also expected to have increased substance use.

The DHS data include data on alcohol and tobacco consumption—two of the most common forms of substance use—among males.[19] We run a DiD regression for each of these outcomes of substance use based on eq. (1), separately for the urban and rural areas. Columns (1) and (2) of Table 5 report the results for alcohol consumption for the urban and rural areas, respectively. They show that there is a significant increase in alcohol consumption due to the earthquake in the urban areas, but no such increase is found in the rural areas. The results for smoking reported in columns (3) and (4) also show similar results. These results are indeed consistent with our hypothesis that the earthquake increased the stress level among those who are affected, which in turn may have led to an increase in physical violence.[20]

[19]Female respondents are asked whether their spouses consume alcohol, whereas male respondents are asked whether they smoke.

[20]As reported in Table A14, our finding remains unchanged when an index of substance use—created from alcohol and tobacco consumption following Kling et al. (2007)—is used. Further, consistent with our finding, there was a significant increase in psychiatric cases, mostly alcohol-related, in a hospital in the vicinity of Kathmandu four months after the earthquake, compared to the same period one year before in a hospital in Kathmandu (Tembe et al., 2018).

Table 5: Impact on male substance use

	(1)	(2)	(3)	(4)
	Alcohol consumption		Smoking	
	Urban	Rural	Urban	Rural
Treat × Post	0.311***	-0.024	0.103*	-0.007
	(0.065)	(0.037)	(0.055)	(0.051)
Treat	-0.125	0.038	-0.111*	0.045
	(0.077)	(0.040)	(0.062)	(0.047)
Post	-0.175***	-0.037	-0.183***	-0.154***
	(0.048)	(0.024)	(0.037)	(0.020)
Observations	1,358	5,699	1,126	4,193
R^2	0.106	0.090	0.101	0.111
Mean of dep var	0.507	0.508	0.223	0.240

Columns (1) and (2) are based on the data from the domestic violence module answered by female respondents. Columns (3) and (4) are based on the data from the male questionnaire answered by male respondents. For columns (1) and (2), controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. For columns (3) and (4), controls include male respondent's age, age of first wife/partner, number of children, and respondent's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

7.2 Nutritional status of females and children

The next set of outcomes we examine is the nutritional status of household members. We focus on the outcomes for females and children in the households due to the data availability. Nutritional status is an outcome of interest on its own, and it is also important for understanding our findings on violence, because increased stress from the earthquake may manifest itself in deteriorated nutritional status through a variety of channels. For example, the economic distress due to the earthquake may result in a lower consumption of food and hence a worsened nutritional status for all household members. It is also possible that the stress caused by the earthquake could lead to abuse or neglect of women or children and decreased food consumption for them. Psychological stress due to the earthquake could also cause an eating disorder, affecting the nutritional status of individuals.

We first examine the nutritional status of female respondents as measured by whether their Body Mass Index (BMI)—weight in kilograms over height in meters squared—is within the normal range between 18.5 and 25. As shown in columns (1) and (2) of Table 6, the BMI of females exposed to the earthquake is significantly less likely to be within the normal range in the urban areas, but no significant impact was observed in the rural areas.[21] This indicates a significant decline in the nutritional status of females due to exposure to the earthquake in the urban areas, hinting heightened psychosocial and/or economic distress.

We also examine the following three nutritional outcomes for children: (moderate or severe) anemia, severe underweight, and severe wasting.[22] Besides the reasons we have mentioned above, nutritional status of children is also of interest, because the difficulty in taking good care of children could be a direct source of stress. As reported in columns (3) and (4) of Table 6, children in the urban areas who were exposed to the earthquake were 16.5 percentage points more likely to be anemic. While we also find that children in rural areas who were exposed to the earthquake were more likely to be anemic, the point estimate for the rural area is only about half of that for the urban area. Next, we look at the impact of the earthquake on the prevalence of severe underweight and severe wasting. As columns (5)–(8) of Table 6 show, no significant impact was found for severe underweight and severe wasting.

The variations in child nutrition status are known to be notoriously difficult to explain because of high natural variations. Furthermore, weight can recover relatively quickly such that the impact may be still apparent at the time of data collection in 2016 only in the areas where the impact of the earthquake was most severe. To explore this possibility, we take the exposure to intensity 7 and 8 as separate treatments and denote the intensity-7 [intensity-8] treatment by Affected7_i [Affected8_i], which takes unity if individual i resides in an area that experienced intensity 7 [intensity 8].[23] As detailed in Table A17, the estimated impacts of exposure to intensity 8 on severe underweight and severe wasting are statistically and economically significant, whereas the impacts in the rural areas are very small and statistically insignificant. The estimated impacts of exposure to intensity 7 are also small and statistically insignificant both in the urban and rural areas. Hence, the impact on child nutrition status was most pronounced in the urban areas that were hit hardest by the earthquake.

7.3 Loss of wealth

As we have discussed in section 2, the 2015 Nepal earthquake has brought about tremendous damage to people and properties. Therefore, it is plausible that those who were affected by the

[21] We also considered BMI below 18.5 (undernutrition) and BMI above 25 (overnutrition) as separate outcomes. The DiD estimates indicate that both undernutrition and overnutriton increased in the urban areas due to the earthquake, even though the estimates are statistically insignificant.

[22] The indicator for severe underweight [severe wasting] takes unity if the child's weight-for-age [weight-for-height] Z-score based on the WHO Child Growth Standards is less than minus three.

[23] As shown in Table A8, both treatments have a positive impact on on any physical violence and intensity-8 treatment has a much larger impact than intensity-7 treatment.

Table 6: Impact on nutritional status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BMI in normal range		Anemia		Severe underweight		Severe wasting	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Treat × Post	-0.153**	-0.026	0.165*	0.089**	0.032	0.006	0.011	-0.005
	(0.065)	(0.036)	(0.088)	(0.040)	(0.037)	(0.023)	(0.023)	(0.014)
Treat	0.159***	-0.043	-0.025	-0.002	-0.103*	-0.004	-0.011	0.008
	(0.061)	(0.037)	(0.088)	(0.038)	(0.061)	(0.025)	(0.042)	(0.014)
Post	-0.071*	-0.054***	-0.029	0.059***	-0.041	-0.012	-0.033*	-0.003
	(0.043)	(0.018)	(0.049)	(0.019)	(0.031)	(0.011)	(0.017)	(0.006)
Observations	1,801	7,536	614	3,536	722	4,006	701	3,957
R^2	0.115	0.033	0.052	0.031	0.083	0.032	0.039	0.004
Mean of dep var	0.592	0.694	0.197	0.235	0.047	0.070	0.018	0.023
Sample	Females	Females	Children	Children	Children	Children	Children	Children

Controls in each regression include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors are clustered at household level. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

earthquake experienced a loss of wealth, an important indicator of economic stress. To this end, we construct a wealth score that is comparable between the two survey rounds, details of which are explained in Appendix A. We use this as an outcome indicator and run DiD regressions. As shown in Table A18, there is no significant impact when the treatment is defined as the areas exposed to intensity 7 or above. However, when we take intensity 7 and intensity 8 as separate treatments, we find that there is a significant decline in the wealth score for those exposed to intensity 8 in the urban areas, but not in the rural areas or those exposed to intensity 7. These results suggest that a significant economic distress remained at the time of the collection of DHS 2016 data only in the urban areas that were most severely hit by the earthquake.

7.4 Loss of white collar job

As an alternative measure of economic stress, we also consider occupational shocks for males. Specifically, we study the binary indicator for males with a white collar job as an outcome, which takes unity if they have a professional, technical, managerial, or clerical job.[24] Since white collar jobs are typically better paying than other jobs, a loss of such jobs would represent economic stress.

The DiD regression results for male white collar job indicate that the earthquake exposure had no significant impact when the treatment area is defined as those area exposed to intensity 7 and above (columns (1) and (2) in Table A19). When we treat intensity 7 and intensity 8 as separate treatments, we find that exposure to intensity 8 had a negative impact on the likelihood of having a white collar job in the urban areas. However, we did not obtain a corresponding finding for those in the rural areas or those exposed to intensity 7 (columns (3) and (4) in Table A19). These results are similar to severe underweight, severe wasting, and wealth score. Therefore, discernible negative economic impacts were observed only for urban residents who were exposed to intensity 8.

7.5 Prior experience of earthquake

To further examine the plausibility of stress as a cause of violence, we have also conducted a triple differences analysis by prior experience of a major earthquake. Specifically, we exploit the variation in the exposure to the earthquake of magnitude 6.9 in 1988, which struck the India-Nepal border region and take the third difference between those with and without the exposure to this earthquake.

Our analysis is motivated partly by the literature on disaster preparedness, which shows that

[24]Other jobs that can be reported in the survey include agriculture, skilled manual labor, unskilled manual labor, and sales and services.

past experience of disasters alters risk perception and precautionary behavior and may enable people to be better prepared for future disasters (Bubeck et al., 2013; Lawrence et al., 2014; Lindell and Hwang, 2008; Tekeli-Yeşil et al., 2010). It is also partly motivated by the loss of control model of family violence (Card and Dahl, 2011), which suggests that a negative event is more likely to trigger violence when it is unexpected for the potential perpetrator. Hence, we would expect that those who had experienced the 1988 earthquake were better prepared for the current earthquake and handled the resulting stress better without losing control and becoming violent. Our results, detailed in Appendix D, indeed provide suggestive evidence that the husbands who had prior experience of a major earthquake were less likely to turn violent than those who did not have such experience.

7.6 Economic and non-economic sources of stress

The set of results presented so far in this section is consistent with the possibility that the earthquake has increased the stress level of those who experienced it. The stress may come from both economic and non-economic factors, and it is generally difficult to determine their relative importance. This is because these factors can interact with and possibly reinforce each other. To see this point, take loss of wealth or white collar jobs as an example. This would negatively affect not only the economic well-being but also psychological well-being of people. A bad mental condition can lower their productivity, which in turn may lead to even lower economic well-being, creating a vicious cycle.

Nevertheless, we argue that the stresses arising from the direct economic impact of the earthquake alone will not be able to explain the increase in any physical violence for two reasons. First, notice that the economic impacts, as measured by wealth score or white collar job, are insignificant both in the urban and rural areas when the treatment area is defined as the areas that were exposed to intensity 7 or above. While it is possible that households exposed to intensity 7 have already recovered from economic losses by the time of the survey, the direct economic impact appears unlikely to be a main causal channel through which earthquake affects IPV.

