Institutions under Pressure: The Effect of Community Groups on Forest Preservation after a Natural Disaster

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Abstract

We study the resilience of community-based institutions when they are under pressure. Specifically, we investigate whether community-based forest user groups lead to a reduction in forest loss when there is a sudden, large increase in demand for forest resources. To this end, we combine remote sensing data with detailed administrative data on community-based forest user groups and exploit spatial variation in the intensity of the 2015 Earthquake in Nepal. We first show that the earthquake led to a significant increase in deforestation in the highly affected areas relative to the less affected areas, due to a large increase in demand for wood after the earthquake, e.g., for reconstruction. In our main finding, we then show that the earthquake-induced increase in deforestation is significantly lower in locations with forest user groups. Disasters can exogenously increase pressure on resources, weaken the functioning of institutions, and affect the enforcement of rules. As such, they can be seen as a lens through which one can analyze possible effects of climate change, migration, and population growth on institutions. Our findings show that promoting community-based institutions can be an effective policy for reducing deforestation even in times of increased pressure on resources and institutions.

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1 Introduction

Community-based institutions are widely used to deal with a range of challenges, including the governance of common resources (Ostrom, 1990), decisions about the use of development aid (Mansuri and Rao, 2012; Casey, 2018), and the identification of individuals who are eligible for aid (Alatas et al., 2012). In particular, community-based forestry institutions, in which local groups of forest users are allowed to design and enforce the rules governing the use of their forest, are frequently employed as a tool to help conserve forests through sustainable use (e.g., Gilmour, 2016). In less developed countries, community-based forestry is also seen as a way to help to improve the welfare of the poor (Persha et al., 2011). Globally, around 15.5% of forests are under community management. The number is even higher in low and middle-income countries, with about 30% of forests managed through community-based forestry (RRI, 2014). Yet, despite a comprehensive literature investigating the effects of community-based forestry, questions about its effects on forest and livelihoods of forest users remain (for meta-analyses see, e.g., Hajjar et al., 2016; Bowler et al., 2012; Pagdee et al., 2006). One particular question that has so far received little attention is about the resilience of these community-based institutions when the pressure on forests suddenly surges. Sustained population growth, migration, and conflicts, in combination with adverse effects of climate change, will further increase the pressure on institutions and resources in many parts of the world and on forests in particular (e.g., Davidson et al., 2012; DeFries et al., 2010; Kirilenko and Sedjo, 2007). Thus, the question of the resilience of community-based institutions, in particular those for forest governance, will continue to increase in importance. Natural disasters can be a lens through which the effect of increased pressure on institutions can be studied.

This paper contributes to a better understanding of the role of community-based institutions in sustainable forest management, with a study of Community Forest User Groups (CFUGs) in Nepal. Specifically, we investigate the effect of these institutions when there is a sudden, large increase in local demand for forest resources. Our study employs a comprehensive administrative database that covers all 75 districts of Nepal and about 20,300 CFUGs, which we combine with remote sensing data on forest loss. To identify causal effects, we exploit spatial variation in the intensity of the large earthquake that hit parts of Nepal in 2015. We proceed in two main steps. We first show – using a difference-in-differences approach – that the earthquake led to a significant increase in deforestation in the more affected areas, as measured by earthquake intensity, relative to those areas that were less affected by the earthquake. We find this increase even after controlling for direct effects through landslides, therefore, we attribute the increased deforestation to a large increase in demand for wood after the earthquake, e.g., for recon-

struction (GoN MoSTE, 2015). In a second step, we then investigate whether CFUGs affect forest loss. Building on the difference-in-differences framework, we use a triple difference specification to show that the effect of the earthquake on deforestation is smaller in localities that have a higher share of forest area under CFUG governance. Finally, we study the heterogeneity of these CFUG effects and find some evidence to suggest that the CFUG effect is larger in locations where households are poorer, where fewer households receive remittances, where there are larger shares of agricultural households, and in locations that are experiencing larger population growth. Further, in locations where voter turnout – a proxy for social capital – is larger, the CFUG effect on forest sustainability is also larger. We also analyze heterogeneous effects of (pre-earthquake) CFUG attributes and find that the effect of CFUGs is larger if more women are involved in CFUG management. Overall, the findings show that community-based institutions are successful in reducing deforestation even in times of stress.

The key empirical difficulty in establishing causality is the non-random allocation of CFUGs. Local socio-economic, geographic, and environmental factors may influence both the presence of CFUGs as well as forest loss. In the central part of the empirical analysis, we employ a triple difference strategy, which exploits variation in the dimensions time, earthquake intensity, and CFUG presence. This approach controls for all ward-level characteristics that are fixed over time (and which may be correlated with CFUG presence). The triple difference specification also rules out that unobserved time-varying effects of CFUG presence bias our result. Yet, one may still be concerned about CFUGs having time-varying effects that depend on ward-level characteristics. We address this possible concern (as well as the more remote concern that earthquake intensity may be correlated with local characteristics that determine the response to the earthquake in a systematic way) using two strategies. First, we demonstrate that baseline results are robust to the inclusion – into the baseline difference-in-differences as well as the triple difference specification – of a large number of additional two-way and three-way controls that interact time, earthquake intensity and local characteristics that may be correlated with earthquake intensity or may determine CFUG presence. Second, we also show robustness of our results based on the method proposed by Oster (2019).

Nepal has a strong focus on community-based forestry. In 1993, the government of Nepal adopted a new "Forest Act, 2049 (1993)" and launched a nationwide initiative to transfer national forests to local communities.[1] The CFUGs - established as a result of this shift in policy - autonomously decide on forest governance, such as managing and protecting forests or distributing the benefits (Agrawal and Ostrom, 2001). In

[1] "Forest Act, 2049 (1993)", section 2h defines "Community Forest" as "the National Forest handed over to users group [...] for the development, protection and utilization of common interest in the interest of the community (Forest Act, 1993, p. 3)."

addition to emphasizing local participation, CFUGs include marginalized groups, such as women and the poor, in the decision-making process (Leone, 2019; Persha et al., 2011; Bhattarai, 1985). Today, about 35% of forests in Nepal are under community management, and Nepal is recognized as one of the first and leading countries to embrace community forestry as its primary national forest policy (Thwaites et al., 2017; Pandit and Bevilacqua, 2011; Charnley and Poe, 2007). Existing studies that have investigated the effect of CFUGs in Nepal on forest sustainability have concluded that CFUGs reduce the use of forest-related resources (e.g., Leone, 2019; Oldekop et al., 2019; Persha et al., 2011; Edmonds, 2002).

This study advances the literature on CFUGs, including several papers that also study Nepal, in the following ways. The main innovation of this paper is to study the resilience of CFUGs in times of stress. Specifically, we exploit a sudden, large increase in pressure on the demand for forest resources, which is due to the 2015 earthquake, to study the effect of CFUGs when pressure on forests is high and institutional oversight from the government's side is likely low because the government is preoccupied with many other pressing concerns in the aftermath of the earthquake. Second, our empirical approach, a triple difference analysis, exploits variation in earthquake intensity and thus uses a novel strategy for identifying the effects of CFUGs. Previous studies have relied on the quasi-random rollout of CFUGs (Edmonds, 2002) or have employed matching procedures (Oldekop et al., 2019). Third, some of the previous papers have relied on data from smaller regions (e.g., Edmonds, 2002). In contrast, this paper uses data that cover all 75 districts of Nepal and data on CFUGs, which collectively cover about half of all Nepalese households.[2] Fourth, we provide an insight into mechanisms, by a comprehensive analysis of heterogeneous effects, based on both CFUG and locality (ward-level) characteristics. Fifth, we use wards (the smallest administrative units in Nepal) as a unit of analysis and thus provide a spatially finely disaggregated analysis.[3]

Our empirical strategy exploits variation in earthquake intensity of the large earthquake of 7.8 magnitude on the Richter Scale that occurred in Nepal on April 25, 2015. This earthquake together with an aftershock in May 2015, led to 9,000 deaths and to 500,000 destroyed and 250,000 partially damaged houses (NPC, 2015).[4] It induced demand of approximately 51.8 million cubic feet of timber for reconstruction (GoN MoSTE, 2015). Other consequences of the earthquake, such as the loss of income sources and the need to build temporary houses, have added to increased demand.[5] Thus, the earth-

[2]About 48% of all Nepalese households, mostly from rural areas, are members of a CFUG.

[3]Oldekop et al. (2019) uses Village Development Committee (VDC), a larger administrative level, as a unit of analysis and considers the CFUG area relative to the total VDC area.

[4]It also destroyed 6,200 government buildings, 1,227 health facilities, and 8,300 school buildings.

[5]The loss of alternative sources of income may have led households (and communities) to rely on income generation by selling timber. Further, there was a need to build temporary housing quickly.

quake generated sudden, enormous pressure on forest resources, particularly in highly affected areas. Consequently, the earthquake increased the need for coordination to avoid the overuse of the common-pool resource forest. Because CFUGs were set up with this goal, we may expect localities with CFUGs to show less forest loss than those without CFUGs.[6] In addition, the central and local governments were preoccupied with handling the immediate implications of the emergency, resulting in a loss of government oversight in many other activities.[7] This lack of government oversight may have restrained citizens even less from overusing forests, thereby increasing the possible role of CFUGs.

At the same time, the earthquake may have led to the reduced functionality of CFUGs. First, the loss of lives, injuries, and damage to houses and livestock may have induced the shifting of priorities of CFUG members from long-term forest sustainability to securing the short-term livelihoods of household members. Second, heterogeneity in earthquake-related impacts may have affected social cohesion within CFUGs. Third, the above-mentioned reduction in government oversight over local activities may have contributed to the reduced functioning of CFUGs. In sum, several channels exist through which the earthquake may have affected both the CFUGs' ability to enforce sustainable use of forests as well as the intensity of the use of forests. The net effect of these channels is unclear. Our primary goal is to investigate empirically this net effect that CFUGs have on forest use in light of varying degrees of earthquake exposure.

Strong earthquakes are not frequent in Nepal. The last major earthquake of a similar magnitude occurred in 1934. Therefore, the earthquake can be assumed to be unanticipated, and the effects are likely not moderated by preventive measures, especially not ones that are correlated with CFUG presence, further supporting our identification strategy. Additionally, the earthquake's timing and location can be relatively cleanly determined, allowing for a clear identification of pre- and post-earthquake periods and of affected (treated) and unaffected (control) areas.[8]

In sum, we demonstrate a link between the community-based forestry institutions, CFUGs, and forest loss. To establish causality, we exploit the quasi-experimental variation in earthquake intensity in a difference-in-differences and a triple difference specification, complemented by various robustness checks. We first show a relatively larger

Temporary houses are more likely to rely on wood for the foundation, the wall, and the roof than permanent houses (NLSS, 2011).

[6]Because of high transportation costs, in particular in the mountainous terrain of Nepal, most demand will be met locally whenever possible. Thus, we expect local variation in demand to translate into local variation in pressure on forests.

[7]For example, in Pathak and Schündeln (forthcoming), we show that the distribution of emergency aid after the earthquake was delegated to local actors, which was accompanied by discrimination and favoritism.

[8]We use Modified Mercalli Intensity (MMI) data, based on the US Geological Survey, as our exogenous measure of earthquake intensity. For details, see the Data section 3.3.

increase in forest loss after the earthquake in areas experiencing greater earthquake intensity. We then show that this effect is smaller in areas with a higher share of CFUGs. The results show that CFUGs lead to a reduction in forest loss, even in times of large pressure on forests, and during times in which CFUG functioning itself might be under pressure.

This paper relates to several areas of research. Our paper is most closely connected to the literature on the role CFUGs play for forest sustainability. While some papers show that CFUGs in various parts of the world are not achieving their goals (for a review see Gilmour (2016), examples include Pacheco et al. (2012), Tole (2010), and Charnley and Poe (2007)), others show moderate successes (this includes papers focusing on Nepal, e.g., Leone (2019), Oldekop et al. (2019), and Edmonds (2002), as well as papers covering larger sets of countries, e.g., Persha et al. (2011) and Chhatre and Agrawal (2009)). Other empirical evidence is either mixed (for meta-analyses see, e.g., Hajjar et al., 2016; Bowler et al., 2012; Pagdee et al., 2006) or context-specific (e.g., Wright et al., 2016; Rasolofoson et al., 2015).[9] The paper further contributes to the literature on the institutional environment, particularly the ownership structure, on forest use.[10] The paper also connects to the large body of literature on communities under pressure during natural disasters (e.g., Ntontis et al., 2020; Wickes et al., 2017) or during major epidemics or pandemics (e.g., Jørgensen et al., 2021; Fong and Chang, 2011; Rubin et al., 2009). Finally, the paper relates to a set of papers that show that communities with larger pre-existing social capital or stronger social networks are more resilient to a disaster (e.g., Misra et al., 2017; Wickes et al., 2017; Aldrich and Meyer, 2015; Norris et al., 2008).

The rest of the paper is organized as follows. The next section provides background on forest and forest management and the 2015 earthquake in Nepal. The third section presents and discusses the data. Section four lays out the empirical strategy and presents the results. A final section concludes.

[9]For example, Rasolofoson et al. (2015) find that only community forests that did not permit the commercial use of forests were successful in reducing deforestation in Madagascar. Wright et al. (2016) show lower levels of deforestation only when CFUGs engage with local government in Bolivia.

[10]For example, various cross-country analyses show that countries with better property rights (e.g., Culas, 2007) have been able to reduce deforestation.

2 Background

2.1 Forests and forest management in Nepal

Forests in Nepal cover about 5.5 million hectares, 37% of its area (DoF MFSC, 1997), ranging from tropical to alpine forests (Negi, 1994). Most Nepalese live in rural areas and rely on forests for a livelihood that includes the use of firewood for fuel, and the use of fodder for their livestock (Kandel et al., 2016; Ojha, 2006). Forests are also used to provide timber for housing construction (GoN MoSTE, 2015). We calculate that 64% of all households use wood as their primary fuel for cooking. Further, about 70% of households use fodder for their livestock, of which 23% is collected from forests.[11]

To conserve previously privately owned forest, and to increase state revenues, the Nationalization Act of 1957 adopted a centralized forest management and handed the forest ownership to the government. However, due to the lack of government's direct involvement in forest affairs (mainly in rural areas), forests continued to be illegally exploited (Carter and Gronow, 2005; Hobley et al., 1996), and deforestation rates were among the world's highest (approximately 2.7% per annum between 1947 and 1980 (Myers, 1986) and 1.7% per annum between 1978 and 1994 (UNEP, 2001)). According to FAO (2011), Nepal lost approximately 1.2 million hectares of forests (24.5% of its forest cover) between 1990 and 2010.

Theoretically, this unsustainable use of forest can be explained by the fact that forests suffer from incentive incompatibility and over-exploitation if the use is not properly governed or formal rules are not enforced, as was largely the case in Nepal. Collective action in the form of community-based management can offer a solution to this "tragedy of the commons" (Ostrom, 2009; Dietz et al., 2003; Ostrom, 1990). With this goal in mind, the forest management act from 1993 implemented community-based management. Specifically, it institutionalized Nepal's Community Forest User Groups (CFUGs).[12]

The CFUG data employed in our analysis consists of 20,365 CFUGs, which cover 1.9

[11] Calculations for firewood use are based on the 2011 National Population and Housing Census and the Housing registration for housing reconstruction survey, 2016. Similar numbers are reported by Kandel et al. (2016), who show that more than 70% of total energy, and 86% of the firewood is derived from forests, and by Edmonds (2002). Calculations for the role of fodder for livestock are based on the 2011 Nepal Living Standard Survey.

[12] Article 43 of Forest Act (1993, p. 21) characterizes a CFUG as an "[...] autonomous and corporate body having perpetual secession. [...] The Users' Group as a person may acquire, possess or transfer or otherwise manage movable and immovable property." CFUGs can manage, sell and distribute forest resources and make forest-use decisions based on their operation plan. The Forest Regulations (1995) further enabled forest user groups to establish wood-based commercial operations, reinforcing the joint initiative towards conservation and development (Hobley and Malla, 1996). The present-day CFUGs are governed and managed according to the forest regulation and operation guidelines (1995) (revised in 2009 and 2014) (Bluffstone et al., 2018).

million hectares of area, accounting for approximately 35% of the total forested area.[13] According to our data, about 2.6 million households are members of a CFUG.

2.2 The 2015 earthquake in Nepal

On April 25, 2015, an earthquake of magnitude 7.8 on the Richter scale struck Nepal, followed by a major aftershock of magnitude 7.3, on May 12. The earthquake led to 9,000 human casualties, and it severely damaged approximately 750,000 private homes and nearly 16,000 public buildings. The total damage was estimated to be USD 7.05 billion (NPC, 2015). The earthquake also led to over 5,000 landslides (Williams et al., 2018). The Department of Forests estimated that the total reconstruction activities required 51.8 million cubic feet of timber (GoN MoSTE, 2015).[14] Thus, we expect the earthquake to result both in a direct loss of forest due to landslides and an indirect loss of forests due to timber demand for reconstruction.

