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Resilience of Paddy Production to Natural Disasters: Evidence from the 2015 Nepal Earthquake

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ABSTRACT

This article attempts to examine the impact of the 2015 Nepal Earthquake on paddy production. The difference-in-differences method has been applied to investigate the short-run and long-run causal impact on paddy production by leveraging the unforeseen exogenous shock brought by the earthquake. The results suggest a transient negative effect of the earthquake on paddy production. However, the effect is not pronounced in the long-run. Quantitatively, the paddy production in severely affected districts declined by about 9 percent in the short-term. In a nutshell, these results provide strong evidence that natural disasters have a short-lived impact on agriculture in developing countries, necessity the maintenance of the minimum buffer stock for food security in case of natural disasters.

JEL Code: Q54, Q15

Keywords: Nepal, Earthquake, Agriculture, Paddy

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I. INTRODUCTION

Natural disasters are nearly inevitable events that engender unparalleled loss of human lives, infrastructure, and ecosystem. According to the Centre for Research on the Epidemiology and Disasters (CRED), 9753 natural disasters have affected the lives of 4.5 billion people, with 1.5 million casualties, and incurred humongous economic losses estimated at USD 4.1 billion. Specifically, droughts have affected 36 percent of the total affected population, while floods for 22 percent of economic losses. Likewise, earthquakes are the cause behind 50 percent of all casualties (CRED, 2023).

The existing literature assesses the impact of natural disaster on various grounds, including agriculture (Chapagain & Raizada, 2017; Epstein et al., 2017; FAO, 2015; Israel & Briones, 2013; Long, 1978; Mohan, 2017; Ray et al., 2018), labor market outcomes (Belasen & Polachek, 2009; Kirchberger, 2017; McIntosh, 2008; Shakya et al., 2022), and growth and development (Charvériat, 2000; Fomby et al., 2013; Noy, 2009; Toya & Skidmore, 2007). However, the bulk of previous literature examining the impact of natural disasters on agriculture focuses on predictable natural disasters, such as hurricanes, typhoons, floods, and droughts. This underscores the need to assess the impact of sudden and unpredictable natural disasters, such as earthquakes, on agriculture, particularly in rural settings characterized by scarce irrigation and rocky mountainous terrain.

The 2015 Nepal earthquake resulted in humanitarian and physical losses commensurate with no prior disaster in the country's history. The earthquake affected 14 districts of Nepal and impacted approximately 8 million people, with colossal economic losses estimated at USD 10 billion, equivalent to nearly half of the Gross Domestic Product (Goda et al., 2015; NPC, 2015a; Shakya et al., 2022). The earthquake wrecked farmhouses, irrigation canals, agriculture tools, and stored seed stocks fundamental to the agriculture sector (NPC, 2015a). However, unique community experiences of dealing with mountain hazards, and several endogenous components of the social-ecological system, such as mutual support and community institutions, reinforced swift recovery (Epstein et al., 2017).

This paper evaluates the impact of the 2015 Nepal Earthquake of 7.8 magnitude on paddy production. The agricultural sector contributes about one-fourth of Nepal's GDP and upholds the livelihood of about 60 percent of the population (NPC, 2015b, 2020; NSO, 2023). Paddy, also known as rice, holds a significant position among the primary food crops cultivated in Nepal, accounting for approximately 50 percent of food crop production. The Nepalese populace has developed a customary practice of incorporating rice as a staple component in their daily dietary intake. The earthquake-affected region accounts for only 10 percent of paddy production, but the subsistence nature of farming practiced in the entire country poses a threat to food security in this region (NPC, 2015a). Concerns raised by FOA (2015) and NPC (2015a, 2015b) regarding probable food shortages and a negative impact on crop production in years to come motivate this research to do. In contrast to FOA (2015) and NPC (2015a, 2015b), Epstein et al. (2017) contend that decades of experience of mitigating natural disasters could potentially diminish the impact of earthquakes on crop production. Thus, accessing the impact of the 2015 Nepal earthquake on paddy production world broaden our understanding of the relationship between natural disasters and crop production under the distinctive settings characterized by bucolic lifestyle, mountainous landscape, and poor infrastructure. Also, the article assesses the short-run and long-run impact of the earthquake on paddy production that enables us to understand whether the impact is transient or perennial.