Second, we also find that the direct impacts of the earthquake on the incidence of any physical violence after controlling for the wealth remains statistically significant and the point estimates remain similar both in the urban and rural areas. That is, we run DiD regressions based on eq. (1) including the wealth score in the set of covariates X_{it}. In this specification, the wealth score can be regarded as a mediator and the estimated coefficient β can be interpreted as the direct effect after shutting off the indirect effect of the earthquake through the wealth score in the framework of standard linear mediation analysis. As shown in columns (5) and (6) of Table A13, the coefficient on Treat $\times$ Post is positive and significant in the urban areas but not in the rural areas even when the wealth score is included in X_{it}. As can be seen from the comparison of these estimates with the corresponding estimates in columns (4) and (5) of Table 2, the point estimates remain similar. The conclusion remains unchanged even when we take exposure to intensity 7 and intensity 8 as separate treatments (details available upon request). While the wealth score alone may not be able to capture all the effects of economic stress, the results above does appear to indicate that stress from non-economic factors is an important source of stress, which in turn may have contributed to increased incidence of IPV.

8 Urban-rural disparity

The results above show considerable impact heterogeneity between the urban and rural areas. In this section, we explore some possible explanations for this heterogeneity. As we learned from the previous sections, differences in the direct economic impact or migration pattern are unlikely to explain this heterogeneity. Further, given that urban areas are generally wealthier than rural areas, it would be surprising if this heterogeneity could be largely accounted for by the direct economic impact. While it is not possible to identify all the potential factors that would affect this heterogeneity, we argue that the the policy environment for reconstruction after the earthquake can explain at least some of the heterogeneity. This is because property loss or damage is among the most grave impacts for the earthquake victims and because the experience of reconstruction appears to have been vastly different between the urban and rural areas.

In the aftermath of the earthquake, the Government of Nepal setup the National Reconstruction Authority (NRA) to oversee all the matters relating to the reconstruction of houses damaged or destroyed in the 2015 earthquake. NRA decided to provide financial assistance in the form of a cash grant of NPR 300,000 (USD 2,600) for reconstruction of damaged houses with earthquake-resistant construction methods in the affected areas.

While the NRA's schemes for reconstruction were well intended, there were considerable issues in their implementation, because the earthquake-resistant housing construction models as suggested by the NRA were not well suited for rural areas. Only two out of the 17 proposed models were mud masonry, the standard housing model in the rural areas. Furthermore, there was a dearth of skilled masons and appropriate construction materials needed in the rural areas to be able to follow the NRA's reconstruction guidelines (Khadka and Jiang, 2019; Gurung et al., 2016; Bhandari and Hodder, 2019; Bothara et al., 2016). Due to this situation, there was a trend for self-construction with locally available materials without following the NRA's guidelines in the rural areas (Khadka and Jiang, 2019).

We verify with the DHS data that the urban and rural areas have different trends in terms of construction materials used. That is, using data on the main material used to construct the walls, roof, and floors of the household's residence, we construct an indicator for the use of construction materials unrecommended by the NRA and/or available cheaply in the local market—such as sand, dung, mud, bamboo, and palm leaves. This indicator takes unity if the floor, wall, and roof have been constructed using these materials and broadly reflects non-compliance of the NRA's guidelines. There was a significant increase in the likelihood of using unrecommended construction materials in the rural areas that experienced intensity 8 but not in the urban areas (columns (3) and (4) of Table A20). This provides suggestive evidence that rural households disregarded NRA guidelines and completed their reconstruction using cheap, locally available materials even if they were not seismically sound. As a consequence, they were able to complete their reconstruction cheaply and rapidly.

Adding to the possibility of self-construction, reconstruction in the urban areas was far more complex than it was in the rural areas due to the scarcity of land, complexities involved with land registration, multi-ownership of land,[25] disputes among kin, higher costs of reconstruction, and so forth (Bothara et al., 2016). Moreover, the grant provided by the NRA was inadequate to reconstruct in accordance with the NRA guidelines. While the NRA's grant was the same between the urban and rural areas, the inadequacy was severer in the urban areas due to high construction costs (Daly et al., 2017; Housing Recovery and Reconstruction Platform, 2018; Schofield et al., 2019).

Furthermore, in the aftermath of the earthquake, most of the relief efforts from international humanitarian agencies were focused on the rural areas in Nepal (Housing Recovery and Reconstruction Platform, 2018; Shelter Project, 2019; Daly et al., 2017; Schofield et al., 2019). The NRA imposed a restriction that any combination of government and donor support should not exceed USD 3,000 per household, which falls far short of the amount needed to rebuild urban settlements. Due to this restriction, external actors ended up focusing more on the rural areas

[25] Multi-ownership of property is more prevalent in the urban areas than in the rural areas. In DHS data, 0.6% [1.7%] of females [males] hold a joint property (including a house, agricultural land, and non-agricultural land) in the rural areas as opposed to 1.3% [3.3%] of females [males] in the urban areas.

than the urban areas (Daly et al., 2017). It has also been observed elsewhere that humanitarian agencies prefer to focus their relief efforts in rural areas when given an option (MacRae and Hodgkin, 2016).

All of the above-mentioned factors suggest that reconstruction in the urban areas was much more complicated than that in the rural areas and that urban victims of the earthquake did not benefit from assistance as much as their rural counterparts. Because of these reasons, it is plausible that reconstruction and subsequent return to normalcy in the urban areas were much slower than those in the rural areas.

We test this possibility using the data from the Inter Agency Common Feedback Project, which include information on the reconstruction experience from respondents in the most affected districts. Table A21 shows that urban residents are less likely than their rural counterparts to have received reconstruction grant and more likely to have experienced delay in disbursal of grant (columns (1)–(3)). The urban residents are also less likely to have completed or even started reconstruction (columns (4)–(5)). Moreover, the urban residents expect longer time to complete reconstruction (columns (6)–(8)). The estimates in column (8) implies that, other things being equal, urban residents expect the time to complete reconstruction to be about 4.4 months longer than rural residents do. Further details of these findings are offered in Appendix E.

While the regression results in Table A21 do not address, among others, the potential endogeneity of the location of residence and not all the results discussed in the preceding paragraph are statistically significant, they are consistent with the possibility that the process of reconstruction for the urban residents were much more prolonged, difficult, and stressful because of its complexity and the lack of adequate assistance. This, in turn, would explain some of the impact heterogeneity between the urban and rural areas observed in the previous sections.

Finally, to rule out the possibility that our results are driven by the extent of damage experienced between the urban and rural areas, we run a regression of the variable measuring damage level on the urban indicator and some other covariates (details available upon request), where the damage level is a categorical variable that takes zero if there was no damage, one if there was minor damage, two if there was heavy damage, or three if the house was completely destroyed. This regression shows that the urban areas did not face significantly higher levels of damage than the rural areas. Hence, consistent with National Planning Commission (2015), the urban-rural disparity in our results was not driven by the urban-rural differences in damage levels.

9 Conclusion

In this paper, we have explored the link between exposure to a natural disaster event and the incidence of IPV, as reported by the victim. Based on a DiD estimation strategy, we conclude that exposure to the Nepal earthquake of 2015 has significantly increased the likelihood of IPV and a family history of violence tends to augment this impact. We also consistently find that the increase in IPV due to the earthquake occurred primarily in the urban areas. This increase is still observed even after taking into account the possibility of selective relocation, co-residence of couples, changes in the pattern of migration and remittances, and covariate-dependent time trend. Evidence from alternative outcome measures, crime statistics, and various other robustness checks also corroborate this result. Our results also suggest that the impact of earthquake on the incidence of IPV was temporary, rather than permanent.

As discussed in section 7, the increase in the incidence of IPV appears to be driven by increased stress in the urban areas. While economic stress may be important in the areas that are hit hardest, non-economic stress appears to be of primary importance. We have provided some evidence in section 8 that the process of reconstruction was prolonged and complicated and that the assistance provided for reconstruction was inadequate in the urban areas. These factors may have led to the disparity between the urban and rural areas in the stress and hence violence experienced by those women who were hit by the earthquake.

While there are studies that suggest the presence of a causal link between natural disasters and IPV, the magnitude of the impact of the former on the latter has not been well known. To our knowledge, this is the first rigorous study based on a quasi-experimental approach to make a sound causal inference about the impact of an earthquake on IPV. While there are a few studies that indicate the relationship between IPV and the earthquake in Nepal based on qualitative evidence (Bista and Sharma, 2019; Chaudhary et al., 2017; Standing et al., 2016), none of these studies provide a quantitative impact estimate or highlight the impact heterogeneity between the urban and rural areas. We argue that knowing the magnitude and heterogeneity of the impact is critical in the times of disasters when resources must be used efficiently.

From the contrast between the large impact in the urban areas and small impact in the rural areas, we see that it is critical to understand the potential sources of stress that may increase the incidence of IPV. Hence, even though creation and enforcement of building codes can potentially save lives (Anbarci et al., 2005), this study also underscores the importance of paying attention to other potentially negative consequences such as increased IPV when introducing such codes. The results of this study elucidate the need to direct relief efforts not just to rebuild houses and physical infrastructure but to mitigate increased stress to support long-term physical, psychological, and economic well-being of the vulnerable victims.

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Appendix

A Construction of comparable wealth score

In every DHS round, the wealth index for each household is calculated on the basis of the amount of assets. This wealth index can be used to compare a given household's wealth against the distribution of the wealth in a given survey round. However, comparisons of the DHS wealth index over time are not possible even within the same country, because the distributions could change over time. In order to address this issue, we created a wealth score for each household by pooling the two rounds (2011 and 2016) of the Nepal DHS data. We then followed the standard methodology used for creating DHS wealth index (Rutstein, 2015). Our inter-temporally comparable wealth score created in this manner has a high correlation coefficient of over 0.987 with the wealth index included in the DHS data for both 2011 and 2016 rounds. Therefore, our wealth score ensures the comparability between the two survey rounds while mostly retaining the features of the original DHS wealth index.