3 Data

This section discusses the main data sources. Other data are described in Appendix A.

3.1 Global Forest Change (GFC) Data

Forest loss is measured using the high-resolution Global Forest Change (GFC) dataset - version 1.6 - based on prior work by Hansen et al. (2013).[15] The resolution of these data is one arc-second, which in Nepal corresponds to a pixel size of approximately 27m $\times$ 27m. For each of these pixels, the data contain information on the baseline tree cover in 2000, i.e., the extent of vegetation taller than 5m. Central to our analysis is the information on the year in which forest loss, i.e., a change from a forest to a non-forest state, was detected between 2001 and 2018 (if forest existed in the base year 2000). This feature of the GFC data focuses our attention on an outcome, complete loss of forest cover, that is indicative of non-sustainable use: While it seems likely and unavoidable under the circumstances of the earthquake that there is a temporarily increased use of forest

[13] DoF MFSC (1997) estimated forested areas in Nepal to be around 5.5 million hectares. Thus, CFUG covers $1.9/5.5\times100\% \approx 35\%$ of the total forested area.

[14] Further, the Government of Nepal identified 22,256 households that need to be relocated (NPC, 2015). The relocation of households to safer (and most likely in previously forested areas) might also contribute to deforestation.

[15] The GFC data can be downloaded from https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.6.html (last accessed January 20, 2022).

resources, sustainable use of the forest is not compatible with the total loss of the forest cover, as it increases subsequent erosion and reduces chances of natural reforestation.

For each pixel, the data also contain a single binary indicator for whether forest gain occurred at some point between the years 2001 and 2012. The GFC data are derived from the Landsat satellite images taken during the growing season, which implies that our 2015 data refer to a period after the earthquake.

For our analysis, we aggregate the forest loss data at the ward level (wards roughly correspond to a village). In our main specification, we use baseline forest cover in 2000 as a weight. In robustness checks, we also show unweighted results (details are provided in Appendix, Section B).

3.2 Community Forest User Group (CFUG) data

Our primary source of information on CFUGs is an administrative database containing information on almost all CFUGs, which we obtained from the Department of Forests (DOF). The database contains information on the location of CFUGs, namely the Village Development Committee (VDC), and the ward(s) covered or partly covered by each CFUG, and the area covered (in hectares). However, for 1,764 out of 19,378 CFUGs that are recorded in the DOF database, the database has missing information on ward location.[16] Therefore, we supplement the DOF database with data from the Community Forest Decentralized Management Information System (CF-DMIS). The CF-DMIS constitutes an alternative database on CFUGs that provides information on the VDC(s) and ward(s) where CFUGs are located. CF-DMIS data allow us to cross-validate the quality of the DOF data and complement the DOF database on ward locations. It also enables us to identify about 1,000 additional CFUGs. A third source, the CFUG data from the Ministry of Forest and Soil Conservation, further allows us to validate the CFUG information from both DOF and CF-DMIS data.[17] In the end, we have complete data, i.e., including information on the CFUG's ward or wards (some CFUGs span multiple wards), for 20,365 CFUGs. The main results are robust to using only data from the DOF and not complementing it with data from CF-DMIS and the Ministry of Forest and Soil Conservation. Since we only consider the CFUGs that were registered before April 25, 2015, the CFUG data is not contemporaneous to the earthquake.

In our main specification, we calculate the share of the CFUG area relative to the ward's total forest area. In cases where CFUGs span multiple wards, we attribute

[16] Information on the VDCs for each CFUGs is almost complete. VDC-level data are used, e.g., in Leone (2019), Oldekop et al. (2019), and Oldekop et al. (2018).

[17] Additionally, for five out of 75 districts, we obtained information on the ward(s) covered by CFUGs through personal communication with district forest officers.

the community forest area to individual wards proportionally to their forest cover area in 2000. In robustness checks, we do not perform this adjustment and attribute the community forest area to affected wards equally.[18] The CFUG data also contain further information on the number of women in the executive committee and a forest condition assessment, which we use in the analysis of heterogeneous effects.

3.3 Modified Mercalli Intensity (MMI) data

To measure earthquake intensity, we use data provided by the US Geological Survey (USGS), namely the Modified Mercalli Intensity (MMI). The spatial MMI data provide a measure of the earthquake intensity, which is exogenous to our regression model.[19] A spatially continuous MMI map for the April 2015 earthquake is generated by the USGS, using ground motion data from 27 seismic stations that are located in Nepal and India, as well as subjective reports provided by citizens (the so-called "Did You Feel It?" (DYFI) system) (USGS, 2015).[20] For further information on MMI and the DYFI system, see Wald et al. (1999), Wald et al. (2011), and Worden et al. (2012). We measure the ward-level MMI at the centroid of the ward. MMI data are not available for the wards that are furthest away from the epicenter (see Figure 1). Given the distance from the epicenter, we assume that these wards belong to the least affected wards. We provide further discussion and robustness checks in Appendix, Section F.4.

3.4 Landslide data

To measure landslides, we use detailed, systematic, and geo-referenced landslide data prepared by Durham University in collaboration with the British Geological Survey (Williams et al., 2018), which identifies 5,578 episodes of landslides from April 25 to June 30, 2015.[21] The landslides are mostly concentrated in Gorkha, Dhading, Nuwakot,

[18]For a small subset (only about 1%) of CFUGs, DOF also provided a shapefile where we know their precise geographical location. In Appendix, Section C and Appendix figure 3, we use these CFUGs to illustrate how the ward level CFUG area share measures were calculated.

[19]While the well-known Richter scale magnitude is measured non-linearly (as the logarithm of the maximum amplitude of the earthquake waves), the MMI is measured linearly (Richter, 1935). Generally, MMIs range from 1 to 12. In our sample, MMIs range from 3.7 to 8.5.

[20]The shapefiles can be downloaded from https://earthquake.usgs.gov/earthquakes/eventpage/us20002926/shakemap/pgv?source=atlas&code=us20002926 (last accessed January 20, 2022).

[21]The data based on Williams et al. (2018) provides the landslide data as polylines. For more information, see http://community.dur.ac.uk/nepal.2015eq/ The data used in this paper were downloaded from https://data.humdata.org/dataset/nepal-earthquake-landslide-locations-30-june-2015 (last accessed May 12, 2020), which is no longer accessible. The full landslide map repository can now be downloaded from https://nepal2015eq.webspace.durham.ac.uk/landslide-maps/ (last accessed January 20, 2022). An alternative estimate of the number of landslides is provided by GoN MoSTE (2015), which estimates about 2,500 landslides. However, this number refers to only those landslides that occurred immediately after the earthquake. We use the data by Williams et al.

Rasuwa, Sindhupalchok, Dolakha, Ramechhap, and Kavre districts, and include landslides caused by the April 25 earthquake and the May 12, 2015 aftershock (Williams et al., 2018).

3.5 Sample restrictions

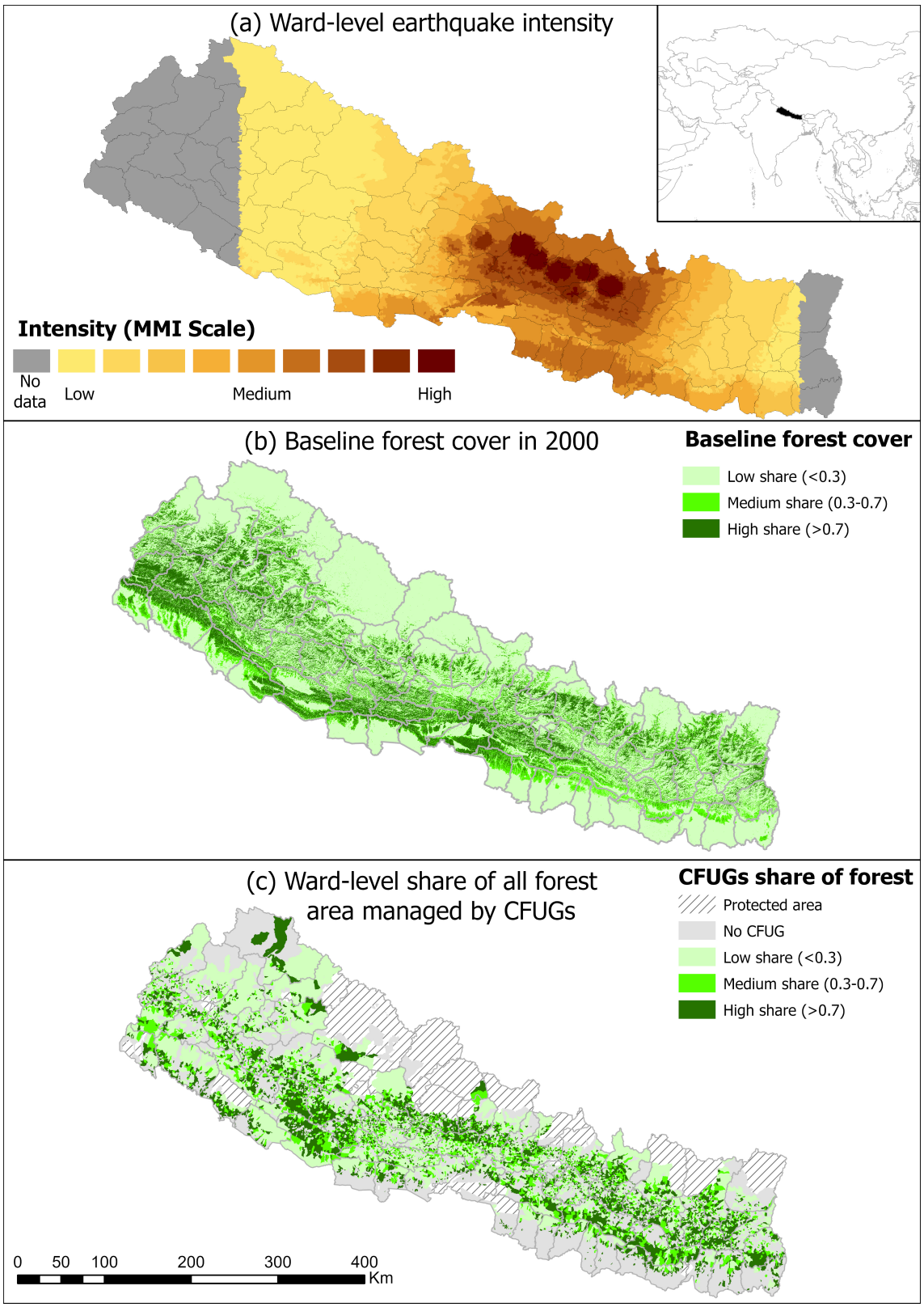
Nepal is divided into 36,288 wards (according to data provided by the Department of Survey of Nepal). Protected areas (national parks, conservation areas, wildlife reserves) fully cover 31 wards, and another 911 wards contain parts of protected areas. Protected areas in these wards are subject to different rules and might directly contribute to the deforestation patterns. Therefore, we omit all wards from our analysis that contain parts of protected areas, leaving us with 35,346 wards. Further, following a strategy similar to Alix-Garcia et al. (2013), we exclude 2,907 wards with no baseline forest cover. Thus, our final dataset contains 32,439 $\times$ 18 = 583,902 ward-year level observations.[22]

Figure 1 (a) shows the spatial distribution of the earthquake intensity measure, MMI, (b) shows the spatial distribution of the baseline forest cover in 2000, and (c) shows the spatial distribution of CFUG share relative to the ward's forested area.

(2018) because it includes landslides that occurred within about 5 weeks after the earthquake (i.e., including the aftershock), and the data also appear to be collected in a more systematic manner.

[22]Our results are robust to keeping wards with no baseline forest cover as well as keeping wards with protected areas. Further, the results are also robust to dropping wards with small shares of forest, with varying cutoffs, instead of dropping wards with no baseline forest at all (results not shown).

Figure 1: (a) Ward-level average earthquake intensity (based on the MMI scale), (b) Baseline forest cover in 2000, and (c) Ward-level average CFUG share relative to the total forested area



Source: Own calculations using USGS (2015), Hansen et al. (2013), and CFUG data

4 Empirical strategy and results

Our main analysis proceeds in two steps: we first show that the earthquake increased pressure on forests by showing that forest loss after the earthquake was larger in areas experiencing greater earthquake intensity. In a second step, we build on the difference-in-differences strategy of the first step and investigate the role of CFUGs on forest loss using a triple difference strategy. In both steps, we perform a large number of robustness checks, including one to investigate robustness to proportional selection of observables and unobservables (Oster, 2019). Finally, we also explore various mechanisms by which CFUGs might play a role in forest sustainability using pre-earthquake CFUG and ward characteristics. Throughout, we show results from OLS regressions, and our baseline is to cluster standard errors at the district level.[23] Our data cover all 75 districts of Nepal.

Landslides that were related to the earthquake led to significant destruction (see, e.g., Roback et al., 2018; Kargel et al., 2016) and more than 2,000 human deaths (GoN MoHA, 2015). The literature provides some evidence of forest loss due to earthquake-induced landslides for other countries (for China and Japan see, e.g., Sidle et al., 2018; Vina et al., 2011; Yin et al., 2009). To be able to focus on the forest loss due to human activity, we partial out forest loss due to landslides, using data on the locations of 5,578 separate landslides that are recorded in Williams et al. (2018). The details regarding the landslides data and the calculation of the magnitude of forest loss net of landslides are shown in Appendix, Section D. The subsequent analysis of loss of forests uses the forest loss net of landslides. To simplify the language, we use "forest loss" and "forest loss net of landslides" interchangeably. On the other hand, we call the value of forest loss that does not take landslides into account "total forest loss". All results are qualitatively and quantitatively very similar when we use total forest loss (see Appendix figure 5 and tables 11 and 12). Summary statistics for all central variables used in the regressions of the paper, as well as for variables that are used in the robustness checks and those that are based on alternative definitions of forest loss, earthquake intensity, and CFUG share in a ward, are provided in Appendix table 7.

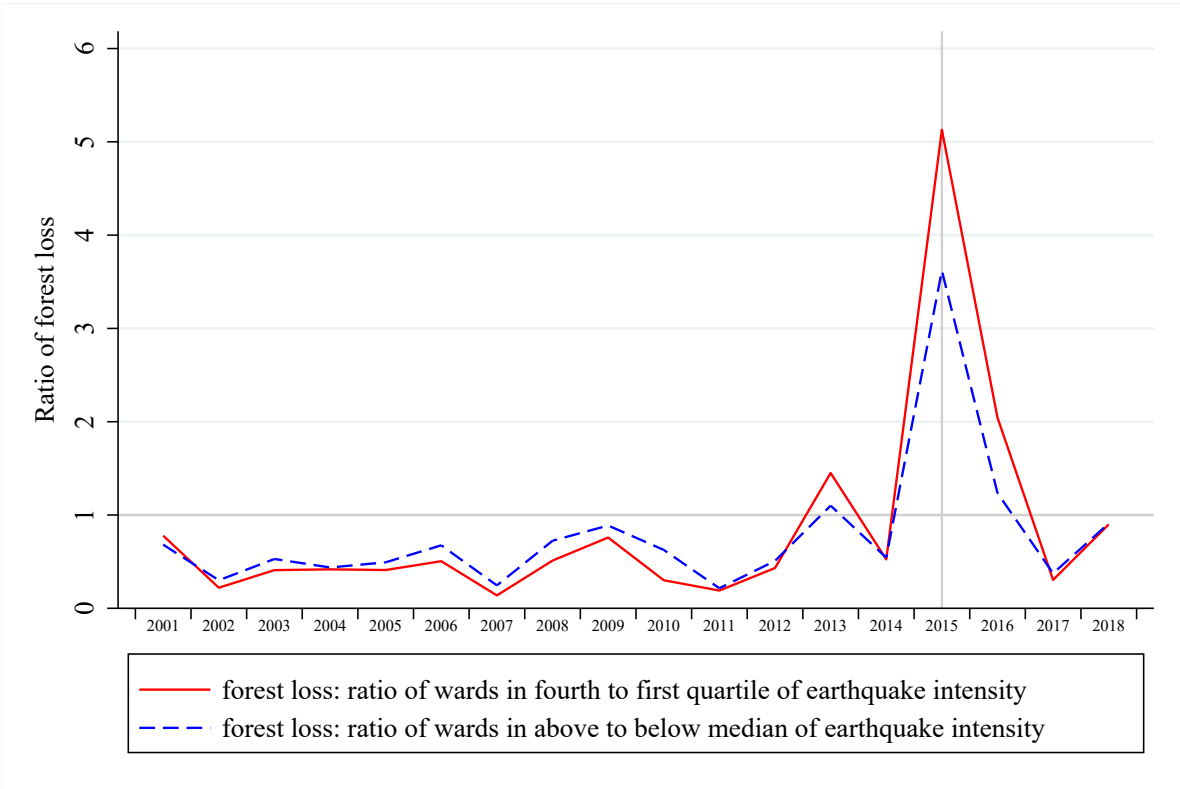
4.1 The effect of earthquake intensity on forest loss

To provide visual evidence of the effect of the earthquake on forest loss (net of landslides), consider Figure 2. This figure shows the ratio of forest loss in highly affected wards relative to wards that experienced a relatively low earthquake intensity, plotted over

[23] We may expect spatial correlation at the district level, given that each district has an autonomous and powerful district forest office to which CFUGs report. We also show robustness checks with Conley standard errors (Conley, 1999), which allow for spatial correlation in the distance dimension.

time. The dashed line is based on a split using the median of the ward-level earthquake intensity to split the sample. We also look at a comparison with even stronger opposites, namely comparing wards at the highest quartile of earthquake intensity with those in the lowest quartile (see the solid line). The earthquake intensity measure is based on the ward-level Modified Mercalli Intensity (MMI). Independent of the approach used to measure the forest loss ratio, the figure shows that the year of the earthquake, 2015, and to some extent the following year, 2016, stand out with respect to deforestation. Before the earthquake, in all but one instance (2013, for the fourth-to-first quartile ratio), the forest loss ratio is below one, indicating that more forest is lost in wards that experienced a relatively low earthquake intensity. In 2015 and 2016, the ratio is flipped, with a much higher loss of forest in wards that were highly affected by the earthquake. Note that the GFC data use satellite images from the growing season. The earthquake took place before the 2015 growing season, and therefore, the 2015 forest data can be considered post-earthquake data. In 2017 and 2018, the ratio is back to below 1 (but as the precise numbers underlying this graph – as well as the subsequent econometric analysis – show, the ratio in 2017 and 2018 is still above the average of the pre-earthquake ratio).