The canonical difference-in-differences (DiD) model is used to evaluate the changes in paddy production in districts that experienced severe damage ("treated") compared to those that remained unaffected ("control") by the earthquake. National Planning Commission (NPC), an apex governmental body for formulating developmental plans in Nepal, identified 14 districts as severely affected by the earthquake, and the remaining 61 districts are the least affected (NPC, 2015a). Therefore, the treatment group consists of 14 districts that have experienced severe impact from the earthquake and the control group encompasses the remaining 61 districts that have been minimally affected. District-level paddy production data obtained from Nepal's Ministry of Agriculture and Livestock Development are used in order to quantify the changes in paddy production. Besides the canonical DiD method, the DiD with controls is also used to circumvent the problem of omitted variable bias. The control variables include district-level paddy cultivation area, rainfall, and quantity sales of chemical fertilizers. We conducted the short-run analysis by considering two years, just before and after the earthquake, while the long-run analysis has been conducted by applying the canonical DiD model, including multiple time periods, before and after the earthquake. Several robustness checks have been conducted to substantiate the results obtained from the short-run and long-run baseline models. These checks encompass placebo tests, alternative identification strategies that exploit districts with fertile lands and irrigation facilities, and incorporate additional control variables, including district-level population, import of chemical fertilizers, and agriculture equipment.

Results illustrates the negative impact of the earthquake on paddy production in the short run, but the effect is not pronounced in the long run. The paddy production in the earthquake-affected districts decreased by about 9 percent in the subsequent year following the earthquake. Farmers prepare nursery beds to produce paddy seedlings in April, and the earthquake occurred in the same month disrupting the entire process. Consequently, the paddy production may have decreased in the subsequent year. The effect of earthquakes is not perceptible in the long run, suggesting a recovery in the following years after the earthquake. More than two-thirds of arable lands are rain-fed. As a result, limited damage to irrigation canals may not have affected the paddy production once the situation returned to normalcy. Likewise, the return of migrant workers and decreased international labor migration in the severely affected districts may have contributed to the recovery of the agriculture sector, including paddy production.

This research contributes to the strand of literature concentrating on natural disasters and crop production. A vast majority of the literature finds varying impacts of natural disasters, depending upon the nature of the crop, time of the disaster, and nature of the disaster itself (Israel & Briones, 2013; Ray et al., 2018). Ray et al. (2018) suggest a short-run impact of drought on crop production, as crop production decreases during drought years and immediately increases after the drought is over. Likewise, Liou et al. (2012) conclude that the earthquake and resulting tsunami caused a direct loss of about 11000 tons in the Miyagi and Fukushima regions of Japan, and anticipate a prolonged impact on paddy production. Likewise, FAO (2015) and NPC (2015a, 2015b) conclude that the 2015 Nepal earthquake caused damages to irrigation canals and agriculture tools, resulting in a detrimental effect on crop production and may heighten the risk of food security for a prolonged period. Conversely, prior literature suggests that the effect of earthquakes on crop production may not be as pronounced due to decades of experience in coping with natural hazards (Epstein et al., 2017) and widespread rain-fed terrains (Shrestha & Aryal, 2011).

The latter section of the article proceeds as follows. Section II describes the data and variables used in the study, while Section III elucidates the estimation strategy and discusses potential threats to identification. Section IV presents the main result, along with several robustness checks. Discussion and conclusion are covered in Section V and Section VI, respectively.