B Details of the placebo test

It is possible that we obtained our results on the impact of earthquake on IPV by chance due to the particular realization of the epicenter location. To address this concern, we conduct a placebo test. Specifically, we randomly pick a sufficiently large (1,500) candidate placebo epicenter points all over Nepal uniformly. Out of these, we drop those impacted by the earthquake with intensity 7 or above because they were genuinely impacted by the earthquake.

Since it is difficult to know the areas that would experience intensity 7 or above when the earthquake occurred at a placebo epicenter, we approximate the treatment areas by a circle with a radius of 50 kilometers. That is, we define the (placebo) treatment area as the area within 50 kilometers of a given placebo epicenter point. To ensure an adequate sample size for the analysis of each placebo epicenter, we only use those placebo epicenter points which have at least three DHS clusters within 50 kilometers of the placebo epicenter in the post-treatment period.[26] From the candidate placebo epicenter points that satisfy the above-mentioned conditions, we randomly pick 400 points for our analysis and run the DiD analysis. Hence, for each of the 400 placebo epicenter

[26] The average cluster size is 30. Hence, a cutoff of three DHS clusters would ensure an adequate number of observations in the treatment group. The results are similar when we change the cutoff for the number of DHS clusters to five. Additionally, we also get similar results when we change the cutoff distance for treatment to 30 kilometers.

points, we have an estimated treatment effect of being within 50 kilometers of the epicenter on experience of any physical violence.[27] In Figure A1, we plot the distribution of treatment effects obtained from the 400 placebo epicenter points. The vertical line indicates the treatment effect from the actual epicenter (0.130) based on the DiD specification where the treatment area is defined as the area within 50 kilometers of the true epicenter (Table A1). As Figure A1 shows, the treatment effect from the actual epicenter is large compared to the entire distribution of placebo treatment effects.

An important point to note here is that the actual epicenter produced imbalance of covariates between the treatment and comparison areas (Table 1). Likewise, when we consider the same covariates but with a treatment definition of 50 kilometers from the epicenter, covariates are also imbalanced. Arguably, if the covariate imbalance observed for the actual epicenter is very different from the covariate (im)balance observed for placebo epicenters, our placebo test may be invalid as it fails to take account of the fact that the treatment and comparison groups significantly differ in various observables.

To address this possibility, we calculate the proportions of the placebo epicenters for which the difference in the covariate means between the treatment and comparison areas is above the corresponding difference for the true epicenter using the treatment definition of 50 kilometers from the epicenter for each of the years 2011 and 2016. We find that, for each of the 10 covariates except the respondent's age in 2011 and the respondent's age and dummies for being Hindu, Buddhist, and Christian in 2016, the proportion lies between 0.05 and 0.95. Further, when the actual treatment areas in Figure 1 instead of 50 kilometer from the epicenter is used for the purpose of comparison, corresponding proportions for all covariates are between 0.05 and 0.95. Hence, the difference between treatment and comparison areas in covariates for the true epicenter is not very different, on avereage, from that for the placebo epicenters, and the placebo test results are unlikely to be driven by the covariate imbalance reported in Table 1.

Note that the distribution given in Figure A1 is only a crude approximation since the placebo test rests on the assumption that the earthquake affects the area within 50 kilometers of epicenter. Nevertheless, the placebo test suggests that the impact of exposure to the earthquake on any physical violence is not simply due to a chance location of the epicenter.

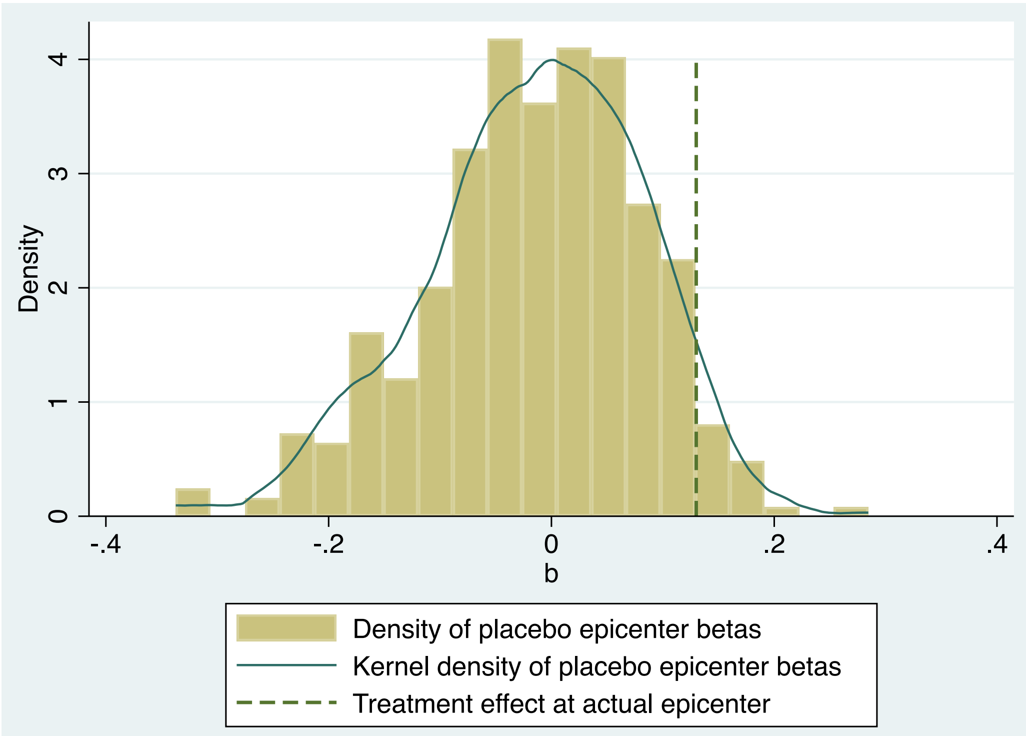
[27] We are unable to meaningfully run the placebo analysis separately for the urban and rural areas. This is because we typically have a very small number of urban observations within 50 kilometers of the actual epicenter in the post-treatment period. Hence, we chose to present the results only for Nepal and not for the urban and rural areas separately.

Table A1: Defining treatment as being within 50 kilometers of epicenter

	(1) Any physical violence
Within 50 km of epicenter×Post	0.130***
	(0.045)
Post	-0.077***
	(0.022)
Within 50 km of epicenter	-0.110***
	(0.033)
Observations	5,523
R^2	0.085
Mean of dep var	0.261

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

Figure A1: Distribution of treatment effects with placebo epicenters



Note: The proportion of placebo epicenters betas greater than the treatment effect beta at the actual epicenter is 0.045.

C Additional robustness checks

C.1 Alternative outcome measures

While our primary outcome of interest is the presence of physical violence, we would expect a similar change in the incidence of emotional violence. As reported in columns (1) and (2) of Table A13, we indeed find that this alternative measure of violence increased with earthquake exposure only in the urban areas but not in the rural areas. While emotional violence is also an important component of IPV, we choose to focus on physical violence elsewhere in this paper, because physical violence is a more objective measure.

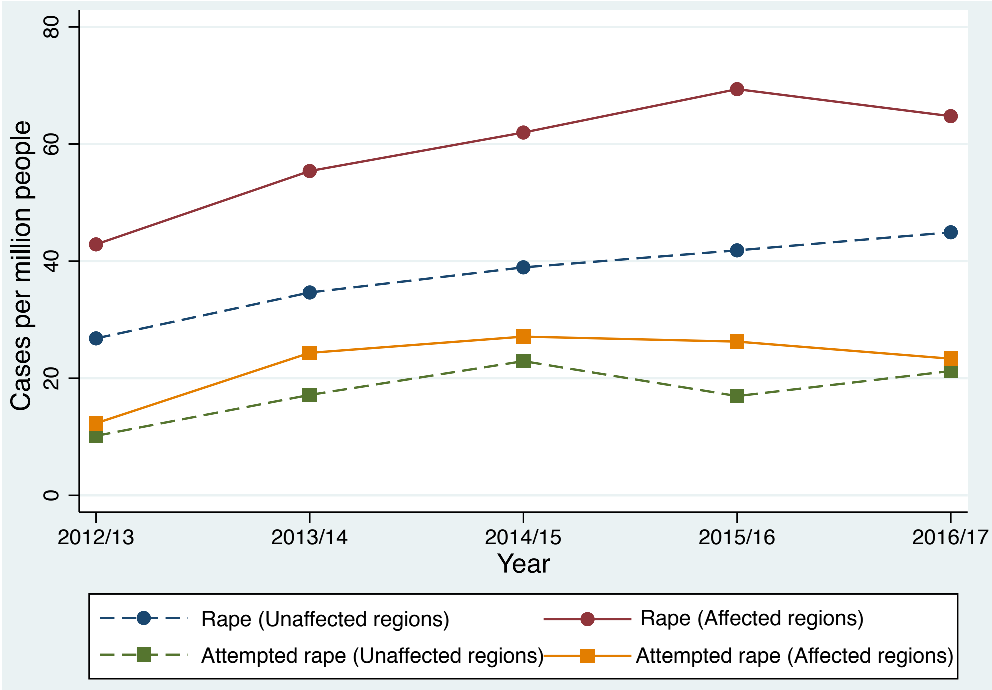
Another alternative outcome we examine is the number of violence types that the respondent experienced. That is, we count for each respondent the total number of violence types experienced among less severe violence, severe violence and sexual violence. Hence, this measure takes an integer value between zero and three. While putting an equal weight to different violence types may be objectionable, the number of violence types arguably supplements our main outcome measure of any physical violence, because the latter is insensitive to the increase in the variety of violence once there is any form of violence experienced by the respondent. The results based on this outcome are given in columns (3) and (4) of Table A13. Consistent with previous results, the urban respondents with an exposure to the earthquake experienced an increase in the number of violence types, but there was no corresponding change for the rural respondents.

Finally, as detailed in Appendix E, we construct a single aggregate index from all indicators of physical violence, following Kling et al. (2007). That is, we standardize the outcomes in the same family to have mean zero and unit standard deviation in the pre-treatment comparison observations and use the average of these standardized outcomes as the dependent variable. As reported in columns (1) and (2) of Table A14 in Appendix E, the results discussed above remains unchanged.