Figure 2: The ratio of forest loss (net of landslides) between high and low earthquake intensity wards



Source: Own calculation using Hansen et al. (2013) and USGS (2015)

Notes: The solid line represents the ratio of forest loss (net of landslides) in wards belonging to the fourth-quartile of earthquake intensity to wards belonging to the first-quartile of earthquake intensity. The dashed line represents the ratio of forest loss (net of landslides) in wards experiencing an above-median earthquake intensity to wards with a below-median earthquake intensity. The vertical bar represents the earthquake year. The GFC data use satellite images from the growing season. The earthquake took place before the 2015 growing season and the effects are therefore already represented in data for 2015.

Figure 2 strongly suggests that the earthquake led to increased pressure on forests in highly affected areas. The figure also shows that the effect of the earthquake on forest loss was strongest in 2015 and 2016. To study the effect of the earthquake in more detail in an econometric analysis, we next employ the following difference-in-differences framework:

$$\log(\text{forest loss}_{wt}) = \beta_1(\text{after earthquake}_t \times \text{high intensity}_w) + \tau_t + \alpha_w + \delta X_{wt} + \epsilon_{wt}$$

where *log(forest loss*$_{wt}$) is the logarithm of forest loss, which we calculate by subtracting the forest loss due to earthquake induced landslides from the total forest loss, w indexes ward, and t indexes time. We use various strategies to deal with the fact that there are many observations with forest loss $= 0$.[24] α_w is a vector of ward-level fixed effects, τ_t, is a

[24]In the baseline approach, we add a small constant of 0.0729 hectares to forest loss values to calculate the log(forest loss$_{wt}$). The choice of 0.0729 hectares is a natural one because this is the area of a single-

vector of time fixed effects. X_{wt} is the set of controls that include monthly precipitation variables, burned forest area (to control for forest loss through forest fires), as well as interaction terms year × high altitude, and year × steep slope.[25] These capture the time-varying effects of altitude and slope. We use ward-level MMI to proxy earthquake intensity.

In most specifications, we use a binary variable *high intensity*, which has a value of one for wards that experienced above-median earthquake intensity and zero otherwise. Our tables of results also show that results are qualitatively not different when using a continuous intensity measure. We prefer the binary *high intensity* variable for two reasons. First, it allows for an easier interpretation of the magnitude than results based on the continuous variable. Second, the earthquake intensity data are not available for about 18% of our sample, namely for those areas that were least affected by the earthquake (i.e., furthest away from the epicenter, see Figure 1(a)). While these wards can still be used in the analysis based on the binary measure (because they are wards with below-median earthquake intensity), there is no straightforward way to employ these wards when we use a continuous measure of earthquake intensity. Thus, in the analyses presented in the main text, we do not consider these wards in the analysis based on the continuous measure.[26]

In our baseline specification, based on the visual findings of Figure 2, we define the years 2015 and 2016 as the post-earthquake period, in which the pressure on forests was most severe. In alternative specifications, we show that results are qualitatively robust to defining the years 2015 to 2018 (i.e., all post-earthquake years for which we have data on forest loss) as post-period. The coefficient of interest is β_1, which is hypothesized to be positive.

Table 1 presents various difference-in-differences specifications evaluating the effect of earthquake intensity on the log of forest loss for the years before and after the earthquake. The unit of observation is ward-year, and a ward roughly corresponds to a village.

Column (1) shows baseline results. The main difference-in-differences coefficient is 0.10, i.e., the difference in forest loss between wards with above-median earthquake in-

pixel in Nepal, i.e., the smallest possible forest loss measure that can be derived from the GFC data, which is about 27m×27m (729 m^2). An analogous approach is also applied, e.g., by Heß et al. (2021). Our results remain qualitatively unchanged when we use the forest loss measure that is not based on a logarithmic transformation (Appendix table 16) and when we take the inverse hyperbolic sine of forest loss (Appendix table 17).

[25] High altitude and steep slope have values of one for wards that have above-median average altitude and slope, respectively, and zero otherwise.

[26] In robustness checks, we show that our results based on the continuous MMI measure are robust to including the wards with missing MMI data, using two different versions of an imputed MMI measure whenever MMI is missing. Further discussion and robustness checks are provided in Appendix, Section F.4 and Appendix table 13.

tensity and wards with below-median earthquake intensity increases by 10% due to the earthquake. We also note that generally (before the earthquake), forest loss is lower by about 9% in wards experiencing above-median earthquake intensity, which is a confirmation of the results from Figure 2. This reflects the higher levels of deforestation in the low altitude (and less earthquake-affected) Terai region, which experienced high within-country in-migration over recent decades, resulting in forests being cleared for new settlements. Further, outside of the main earthquake-affected regions, 2015 and 2016 are the years with deforestation lower than the average of the years 2001 to 2014.

Columns (2) through (7) show the robustness of the main results. Column (2) controls for ward fixed effects and a number of further controls, including those that allow for time-varying effects of location characteristics such as slope and altitude. The magnitude of the main difference-in-differences coefficient decreases only slightly with the inclusion of those additional controls.

To distinguish the earthquake's medium-run effect on forest loss from the short-run effect, columns (3) and (4) add the years 2017 and 2018 to the estimation sample. Column (3) splits the post-earthquake period into two periods (2015-16 and 2017-18), while column (4) merges these two periods. The interaction coefficient for 2017-18 and *high intensity* is only slightly smaller than the interaction coefficient for 2015-16 and *high intensity* and statistically significant, thus showing that the earthquake affects forest loss even three to four years after it occurred. In column (5), we show that the results are also robust to restricting the sample to years 2011 to 2018 to obtain two symmetric four-year periods as pre- and post-earthquake periods.

Table 1: The effect of earthquake intensity on forest loss (net of landslides)

	Dependent variable is log(forest loss)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2015-16 × high intensity	0.10	0.094	0.095				
	(0.03)***	(0.03)***	(0.03)***				
2015-16	-0.18						
	(0.02)***						
high intensity	-0.088						
	(0.03)***						
2017-18 × high intensity			0.085				
			(0.03)***				
2015-18 × high intensity				0.090	0.093	0.088	
				(0.03)***	(0.03)***	(0.03)***	
2011-14 × high intensity						-0.0075	
						(0.01)	
2015-16 × MMI (0,1)							0.18
							(0.06)***
ward fixed effects		✓	✓	✓	✓	✓	✓
year fixed effects		✓	✓	✓	✓	✓	✓
monthly precipitation vars		✓	✓	✓	✓	✓	✓
burned forest area		✓	✓	✓	✓	✓	✓
year × steep slope		✓	✓	✓	✓	✓	✓
year × high altitude		✓	✓	✓	✓	✓	✓
Districts	75	75	75	75	75	75	66
N	519024	519008	583884	583884	259504	583884	428240
R^2	0.013	0.40	0.36	0.36	0.34	0.37	0.40
Years covered	2001-16	2001-16	2001-18	2001-18	2011-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel to deal with observations where the area of forest loss (net of landslides) is zero. In columns (1)-(6), *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity. Column (7) uses the continuous intensity measure, *MMI (0,1)*. In columns (1) and (2), *2015-16* is a dummy that is equal to one for the years 2015 and 2016, i.e., the years immediately after the earthquake, and 2001-14 is the omitted period. Column (3) splits the post-earthquake period into 2015-16 and 2017-18. Column (4) pools all the post-earthquake years together, column (5) restricts the pre-earthquake years to 2011-14 to obtain two symmetric four-year pre- and post-earthquake periods. Column (6) tests for pre-trends. The unit of observation is ward-year.

Next, to investigate whether trends in the pre-earthquake period were parallel, we introduce, in column (6), a dummy that is one for the years 2011-14. Indeed, the interaction coefficient of *high intensity* with this dummy for years 2011-14 is insignificant and small in size, in line with the absence of significant pre-trends.

We also show robustness to using a continuous intensity measure. In columns (1)-(6) *high intensity* is a dummy variable, indicating wards that experienced above-median

earthquake intensity. In column (7), we use the continuous underlying earthquake intensity measure (MMI). For comparability, we linearly transform MMI to lie between 0 and 1 such that magnitudes of coefficients across different earthquake intensity measures have comparable ranges. We call this variable *MMI (0,1)*. Using this variable, the results are qualitatively robust.

Our analysis assumes that the timing and the intensity of the earthquake (i.e., the interaction of post-earthquake years 2015-16 and earthquake intensity) are exogenous. Despite the historical pattern of larger earthquakes in Nepal, which are relatively rare and suggest no systematic correlation with local characteristics, one may still be concerned about this assumption. We therefore first note that ward-level fixed effects capture all effects that are fixed over time (and which may be correlated with earthquake intensity of a location). The specifications shown in Table 1 also include interaction terms of time and geographic characteristics of a ward. To address the remaining possibility that socio-economic characteristics of a location that happen to be correlated with earthquake intensity affect the post-earthquake deforestation patterns, we show that our results are robust to including a large number of additional controls at the time-location level. In particular, we use interaction terms of post-earthquake with ward-level characteristics that we obtain from census data (Appendix table 8). In addition, we also apply the method suggested by Oster (2019), which further provides evidence for the robustness of the difference-in-differences results (see Appendix table 10).

4.2 The effect of CFUGs in times of increased pressure on forest resources

The previous section suggests that the earthquake put significant pressure on forests, resulting in significant additional forest loss in wards with higher earthquake intensity. In this section, we ask whether CFUGs are effective even in these times of increased pressure on forest resources. To investigate this question, we use the following triple difference specification. Our measure of CFUG presence in a ward is the share of CFUG area in a ward relative to the ward's total forested area in 2000, a variable which we call *CFUG share*$_w$.[27]

$$\log(\text{forest loss}_{wt}) = \beta_1(\mathbb{1}(t \in [2015, 16]) \times \text{high intensity}_w \times \text{CFUG share}_w) + \tau_t + \alpha_w + \delta X_{wt} + \epsilon_{wt}$$

[27] One empirical difficulty is how to deal with CFUGs that spread over several wards. In our baseline approach, we split the CFUG area into different wards weighted by the total forested area in the ward in 2000. Results are robust to an alternative specification, in which we distribute the CFUG area equally among all wards to which it belongs (Appendix table 18). The details of the CFUG area share calculation are shown in Appendix, Section C.

The coefficient of interest is β_1, which is hypothesized to be negative if CFUGs lead to more sustainable forest use in the post-earthquake period. Note that we do not independently include high intensity$_w$, CFUG share$_w$, high intensity$_w$ $\times$ CFUG share$_w$, 2015-16 $\times$ high intensity$_w$, and 2015-16 $\times$ CFUG share$_w$ in this specification because we control for the vector of ward-level fixed effects, year fixed effects, year $\times$ high intensity$_w$, year $\times$ CFUG share$_w$. The additional controls and our approach to dealing with forest loss of zero are similar to the difference-in-differences specification shown above.[28]

Table 2, column (1) presents the baseline triple difference results. The main triple difference coefficient implies a reduction in overall forest loss through CFUGs by about 10%, i.e., the difference in forest loss after the earthquake between wards experiencing above-median earthquake intensity and wards experiencing below-median earthquake intensity decreases by 10% when the share of CFUGs changes from 0 to 1. Column (2) additionally controls for *year* $\times$ *CFUG share* and *year* $\times$ *high intensity*. In both these specifications, 2001-14 is the omitted period.

To distinguish the medium-run effect from the short-run effect, as before, columns (3) and (4) add the years 2017 and 2018 to the estimation sample and present the triple difference results, once splitting the post-earthquake period into 2015-16 and 2017-18 periods (column 3), and then pooling all four post-earthquake years together (column 4). The triple interaction coefficient on the *2015-16* is negative and statistically significant. Similarly, the triple interaction coefficient on the *2017-18* is also negative but smaller in absolute size and statistically insignificant. The results suggest that the earthquake-specific CFUG effect on forest loss in highly affected areas was especially strong in the first one to two years after the earthquake. The results are also robust to pooling all the post-earthquake years together (column 4) or restricting the sample to 2011-18 in order to have symmetric four-year periods each for both pre- and post-earthquake periods (column 5). In both cases, the reduction in overall forest loss remains about 6%.

In an investigation of whether trends were parallel before the earthquake, column (6) shows that the triple interaction coefficient on the *2015-18* is negative, but *2011-14* is statistically insignificant, suggesting no pre-existing differences in trends between highly earthquake-affected wards and other wards. Finally, we also find a negative triple interaction term when using the continuous measure of earthquake intensity (column 7).

[28]Recall that in baseline specifications, we add a small number to forest loss to be able to calculate the logarithm if forest loss is zero. Results using alternative strategies, including using the inverse hyperbolic sine transformation, are shown in Appendix tables 16 and 17.

Table 2: CFUGs and forest loss (net of landslides): Triple difference results

	Dependent variable is log(forest loss)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2015-16 × high intensity × CFUG share	-0.099	-0.098	-0.099				
	(0.03)***	(0.03)***	(0.03)***				
2015-16 × high intensity	0.13						
	(0.03)***						
2015-16 × CFUG share	0.061						
	(0.02)**						
2017-18 × high intensity × CFUG share			-0.037				
			(0.03)				
2015-18 × high intensity × CFUG share				-0.068	-0.059	-0.071	
				(0.03)**	(0.03)**	(0.03)**	
2011-14 × high intensity × CFUG share						-0.011	
						(0.02)	
2015-16 × MMI (0,1) × CFUG share							-0.21
							(0.06)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓
year × CFUG share		✓	✓	✓	✓	✓	✓
year × high intensity		✓	✓	✓	✓	✓	
year × MMI (0,1)							✓
Districts	75	75	75	75	75	75	66
N	519008	519008	583884	583884	259504	583884	428240
R^2	0.40	0.40	0.37	0.37	0.34	0.37	0.40
Years covered	2001-16	2001-16	2001-18	2001-18	2011-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. In columns (1)-(6) *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. Column (7) uses the continuous intensity measure, *MMI (0,1)*. *CFUG share* is the share of CFUG area in a ward relative to the ward's total forested area in 2000. The unit of observation is ward-year.

A threat to identification arises due to the fact that CFUGs are not randomly assigned. The triple difference analysis deals with this to an important extent, by including ward fixed effects, and therefore controlling for all local characteristics that may determine CFUG presence, as well as interactions of CFUG presence with time and interactions of CFUG presence with earthquake intensity, which control for time-varying effects of CFUGs and effects of CFUGs that are specific to certain local characteristics. Yet, this specification leaves the possibility of a time variation in the role of CFUG presence that interacts with local characteristics. In particular, differences in local characteristics (e.g., education levels) may determine differences in effects of CFUGs during the post-earthquake period in the high-earthquake-intensity areas. To address this issue, we employ two strategies. First, we include a large number of additional controls at this triple-interaction level. In particular, similar to our approach in the case of the difference-in-differences, we use triple interactions of the interaction term (2015-16 $\times$ high earthquake intensity) with ward-level characteristics that we obtain from census data. The results in Appendix table 9 show the robustness of our main results to this variation of the specification. Secondly, we apply the method proposed by Oster (2019) to investigate robustness to proportional selection of observables and unobservables (see Appendix table 10). We find that unobserved variables would have to have disproportionate importance relative to the observable variables to eliminate the observed effect. This is quantified by the proportional degree of selection (δ in Oster's notation), which is still 2.2 in Panel C, even after adding the largest number of additional control variables to the controlled regression, including all of the additional triple interactions of CFUG presence, time, and local socio-economic characteristics. Thus, the selection on unobservables needs to be at least 2.2 times larger than the selection on observables to produce a treatment effect of zero, i.e., to "explain away" the effect of CFUGs on forest loss in times of increased pressure on forest resources. In particular, this proportional degree of selection is much larger than the reference value of 1 that Oster (2019) suggests. The finding is mirrored by the bound estimates, which exclude 0. Thus, these results further demonstrate the robustness of our main findings.