II. DATA AND VARIABLES

The study uses panel data on paddy production, paddy cultivation area, rainfall, population, and quantity sales of chemical fertilizers. The district-level data on paddy production in metric tons and paddy cultivation area in hectares from FY2010/11 to FY2019/20 have been compiled from Statistical Information on Nepalese Agriculture published by the Ministry of Agriculture and Livestock Development (MoALD). A report published by the National Planning Commission (NPC) is followed to construct the treatment and control groups (NPC, 2015a). The report defines 14 out of 75 districts as severely affected by the earthquake. A complete list of districts, along with treatment status, is presented in Appendix (Table A1). The district-level rainfall data from 2008 to 2019 has been obtained from District Wise Climate Data for Nepal maintained by the Nepal Open Data Portal. They have compiled data from 93 metrological stations spanning 62 districts maintained by the Department of Hydrology and Metrology, Nepal. These 62 districts include 12 treatment districts and 50 control districts. The rainfall data of two missing treatment districts has been purchased from the Department of Department of Hydrology and Metrology. The district-level population data from FY2011/12 to FY2019/20 has been estimated using the population data of census 2011 and 2021. We use exponential growth to estimate the district-wise population for each fiscal year. The data on quantity sale of chemical fertilizers for FY2014/15 and FY2015/16 has been compiled from Statistical Information on Nepalese Agriculture.

Table 1: Description of variables

SN	Variables	Districts	Fiscal Year	Nature	Source
1	Paddy Production in metric ton	75	2011/12 to 2018/19	Log	Ministry of Agriculture and Livestock Development, Nepal
2	Paddy cultivation area in hectares	75	2011/12 to 2018/19	Log	Ministry of Agriculture and Livestock Development, Nepal
3	Rainfall in mm@	64	2008 to 2019	Log	Department of Hydrology and Metrology, Nepal and National Statistics Office, Nepal
4	Chemical fertilizers in metric tons #	75	2014/15 and 2015/16	Log	Ministry of Agriculture and Livestock Development, Nepal
5	Import of chemical fertilizers (annual series)	-	2007/08 to 2018/19	Log	Department of Customs, Nepal
6	Population	75	2010/11 to 2020/21	Log	Interpolated using census data of 2011 and 2021.

Note: @ Data for annual rainfall is available for all 14 treated districts and 50 control districts. The districts without rainfall data have been visualized in Appendix. # The data on district-wise sale of chemical fertilizers cannot be obtained for other years.

III. ESTIMATION STRATEGY

The availability of district-level data on paddy production for pre- and post-earthquake periods, along with the identification of earthquake-affected districts, enables us to create treatment and control groups across two distinct timeframes – before and after the event. Leveraging the available data, we apply difference-in-differences (DiD) to assess the impact of earthquakes on paddy production.

3.1. Difference-in-Differences (DiD)

Estimation of the canonical DID model is done using the following equation:

$$Y_{i,t} = \beta_0 + \beta_1 treat_i + \beta_2 post_t + \Gamma(treat_i \times post_t) + e_{it} ----------------(i)$$

Equation (i) presents the canonical DID model, where index i and t represent district and year respectively. Y_{it} is the outcome variable, which is paddy production in log scale for each district i at year t. $treat_i$ represents the treatment status of district i that takes value 1 if a district is severely affected by the earthquake, else 0. Likewise, $post_i$, a variable representing time frames, takes value 1 for post 2015 Nepal Earthquake and 0 otherwise. $treat_i \times post_i$ is the interaction term that takes value 1 for a district severely affected after 2015 Nepal Earthquake and 0 otherwise.

$\beta_0, \beta_1, \beta_2,$ and Γ are the coefficients. β_0 is the intercept term that captures the pre-earthquake average paddy production among the control districts. The $treat$ coefficient, β_1, provides the difference in paddy production between treated and control districts before the earthquake. The $post$ coefficient, β_2, gives the difference in average paddy production in pre- and post-earthquake periods. Finally, Γ is the coefficient of interest that produces the average difference in paddy production in the treated district compared to the control district after capturing time and district invariant unobserved heterogeneity.

The coefficients of equation (i) can be expressed as:

$$\beta_0 = E[Y(0), post = 0]$$

$$\beta_1 = E[Y(1), post = 0] - E[Y(0), post = 0]$$

$$\beta_2 = E[Y(0), post = 1] - E[Y(0), post = 0]$$

$$\Gamma = \big(E[Y(1), post = 1] - E(Y(0), post = 1)\big) - \big(E[Y(1), post = 0] - E(Y(0), post = 0)\big)$$