C.2 Evidence on violent crimes against women

We also use an additional data source to verify that crimes against women increased in response to the earthquake. While the violence measure we have studied so far is IPV, we hypothesize that there may be an overall increase in other forms of violence against women, such as rape and attempted rape, as a result of the earthquake. Since there are no spatially disaggregated crime statistics that cover both pre-treatment and post-treatment periods from a single data source, we compiled crime statistics from various sources.

Figure A2: Rape and attempted rape cases per million people



Specifically, we use the region-level data reported in the AROAG for the years FY2012/13–14/15 and the district-level data for the years FY2015/16–16/17 acquired from the Nepal Police. We cross-check these disaggregate data against the national statistics published in the Nepal Police.[28] The numbers of rape and attempted rape cases were found to be comparable between different sources and are used in our analysis.[29] We then aggregate the district-level data to the level of six regions[30] and express the number of cases per million people by dividing by the population in the region. In the final data, we have the numbers of rape and attempted rape cases per million people for each year between FY2012/13 and FY2016/17 in each of the six regions. Out of these, two regions—Mid and Valley regions—were most severely affected by the earthquake. We label them as "affected regions" and the rest as "unaffected regions."

In Figure A2, we plot the mean of rape and attempted rape cases per million people for the affected and unaffected regions separately. In this analysis, we find that the trends are similar between affected and unaffected regions in the pre-treatment trends, whereas the gap in crime rates widened for both rape and attempted rape in FY 2015/16. The gap then diminished in FY 2016/17. These indicate that the impact of the earthquake on violence is likely to be temporary

[28] `https://cid.nepalpolice.gov.np/index.php/cid-wings/women-children-service-directorate` accessed on November 29, 2020.

[29] While crime statistics for domestic violence are also available, there is unfortunately a large discrepancy between the AROAG and national statistics. For example, there is only one case of domestic violence in FY 2014/15 according the AROAG, but there are 8,268 cases according to the national statistic.

[30] These regions are Eastern, Mid, Valley, Western, Mid Western, and Far Western.

rather than permanent.[31]

C.3 Test of pre-treatment parallel trend

Another possible test would be to check if there are pre-treatment parallel trends, or parallel trends in the outcomes of interest between the treatment and comparison areas before the earthquake. To this end, we use the Nepal DHS for the year 2006. Since the Nepal DHS 2006 does not have a domestic violence module, we are unable to test pre-treatment parallel trend in any physical violence.[32]. However, it contains other intermediate outcomes such as male substance use, BMI of females, and nutritional status of children, which are affected by the earthquake as discussed in section 7. To test the pre-treatment parallel trends, we use the same specification as those used in section 7 and run the same DID regressions, except that we only use data from 2006 and 2011 and that Post is a dummy variable for 2011. If Treat×Post is statistically significant and has the same sign as those reported in section 7, it suggests that our results are driven by diverging time trends in the treatment and comparison areas.

Table A2 reports this analysis for smoking and white collar jobs for males and BMI for females, whereas Table A3 reports the same analysis for the nutritional outcomes of children. In both tables, the coefficient on Treat×Post is mostly insignificant and close to zero. The only exception is child anemia, where the pre-treatment trend appears to suggest that the children in the treatment areas are getting marginally *less* anemic relative to those in the comparison areas over time in the rural area. Taken together, there is no evidence that our results in section 7 are driven by diverging parallel trends between the treatment and comparison areas. This supports our argument that the estimated impact of the earthquake on IPV is driven by the stress it caused and not because of the diverging trends between the treatment and comparison areas.

C.4 Changes-in-changes estimation

In addition, we also consider the changes-in-changes model proposed by Athey and Imbens (2006). This model extends the standard DiD method to allow the time and treatment effects to differ

[31] In additional regression analyses (available on request), we regress rape per million people or attempted rape per million people on region dummies and year dummies plus an interaction term between the affected region dummy and a dummy for each of FY2012/13–16/17. For both rape and attempted rape specifications, we find that the coefficient of the interaction term is the largest for the year FY2015/16 with the p-value of around 0.115. For the remaining years, the coefficient is much smaller and p-value much larger.

[32] DHS survey does have questions concerning women's status, particularly questions pertaining to different scenarios under which respondents or their spouses agree that "beating is justified". However, we don't analyse these outcomes in the pre-treatment parallel trends analysis because they are not strongly correlated with actual experience of violence. The pairwise correlation coefficient is 0.0754, suggesting that the self-reported attitude towards violence is not a good predictor for actual incidence of violence.

Table A2: Test of pre-treatment parallel trends: Adult outcomes

	(1) Smoking	(2)	(3) White collar job	(4)	(5) BMI in normal range	(6)
	Urban	Rural	Urban	Rural	Urban	Rural
Treatment×Post	-0.018	-0.027	0.001	0.033	0.025	-0.024
	(0.045)	(0.037)	(0.062)	(0.035)	(0.046)	(0.029)
Treatment	-0.075*	0.117***	-0.040	0.000	0.002	-0.013
	(0.043)	(0.044)	(0.069)	(0.028)	(0.042)	(0.029)
Post	0.017	0.047**	0.002	-0.012	-0.059***	0.029**
	(0.027)	(0.019)	(0.038)	(0.015)	(0.022)	(0.014)
Observations	2,493	6,025	1,910	5,109	2,785	8,115
R^2	0.098	0.143	0.135	0.100	0.137	0.123
Sample	Males	Males	Males	Males	Females	Females
Mean of dep var	0.266	0.328	0.241	0.117	0.709	0.797

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

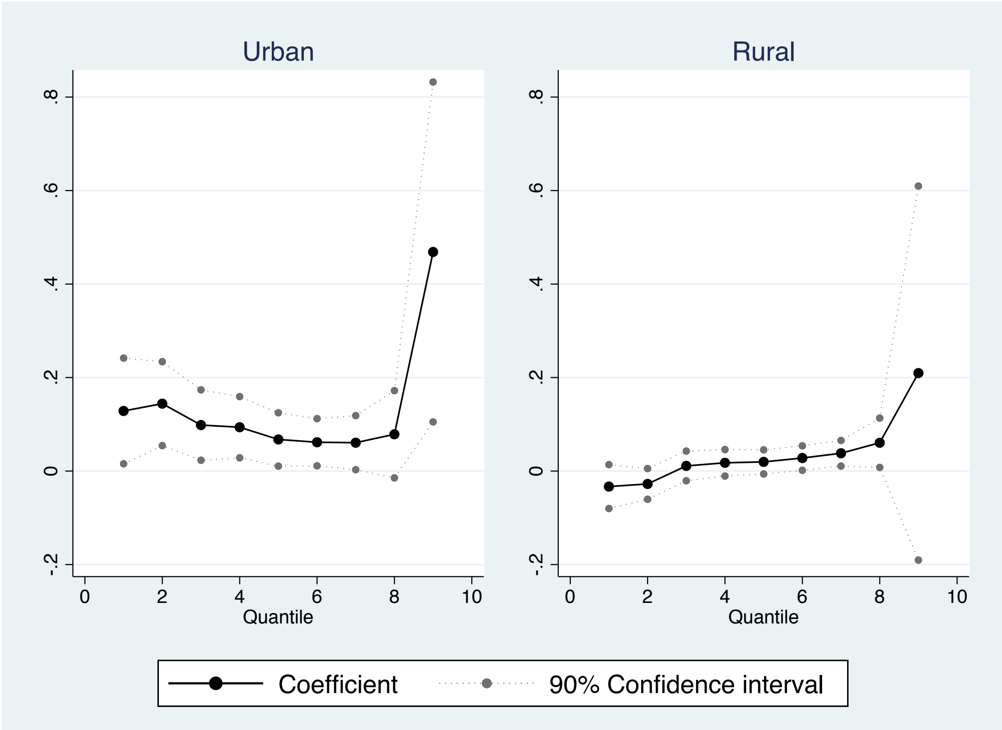
Table A3: Test of pre-treatment parallel trends: Child outcomes

	(1) Severe underweight	(2)	(3) Severely wasting	(4)	(5) Anemia	(6)
	Urban	Rural	Urban	Rural	Urban	Rural
Treatment × Post	-0.010	-0.014	0.007	0.002	-0.031	-0.069*
	(0.035)	(0.024)	(0.025)	(0.014)	(0.052)	(0.036)
Treatment	-0.038	-0.004	0.007	0.007	-0.056	0.009
	(0.035)	(0.023)	(0.015)	(0.011)	(0.055)	(0.029)
Post	0.011	-0.027**	0.016	-0.003	0.012	-0.018
	(0.029)	(0.011)	(0.019)	(0.006)	(0.038)	(0.016)
Observations	1,617	5,946	1,588	5,883	1,393	5,296
R^2	0.050	0.043	0.023	0.011	0.059	0.040
Mean	0.0726	0.107	0.0211	0.0290	0.188	0.221

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of household are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

systematically across individuals. In our context, this enables us to rule out the possibility that our estimates are confounded with the systematic difference between the treatment and comparison

Figure A3: Quantile change-in-change treatment effect on the treated in urban and rural areas



areas in the outcome measure in the pre-treatment period and its (counterfactual) time trend in the absence of earthquake.

Using a standardized measure of violence described in Section C.1 as the dependant variable, we estimate the quantile treatment effects on the treated.[33] In Figure A3, we report the treatment effects on the treated by conditional quantile change-in-change. The estimated impact of earthquake on violence for the treated subjects in 2016 is positive and significant at the mean and nearly every decile in the urban areas, but this is not the case in rural areas. For both areas, the impact appears to be similar across quantiles, except that the impact in the top quantiles in much larger than the rest. This appears to indicate that those who were at the highest risk of violence in the treated group in 2016 were affected most by the earthquake.

C.5 Clustering standard errors at alternate geographic levels

So far, we reported standard errors clustered at the level of DHS clusters. While this is a natural choice given the sampling design, one may argue that there may be correlations among unobservable terms at higher levels of aggregation. Therefore, we report the results with errors clustered at the levels of village development committee (VDC)/municipality and district in Table A4. We find that our main results are robust to clustering at these levels.

[33]We use STATA implementation module `cic` developed by Kranker (2019) to run this analysis.