The results are also robust to a number of further changes in the specification. Appendix, Section F.3 shows that our main difference-in-differences and triple difference results are not substantially different when we consider total forest loss instead of forest loss net of landslides. Indeed, the magnitudes are slightly larger, and the direction and significance remain very similar. While our main results use the forest loss measure that uses baseline forest cover in 2000 as a weight, results are also robust to using the unweighted measure of forest loss (Appendix table 14). Similarly, results are robust to using forest cover in 2012 as a weight and restricting the analysis to years after 2012

(Appendix table 15).[29] Despite the fact that this introduces additional noise, results are also robust to considering two-year aggregates (Appendix tables 19 and 20), and even changes year-by-year individually (Appendix tables 21 and 21). Finally, results are robust to allowing for spatial correlation in the distance dimension instead of clustering at the district level (see Appendix table 23). Overall, the results provide robust evidence that the CFUGs reduce deforestation even in times of pressure.

4.3 Mechanisms: Investigating heterogeneous effects

The previous section strongly suggests a reduction in forest loss in times of heightened pressure on forests in wards with a higher share of CFUGs. To study possible mechanisms associated with CFUGs after the earthquake, this section investigates whether these reductions due to CFUGs are related to certain ward and CFUG characteristics.[30]

We build our analysis of heterogeneous effects on the above difference-in-differences and triple difference specifications. To avoid having to add further interaction terms, we investigate heterogeneous effects by splitting the sample into quartiles of the variable under consideration (e.g., ward-level poverty rate), and then compare the triple difference coefficient for the top quartile (e.g., the wards with the largest share of poor households), with the lowest quartile (e.g., the wards with the lowest share of poor households). Although we do not show full results with four-way interactions (that interact triple interactions with quartile), we test formally for the difference between the fourth and first quartile coefficients, results of these tests are shown in the "difference" columns. The main result of interest is the difference between the triple difference coefficients, namely, *2015-16* $\times$ *CFUG share* $\times$ *high intensity* between fourth and first quartiles of the variable under consideration.[31] Further, the difference column also shows the difference between *2015-16* $\times$ *high intensity* between fourth and first quartiles of the variable under consideration, which highlights the difference in deforestation (in earthquake-affected areas) between the first and the fourth quartile.

[29] While the forest loss data are available for each year between 2001 and 2018, the data also contain a single binary indicator for whether the gain occurred at some point between 2001 and 2012. In the data, we observe 602,028 total loss pixels and 184,290 gain pixels between 2001 and 2012. We use the baseline forest cover in 2000 as well as forest loss and gain that occurred between 2001 and 2012 to create a new baseline forest cover data for 2012. The details of creating the baseline forest cover data for 2012 are shown in Appendix, Section B.

[30] Ward-level characteristics are calculated from Nepal's National Population and Housing Census 2011 (population growth is based on Censuses 2001 and 2011), and voter turnout is calculated using constituency election results from 2013.

[31] Specifically, we interact all the variables from the triple difference specifications, including all the controls, with a dummy variable equaling one if belonging to the fourth quartile and zero if belonging to the first quartile of the variable under consideration. Thus, estimates of the respective interaction terms give the *difference* coefficient and the associated standard errors.

In Appendix tables 24 and 25, we show that we obtain qualitatively similar results when we use a continuous variable for each dimension (e.g., the continuous poverty index instead of the distinction into "highest quartile of poverty" and "lowest quartile of poverty").

4.3.1 Heterogeneity with respect to ward characteristics

CFUGs may lead to sustainable forest use, especially in times of generally increased demand for forest resources, through a number of channels.

Poverty and remittances

Generally, there is a tension between the short-term benefit from using the forest resources, e.g., for income generation, firewood collection, and other needs, and the need to sustain forests for the longer run. The earthquake led to shocks to health, to the loss of income opportunities, and to a loss of assets (houses, livestock), while rebuilding of houses required not only physical resources (timber) but also additional financial resources. Thus, many households' livelihoods were at immediate risk, and the earthquake therefore made short-term considerations more important. This effect can be expected to be particularly strong for poor households. On the other hand, we expect the effect to be less important for households that have alternative income sources, in particular those with remittance incomes (e.g., Oldekop et al., 2018; Hecht et al., 2015; Manning and Taylor, 2014; Robson and Berkes, 2011).[32] The constraints on forest use imposed by CFUGs may therefore have helped to reduce forest loss specifically in wards with a large number of poor households and with a lower number of migrants (household members living abroad), where the relation to migrants indicates alternative income sources for households, in particular through remittances.[33]

The coefficients on the interaction 2015-16 × high intensity in Table 3, columns (1)-(3) first show that forest loss due to the earthquake in wards without CFUGs is significantly higher in poorer wards than in relatively better-off wards. Considering the effect of CFUGs, the triple difference terms in these columns show a significant reduction in deforestation through CFUGs only in wards belonging to the highest quartile in the poverty index. Thus, CFUGs make poorer wards resilient and lead to more sustainable use of forests.

With regard to the role of the migrant's share, results in columns (4)-(6) show a

[32] According to the Nepal Census 2011, around 29% of Nepalese households had at least one member living abroad in 2011, and according to Ratha et al. (2016), remittances accounted for approximately 25% of Nepal's GDP in 2013.

[33] The share of poor households is calculated based on a poverty index (following Oldekop et al., 2019), and the migration share is the share of households with at least one person living abroad.

significant reduction in deforestation through CFUGs in wards belonging to the lowest quartile in terms of the share of households with at least one member living abroad. In the absence of remittance, these households might be engaged in subsistence agriculture or are more likely to be poor, the characteristics associated with a reduction in deforestation in our case.

Table 3: Heterogeneity with respect to ward characteristics

	Dependent variable is log(forest loss)					
	poverty index			migration share		
	(1)	(2)	(3)	(4)	(5)	(6)
	first quartile	fourth quartile	difference	first quartile	fourth quartile	difference
	richest	**poorest**	**poorest -richest**	**least migrants**	**most migrants**	**most-least migrants**
2015-16 × high intensity	-0.023	-0.26	-0.24	-0.18	-0.056	0.13
× CFUG share	(0.02)	(0.06)***	(0.06)***	(0.05)***	(0.04)	(0.06)**
2015-16 × high intensity	0.030	0.26	0.23	0.20	0.079	-0.12
	(0.02)	(0.07)***	(0.07)***	(0.05)***	(0.04)*	(0.06)**
2015-16 × CFUG share	0.030	0.089	0.059	0.15	0.055	-0.098
	(0.01)**	(0.04)**	(0.04)	(0.04)***	(0.01)***	(0.04)**
ward fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓
monthly precipitation vars	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓
year × splitting variable	✓	✓	✓	✓	✓	✓
Districts	75	71	75	71	68	75
N	129968	129024	258992	129760	129680	259440
R^2	0.29	0.47	0.42	0.44	0.37	0.41
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. *splitting variable* is the continuous variable under consideration that is used for splitting the sample into quartiles. The unit of observation is ward-year.

Firewood and agriculture

The effect of the earthquake on forest use is less clear for households that generally rely on forest and agriculture. On the one hand, the above-mentioned need to replace lost incomes and/or generate additional incomes may lead to an expansion of agricultural land at the expense of forests. On the other hand, the need to find new sources of income may be more pressing for households outside of agriculture. Similarly, in locations that rely heavily on forests for firewood collection to begin with, the earthquake may have induced even heavier use of forests for this purpose, either to substitute firewood for costlier sources of fuel or because households start using the sale of firewood as a source of income. At the same time, there may be limited scope for additional firewood collection in those areas that already rely heavily on firewood as fuel, and the effect of the earthquake on firewood collection might be larger in places that traditionally used other sources of fuel.

Results in Table 4 show that there is a significant reduction in deforestation through CFUGs in high-earthquake intensity wards in the quartile of wards with the highest share of households using firewood as a source of fuel, while there is no reduction in the wards with the lowest share of households using firewood as a source of fuel (columns 1-3). Similarly, we find a strong effect of CFUGs in largely agriculturally-oriented wards, while there is no such effect in wards with few households engaged in agriculture (columns 4-6).

Table 4: Heterogeneity with respect to other ward characteristics

	Dependent variable is log(forest loss)					
	share of households using firewood as main source of fuel			share of households with at least one member in agriculture		
	(1)	(2)	(3)	(4)	(5)	(6)
	first quartile **least firewood use**	fourth quartile **most firewood use**	difference **most-least firewood use**	first quartile **least farming**	fourth quartile **most farming**	difference **most-least farming**
2015-16 × high intensity	0.039	-0.064	-0.10	-0.0069	-0.093	-0.086
× CFUG share	(0.04)	(0.03)*	(0.05)**	(0.04)	(0.03)***	(0.04)**
2015-16 × high intensity	0.029	0.10	0.072	0.085	0.10	0.015
	(0.02)*	(0.04)**	(0.05)	(0.03)***	(0.03)***	(0.04)
2015-16 × CFUG share	-0.067	0.094	0.16	-0.040	0.10	0.14
	(0.03)**	(0.02)***	(0.04)***	(0.03)	(0.02)***	(0.03)***
ward fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓
monthly precipitation vars	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓
year × splitting variable	✓	✓	✓	✓	✓	✓
Districts	72	73	75	75	74	75
N	129680	168384	298064	129568	173120	302688
R^2	0.37	0.36	0.37	0.40	0.37	0.39
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *splitting variable* is the continuous variable under consideration that is used for splitting the sample into quartiles. The unit of observation is ward-year.

Population growth and social capital

Population growth can accelerate deforestation through an increase in human demand for forest resources. Further, population growth provides a higher workforce to deplete forests (Busch and Ferretti-Gallon, 2017). Thus, in the wards with high population growth, it might be more important that CFUGs put constraints on forest use. Finally, CFUGs rely on cooperation (Leone, 2019; Bhattarai, 1985), and cooperation might work better in locations with higher levels of social capital. We approximate social capital with voter turnout and investigate whether CFUGs are more effective in locations with larger voter turnout.[34]

[34]To measure voter turnout, we use the proportion of total votes cast (both valid and invalid votes) in a given constituency in the 2013 Constituent Assembly election relative to the total number of registered voters in that constituency (there were 240 constituencies in the 2013 election). We match these data to the respective wards from that constituency. We use constituency-level data because the last municipal-level election before the earthquake took place in 1997.

Results in Table 5 show that there is a significant reduction in earthquake-induced deforestation through CFUGs in the quartile of wards with the highest population growth, while there is no such effect in wards with the least population growth (columns 1-3). Results in columns (4)-(6) show a significant reduction in deforestation in the quartile of wards with the highest political participation, as measured by voter turnout.

Table 5: Heterogeneity with respect to other ward characteristics

	Dependent variable is log(forest loss)					
	population growth			voter turnout (social capital)		
	(1)	(2)	(3)	(4)	(5)	(6)
	first quartile **least growth**	fourth quartile **most growth**	difference **most-least growth**	first quartile **least turnout**	fourth quartile **most turnout**	difference **most-least turnout**
2015-16 × high intensity	0.0062	-0.20	-0.20	-0.0072	-0.21	-0.21
× CFUG share	(0.03)	(0.05)***	(0.06)***	(0.04)	(0.07)***	(0.08)***
2015-16 × high intensity	-0.0023	0.28	0.28	0.045	0.20	0.16
	(0.03)	(0.05)***	(0.06)***	(0.06)	(0.07)***	(0.09)*
2015-16 × CFUG share	0.049	0.099	0.049	0.013	0.17	0.16
	(0.02)***	(0.04)**	(0.05)	(0.02)	(0.06)***	(0.06)**
ward fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓
monthly precipitation vars	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓
year × splitting variable	✓	✓	✓	✓	✓	✓
Districts	60	70	75	30	32	57
N	129760	129632	259392	129872	129264	259136
R^2	0.31	0.45	0.40	0.38	0.44	0.41
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *splitting variable* is the continuous variable under consideration that is used for splitting the sample into quartiles. Political participation is used as a proxy for social capital. The unit of observation is ward-year.

4.3.3 Heterogeneity with respect to CFUG characteristics

We now turn to an investigation of CFUG characteristics in determining sustainable use of forests when it is under particular pressure. In this sub-section, we therefore restrict the analysis to wards that have at least one CFUG. In particular, we consider the gender composition of the CFUG management and an assessment of the past "quality" of the CFUG.

A number of arguments suggest that CFUGs achieve the goal of sustainable forest use better if there is a larger share of women involved in the CFUGs. In Nepal, women are the primary users of forest products, bear the sole burden of firewood collection, and are engaged in collecting resources from forests (Gurung, 2002). Forest depletion directly affects their time and effort as they have to walk long distances to collect firewood if forests are lost (Cooke, 1998). Consequently, women have higher immediate incentives to ensure that forests are not depleted (Acharya and Gentle, 2006). In addition, evidence shows women representatives in CFUGs have place-specific knowledge (Somanathan et al., 2009), are better able to design and enforce forest protection rules and detect illegal extractions quicker than forest guards, who are generally men (Gurung, 2002). Furthermore, women leaders prioritize conservation and reduce over-exploitation of forests (Giri and Darnhofer, 2010; Agarwal, 2009; Maskey et al., 2006). For example, female leaders design policies to discourage forest grazing and encourage households to cultivate fodder in their own farms (Acharya and Gentle, 2006). Thus, in the following, we specifically investigate the role of female participation in CFUGs during the period of increased pressure on forest resources.

Indeed, results in Table 6, columns (1)-(3) show a significant reduction in deforestation in the quartile of wards with the highest female participation in the CFUG executive committees, indicating that female participation is effective in reducing forest loss.[35] Our result complements the work by Leone (2019), who shows that higher female participation in the CFUG executive committee led to a reduction in firewood collection, and results by Mai et al. (2011) and Agarwal (2009)

In the same vein, CFUGs with past successes might continue to achieve success in managing and preserving forests. However, the successes might be derived at the cost of forest exploitation such that the same level of success is no longer possible. Barsimantov and Kendall (2012) show evidence that community forests with better forest governance were able to reduce deforestation in Mexico. Baland and Platteau (1996) and Wade (1988) also show that CFUGs with a proven track of success enable sustainable forest management.

To measure the quality of the CFUG, we use a variable in our dataset that indicates the condition of the forest.[36] We use the share of CFUGs that are in a "very good condition" category to indicate past successes of CFUGs in a ward.[37] Results in Table

[35]To calculate the female share in the executive committees, we first count all the female executive committee members in a ward and divide it by the total number of executive members in that ward. We then split the wards into the highest and the lowest quartile based on this share measure.

[36]The district forest officers assessed CFUGs based on their condition and categorized them into "very good", "good", "degraded", and "very degraded" conditions.

[37]In a ward, we first count the number of CFUGs that are categorized as "very good" and divide it by the number of CFUGs in that ward to calculate the share of "very good" CFUGs. We then split the wards into the highest and the lowest quartile based on this share measure.

6, columns (4)-(6) show a significant reduction in deforestation in the quartile of wards with the highest proportion of the CFUGs that are in a "very good" condition and the within ward CFUG number. Thus, our results provide evidence that CFUGs that are considered "very good" in "normal" times reduce forest loss even in times of pressure relative to other CFUGs.

In sum, although the difference between the highest and lowest quartile is only statistically significant for the "condition of forest" variable (for the female participation variable, the p-value is 0.134, see column 3), the results suggest that female participation and locations with a higher share of CFUGs that are in the "very good condition" category strongly increase the sustainable use of forests.

Table 6: Heterogeneity with respect to CFUG characteristics

	Dependent variable is log(forest loss)					
	female representation in CFUG management			CFUG is in a very good condition		
	(1)	(2)	(3)	(4)	(5)	(6)
	first quartile **least represented**	fourth quartile **most represented**	difference **most-least represented**	first quartile **worse condition**	fourth quartile **better condition**	difference **better-worse condition**
2015-16 × high intensity	-0.012	-0.16	-0.15	-0.041	-0.26	-0.22
× CFUG share	(0.06)	(0.09)*	(0.10)	(0.05)	(0.1)**	(0.10)**
2015-16 × high intensity	0.073	0.23	0.15	0.092	0.33	0.24
	(0.06)	(0.08)***	(0.09)*	(0.06)	(0.1)***	(0.09)**
2015-16 × CFUG share	0.14	0.36	0.22	0.20	0.44	0.24
	(0.04)***	(0.09)***	(0.09)**	(0.04)***	(0.09)***	(0.08)***
ward fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓
monthly precipitation vars	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓
year × splitting variable	✓	✓	✓	✓	✓	✓
Districts	74	73	74	74	63	74
N	63328	63280	126608	247936	32464	280400
R^2	0.34	0.46	0.41	0.38	0.51	0.41
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *splitting variable* is the continuous variable under consideration that is used for splitting the sample into quartiles. The unit of observation is ward-year.

5 Conclusion

Disasters can exogenously increase pressure on resources, weaken the functioning of institutions, and affect the enforcement of rules. As such, they can be seen as a lens through which one can analyze the possible effects of climate change, migration, and population growth on institutions. To this end, we study the effects of the 2015 earthquake in Nepal. We first show that the earthquake increased the pressure on forest resources. On average, in the years before the earthquake, the highly earthquake-affected locations have been experiencing lower forest loss than less affected locations in pre-earthquake years, presumably because of their more rugged nature. The earthquake changes this: in the period immediately after the earthquake, deforestation is substantially higher in locations that are more affected by the earthquake than in locations that are less affected. Secondly, we study the role of a specific institution under these circumstances, namely community forest user groups (CFUGs). In our main result, we find that user groups reduce the forest loss in the post-earthquake period and seem to contribute to a more sustainable use of forests. Thus, our results extend the findings from previous studies – which show the positive effects of community-based forestry management institutions – in that we show that these institutions can withstand significantly increased pressure on the forest. Further, analyses of heterogeneity suggest that the role of CFUGs for sustainable forest use is particularly important in locations with characteristics that imply particularly large pressure on forests, such as high poverty levels and high population growth.

It is expected that population growth and climate change will increase the pressure on forests even further beyond already high levels, therefore the question of resilience will continue to increase in importance. The findings show that community-based institutions can play an important part in the strategies needed to build resilience of forests.

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Appendix

A Data sources not described in the main text

A.1 National population and housing census (2001 and 2011)

We use data from the National Population and Housing Censuses in 2001 and 2011 to determine pre-earthquake ward characteristics. Wards are the lowest administrative level in Nepal.[38]

In particular, the 2011 National Population and Housing Census data are used to calculate the poverty index. Following the methodology by Oldekop et al. (2019), who use the multidimensional poverty index proposed by Alkire and Santos (2014), we calculate our measure of the poverty index.[39] We also use the 2011 Census to calculate the share of households with at least one member whose main occupation is agriculture, with firewood as the main source of cooking fuel, and with at least one household member living abroad. Population growth is calculated as the growth between the census years 2001 and 2011. These measures are used in the heterogeneous effects section.

A.2 2013 constituent assembly election results

The voter turnout variable is calculated using the 2013 constituent assembly election of Nepal. The data are publicly available and can be obtained from the Election Commission of Nepal. Voter turnout variable is used to proxy social capital in the heterogeneous effects section.

A.3 Burned forest data

All of our regressions control for forest loss through forest fires. Burned forest area calculation is based on the MODIS Fire_cci Burned Area pixel product version 5.1 dataset.[40] The data are available from 2001 to 2017 and at a 250m × 250m resolution. We calculate

[38]The National Population and Housing Census data from 2001 and 2011 can be purchased from the Central Bureau of Statistics Nepal for scientific purposes. For detailed information concerning data description, access, costs, and how to submit an access request, see https://microdata.cbs.gov.np/index.php/catalog/54 and https://microdata.cbs.gov.np/index.php/catalog/42 (accessed January 18, 2022).

[39]The poverty index is based on indicators of (low) levels of health, education, and living standards more generally. Each dimension receives equal weight in the calculation of the poverty index. For details see Oldekop et al. (2019).

[40]The Burned forest data can be downloaded from https://developers.google.com/earth-engine/datasets/catalog/ESA_CCI_FireCCI_5_1?hl=en.

burned forest area for each of the wards by considering only those areas in the MODIS Burned Area database that can be considered "forest", i.e. those that are labelled as one of the following:

1. Tree cover, broadleaved, evergreen, closed to open (>15%)
2. Tree cover, broadleaved, deciduous, closed to open (>15%)
3. Tree cover, broadleaved, deciduous, closed (>40%)
4. Tree cover, needleleaved, evergreen, closed to open (>15%)
5. Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
6. Mosaic herbaceous cover (>50%) / tree and shrub (<50%)

To calculate the annual burned area by ward, we take the sum of all monthly burned areas. Since burned data are only available from 2001 to 2017, we proxy the burned forest area for 2018 using the burned forest area data from 2017.

A.4 Digital elevation data

We use ASTER Global Digital Elevation Model (V003) provided by NASA/METI/AIST/Japan Spacesystems, and U.S./Japan ASTER Science Team (2019) to calculate the mean height and slope within wards.[41]

A.5 Daily precipitation data

The Department of Hydrology and Meteorology in Nepal provides daily precipitation data. We aggregate the daily precipitation data from 2001 to 2018 to generate an average and total monthly precipitation for each of the 250 weather stations, roughly covering the entire country. We interpolate these monthly averages of precipitation from 2001 to 2018 for each ward using the monthly data from these stations.[42]

A.6 ArcMap at the fifth administrative (ward) level

We use data from the ArcMap shapefile at the ward level (the lowest administrative level, roughly corresponding to a village) to match the spatial data, including the GFC data, to earthquake intensity data based on the MMI, the CFUG data, and the demographic and socioeconomic data from the 2011 National Population and Housing Census.[43]

[41] The data can be downloaded from https://doi.org/10.5067/ASTER/ASTGTM.003 (accessed May 12, 2020)

[42] The daily precipitation data can be purchased from the Department of Hydrology and Meteorology, Nepal, For detailed information concerning data costs, see http://dhm.gov.np/requestfordata/ (accessed May 20, 2020).

[43] The Department of Survey of Nepal provides the shape-files at the ward level. For detailed information concerning data access and costs, see http://dos.gov.np/products-and-services (accessed May 20, 2020).

B Forest loss data: aggregating to the ward-year level

We calculate three different variants of yearly *total forest loss*, i.e., the measure of forest loss that includes the forest loss through landslides, at the ward level.

The **first variant** of our variable of *total forest loss*, the one used in our main specification, uses the baseline forest cover in 2000 as a weight. To calculate total forest loss for a specific pixel and specific year, we multiply a dummy variable that is equal to one if the GFC indicates forest loss, with the corresponding share of forest cover (relative to full tree canopy) in 2000. We then sum the product (forest loss $\times$ share of forest cover in 2000) over all pixels within a each ward and convert it to hectares.

The **second variant** of *total forest loss* does not use the baseline forest cover in 2000 as a weight. Results are robust to not weighting by forest cover in 2000, as shown in Appendix table 14.

The **third variant** of *total forest loss* includes the available limited information on forest gain. As explained in section 4.2 (Empirical strategy and results), Hansen et al. (2013) data also contain a single binary indicator for whether the gain occurred at some point between 2001 and 2012. We use this gain data and yearly forest loss data between 2001 and 2012 to update the baseline forest information from 2000 to 2012. Thus, for the third variant, we calculate *total forest loss* using a similar methodology as for the first variant but this time taking into account baseline forests in 2012 instead of baseline forest in 2000. Here, for each pixel in years 2013 to 2018, we multiply the forest loss with the updated baseline forest cover in 2012. However, given that only coarse information is available on forest gain, we have to make fairly strong assumptions to generate a new baseline forest cover value for 2012, so the results of this analysis should mainly be interpreted qualitatively and less with a view on the precise quantitative numbers. In particular, we make the following assumptions to update the baseline forest data from 2000 to 2012:

1. If a pixel neither experienced a loss nor a gain between 2000 and 2012, we assume that the baseline forest cover in 2012 is equal to the baseline forest cover in 2000.

2. If a pixel only experienced a loss between 2000 and 2012, we assume that the baseline forest cover in 2012 is 10% of full tree canopy.

3. If a pixel only experienced a gain between 2000 and 2012, we assume that the baseline forest cover in 2012 is 90% of full tree canopy.

4. For the pixel where we observed both forest loss and gain between 2000 and 2012:[44]

   (a) If a gain pixel experienced a loss after 2009, we assume that the baseline forest cover in 2012 is 10% of full tree canopy, assuming that the pixel experienced a loss after it experienced a gain.[45]

   (b) If a gain pixel experienced a loss before 2004, we assume that the baseline forest cover in 2012 is 90% of full tree canopy, assuming that the pixel experienced a loss before it experienced a gain.[46]

   (c) If a gain pixel experienced a loss between 2004 and 2009, we assume that the baseline forest cover in 2012 is equal to the baseline forest cover in 2000, assuming that the loss and gain cancel each other out.

Results of robustness checks using this variant of the total forest loss variable are shown in Appendix table 15.

C Community Forest User Group (CFUG) data: aggregating to the ward level

The CFUG data contain information on the VDC in which a CFUG is located, the ward(s) in which a CFUG operates, and the area of the CFUG (in hectares). Starting from this information, we calculate two different variants of the share of the CFUG area relative to the total forest area at the ward level. In cases where CFUGs span multiple wards, we either attribute the community forest area to individual wards proportionally to their forest cover area in 2000 or divide it equally among these wards.

To calculate the **first variant** of the share of the CFUG area relative to the ward's total forest area, which we use in all specifications of the main text, we use the data of Hansen et al. (2013) on forest cover in 2000 and include areas with more than 10% of tree canopy cover. Here, when the CFUG falls in a single ward, we simply attribute the total community forest area to this ward. However, when the CFUG spans two (or more) wards, we attribute the community forest area to individual wards proportionally to their forest cover area in 2000. To illustrate this, consider Figure 3. For example, if the top ward contains 60% of the total forest cover (in 2000) relative to the total forest cover of the two wards and the bottom ward contains 40% of the two wards' total forest cover (in 2000), then we attribute 60% of the CFUG area to the top ward and 40% of

[44] Only about 3% of the forest gain pixels simultaneously experience a forest loss between 2000 and 2012.

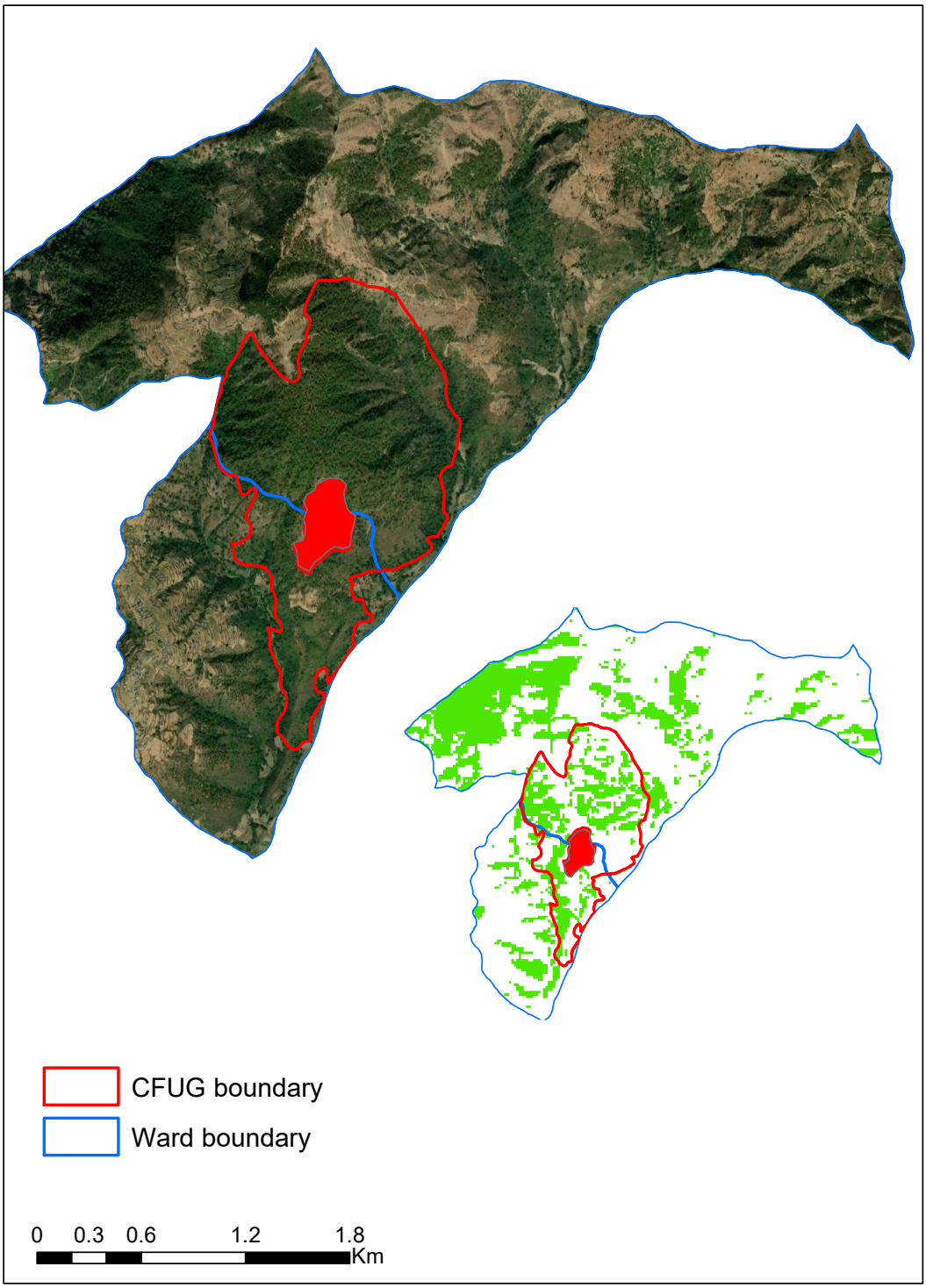
[45] This occurred in less than 1% of the total forest gain pixels in our data.

[46] This also occurred in less than 1% of the total forest gain pixels in our data.

the CFUG area to the bottom ward. We then sum up the resulting CFUG areas for all CFUGs in a ward. The share of the CFUG area relative to the ward's total forest area is calculated by dividing the aggregated CFUG areas by the ward's total forest area in 2000.

We calculate a **second variant** of the share of the CFUG area relative to the ward's total forest area, which we use in robustness checks (see Appendix table 18). To calculate this variable, we proceed as follows. When the CFUG falls in a single ward, we (again) simply attribute the total community forest area to this ward. However, when the CFUG span two (or more) wards, in this variant we attribute the community forest area to individual wards equally. Based on this equal split we further proceed as with the first variant to calculate the ward-level share of forest covered by CFUGs.

Figure 3: CFUG area calculation (CFUG lies in two different wards)



Notes: For a very small sample of CFUGs, we know their actual geographical boundaries (see data section). Here, we use these data to illustrate a case of CFUG (shown in red) that lies in two wards separated by the blue line. The area highlighted in red represents settlement areas.

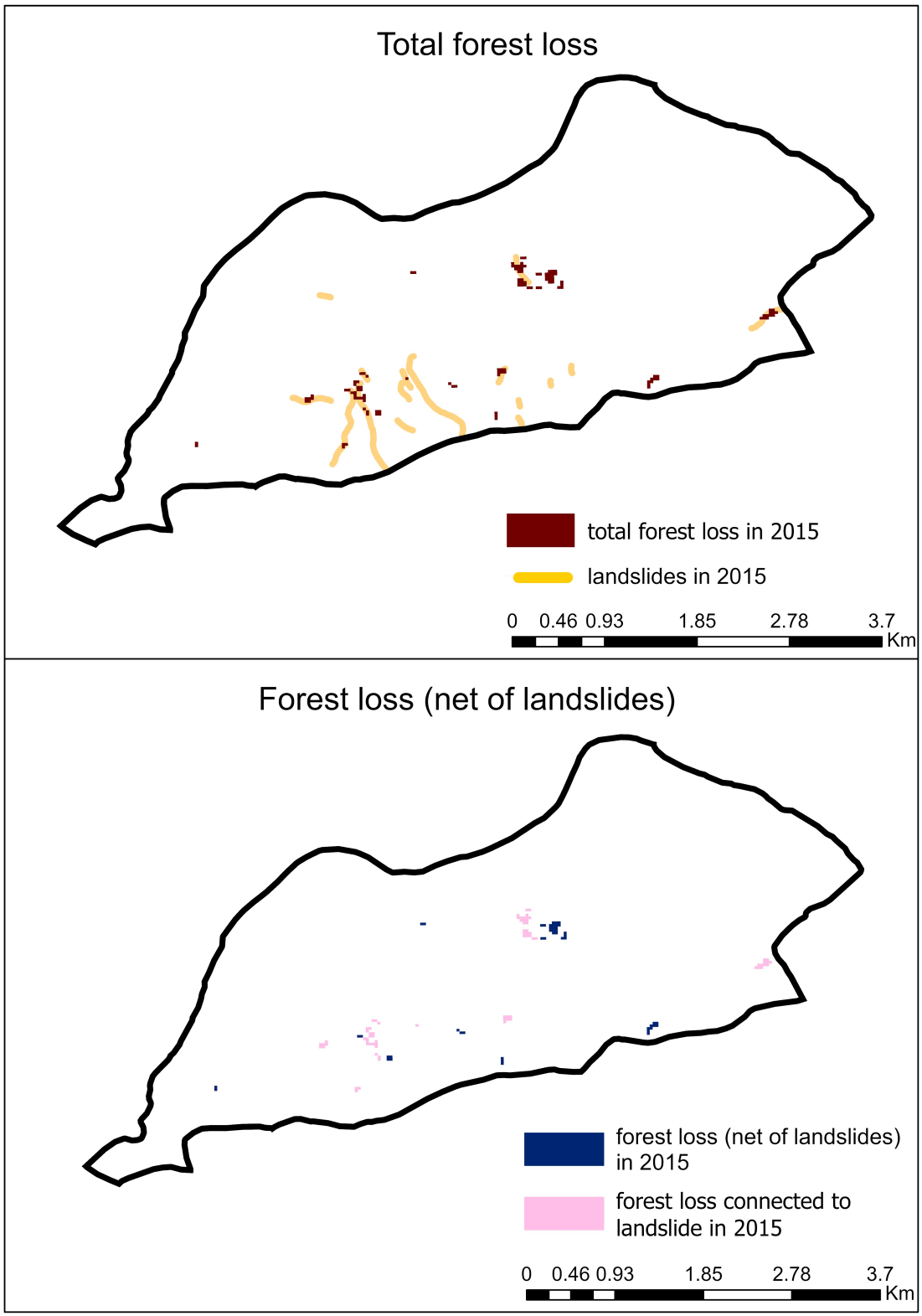
D Taking landslides into account

Data prepared by Durham University in collaboration with the British Geological Survey (Williams et al., 2018) contain 5,578 episodes of landslides, which are geo-referenced and provided as poly-lines. To calculate the forest loss due to earthquake-induced landslides, we first identify all the forest-loss pixels for the years 2015-2018 that intersect with the landslide poly-lines. Second, we multiply these intersecting pixel areas with their corresponding forest cover in 2000, and aggregate these by wards (and then covert the result to hectares).[47] Third, we subtract the forest loss due to landslides from the total forest loss to calculate the forest loss (net of landslides) in hectares.