Table A4: Clustering standard errors at alternative levels

Level of clustering	(1) VDC/Municipality	(2)	(3) District	(4)
Dep var: Any physical violence	Urban	Rural	Urban	Rural
Treat×Post	0.309***	0.025	0.309***	0.025
	(0.068)	(0.043)	(0.065)	(0.048)
Treat	-0.415***	-0.019	-0.415***	-0.019
	(0.104)	(0.052)	(0.110)	(0.064)
Post	-0.146***	-0.047**	-0.146***	-0.047**
	(0.043)	(0.022)	(0.042)	(0.023)
Observations	1,358	5,699	1,358	5,699
R^2	0.156	0.085	0.156	0.085
Mean of dep var	0.263	0.261	0.263	0.261

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Clustered standard errors are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

C.6 Distance from epicentre as treatment

Instead of discrete treatment, we also consider distance from the epicenter as an alternative, continuous definition of (lack of) treatment, since households closer to the epicenter tend to be exposed to more violent earthquake. As Table A5 shows, we find that being closer to the epicentre is associated with a significant increase in the likelihood of experiencing any physical violence in the urban areas but not in the rural areas.

D Details of the analysis of prior earthquake experience

To lend further credence to our hypothesis that stress could be a cause of violence, we adopt a triple difference specification in which the third difference is taken by the presence of prior experience of a major earthquake in addition to the differences between pre-treatment and post-treatment periods and between the treatment and comparison areas. Specifically, we look at whether individuals experienced the earthquake of magnitude 6.9 occurred in Nepal near the India-Nepal border region on August 21, 1988. This earthquake is reported to have killed 721 people, injured 6,553 people, and damaged 64,470 buildings in eastern Nepal (USGS, 2020a).[34]

[34]There was another earthquake that happened in 2011 near the border of Nepal and the Indian state of Sikkim. We don't consider this earthquake in the prior earthquake experience analysis because it only had a limited impact with six deaths (Wikipedia, 2023).

Table A5: Alternative treatment definition: Distance from epicenter

Dep var: Any physical violence	(1) Urban	(2) Rural
Distance from epicenter in km/100 × Post	-0.090***	-0.004
	(0.027)	(0.014)
Distance from epicenter in km/100	0.123***	0.046**
	(0.043)	(0.019)
Post	0.161**	-0.032
	(0.065)	(0.034)
Observations	1,358	5,699
R-squared	0.140	0.087
Mean	0.263	0.261

Distance from epicenter is measured in 100 kilometers. Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Clustered standard errors are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

Our hypothesis is that those individuals who have experienced this earthquake previously are likely to respond differently to the 2015 earthquake. If stress is indeed a mediating factor as we argued in the main text, we would expect to find that those with past experience of a major earthquake are less likely to become violent in the aftermath of the 2015 earthquake in comparison with those without such experience. Similar to the main analysis, we were able to identify those impacted by the 1988 earthquake using the ShakeMap of the earthquake by USGS (USGS, 2020b).

Even though some areas in Nepal experienced intensity 7 in the 1988 earthquake, none of the treatment clusters in DHS 2011 and 2016 data belongs to these areas. Therefore, we use the experience of intensity-6 earthquake in 1988 as the source of the third difference. While the damage from an intensity-6 earthquake is typically small in developed countries, it was clearly not the case in Nepal in 1988. For example, hundreds or thousands of residential buildings were damaged or collapsed in 24 districts, many of which experienced only intensity-6 earthquake (see Table 1.6 of Chaulagain et al. (2018)). This significant damage despite moderate intensity may be attributed to the heavy rainfall prior to the earthquake, which has weakened mud-stone and brick masonry buildings that are common in Nepal (Fujiwara et al., 1989). Hence, the exposure to intensity-6 earthquake in 1988 would count as relevant prior earthquake experience.

Specifically, we use the following triple-difference specification for our analysis:

$$\begin{aligned}\text{DV}_{it} &= \alpha + \delta_1 \text{Exp88Eq6}_i + \delta_2 \text{Post}_t + \delta_3 \text{Treat}_i + \gamma_1 \text{Post}_t \times \text{Exp88Eq6}_i \\ &\quad + \gamma_2 \text{Treat}_i \times \text{Exp88Eq6}_i + \gamma_3 \text{Treat}_i \times \text{Post}_t \\ &\quad + \beta \text{Treat}_i \times \text{Post}_t \times \text{Exp88Eq6}_i + \alpha_1 \text{Area88Eq6}_i \\ &\quad + \delta_4 \text{Exp88Eq7}_i + \gamma_4 \text{Post}_t \times \text{Exp88Eq7}_i + \alpha_2 \text{Area88Eq7}_i \\ &\quad + \alpha_3 \text{Alive88Eq}_{it} + \omega X_{it} + \lambda_{p(i)} + \epsilon_{it}, \end{aligned} \tag{3}$$

where Area88Eq6 [Area88Eq7] is a dummy variable for those who are in the area hit by the 1988 earthquake with intensity 6 [intensity 7], and Alive88Eq is a dummy variable for those who were alive (already born) at the time of 1988 earthquake. The interaction of these two dummy variables, Exp88Eq6 [Exp88Eq7], is a dummy variable for those who have experienced the 1988 earthquake with intensity 6 [intensity 7].

Our primary interest is in the respondents' exposure to the 1988 earthquake with intensity 6. In particular, we are interested in the coefficient β on the triple interaction term in eq. (3). However, we also include in eq. (3) the same set of terms for intensity 7 as that for intensity 6 to control for the effect of intensity 7 earthquake, except for those terms that involve Treat × Exp88Eq7 as they are all equal to zero in our sample.

We define Alive88Eq, and Exp88Eq6, and Exp88Eq7 in two alternative ways, one in which the status of being alive in 1988 is based on the husband's age and the other based on the wife's age. Table A6 reports the regression results based on eq. (3), where columns (1)–(3) and columns (4)–(6) use the definition of being alive in 1988 using the husband's age and wife's age, respectively.

In columns (1) and (4) of Table A6, we show the regression results for the entire sample. The coefficient on the triple difference term is negative but insignificant in both columns. In columns (2) and (5), we drop the marginal observations, or those who were less than 8 years old at the time of the earthquake. We do this because they may have been too young to remember the experience of the 1988 earthquake. Dropping the marginal observations make the coefficient on the triple difference term larger in absolute value when the prior experience is defined by husband's age. In columns (3) and (6), we further restrict our sample by dropping those who have not lived in the current location of residence for more than two years, since they may have migrated because of the 2015 Nepal earthquake (similar to the analysis in Table A9). Dropping those who have potentially migrated has made the coefficient even larger in absolute value when the prior experience is based

Table A6: Impact on violence by prior experience of earthquake: Triple differences

Prior experience by	Husband			Wife		
Dep var: Any physical violence	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post × Exp88Eq6	-0.116	-0.158	-0.187*	-0.146	-0.098	-0.123
	(0.101)	(0.111)	(0.112)	(0.106)	(0.129)	(0.131)
Treat × Post	0.101***	0.122***	0.151***	0.108***	0.118***	0.145***
	(0.034)	(0.041)	(0.044)	(0.035)	(0.040)	(0.042)
Treat × Exp88Eq6	0.114	0.080	0.087	0.074	0.030	0.036
	(0.082)	(0.090)	(0.091)	(0.085)	(0.091)	(0.091)
Post × Exp88Eq6	-0.027	-0.013	-0.008	-0.017	-0.007	-0.000
	(0.045)	(0.055)	(0.056)	(0.051)	(0.065)	(0.065)
Treat	-0.033	-0.019	-0.023	-0.011	-0.024	-0.024
	(0.039)	(0.045)	(0.046)	(0.040)	(0.050)	(0.052)
Post	-0.048**	-0.054**	-0.056**	-0.061***	-0.070**	-0.073***
	(0.021)	(0.025)	(0.025)	(0.022)	(0.027)	(0.028)
Exp88Eq6	0.014	0.035	0.026	0.037	0.030	0.023
	(0.051)	(0.053)	(0.055)	(0.049)	(0.053)	(0.054)
Area88Eq6	0.030	0.056	0.074	0.040	0.053	0.067
	(0.053)	(0.056)	(0.057)	(0.045)	(0.053)	(0.053)
Alive88Eq	0.016	0.001	-0.007	-0.007	-0.021	-0.022
	(0.022)	(0.035)	(0.034)	(0.022)	(0.043)	(0.045)
Post × Exp88Eq7	-0.126*	-0.147**	-0.141*	-0.095	-0.208***	-0.202***
	(0.067)	(0.073)	(0.074)	(0.067)	(0.072)	(0.073)
Exp88Eq7	0.134*	0.147**	0.160**	0.064	0.129**	0.133**
	(0.070)	(0.074)	(0.080)	(0.065)	(0.060)	(0.064)
Area88Eq7	0.098	0.131*	0.130	0.165***	0.180***	0.185**
	(0.065)	(0.070)	(0.079)	(0.060)	(0.069)	(0.075)
Observations	7,057	4,876	4,683	7,057	4,689	4,457
R^2	0.093	0.094	0.090	0.092	0.094	0.089
Incl those aged 0-7 in 1988	Yes	No	No	Yes	No	No
Incl those moved last 2 years	Yes	Yes	No	Yes	Yes	No
Mean of dep var	0.261	0.268	0.273	0.261	0.264	0.271

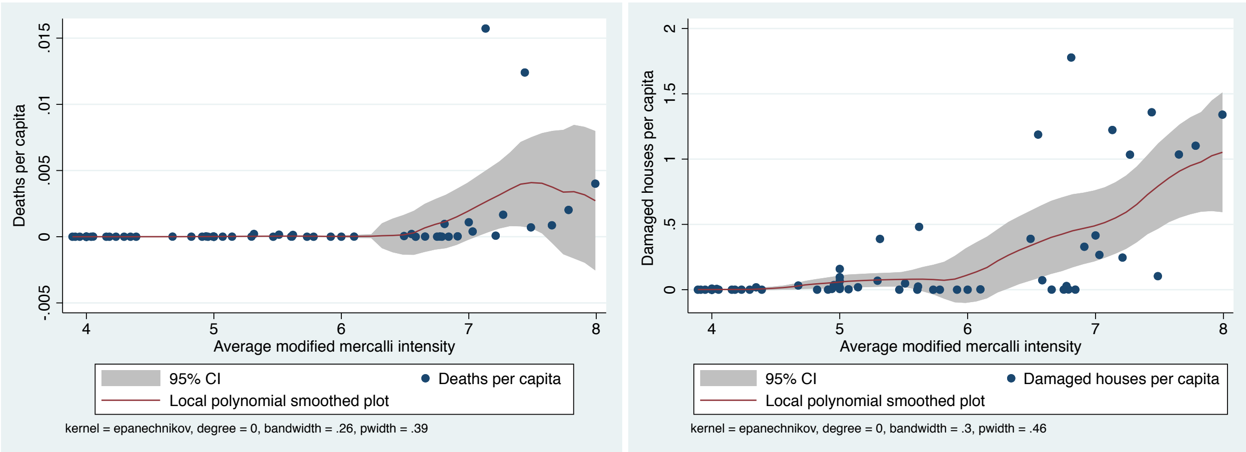
Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

on the husband's age. Indeed, the point estimate reported in column (3) is statistically significant, albeit marginally.

Overall, Table A6 indicates that those who were affected by the 1988 earthquake did not become as violent as those who were not, when the past experience is defined by the husband's age. Because the husband is the perpetrator of IPV in our context, it is not surprising that husband's prior experience affects the impact of earthquake on IPV more than his wife's experience. Taken together, the results presented in Table A6 corroborates our hypothesis that the past experience of a major earthquake has altered the propensity for the husband to become violent in the aftermath of the 2015 earthquake, possibly because the past experience lead to better disaster-preparedness, less stress, and/or lower likelihood of losing control.

E Supplementary Figures and Tables

Figure A4: Local polynomial smoothed plots of earthquake damage versus average MMI at the district level



(a) Deaths per capita

(b) Damaged houses per capita

Note: Graph (a) plots the local polynomial smoothed plot of deaths per capita at the district level versus the average MMI felt in the district. Graph (b) plots the local polynomial smoothed plot of damaged houses per capita at the district level versus the average MMI felt in the district. Data on district-level deaths and damaged houses caused by the earthquake was obtained from Nepal Disaster Risk Reduction Portal (2022).

In Figure A4, we present the local polynomial smoothed plots of the actual district-level damages caused by the earthquake as measured by deaths per capita and damaged houses per capita against the average district-level Modified Mercalli Intensity (MMI) using data from Nepal Disaster Risk Reduction Portal (2022).

Table A7 reports the results of baseline regressions with the cut-off varied from eight to five. That is, columns (1) and (2) report the regression results when treatment areas are those felt intensity 8 and above, columns (3) and (4) intensity 7 and above (these replicate columns (4) and (5) of Table 2), columns (5) and (6) intensity 6 and above, and columns (7) and (8) intensity 5 and above. As this table shows, exposure to the earthquake has significant impact on the likelihood of experiencing violence only for treatment definitions of intensity 7 and above and intensity 8 and above. For the remaining treatment definitions, we don't find any evidence of significant impact of exposure to the earthquake. As with Figure A4, Table A7 suggests that intensity 7 and above is a treatment defintion that is relevant in our context.

In Table A7, we present the results with alternative threshold MMI for the definition of

Table A7: Different intensity levels as treatment definitions

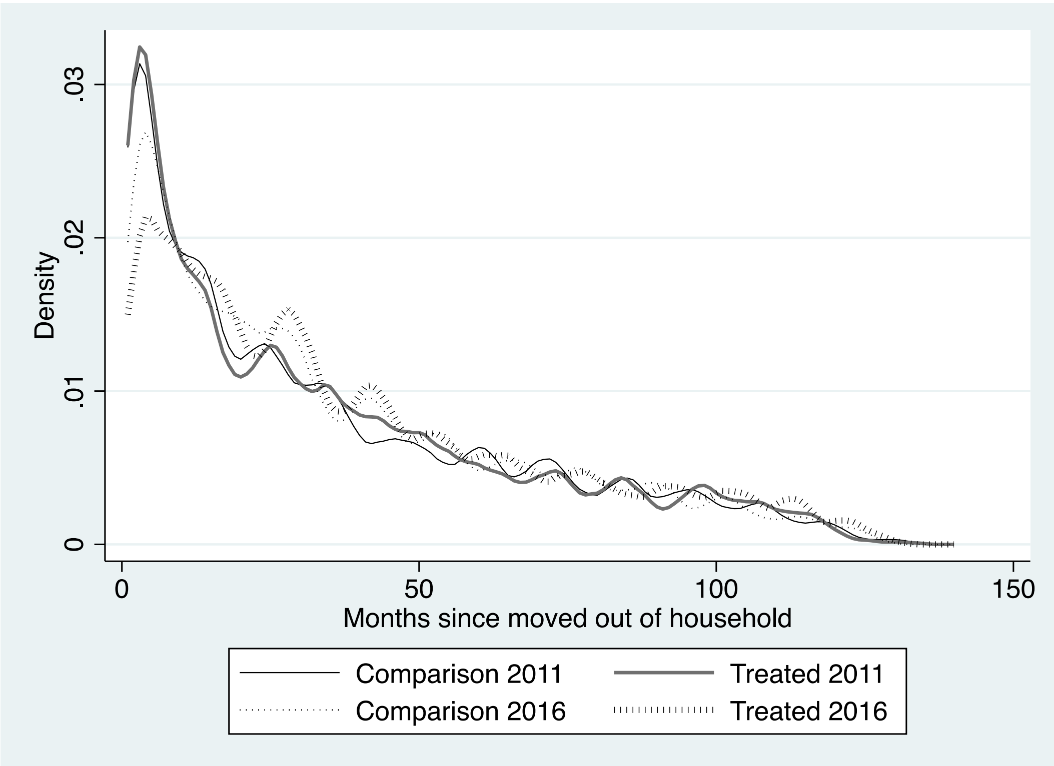
Dep var: Any physical violence	(1) Urban	(2) Rural	(3) Urban	(4) Rural	(5) Urban	(6) Rural	(7) Urban	(8) Rural
Intensity8above×Post	0.345***	0.077						
	(0.074)	(0.055)						
Intensity8above	-0.131***	-0.016						
	(0.045)	(0.050)						
Intensity7above×Post			0.309**	0.025				
			(0.065)	(0.042)				
Intensity7above			-0.415**	-0.019				
			(0.100)	(0.053)				
Intensity6above×Post					0.131	-0.003		
					(0.082)	(0.038)		
Intensity6above					-0.034	0.064		
					(0.089)	(0.044)		
Intensity5above×Post							0.122	-0.011
							(0.097)	(0.037)
Intensity5above							-0.000	0.058
							(0.062)	(0.035)
Post	-0.098**	-0.046**	-0.146***	-0.047**	-0.093**	-0.040*	-0.125	-0.035
	(0.045)	(0.020)	(0.049)	(0.023)	(0.045)	(0.021)	(0.081)	(0.027)
Observations	1,358	5,699	1,358	5,699	1,358	5,699	1,358	5,699
R-squared	0.148	0.086	0.156	0.085	0.128	0.086	0.126	0.086
Mean	0.263	0.261	0.263	0.261	0.263	0.261	0.263	0.261

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

treatment areas. In Columns (1)–(2), we take the areas experienced intensity 8 and above as the treatment areas. Columns (3)–(4) use intensity 7 as the threshold as was done in the main text. Hence these columns provides the same results as Columns (4)–(5) of Table 2. Columns (5)–(6) and (7)–(8) respectively use intensity 6 and intensity 5 as the threshold.

In Table A8, we present the results of the same regressions as the first two columns of Table 2 disaggregated by the urban and rural areas (columns (1)–(4)). We also disaggregate the treatment by treating intensity 7 and intensity 8 as separate treatments (columns (5)–(8)). In Table A9, we present the analysis of selective migration of husbands/partners. We remove the households in DHS 2016 that have been in their current place of residence for less than two years, since they may have potentially moved due to the earthquake (columns (1)–(2)). We also analyze a sample of those female respondents who are residing with their husbands/partners to address the possibility of selective migration of husbands (columns (3)–(4)). Table A10 presents the analysis of the pattern of marriage in two ways. First, we take the dummy variable for married respondents as the dependent variable (columns (1)–(2)). Second, we add an interaction term of Treat×Post with years since cohabitation to the set of covariates in our baseline specification eq. (1) (columns (3)–(4)).

Figure A5: Kernel density estimates of the months since migrant moved away



Note: The graphs above show the kernel density estimates of the number of months since a migrant moved away in the treatment and comparison areas for years 2011 and 2016. We use Epanechnikov kernel function with a bandwidth of two months.

Table A8: Disaggregation by urban and rural areas and by treatment intensity without controls

Dep var: Any physical violence	(1) Urban	(2) Rural	(3) Urban	(4) Rural	(5) Urban	(6) Rural	(7) Urban	(8) Rural
Treat × Post	0.265***	0.001	0.294***	0.032				
	(0.066)	(0.050)	(0.068)	(0.046)				
Treat	-0.198***	0.019	-0.411***	-0.039				
	(0.046)	(0.041)	(0.108)	(0.057)				
Affected8 × Post					0.383***	0.061	0.399***	0.088
					(0.081)	(0.060)	(0.080)	(0.060)
Affected7 × Post					0.154**	-0.020	0.179***	0.008
					(0.061)	(0.059)	(0.066)	(0.054)
Affected8					-0.231***	-0.051	-0.395***	-0.035
					(0.050)	(0.046)	(0.112)	(0.062)
Affected7					-0.171***	0.044	-0.326***	-0.031
					(0.050)	(0.048)	(0.110)	(0.061)
Post	-0.134***	-0.039	-0.149***	-0.064***	-0.134***	-0.039	-0.149***	-0.064***
	(0.051)	(0.026)	(0.050)	(0.024)	(0.051)	(0.026)	(0.050)	(0.024)
Observations	1,411	5,920	1,411	5,920	1,411	5,920	1,411	5,920
R^2	0.026	0.002	0.046	0.030	0.037	0.004	0.054	0.031
Controls	No	No	No	No	No	No	No	No
Province FE	No	No	Yes	Yes	No	No	Yes	Yes
Mean of dep var	0.263	0.261	0.263	0.261	0.263	0.261	0.263	0.261

Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

In Figure A5, we show the kernel density estimates of the number of months since a migrant moved away for the treatment and comparison areas in 2011 and 2016. The densities are similar across different subsamples except in the months immediately before the survey.