To illustrate the difference between total forest loss and forest loss (net of landslides), consider Figure 4, which shows an illustrative ward. The top panel shows pixels that are recorded as loss in 2015 in the GFC data, as well as the landslides that occurred due to the earthquake for the same period. To calculate the **total forest loss** measure, we do not account for forest loss due to landslides and simply aggregate all the forest loss pixels that are multiplied with the share of forest cover in 2000. To calculate the **forest loss (net of landslides)**, in the bottom figure, we remove the forest loss pixels (weighted by their forest cover in 2000) that intersect with the earthquake-induced landslides.

[47] Most of the loss pixels intersect with landslide poly-lines in 2015, followed by 2016. Very few loss pixels intersect with the landslide poly-lines in 2017 and 2018.

Figure 4: Forest loss and landslide data illustration



Notes: Using a ward from Sindhupalchok district as an illustration, the top panel represents the total forest loss pixels in 2015 and the landslides data that are based on the work by Williams et al. (2018). To calculate forest loss (net of landslides), we subtract the forest loss due to earthquake-induced landslides (the intersection of total forest loss with the earthquake-induced landslide poly-line) in the bottom panel. The calculation of *total forest loss* and *forest loss* are weighted by the share of forest cover in 2000, described in Appendix, Section B.

E Summary statistics

Table 7: Summary statistics

	Summary Statistics					
	Total sample mean	Total sample std. dev	Mean by quartile of distribution of earthquake intensity (MMI)			
			first quartile	second quartile	third quartile	fourth quartile
Forest loss related variables						
log(forest loss) = log(forest loss net of landslides, weighted by 2000 forest cover)	-2.47	0.51	-2.40	-2.48	-2.54	-2.47
log(total forest loss) = log(total forest loss, weighted by 2000 forest cover)	-2.47	0.51	-2.40	-2.48	-2.54	-2.47
log(forest loss, unweighted) = log(forest loss net of landslides, not weighted by 2000 forest cover)	-2.42	0.63	-2.32	-2.43	-2.50	-2.41
log(forest loss, weighted 2012) = log(forest loss net of landslides, weighted by 2012 forest cover)	-2.59	0.21	-2.59	-2.60	-2.61	-2.58
forest loss = forest loss net of landslides, weighted by 2000 forest cover	0.05	0.65	0.09	0.04	0.03	0.04
ihs(forest loss) = ihs(forest loss net of landslides, weighted by 2000 forest cover)	0.03	0.18	0.06	0.03	0.02	0.03
Damage-related variables						
high intensity	0.47	0.50	0.00	0.00	1.00	1.00
MMI (0,1)	0.39	0.23	0.04	0.21	0.45	0.71
MMI $(0,1)_{\text{imputeUse3}}$ (see Section F.4)	0.39	0.26	0.05	0.31	0.52	0.75
MMI $(0,1)_{\text{imputeReg}}$ (see Section F.4)	0.41	0.23	0.14	0.31	0.53	0.75
CFUG related variables						
CFUG share = CFUG share (proportional distribution across wards)	0.31	0.39	0.32	0.40	0.16	0.36
CFUG $\text{share}_{[\text{equal}]}$ = CFUG share (equal distribution across wards)	0.33	0.41	0.35	0.42	0.17	0.39
Other control variables						
burned forest area	5.41	93.9	11.09	6.25	2.50	0.97
high altitude	0.54	0.50	0.74	0.66	0.12	0.68
steep slope	0.54	0.50	0.73	0.71	0.17	0.60
Ward characteristics related variables						
poverty index	0.30	0.10	0.33	0.27	0.34	0.23
migration share	0.26	0.17	0.22	0.35	0.23	0.21
firewood-based household share	0.82	0.31	0.95	0.92	0.57	0.84
agriculture-based household share	0.80	0.24	0.84	0.84	0.70	0.81
population growth	0.10	0.51	0.21	-0.01	0.12	0.08
voter turnout (social capital)	0.77	0.04	0.78	0.75	0.79	0.78
CFUG characteristics related variables						
female representation in CFUG management	0.31	0.21	0.30	0.32	0.32	0.28
CFUG is in a very good condition	0.07	0.23	0.08	0.07	0.09	0.06
Observations[(a)]	583884	583884	148410	160812	159264	115398

(a) Note that the numbers of observations are different across quartiles, because MMI is a categorical variable, with values such as 5, 5.2, 5.4 etc.

F Robustness checks

F.1 Adding further controls to the difference-in-differences and triple difference specifications

Table 8: Difference-in-differences results: Robustness to inclusion of further controls

	Dependent variable is log(forest loss)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2015-16 × high intensity	0.087	0.10	0.072	0.092	0.093	0.10	0.10	0.072
	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***
2015-16 × poverty index	-0.37							
	(0.09)***							
2015-16 × migration share		0.17						
		(0.06)***						
2015-16 × firewood fuel share			-0.16					
			(0.02)***					
2015-16 × agriculture share				-0.12				
				(0.02)***				
2015-16 × population growth					-0.039			
					(0.01)***			
2015-16 × voter turnout						-0.48		
						(0.3)*		
2015-16 × primary education share							0.26	
							(0.09)***	
2015-16 × upper caste share								-0.096
								(0.03)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
Districts	75	75	75	75	75	75	75	75
N	518880	518720	518720	518256	518576	519008	518576	518720
R^2	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. The unit of observation is ward-year.

Table 9: CFUGs and forest loss (net of landslides): Robustness to inclusion of further controls

	Dependent variable is log(forest loss)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2015-16 × high intensity × CFUG share	-0.090	-0.089	-0.083	-0.095	-0.098	-0.084	-0.096	-0.075
	(0.03)***	(0.03)***	(0.02)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)**
2015-16 × high intensity × poverty index	0.77							
	(0.2)***							
2015-16 × high intensity × migration share		-0.32						
		(0.1)***						
2015-16 × high intensity × firewood fuel share			0.13					
			(0.05)**					
2015-16 × high intensity × agriculture share				0.019				
				(0.05)				
2015-16 × high intensity × population growth					0.061			
					(0.02)**			
2015-16 × high intensity × voter turnout						1.30		
						(0.5)**		
2015-16 × high intensity × primary education share							-0.73	
							(0.2)***	
2015-16 × high intensity × upper caste share								-0.018
								(0.05)
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
year × high intensity	✓	✓	✓	✓	✓	✓	✓	✓
year × CFUG share	✓	✓	✓	✓	✓	✓	✓	✓
year × census-based covariate	✓	✓	✓	✓	✓	✓	✓	✓
Districts	75	75	75	75	75	75	75	75
N	518880	518720	518720	518256	518576	519008	518576	518720
R^2	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. *census-based covariate* is the variable considered in the respective column at the triple-interaction level (e.g., poverty index in column 1, etc.). The unit of observation is ward-year.

F.2 Investigating possible selection on unobservables

Table 10: Using Oster's (2019) method to investigate robustness to proportional selection of observables and unobservables

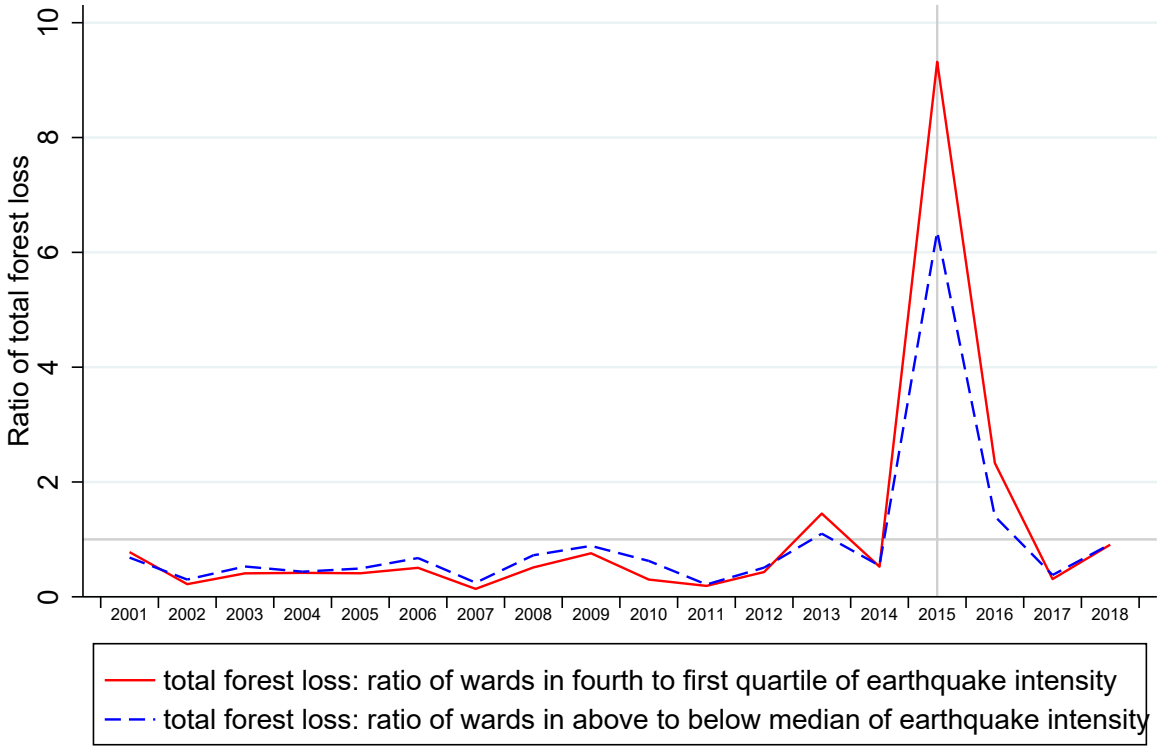
	Dependent variable is log(forest loss)				
	(1)	(2)	(3)	(4)	(5)
	point estimate from an Uncontrolled reg. [R^2]	N	point estimate from a Controlled reg. [$\tilde{R}^2$]	R_{max} =1.3 × $\tilde{R}^2$	
					Bound estimates
			$\beta_{\delta=0}$	$\delta_{\beta=0}$	$\beta_{\delta=[0,1]}$
Panel A: Analysis for Table 1, column (2)					
2015-16 × high intensity	0.101 [0.013]	519,008	0.094 [0.400]	10.3	[0.092, 0.094]
Panel B: Analysis for Table 2, column (2)					
2015-16 × high intensity × CFUG share	-0.097 [0.036]	519,008	-0.098 [0.403]	715.4	[-0.099, -0.098]
Panel C: Analysis for Table 9					
(adding all further controls at the triple difference level)					
2015-16 × high intensity × CFUG share	-0.096 [0.035]	517,824	-0.046 [0.411]	2.2	[-0.046, -0.026]

Notes: Results apply Oster's (2019) method. R-squared values are in square brackets. Column (1) presents results for the so-called "uncontrolled" or parsimonious regression. The results individually control for *2015-16* and *high intensity* (Panel A) and *high intensity*, *CFUG share*, year fixed effects, *high intensity* × *CFUG share*, *year* × *high intensity*, and *year* × *CFUG share* (Panels B and C). Column (2) shows the number of observations. To estimate the relative degree of selection, $\beta_{\delta=0}$, and bounds, in column (3), we add a large set of explanatory variables in addition to the "uncontrolled" effect from column (1). R_{max} is the R-squared from a hypothetical regression that includes both (observable and unobservable) controls. $\tilde{R}^2$ is the R-squared from the regression with full observed controls from the regression of interest. Columns (4) and (5) use $R_{max} = 1.3 \times \tilde{R}^2$ and present results for the $\beta_{\delta=0}$ and the estimated bounds, where 1.3 is the parameter value suggested by Oster (2019). For a given R_{max}, one of the bounds for the coefficient is calculated by assuming that the selection on observables (based on a large set of controls) equals the selection on unobservables, $\beta_{\delta=0} = 1$, and the other bound is calculated from column (3). The results from the uncontrolled regressions in Panels B and C are slightly different because there is a small number of missing values for the census-based characteristics that we employ in the controlled regression in Panel C (see column 2). The uncontrolled regression in Panel C also excludes those observations, and is therefore based on a different sample than the one in Panel B.

F.3 Results using total forest loss

Figure 6 provides visual evidence of the effect of the earthquake on forest loss, analogous to figure 2 in the main text. Here, we use total forest loss instead of forest loss net of landslides. The resulting ratios during the earthquake-affected years 2015 and 2016 are even larger than in figure 2.

Figure 5: The ratio of total forest loss between high and low earthquake intensity wards (not taking landslides into account)



Source: Own calculation using Hansen et al. (2013) and USGS (2015)

Notes: The solid line represents the ratio of total forest loss in wards belonging to the fourth quartile of earthquake intensity to wards belonging to the first quartile of earthquake intensity. The dashed line represents the ratio of total forest loss in wards experiencing an above-median earthquake intensity to wards with a below-median earthquake intensity. The vertical bar represents the earthquake year. The GFC data use satellite images from the growing season. The earthquake took place before the 2015 growing season and is therefore already represented in data in 2015.

In Table 11, we show that the difference-in-differences results are robust to using total forest loss and not taking into account the effect of earthquake-induced landslides. Each column corresponds to the respective column of Table 1. The results show that the difference-in-differences coefficient is again significant throughout, and its magnitude is slightly higher when not taking landslides into account in the calculation of forest loss.

Table 11: The effect of earthquake intensity on total forest loss (not taking landslides into account)

	Dependent variable is log(total forest loss)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2015-16 × high intensity	0.11	0.10	0.10				
	(0.03)***	(0.03)***	(0.03)***				
2015-16	-0.18						
	(0.02)***						
high intensity	-0.088						
	(0.03)***						
2017-18 × high intensity			0.086				
			(0.03)***				
2015-18 × high intensity				0.095	0.099	0.093	
				(0.03)***	(0.03)***	(0.03)***	
2011-14 × high intensity						-0.0077	
						(0.01)	
2015-16 × MMI (0,1)							0.21
							(0.06)***
ward fixed effects		✓	✓	✓	✓	✓	✓
year fixed effects		✓	✓	✓	✓	✓	✓
monthly precipitation variables		✓	✓	✓	✓	✓	✓
burned forest area		✓	✓	✓	✓	✓	✓
year × steep slope		✓	✓	✓	✓	✓	✓
year × high altitude		✓	✓	✓	✓	✓	✓
Districts	75	75	75	75	75	75	66
N	519024	519008	583884	583884	259504	583884	428240
R^2	0.013	0.40	0.36	0.36	0.34	0.36	0.39
Years covered	2001-16	2001-16	2001-18	2001-18	2011-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of total forest loss per year plus the area of a single 27 m × 27 m pixel to deal with observations where the area of total forest loss is zero. In columns (1)-(6), *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity. Column (7) uses *MMI (0,1)*. The unit of observation is ward-year.

In Table 12, we show that the triple difference results are robust to using total forest loss and not taking into account the effect of earthquake-induced landslides. Each column corresponds to the respective column of Table 2. The results show that the triple difference coefficient is again significant throughout, and its magnitude is slightly higher when not taking landslides into account in the calculation of forest loss.