In Table A11, we combine DiD approach with kernel propensity score matching (Blundell and Dias, 2009; Villa, 2016). In this method, the post-treatment observations in the treated areas are matched with each of the post-treatment observations in the comparison areas, pre-treatment observations in the treatment areas, and pre-treatment observations in the comparison areas by some time-invariant covariates. The kernel densities of the propensity scores estimates in the treatment and comparison areas match up closely (results available upon request). Our results do not change much even when we restrict the sample to the common support of the propensity score (results available upon request). This suggests that our main results are unlikely to be driven by a combination of covariate-dependent time trend and unbalanced covariates. In Table A12, we alternatively include an interaction term of each control variable with Post in our baseline specification. Almost all the coefficients on the interaction terms with control variables are close to zero and statistically insignificant. Further, the coefficient on Treat×Post remains quantitatively similar. Taken together, there is no evidence that our results are driven by covariate-dependent time trend.

In Table A13, we report the regression results for alternative outcome measures or specifications. First, we use emotional violence as an alternative measure of violence—a dummy variable taking

Table A9: Removing relocating households and households with husbands/partners not residing together

	(1)	(2)	(3)	(4)
Sample	HH in current location for at least two years		Partners residing together	
Dep var: Any physical violence	Urban	Rural	Urban	Rural
Treat × Post	0.334***	0.038	0.274***	0.023
	(0.071)	(0.043)	(0.072)	(0.048)
Treat	-0.434***	-0.019	-0.430***	-0.040
	(0.109)	(0.054)	(0.122)	(0.063)
Post	-0.154***	-0.048**	-0.103*	-0.038
	(0.053)	(0.023)	(0.053)	(0.029)
Observations	1,306	5,474	993	3,674
R^2	0.152	0.081	0.129	0.072
Mean of dep var	0.266	0.266	0.258	0.262

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

Table A10: Marriage patterns

	(1)	(2)	(3)	(4)
	Married		Any physical violence	
	Urban	Rural	Urban	Rural
Treat×Post×Years since cohabitation			0.002	-0.000
			(0.003)	(0.002)
Treat×Post	-0.001	0.000	0.213***	0.046
	(0.001)	(0.000)	(0.065)	(0.044)
Treat	0.000	-0.000	-0.311***	-0.021
	(0.000)	(0.001)	(0.082)	(0.039)
Post	0.001	-0.001**	-0.122***	-0.058***
	(0.001)	(0.000)	(0.042)	(0.019)
Observations	3,765	15,534	1,358	5,699
R^2	0.002	0.001	0.166	0.096
Mean of dep var	0.707	0.771	0.263	0.261

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

unity if the respondent reports that she has ever been humiliated, threatened, or insulted by her partner and zero otherwise (columns (1)–(2)). Next, we use the total number of violence types experienced by the respondent among less severe violence, severe violence, and sexual violence,

Table A11: Matched DiD analysis

Dep var: Any physical violence	(1) Urban	(2) Rural
Treat × Post	0.269**	0.037
	(0.134)	(0.088)
Post	-0.182	-0.044
	(0.127)	(0.082)
Treat	-0.090	-0.005
	(0.107)	(0.056)
Observations	671	2,483
R^2	0.032	0.002
Mean of dep var	0.263	0.261

Covariates for propensity score matching include religion dummies, respondent's years of education, husband/partner's years of education, native language dummies and region dummies. Propensity scores are estimated with the DHS sample weights. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

which takes an integer value between zero and three (columns (3)–(4)). Finally, we include wealth as a control in the baseline model of any physical violence (columns (5)–(6)).

In Table A14, we create standardized outcome measures for each family of outcomes such as violence, substance use, and child nutrition, following Kling et al. (2007). For example, the standardized outcome measure for violence is created by normalizing a total of 12 component variables for less severe violence, severe violence, sexual violence, and violence-related injuries by subtracting the mean and dividing by the standard deviation of the pre-treatment comparison observations and then taking the average of the normalized variables. We construct the substance use index in a similar manner from alcohol consumption and smoking, and child nutrition index from severe underweight, severe wasting, and anemia. For each standardized outcome measure, we have only used observations for which all the component variables are non-missing.

In Table A15, we use the following three violence outcomes in the last one year: any physical violence (columns (1) and (2)), standardized physical violence (columns (3) and (4)), which applies Kling et al. (2007) to the underlying violence indicators in the same way as Table A14, and the number of violence types. In Table A16, we focus on the violence experienced in the last one year in the urban areas, and divide our observations into two samples: those who were surveyed in the first half of the data collection period ("early sample") and those who were surveyed in the second half of the data collection period ("late sample") in each survey round and report the results separately for each of them.

In Table A17, we explore the impact of the earthquake on two measures of child nutrition—being severely underweight and severely wasted with intensity 7 and intensity 8 considered as

Table A12: Adding interactions of control variables with post dummy

Dep var: Any physical violence	(1) Urban	(2) Rural
Treat×Post	0.298***	0.033
	(0.068)	(0.044)
Treat	-0.403***	-0.021
	(0.103)	(0.056)
Post	-0.133	-0.125
	(0.203)	(0.130)
Respondent's age	0.006	0.003
	(0.006)	(0.003)
Number of children	0.057***	0.010
	(0.021)	(0.011)
Husband/Partner's age	-0.009*	-0.003
	(0.005)	(0.002)
Respondent's education (years)	-0.009	-0.010***
	(0.005)	(0.004)
Husband/Partner's education (years)	-0.020**	-0.014***
	(0.008)	(0.003)
Hindu	0.012	-0.088
	(0.128)	(0.093)
Muslim	0.033	0.132
	(0.187)	(0.188)
Christian	-0.083	0.170
	(0.170)	(0.123)
Buddhist	-0.042	-0.135
	(0.148)	(0.097)
Age × Post	-0.000	-0.003
	(0.008)	(0.004)
Number of children×Post	-0.035	-0.009
	(0.032)	(0.014)
Husband/ Partner's age×Post	0.006	0.001
	(0.007)	(0.003)
Respondent's education (years)×Post	0.011	0.002
	(0.010)	(0.005)
Husband partner's education (years)×Post	-0.017	-0.005
	(0.012)	(0.004)
Hindu×Post	-0.080	0.191*
	(0.179)	(0.113)
Muslim×Post	-0.128	0.001
	(0.273)	(0.202)
Christian×Post	-0.113	0.080
	(0.243)	(0.155)
Buddhist×Post	-0.082	0.134
	(0.198)	(0.119)
Observations	1,358	5,699
R^2	0.163	0.089

Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

separate treatments.

In Table A18, the dependent variable is the wealth score, which was constructed following the standard DHS methodology as detailed in Appendix A. We first combine intensity 7 and intensity 8

Table A13: Emotional violence, number of violence types, and inclusion of wealth score in control

	(1)	(2)	(3)	(4)	(5)	(6)
	Emotional violence		Number of violence types		Any physical violence	
	Urban	Rural	Urban	Rural	Urban	Rural
Treat × Post	0.234***	0.015	0.532***	0.009	0.303***	0.025
	(0.054)	(0.032)	(0.120)	(0.072)	(0.065)	(0.042)
Treat	-0.277***	0.039	-0.705***	0.087	-0.398***	-0.020
	(0.067)	(0.036)	(0.172)	(0.083)	(0.100)	(0.053)
Post	-0.130***	-0.037**	-0.218***	-0.078**	-0.136***	-0.049**
	(0.035)	(0.014)	(0.083)	(0.033)	(0.047)	(0.023)
Wealth					-0.050**	0.007
					(0.025)	(0.011)
Observations	1,358	5,699	1,358	5,699	1,358	5,699
R^2	0.091	0.035	0.145	0.084	0.162	0.085
Mean of dep var	0.148	0.151	0.432	0.443	0.263	0.261

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Columns (5) and (6) include wealth score as an additional control. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

as one treatment (columns (1)–(2)) and then take them as separate treatments (columns (3)–(4)).

In Table A19, we take the dummy variable for males with a white collar job as the dependent variable, which takes unity if the male respondent is employed in a professional, technical, managerial, or clerical job, and zero otherwise. We first combine intensity 7 and intensity 8 as one treatment (columns (1)–(2)) and then take them as separate treatments (columns (3)–(4)).

In Table A20, our dependant variable is an indicator for the use of construction materials which were not recommended by the NRA. This variable takes unity if the floors, walls, and roof have been constructed using cheap and locally available materials that are not recommended by the NRA construction guidelines such as sand, dung, mud, bamboo, and palm leaves. We first combine intensity 7 and intensity 8 as one treatment (columns (1)–(2)) and then take them as separate treatments (columns (3)–(4)).

In Table A21, we use data from the Inter Agency Common Feedback Project regarding the reconstruction experience of those residing in the most affected districts. We find a negative relationship between the receipt of reconstruction grant and the urban dummy, though the relationship is statistically insignificant (column (1)). Among those who did not receive the

Table A14: Standardized outcome measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Any physical Violence (std)		Substance use (std)		Child nutrition (std)	
	Urban	Rural	Urban	Rural	Urban	Rural
Treatment×Post	0.291***	0.024	0.488***	-0.045	0.164*	0.069
	(0.081)	(0.040)	(0.113)	(0.088)	(0.087)	(0.060)
Treatment	-0.382***	0.053	-0.222	0.166*	-0.089	0.021
	(0.091)	(0.039)	(0.137)	(0.093)	(0.119)	(0.060)
Post	-0.072**	-0.030	-0.472***	-0.192***	-0.112**	0.018
	(0.037)	(0.020)	(0.085)	(0.042)	(0.054)	(0.027)
Observations	1,358	5,699	737	2,900	610	3,511
R^2	0.127	0.059	0.203	0.157	0.037	0.033
Mean of dep var	-0.105	-0.0759	-0.175	-0.131	-0.0738	-0.00566

The outcome variables are standardized outcome variables for each family of outcomes created using Kling et al. (2007). Each index variable is created by first normalizing the component variables by subtracting the pre-treatment comparison mean and dividing by the pre-treatment comparison standard deviation and then, taking the average of the normalized component variables. For each standardized outcome measure, only those observations are included for which there are non-missing values for all components. Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

Table A15: Violence in last one year

	(1)	(2)	(3)	(4)	(5)	(6)
	Any physical violence in last year		Any physical violence in last year (std)		Number of violence types in last year	
Subsample	Urban	Rural	Urban	Rural	Urban	Rural
Treat × Post	0.126***	0.041*	0.059	0.010	0.115*	0.030
	(0.042)	(0.023)	(0.067)	(0.045)	(0.068)	(0.041)
Treat	-0.146***	-0.027	-0.116	0.009	-0.163*	0.001
	(0.049)	(0.021)	(0.086)	(0.040)	(0.086)	(0.036)
Post	-0.087***	-0.027**	-0.009	-0.027	-0.071	-0.041*
	(0.030)	(0.013)	(0.043)	(0.022)	(0.046)	(0.022)
Observations	1,358	5,699	1,358	5,699	1,358	5,699
R^2	0.092	0.038	0.070	0.029	0.084	0.035
Mean of dep var	0.151	0.134	-0.0426	-0.0269	0.231	0.219

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

grant, respondents in the urban areas are significantly more likely to report a delay in disbursal as the reason for not receiving the grant (column (2)), and this finding remains qualitatively the same when the entire sample is used (column (3)). Hence, urban residents were more likely to report non-receipt of the grant because of disbursal delay. These results hold, even when we

Table A16: Violence in last one year in the urban areas: First half vs second half of data collection

	(1)	(2)	(3)	(4)	(5)	(6)
	Any violence in last year		Any violence (std) in last year		Number of violence types in last year	
Subsample	First half	Second half	First half	Second half	First half	Second half
Treat × Post	0.198***	0.070	0.169	0.004	0.227*	0.054
	(0.070)	(0.045)	(0.116)	(0.070)	(0.119)	(0.068)
Treat	-0.135**	-0.100**	-0.212***	-0.064	-0.176**	-0.113
	(0.058)	(0.047)	(0.063)	(0.118)	(0.072)	(0.102)
Post	-0.156***	-0.030	-0.112*	0.046	-0.192***	0.007
	(0.037)	(0.038)	(0.059)	(0.054)	(0.064)	(0.055)
Observations	680	678	680	678	680	678
R^2	0.156	0.082	0.123	0.066	0.130	0.082
Mean of dep var	0.160	0.141	-0.0119	-0.0737	0.257	0.204

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. First half [second half] subsample refers to those who were interviewed in the first [second] half of data collection in each survey round. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

Table A17: Children's nutritional status

	(1)	(2)	(3)	(4)
	Severe underweight		Severe wasting	
	Urban	Rural	Urban	Rural
Affected8 × Post	0.055*	0.016	0.054**	-0.020
	(0.033)	(0.041)	(0.027)	(0.014)
Affected7 × Post	0.014	0.001	-0.023	0.001
	(0.048)	(0.026)	(0.030)	(0.017)
Affected8	-0.120**	0.021	-0.047	-0.007
	(0.059)	(0.031)	(0.044)	(0.016)
Affected7	-0.092	-0.005	0.010	0.008
	(0.065)	(0.027)	(0.046)	(0.016)
Post	-0.041	-0.012	-0.033*	-0.003
	(0.031)	(0.011)	(0.017)	(0.006)
Observations	722	4,006	701	3,957
R^2	0.084	0.033	0.050	0.005
Mean of dep var	0.0467	0.0704	0.0184	0.0228

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the household level are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

control for the amount of damage that the respondents' houses sustained (results available upon request). We also run OLS regressions of the dummy variables for completing and starting

Table A18: Impact on wealth score

Dep var: Wealth score	(1) Urban	(2) Rural	(3) Urban	(4) Rural
Treat × Post	-0.115	-0.015		
	(0.163)	(0.117)		
Treat	0.350**	0.201**		
	(0.165)	(0.092)		
Affected8 × Post			-0.310*	-0.080
			(0.172)	(0.256)
Affected7 × Post			0.012	0.023
			(0.187)	(0.116)
Affected8			0.628***	0.026
			(0.167)	(0.232)
Affected7			0.251	0.209**
			(0.182)	(0.092)
Post	0.218*	0.189***	0.221*	0.190***
	(0.124)	(0.053)	(0.124)	(0.053)
Observations	1,358	5,699	1,358	5,699
R^2	0.511	0.423	0.516	0.427
Mean of dep var	0.645	-0.399	0.645	-0.399

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

reconstruction, and find that urban respondents were less likely to have started or completed reconstruction than their rural counterparts, even though the difference is statistically significant only marginally at best (columns (4)–(5)).

We further report ordered probit regressions of the expected time to complete reconstruction, which is a categorical variable.[35] The urban respondents are likely to report longer expected time to complete reconstruction among those who have not yet completed reconstruction (column (6)). We then construct the "zero-th" category for those who have already completed reconstruction and include it in the regression using the entire sample. In this case, the expected time to complete reconstruction is considered to be negative for those who have already completed reconstruction. The results are qualitatively similar even when we add the "zero-th" category (column (7)). To enable quantitative interpretation of estimated coefficient, we add a linear constraint that is consistent with the choices detailed in footnote 35. To express this idea clearly,

[35] The way the question was asked was unfortunately not sufficiently clear. The choices that are available to the respondents were (i) 1-5 months, (ii) 6-11 months, (iii) 1 year, (iv) 2 years, (v) 3 years, and (vi) more than 3 years. We chose to merge (vi) into (v) together and interpret the remaining choices as follows: (i) no more than 6 months, (ii) at least 6 months and no more than a year, (iii) at least a year and no more than two years, (iv) at least two years and no more than three years, and (v) at least three years.

Table A19: Impact on white collar job

Dep var: White collar jobs	(1) Urban	(2) Rural	(3) Urban	(4) Rural
Treat × Post	-0.094	0.036		
	(0.064)	(0.028)		
Treat	-0.024	-0.001		
	(0.072)	(0.022)		
Affected8 × Post			-0.169**	-0.007
			(0.074)	(0.045)
Affected7 × Post			-0.004	0.052
			(0.072)	(0.032)
Affected8			-0.001	0.065**
			(0.086)	(0.032)
Affected7			-0.074	-0.018
			(0.073)	(0.022)
Post	0.032	-0.004	0.032	-0.004
	(0.038)	(0.012)	(0.038)	(0.012)
Observations	1,053	3,806	1,053	3,806
R^2	0.137	0.098	0.144	0.101
Mean of dep var	0.223	0.240	0.223	0.240

Controls include male respondent's age, first wife/partner's age, number of children, respondent's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

let a_k for $k \in \{1, 2, \cdots, 5\}$ be the cut-off between $(k-1)$th and kth categories. Then, a_1, a_2, a_3, a_4, and a_5 correspond to the cut-off for 0, 6, 12, 24, and 36 months, respectively. This implies the following constraint:

$$a_2 - a_1 = (a_3 - a_1)/2 = (a_4 - a_1)/4 = (a_5 - a_1)/6. \quad (4)$$

The coefficient remains similar even when eq. (4) is imposed as a constraint in the ordered probit regression (column (8)). Since $a_2 - a_1$ represents six months in this regression, we can also compute the implied delay in expected time to complete reconstruction in the urban area relative to the rural area. Based on this calculation, the coefficient of 0.358 in the urban area implies 4.4 months (s.e.: 2.1 months) delay in the expected time to complete reconstruction. However, this estimate needs to be taken with a grain of salt for two reasons. First, as discussed in footnote 35, the wording of the choices for the expected time to complete reconstruction was not sufficiently clear. Second, the joint test of the equality constraints in eq. (4) using the unconstrained estimates (column (7)) is rejected at a 1 percent level of significance. Nevertheless, because the estimates of

Table A20: Impact on the use of unrecommended construction materials

Dep var: Using unrecommended materials	(1) Urban	(2) Rural	(3) Urban	(4) Rural
Treat × Post	0.022	0.043		
	(0.026)	(0.032)		
Treat	-0.100*	-0.114**		
	(0.057)	(0.048)		
Affected8 × Post			0.024	0.067**
			(0.024)	(0.026)
Affected7 × Post			0.021	0.035
			(0.029)	(0.039)
Affected8			-0.110*	-0.147***
			(0.056)	(0.042)
Affected7			-0.099*	-0.106**
			(0.058)	(0.052)
Post	-0.028	-0.060***	-0.028	-0.060***
	(0.025)	(0.020)	(0.025)	(0.020)
Observations	3,765	15,534	3,765	15,534
R^2	0.132	0.085	0.133	0.086
Mean of dep var	0.0271	0.0739	0.0271	0.0739

Controls include respondent's age, husband/partner's age, number of children, respondent's years of education and husband/partner's years of education, religion dummies for Hinduism, Islam, Christianity, and Buddhism, and provincial fixed effects. Standard errors clustered at the level of DHS clusters are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.

$a_1, \cdots, a_5$ are quantitatively similar with or without the constraint (details available upon request), the implied delay in the expected time to complete reconstruction calculated here would still serve as a crude guide.

Table A21: Urban-rural disparity: Reconstruction assistance and timeline

	(1) Grant received	(2) Delay in disbursal	(3) Delay in disbursal	(4) Reconst. complete	(5) Reconst. started	(6) Expected timeline	(7) Expected timeline	(8) Expected timeline
Urban	-0.067	0.212**	0.061*	-0.046	-0.038*	0.389**	0.353**	0.358**
	(0.048)	(0.090)	(0.032)	(0.028)	(0.023)	(0.186)	(0.171)	(0.174)
Observations	2,029	408	2,029	2,066	2,066	1,377	1,587	1,587
R^2	0.119	0.244	0.126	0.076	0.050	0.284[a]	0.199[a]	0.210[a]
Model	OLS	OLS	OLS	OLS	OLS	Unconst. oprobit	Unconst. oprobit	Const. oprobit
Sample	All	Grant not received	All	All	All	Reconst. incomplete	All	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.798	0.156	0.0315	0.106	0.121	2.651	2.295	2.295

Controls include respondent's age, gender, caste, occupation and district fixed effects. Standard errors clustered at the ward level are reported in parentheses. Statistical significance at 1, 5, and 10 percent levels are denoted by ***, **, and *, respectively.
[a]: Pseudo R^2 by McKelvey and Zavoina (1975). This measure mimics the underlying continuous-data R^2 (Veall and K.F., 1992).

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