Table 12: CFUGs and total forest loss: Triple difference results (not taking landslides into account)

	Dependent variable is log(total forest loss)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2015-16 × high intensity × CFUG share	-0.10	-0.10	-0.10				
	(0.03)***	(0.03)***	(0.03)***				
2015-16 × high intensity	0.14						
	(0.03)***						
2015-16 × CFUG share	0.062						
	(0.02)**						
2017-18 × high intensity × CFUG share			-0.038				
			(0.03)				
2015-18 × high intensity × CFUG share				-0.070	-0.062	-0.073	
				(0.03)**	(0.03)**	(0.03)**	
2011-14 × high intensity × CFUG share						-0.011	
						(0.02)	
2015-16 × MMI (0,1) × CFUG share							-0.23
							(0.06)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓
year × CFUG share		✓	✓	✓	✓	✓	✓
year × high intensity		✓	✓	✓	✓	✓	
year × MMI (0,1)							✓
Districts	75	75	75	75	75	75	66
N	519008	519008	583884	583884	259504	583884	428240
R^2	0.40	0.40	0.37	0.37	0.34	0.37	0.40
Years covered	2001-16	2001-16	2001-18	2001-18	2011-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of total forest loss per year plus the area of a single 27 m × 27 m pixel. In columns (1)-(6) *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. Column (7) uses *MMI (0,1)*. *CFUG share* is the share of CFUG area in a ward relative to the ward's total forested area in 2000. The unit of observation is ward-year.

F.4 Alternative results using imputed earthquake intensity measures

As explained in section 4.1 (Empirical strategy and results), the earthquake intensity data are not available for about 18% of our sample, namely for those areas that were least affected by the earthquake (i.e., furthest away from the epicenter, see figure 1(a)). This is not a concern for the analysis based on the binary measure (above/below median earthquake intensity) because the wards with missing MMI data are wards with below-median earthquake intensity. However, because of the missing data, we need to restrict the analysis based on continuous MMI measure in the main text to wards with non-missing MMI data. To investigate whether the missing MMI data affect those results, we consider in this appendix two strategies to impute the missing MMI data for the wards with the lowest earthquake intensity. First, we impute missing data with a fixed MMI value. Because the lowest MMI value in the data is 3.7, we set missing MMI values equal to 3, as most of these areas are further away from the epicenter than the wards with MMI of 3.7. We then rescale the resulting variable so that it lies between 0 and 1 (as before in the main text). We call this alternative variable $MMI\ (0,1)_{imputeUse3}$.

Second, we run – using wards as the level of observation – a regression of the (non-missing) MMI data on the distance to the epicenter, the square of the distance to the epicenter, latitude, longitude, minimum, maximum, and average altitude, and minimum, maximum, and average slope in the ward. We use the estimates of this regression to predict values for the missing MMI data. We call this alternative variable $MMI\ (0,1)_{imputeReg}$.

Table 13 presents the results of these robustness analyses. For comparison, columns (1) and (4) repeat the difference-in-differences and triple difference results from column (7) of Tables 1 and 2, respectively.

Columns (2) and (5) use the imputed MMI values based on the first approach, columns (3) and (6) are based on the second approach to imputation. In regressions that use these imputed values, we also include a dummy variable that indicates whether an observation uses an imputed MMI value, as well as interactions of this dummy variable with a dummy indicating the post-earthquake time period (2015-2016) and the CFUG share variable in the difference-in-differences specifications (columns 2 and 3), as well as the triple interaction of these variables in the triple difference specification (columns 5 and 6).

Overall, the results show that the main findings are robust to using the imputed values for the wards with missing MMI data.

Table 13: Robustness to using the imputed MMI intensity measure

	Dependent variable is log(forest loss)					
	difference-in-differences			triple difference		
	(1)	(2)	(3)	(4)	(5)	(6)
2015-16 × MMI (0,1)	0.18					
	(0.06)***					
2015-16 × MMI $(0,1)_{\text{imputeReg}}$		0.22				
		(0.07)***				
2015-16 × MMI $(0,1)_{\text{imputeUse3}}$			0.24			
			(0.06)***			
2015-16 × MMI (0,1) × CFUG share				-0.21		
				(0.06)***		
2015-16 × MMI $(0,1)_{\text{imputeReg}}$ × CFUG share					-0.26	
					(0.07)***	
2015-16 × MMI $(0,1)_{\text{imputeUse3}}$ × CFUG share						-0.21
						(0.07)***
ward fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓
year × CFUG share				✓	✓	✓
imputed dummy interactions		✓	✓		✓	✓
year × MMI (0,1)				✓		
year × MMI $(0,1)_{\text{imputeReg}}$					✓	
year × MMI $(0,1)_{\text{imputeReg}}$						✓
Districts	66	75	75	66	75	75
N	428240	519008	519008	428240	519008	519008
R^2	0.40	0.40	0.40	0.40	0.40	0.40
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16
Approach to dealing with missing MMI (0,1)	drop missing	imputation by assuming 3	imputation via Regression	drop missing	imputation by assuming 3	imputation via Regression

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *MMI (0,1)* is a continuous variable based on the exogenous earthquake intensity measure, MMI, scaled to 0 and 1. In *MMI* $(0,1)_{imputeUse3}$, imputation of data is done by setting missing MMI values equal to 3, and rescaling the resulting variable so that it lies between 0 and 1. In *MMI* $(0,1)_{imputeReg}$, imputation of data is done by running a regression of the (non-missing) MMI data on the distance to the epicenter, the square of the distance to the epicenter, latitude, longitude, minimum, maximum, and average altitude, and minimum, maximum, and average slope and using the estimates of this regression to predict values for the missing MMI data. *CFUG share* is the share of CFUG area in a ward relative to the ward's total forested area in 2000. The unit of observation is ward-year.

F.5 Not weighting by the baseline forest cover in 2000

Table 14: Robustness to not weighting by their forest cover in 2000

	Dependent variable is log(forest loss, unweighted)							
	difference-in-differences				triple difference			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2015-16 × high intensity	0.13	0.13						
	(0.04)***	(0.04)***						
2017-18 × high intensity		0.12						
		(0.03)***						
2015-18 × high intensity			0.12					
			(0.03)***					
2011-14 × high intensity			-0.011					
			(0.02)					
2015-16 × MMI (0,1)				0.27				
				(0.08)***				
2015-16 × high intensity × CFUG share					-0.12	-0.12		
					(0.04)***	(0.04)***		
2017-18 × high intensity × CFUG share						-0.034		
						(0.04)		
2015-18 × high intensity × CFUG share							-0.075	
							(0.04)*	
2011-14 × high intensity × CFUG share							0.0024	
							(0.02)	
2015-16 × MMI (0,1) × CFUG share								-0.24
								(0.08)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
year × CFUG share					✓	✓	✓	✓
year × high intensity					✓	✓	✓	
year × MMI (0,1)								✓
Districts	75	75	75	66	75	75	75	66
N	519008	583884	583884	428240	519008	583884	583884	428240
R^2	0.39	0.35	0.35	0.39	0.40	0.36	0.36	0.39
Years covered	2001-16	2001-18	2001-18	2001-16	2001-16	2001-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. Here, forest loss data and forest loss data due to landslides are not weighted by their forest cover in 2000. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *MMI (0,1)* is a continuous variable based on MMI, scaled to 0 and 1. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. The unit of observation is ward-year. Columns (1)-(4) show the analogue of the difference-in-differences results from columns (2), (3), (6), and (7) of Table 1, respectively. Similarly, columns (5)-(8) show the analogue of the triple difference results from columns (2), (3), (6), and (7) of Table 2, respectively.

F.6 Taking forest gain data into account

To investigate whether the forest gain data affect the results, we use the **third variant** of **total forest loss** that is explained in Appendix, Section B. Table 15 presents the results of the robustness analyses of the forest loss that uses the baseline forest cover in 2012 as weights. Given the coarse information on forest gain, we have to make strong assumptions to generate a new baseline forest cover (see appendix B above), so the results of this robustness analysis should mainly be interpreted qualitatively and less with a view on the precise quantitative numbers.

Overall, the results show that the main findings are robust to weighting by forest cover in 2012 that takes into account the forest gain that occurred between 2000 to 2012.

Table 15: Robustness to using 2012 forest cover weights

	Dependent variable is log(forest loss, weighted 2012)							
	difference-in-differences				triple difference			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2015-16 × high intensity	0.051	0.052	0.055		0.067			
	(0.02)**	(0.03)*	(0.02)**		(0.03)**			
2015-16	-0.081							
	(0.01)***							
high intensity	-0.038							
	(0.02)*							
2017-18 × high intensity			0.015					
			(0.02)					
2015-16 × MMI (0,1)				0.15				
				(0.06)**				
2015-16 × high intensity × CFUG share					-0.043	-0.042	-0.047	
					(0.02)**	(0.02)**	(0.02)***	
2015-16 × CFUG share					0.028			
					(0.01)**			
2017-18 × high intensity × CFUG share							0.014	
							(0.02)	
2015-16 × MMI (0,1) × CFUG share								-0.087
								(0.05)*
ward fixed effects		✓	✓	✓	✓	✓	✓	✓
year fixed effects		✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables		✓	✓	✓	✓	✓	✓	✓
burned forest area		✓	✓	✓	✓	✓	✓	✓
year × steep slope		✓	✓	✓	✓	✓	✓	✓
year × high altitude		✓	✓	✓	✓	✓	✓	✓
year × CFUG share						✓	✓	✓
year × high intensity						✓	✓	
year × MMI (0,1)								✓
Districts	75	75	75	66	75	75	75	66
N	129754	129750	194626	107058	129750	129750	194626	107058
R^2	0.0096	0.43	0.33	0.43	0.43	0.43	0.33	0.43
Years covered	2013-2016	2013-2016	2013-2018	2013-2016	2013-2016	2013-2016	2013-2018	2013-2016

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. Forest gain data between 2001 and 2012 are used in the calculation of baseline forest cover in 2012. Here, the dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. Here, both forest loss data and forest loss due to landslides data are weighted by the baseline forest cover in 2012. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *MMI (0,1)* is a continuous variable based on MMI, scaled to 0 and 1. *CFUG share* is the share of CFUG area in a ward relative to the ward's total forested area in 2000. The unit of observation is ward-year. Columns (1)-(4) show the analogue of the difference-in-differences results from columns (1)-(3) and (7) of Table 1, respectively. Similarly, columns (5)-(8) show the analogue of the triple difference results from columns (1)-(3) and (7) of Table 2, respectively.

F.7 Alternative approaches to dealing with zero forest loss

Table 16: Robustness to using forest loss without logarithmic transformation

	Dependent variable is forest loss							
	difference-in-differences				triple difference			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2015-16 × high intensity	0.047	0.047						
	(0.01)***	(0.01)***						
2017-18 × high intensity		0.036						
		(0.02)**						
2015-18 × high intensity			0.038					
			(0.01)***					
2011-14 × high intensity			-0.014					
			(0.02)					
2015-16 × MMI (0,1)				0.090				
				(0.03)***				
2015-16 × high intensity × CFUG share					-0.043	-0.042		
					(0.02)***	(0.02)***		
2017-18 × high intensity × CFUG share						-0.0037		
						(0.02)		
2015-18 × high intensity × CFUG share							-0.025	
							(0.02)	
2011-14 × high intensity × CFUG share							-0.0074	
							(0.01)	
2015-16 × MMI (0,1) × CFUG share								-0.097
								(0.03)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
year × CFUG share					✓	✓	✓	✓
year × high intensity					✓	✓	✓	
year × MMI (0,1)								✓
Districts	75	75	75	66	75	75	75	66
N	519008	583884	583884	428240	519008	583884	583884	428240
R^2	0.22	0.20	0.20	0.21	0.22	0.20	0.20	0.21
Years covered	2001-16	2001-18	2001-18	2001-16	2001-16	2001-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the untransformed area of forest loss per year minus the area of forest loss due to landslides. Here, both forest loss data and forest loss due to landslides data are weighted by their forest cover 2000. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *MMI (0,1)* is a continuous variable based on MMI, scaled to 0 and 1. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. The unit of observation is ward-year. Columns (1)-(4) show the analogue of the difference-in-differences results from columns (2), (3), (6), and (7) of Table 1, respectively. Similarly, columns (5)-(8) show the analogue of the triple difference results from columns (2), (3), (6), and (7) of Table 2, respectively.

Table 17: Robustness to using the inverse hyperbolic sine transformation of forest loss

	Dependent variable is inverse hyperbolic sine of forest loss							
	difference-in-differences				triple difference			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2015-16 × high intensity	0.030	0.030						
	(0.008)***	(0.008)***						
2017-18 × high intensity		0.025						
		(0.008)***						
2015-18 × high intensity			0.027					
			(0.007)***					
2011-14 × high intensity			-0.0019					
			(0.005)					
2015-16 × MMI (0,1)				0.057				
				(0.02)***				
2015-16 × high intensity × CFUG share					-0.028	-0.028		
					(0.009)***	(0.009)***		
2017-18 × high intensity × CFUG share						-0.0073		
						(0.007)		
2015-18 × high intensity × CFUG share							-0.019	
							(0.008)**	
2011-14 × high intensity × CFUG share							-0.0035	
							(0.005)	
2015-16 × MMI (0,1) × CFUG share								-0.065
								(0.02)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
year × CFUG share					✓	✓	✓	✓
year × high intensity					✓	✓	✓	
year × MMI (0,1)								✓
Districts	75	75	75	66	75	75	75	66
N	519008	583884	583884	428240	519008	583884	583884	428240
R^2	0.37	0.33	0.33	0.36	0.37	0.33	0.33	0.36
Years covered	2001-16	2001-18	2001-18	2001-16	2001-16	2001-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the inverse hyperbolic sine of the area of forest loss per year minus the area of forest loss due to landslides. Here, both forest loss data and forest loss due to landslides data are weighted by their forest cover 2000. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *MMI (0,1)* is a continuous variable based on MMI, scaled to 0 and 1. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. The unit of observation is ward-year. Columns (1)-(4) show the analogue of the difference-in-differences results from columns (2), (3), (6), and (7) of Table 1, respectively. Similarly, columns (5)-(8) show the analogue of the triple difference results from columns (2), (3), (6), and (7) of Table 2, respectively.

F.8 Alternative strategies for calculating CFUG share

Table 18: Robustness to attributing the community forest area to individual wards equally

	Dependent variable is log(forest loss)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2015-16 × high intensity × CFUG share$_{[equal]}$	-0.12	-0.12	-0.12				
	(0.03)***	(0.03)***	(0.03)***				
2015-16 × high intensity	0.14						
	(0.03)***						
2015-16 × CFUG share$_{[equal]}$	0.090						
	(0.02)***						
2017-18 × high intensity × CFUG share$_{[equal]}$			-0.047				
			(0.03)*				
2015-18 × high intensity × CFUG share$_{[equal]}$				-0.082	-0.075	-0.085	
				(0.03)***	(0.03)***	(0.03)***	
2011-14 × high intensity × CFUG share$_{[equal]}$						-0.010	
						(0.01)	
2015-16 × MMI (0,1) × CFUG share$_{[equal]}$							-0.24
							(0.06)***
ward fixed effects	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓
year × CFUG share$_{[equal]}$		✓	✓	✓	✓	✓	✓
year × high intensity		✓	✓	✓	✓	✓	
year × MMI (0,1)							✓
Districts	75	75	75	75	75	75	66
N	519008	519008	583884	583884	259504	583884	428240
R^2	0.40	0.40	0.37	0.37	0.34	0.37	0.40
Years covered	2001-16	2001-16	2001-18	2001-18	2011-18	2001-18	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. In columns (1)-(6) *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. Column (7) uses *MMI (0,1)*. Here, when the CFUG span multiple wards, the community forest area to individual wards is attributed equally and *CFUG share$_{[equal]}$* is the share of CFUG area in a ward based on this approach relative to the ward's total forested area in 2000. The unit of observation is ward-year. Different columns show the analogue of the triple difference results from Table 2.

F.9 Consider forest loss by two-year aggregates

Table 19: Difference-in-differences results considering forest loss by two-year aggregates

	Dependent variable is		
	forest loss	log(forest loss)	ihs(forest loss)
	(1)	(2)	(3)
[2003/4] × high intensity	0.0046	0.025	0.0054
	(0.01)	(0.02)	(0.007)
[2005/6] × high intensity	-0.0051	-0.0076	-0.0018
	(0.01)	(0.02)	(0.007)
[2007/8] × high intensity	-0.029	-0.046	-0.016
	(0.01)**	(0.02)**	(0.007)**
[2009/10] × high intensity	0.012	0.067	0.017
	(0.02)	(0.02)***	(0.007)**
[2011/12] × high intensity	-0.054	-0.036	-0.015
	(0.04)	(0.03)	(0.01)
[2013/14] × high intensity	0.020	0.037	0.013
	(0.01)*	(0.02)*	(0.007)*
[2015/16] × high intensity	0.039	0.10	0.030
	(0.01)***	(0.03)***	(0.008)***
[2017/18] × high intensity	0.028	0.091	0.025
	(0.02)*	(0.03)***	(0.009)***
ward fixed effects	✓	✓	✓
year fixed effects	✓	✓	✓
monthly precipitation variables	✓	✓	✓
burned forest area	✓	✓	✓
year × steep slope	✓	✓	✓
year × high altitude	✓	✓	✓
Districts	75	75	75
N	583884	583884	583884
R^2	0.20	0.37	0.33
Years covered	2001-18	2001-18	2001-18

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The two years are combined into a single period and thus, the omitted period is [2001/2]. The dependent variable in column (1) is the area of forest loss per year minus the area of forest loss due to landslides. The dependent variable in column (2) is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel and in column (3) is the inverse hyperbolic sine of the area of forest loss per year minus the area of forest loss due to landslides. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. The unit of observation is ward-year.

Table 20: Triple difference results considering forest loss by two-year aggregates

	Dependent variable is		
	forest loss	log(forest loss)	ihs(forest loss)
	(1)	(2)	(3)
[2003/4] × high intensity × CFUG share	0.0068	0.034	0.0082
	(0.02)	(0.02)	(0.008)
[2005/6] × high intensity × CFUG share	0.0052	0.032	0.0089
	(0.02)	(0.02)	(0.006)
[2007/8] × high intensity × CFUG share	0.015	0.057	0.015
	(0.02)	(0.02)***	(0.007)**
[2009/10] × high intensity × CFUG share	0.021	0.030	0.011
	(0.02)	(0.02)	(0.008)
[2011/12] × high intensity × CFUG share	0.029	0.059	0.017
	(0.03)	(0.03)**	(0.009)*
[2013/14] × high intensity × CFUG share	-0.024	-0.020	-0.0069
	(0.02)	(0.03)	(0.008)
[2015/16] × high intensity × CFUG share	-0.035	-0.072	-0.021
	(0.02)*	(0.03)**	(0.009)**
[2017/18] × high intensity × CFUG share	0.0037	-0.0096	0.00018
	(0.02)	(0.03)	(0.008)
ward fixed effects	✓	✓	✓
year fixed effects	✓	✓	✓
monthly precipitation variables	✓	✓	✓
burned forest area	✓	✓	✓
year × steep slope	✓	✓	✓
year × high altitude	✓	✓	✓
year × high intensity	✓	✓	✓
year × CFUG share	✓	✓	✓
Districts	75	75	75
N	583884	583884	583884
R^2	0.20	0.37	0.33
Years covered	2001-18	2001-18	2001-18

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The two years are combined into a single period and thus, the omitted period is [2001/2]. The dependent variable in column (1) is the area of forest loss per year minus the area of forest loss due to landslides. The dependent variable in column (2) is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel and in column (3) is the inverse hyperbolic sine of the area of forest loss per year, minus the area of forest loss due to landslides. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. The unit of observation is ward-year.

F.10 Consider forest loss year-by-year individually

Table 21: Difference-in-differences results considering forest loss year-by-year individually

	Dependent variable is		
	forest loss	log(forest loss)	ihs(forest loss)
	(1)	(2)	(3)
2002 × high intensity	-0.030	-0.084	-0.019
	(0.01)**	(0.03)**	(0.009)**
2003 × high intensity	0.0086	0.045	0.011
	(0.02)	(0.03)	(0.009)
2004 × high intensity	-0.028	-0.078	-0.019
	(0.02)*	(0.03)***	(0.008)**
2005 × high intensity	-0.032	-0.088	-0.021
	(0.02)*	(0.03)***	(0.01)**
2006 × high intensity	-0.0076	-0.011	-0.0017
	(0.02)	(0.03)	(0.009)
2007 × high intensity	-0.078	-0.15	-0.043
	(0.03)***	(0.03)***	(0.01)***
2008 × high intensity	-0.0093	-0.018	-0.0069
	(0.01)	(0.02)	(0.007)
2009 × high intensity	0.011	0.097	0.023
	(0.03)	(0.03)***	(0.01)**
2010 × high intensity	-0.011	-0.030	-0.0049
	(0.01)	(0.03)	(0.008)
2011 × high intensity	-0.100	-0.093	-0.030
	(0.07)	(0.04)**	(0.02)*
2012 × high intensity	-0.036	-0.061	-0.018
	(0.02)**	(0.04)	(0.01)
2013 × high intensity	0.015	0.022	0.0090
	(0.01)	(0.03)	(0.007)
2014 × high intensity	-0.00099	-0.028	-0.00090
	(0.01)	(0.03)	(0.008)
2015 × high intensity	0.034	0.061	0.022
	(0.01)**	(0.03)**	(0.007)***
2016 × high intensity	0.018	0.063	0.022
	(0.01)	(0.03)**	(0.007)***
2017 × high intensity	0.0020	0.042	0.013
	(0.02)	(0.03)	(0.010)
2018 × high intensity	0.027	0.060	0.020
	(0.02)*	(0.03)**	(0.008)**
ward fixed effects	✓	✓	✓
year fixed effects	✓	✓	✓
monthly precipitation variables	✓	✓	✓
burned forest area	✓	✓	✓
year × steep slope	✓	✓	✓
year × high altitude	✓	✓	✓
Districts	75	75	75
N	583884	583884	583884
R^2	0.20	0.37	0.33
Years covered	2001-18	2001-18	2001-18

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The omitted year is 2001. The dependent variable in column (1) is the area of forest loss per year minus the area of forest loss due to landslides. The dependent variable in column (2) is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel and in column (3) is the inverse hyperbolic sine of the area of forest loss per year minus the area of forest loss due to landslides. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. The unit of observation is ward-year.

Table 22: Triple difference results considering forest loss year-by-year individually

	Dependent variable is		
	forest loss	log(forest loss)	ihs(forest loss)
	(1)	(2)	(3)
2002 × high intensity × CFUG share	0.0065	-0.0074	0.00016
	(0.02)	(0.03)	(0.009)
2003 × high intensity × CFUG share	0.018	0.062	0.016
	(0.02)	(0.03)**	(0.01)
2004 × high intensity × CFUG share	0.0022	-0.00045	0.00070
	(0.02)	(0.02)	(0.008)
2005 × high intensity × CFUG share	-0.0070	0.014	0.0042
	(0.02)	(0.03)	(0.009)
2006 × high intensity × CFUG share	0.024	0.043	0.014
	(0.02)	(0.02)*	(0.008)*
2007 × high intensity × CFUG share	0.046	0.066	0.024
	(0.02)**	(0.03)**	(0.01)**
2008 × high intensity × CFUG share	-0.0087	0.042	0.0061
	(0.02)	(0.03)	(0.008)
2009 × high intensity × CFUG share	0.056	0.049	0.020
	(0.04)	(0.03)	(0.01)*
2010 × high intensity × CFUG share	-0.0066	0.0043	0.0018
	(0.02)	(0.02)	(0.007)
2011 × high intensity × CFUG share	0.011	-0.036	-0.0072
	(0.04)	(0.03)	(0.01)
2012 × high intensity × CFUG share	0.053	0.15	0.041
	(0.02)**	(0.05)***	(0.01)***
2013 × high intensity × CFUG share	-0.016	-0.019	-0.0057
	(0.01)	(0.02)	(0.006)
2014 × high intensity × CFUG share	-0.026	-0.028	-0.0079
	(0.02)	(0.03)	(0.008)
2015 × high intensity × CFUG share	-0.045	-0.082	-0.023
	(0.02)***	(0.02)***	(0.007)***
2016 × high intensity × CFUG share	-0.018	-0.068	-0.018
	(0.02)	(0.03)**	(0.008)**
2017 × high intensity × CFUG share	0.014	-0.018	0.00025
	(0.03)	(0.03)	(0.009)
2018 × high intensity × CFUG share	0.00010	-0.0084	0.00032
	(0.02)	(0.03)	(0.007)
ward fixed effects	✓	✓	✓
year fixed effects	✓	✓	✓
monthly precipitation variables	✓	✓	✓
burned forest area	✓	✓	✓
year × steep slope	✓	✓	✓
year × high altitude	✓	✓	✓
year × high intensity	✓	✓	✓
year × CFUG share	✓	✓	✓
Districts	75	75	75
N	583884	583884	583884
R^2	0.20	0.37	0.33
Years covered	2001-18	2001-18	2001-18

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The omitted year is 2001. The dependent variable in column (1) is the area of forest loss per year minus the area of forest loss due to landslides. The dependent variable in column (2) is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel and in column (3) is the inverse hyperbolic sine of the area of forest loss per year, minus the area of forest loss due to landslides. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. The unit of observation is ward-year.

F.11 Estimating standard errors that allow for spatial correlation in the distance dimension

Table 23: Allowing for spatial correlation in the distance dimension

	Dependent variable is log(forest loss)					
	Table 1, column 2			Table 2, column 2		
	(1)	(2)	(3)	(4)	(5)	(6)
2015-16 × high intensity	0.094	0.094	0.094			
	(0.03)***	(0.04)**	(0.03)***			
2015-16 × high intensity				-0.098	-0.098	-0.098
× CFUG share				(0.03)***	(0.04)**	(0.04)**
ward fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓
year × CFUG share				✓	✓	✓
year × high intensity				✓	✓	✓
SE cluster	District	Spatial	Spatial	District	Spatial	Spatial
District clusters	75			75		
Distance cutoff (in km)		100	500		100	500
Districts	75	75	75	75	75	75
N	519008	519008	519008	519008	519008	519008
R^2	0.40	0.40	0.40	0.40	0.40	0.40
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parenthesis. Columns (1)-(3) refer to results from Column (2) of Table 1. Column (1), for comparison, shows standard errors that allow for clustering of the model error at the district level, as in all baseline results. In columns (2) and (3) standard errors allow for correlation within a 100 km and 500 km radius (Conley 1999). Columns (4)-(6) perform an analogous analysis referring to results from Column (2) of Table 2. For spatial correlation, we use the latitude and longitude information from the centroid of the ward and assume the correlation between the error term of two observations beyond 100 km and 500 km, respectively, to be zero. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward.

F.12 Robustness checks: heterogeneous effects

Table 24: Triple difference results (DiD results interacted with the ward and CFUG characteristics)

	Dependent variable is log(forest loss)							
	ward characteristics						CFUG characteristics	
	(1) poverty index	(2) migration share	(3) firewood fuel share	(4) agriculture share	(5) population growth	(6) voter turnout	(7) female rep. in CFUG	(8) CFUG condition very good
2015-16 × high intensity	0.82	-0.34	0.10	0.012	0.063	1.39	0.0071	0.12
× census-based covariate	(0.2)***	(0.1)***	(0.05)**	(0.05)	(0.02)**	(0.5)**	(0.07)	(0.08)
2015-16 × high intensity	-0.15	0.19	-0.020	0.083	0.088	-0.98	0.094	0.081
	(0.04)***	(0.04)***	(0.03)	(0.04)**	(0.03)***	(0.4)**	(0.04)**	(0.03)**
2015-16 × census-based covariate	-0.80	0.32	-0.25	-0.13	-0.060	-1.04	-0.053	-0.14
	(0.1)***	(0.08)***	(0.04)***	(0.03)***	(0.02)***	(0.4)***	(0.05)	(0.07)**
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
Districts	75	75	75	75	75	75	74	74
N	518880	518720	518720	518256	518576	519008	253184	280400
R^2	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. *census-based covariates* are the third term of the triple difference and are indicated below the column numbers. The unit of observation is ward-year.

Table 25: Fourth difference results (TD results interacted with the ward and CFUG characteristics)

	Dependent variable is log(forest loss)							
	ward characteristics						CFUG characteristics	
	(1) poverty index	(2) migration share	(3) firewood fuel share	(4) agriculture share	(5) population growth	(6) voter turnout	(7) female rep. in CFUG	(8) CFUG condition very good
2015-16 × high intensity × CFUG share	-0.98	0.32	-0.18	-0.20	-0.097	-1.39	-0.27	-0.31
× census-based covariate	(0.3)***	(0.1)**	(0.07)**	(0.07)***	(0.04)***	(0.6)**	(0.1)*	(0.1)**
2015-16 × high intensity × CFUG share	0.18	-0.17	0.095	0.074	-0.088	0.98	0.015	-0.038
	(0.06)***	(0.06)***	(0.06)	(0.06)	(0.03)***	(0.4)**	(0.06)	(0.05)
2015-16 × high intensity	1.01	-0.40	0.16	0.083	0.098	1.74	0.16	0.29
× census-based covariate	(0.2)***	(0.1)***	(0.05)***	(0.05)	(0.03)***	(0.6)***	(0.1)	(0.1)**
2015-16 × CFUG share	0.30	-0.13	0.21	0.24	0.061	0.83	0.31	0.24
× census-based covariate	(0.2)	(0.1)	(0.06)***	(0.05)***	(0.03)**	(0.5)*	(0.1)**	(0.1)**
ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
monthly precipitation variables	✓	✓	✓	✓	✓	✓	✓	✓
burned forest area	✓	✓	✓	✓	✓	✓	✓	✓
year × steep slope	✓	✓	✓	✓	✓	✓	✓	✓
year × high altitude	✓	✓	✓	✓	✓	✓	✓	✓
year × high intensity	✓	✓	✓	✓	✓	✓	✓	✓
year × CFUG share	✓	✓	✓	✓	✓	✓	✓	✓
2015-16 × census-based covariate	✓	✓	✓	✓	✓	✓	✓	✓
Districts	75	75	75	75	75	75	74	74
N	518880	518720	518720	518256	518576	519008	253184	280400
R^2	0.40	0.40	0.40	0.40	0.40	0.40	0.41	0.41
Years covered	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16	2001-16

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and allow for clustering of the model error at the district level. The dependent variable is the logarithm of the area of forest loss per year, minus the area of forest loss due to landslides, plus the area of a single 27 m × 27 m pixel. *high intensity* is a dummy equaling one for wards that experienced above-median earthquake intensity based on the exogenous earthquake intensity measure, MMI. *CFUG share* is the share of CFUG area relative to the total forested area in the ward. *census-based covariates* are the fourth term of the fourth difference and are indicated below the column numbers. The unit of observation is ward-year.

Table 26: Variable description

variable name	variable definition	variable type
dependent variables		
log(forest loss)=log(net forest loss)	log((forest loss-landslides loss) × forests in 2000+0.0729)	continuous
log(total forest loss)	log(forest loss × forests in 2000+0.0729)	continuous
log(loss and gain)	log(forest loss × forests in 2012+0.0729)	continuous
log(net loss and gain)	log(forest loss-landslides loss × forests in 2012+0.0729)	continuous
explanatory variables		
intensity	earthquake intensity at the centroid of the ward	continuous (in MMI)
intensity (aftershock)	aftershock intensity at the centroid of the ward	continuous (in MMI)
high intensity	above median earthquake intensity based on MMI	dummy
MMI (0,1)	earthquake intensity based on MMI rescaled to [0,1]	continuous [0,1]
CFUG share	$\frac{\text{CFUG area}}{\text{ward's forested area}}$ (proportional distribution)	continuous [0,1]
CFUG share$_{[\text{equal}]}$	$\frac{\text{CFUG area}}{\text{ward's forested area}}$ (equal distribution)	continuous [0,1]
forest area	total forest area in a ward	continuous (in ha)
ward area	total area in a ward	continuous (in ha)
main control variables		
month1 - month12	monthly average of 2000-18 daily rainfall (Jan-Dec)	continuous (in mm^3)
forest loss (burning)	annual forest loss area due to burning	continuous (in ha))
high altitude	above median of the altitude averages	dummy
steep slope	above median of the slope averages	dummy
ward characteristics		
poverty index (see footnote 47)	$\frac{\text{low health + low education + low living standards}}{3}$	continuous [0,1]
low health	$\frac{\text{high child mortality + high pre-mature mortality}}{2}$	continuous [0,1]
low education	$\frac{\text{low school attendance + low schooling}}{2}$	continuous [0,1]
low living standards	$\frac{\text{firewood as fuel + lack (electricity + clean water + sanitation)}}{4}$	continuous [0,1]
migration share	$\frac{\text{households with at least one member living abroad}}{\text{ward's total households}}$	continuous [0,1]
firewood-based hh share	$\frac{\text{households using firewood for cooking}}{\text{ward's total households}}$	continuous [0,1]
agriculture-based hh share	$\frac{\text{households with at least one member in agriculture}}{\text{ward's total households}}$	continuous [0,1]
voter turnout	$\frac{\text{number of casted votes (valid + invalid votes)}}{\text{total voters in 2013 constituent assembly election}}$	continuous [0,1]
population growth	total population growth in a VDC (2001 to 2011)	continuous
CFUG characteristics		
female representation in CFUG	$\frac{\text{female executive members}}{\text{total executive members in the CFUG management}}$	continuous [0,1]
"very good" CFUG condition share	$\frac{\text{number of very-good condition CFUGs}}{\text{total CFUGs in the ward}}$	continuous [0,1]
alternative dependent variables		
log(net forest loss no 2000)	log(forest loss-landslides loss+0.0729)	continuous
net forest loss	forest loss-loss due to landslides × forests in 2000	continuous (in ha)
ihs(net forest loss)	log(net forest loss + $\sqrt{1 + \text{net forest loss}^2}$)	continuous