3.2. DiD with control

Canonical DiD captures time and district-invariant factors but omits potential variables that may influence paddy production. Zeldow and Hatfield (2021) suggest adjusting the control variables that directly influence the outcome variable. We include three major control variables, paddy area, rainfall, and chemical fertilizer, in our canonical DiD. Nepal's paddy production is highly sensitive to monsoon due to the limited availability of irrigation facilities and more than two-thirds of the total paddy area is dependent on rainfall (Shrestha & Aryal, 2011). Besides monsoon, the use of chemical fertilizers increases paddy production, but the effect of chemical fertilizers on paddy production may not be perceptible due to persistent inadequate supply of fertilizers.

$$Y_{i,t} = \beta_0 + \beta_1 treat_i + \beta_2 post_t + \Gamma(treat_i \times post_t) + \Theta A_{i,t} + \lambda R_{i,t} + \Lambda F_{i,t} + \epsilon_{i,t} - - - - - (ii)$$

$A_{i,t}, R_{it}, and\ F_{i,t}$ represents log transformation of paddy cultivation area, rainfall, and sale of chemical fertilizer across district i in year t respectively. Γ, the parameter of interest, captures the difference in average paddy production in log scale between the treated and control districts after controlling for time and district in-variant unobserved heterogeneity and other control variables. All other notations have similar interpretations as in Equation (i).

We conduct short-run impact analysis by incorporating only two time periods, that is, a year just before the earthquake and immediately after the earthquake, in equation (i) and equation (ii). This strategy helps us to capture the immediate impact of earthquakes by curtailing the effect of distant years. Similarly, for long-run impact analysis, we include five years before and after the earthquake that capture the long-run trajectory of paddy production. However, the sale of chemical fertilizers has been dropped in the long-run model due to data unavailability.

In Equation (i) and Equation (ii), the standard errors have been clustered at the district level to correct potential intra-correlation between districts (Bertrand et al., 2004). Moreover, heteroscedasticity robust standard errors have been reported.

3.3. Underlying assumptions

DiD approach identifies the average treatment effect on the treated (ATT) if two fundamental assumptions, (i) parallel trend assumption and (ii) no anticipatory effect, hold.

Parallel trend assumption

The major challenge in estimating the causal effect of treatment, Γ, is that the untreated potential outcome is never observed for the treated group. The parallel trend assumption implies that the average outcome in treated and control groups would have evolved in parallel in the absence of the treatment (Roth et al., 2023). Parallel trend assumptions must hold to ensure that the causal effect, Γ, is not due to the other factors that may affect the outcome. We confirm the parallel trend assumption through graphical inspection and formal econometric tests consisting of a linear trend model (Luedicke, 2022).

No anticipatory effect

No anticipatory effect holds if the treated units cannot anticipate the event. This ensures that the treatment (or event) does not affect the outcome variable before it occurs (Roth et al., 2023). The anticipation of the treatment may result in changes in behavior or outcome before the actual implementation of the treatment that may violate the parallel trend assumption. Although Nepal is situated in a seismically active region, earthquakes are inherently unpredictable in terms of timing, magnitude, and precise location. Thus, no anticipatory effect assumption undoubtedly holds for our case.

3.4. Threats to identification

The 2015 Nepal Earthquake of 7.8 magnitude caused widespread devastation in 14 districts of Nepal. These 14 districts lie in either the Himalayan or Hilly belt. Terai region, which consists of 20 districts, has the most fertile plain land, irrigation facilities extended to 80 percent of irrigable lands, and is recognized for its significant crop production (NPC, 2015a; Yadav, 1987). The soil quality and irrigation facilities are likely to affect paddy production, but we do not have district-level data on these variables. The baseline estimates may suffer from omitted variable bias in the absence of these variables.

The earthquake had an epicenter at Barpak, located in Gorkha district. The shaking intensity varies across the region, with the farthest region experiencing less tremor and corresponding damages. Moreover, Sindhuli and Makwanpur are inner Terai districts and lie far from the epicenter compared to other severely affected districts. Therefore, these districts are less vulnerable to earthquake-triggered landslides compared to other Hilly or Himalayan districts.

Nepal's agricultural practices are still traditional, and the majority of the farmers practice subsistence farming. Farm power in Nepal comes from human and animal labor (NPC, 2015b). Hence, it is imperative to include district-level population data in our baseline model. However, statistical agencies have not published annual district-level population data or projections. Hence, the baseline model has not incorporated population despite its relevance.

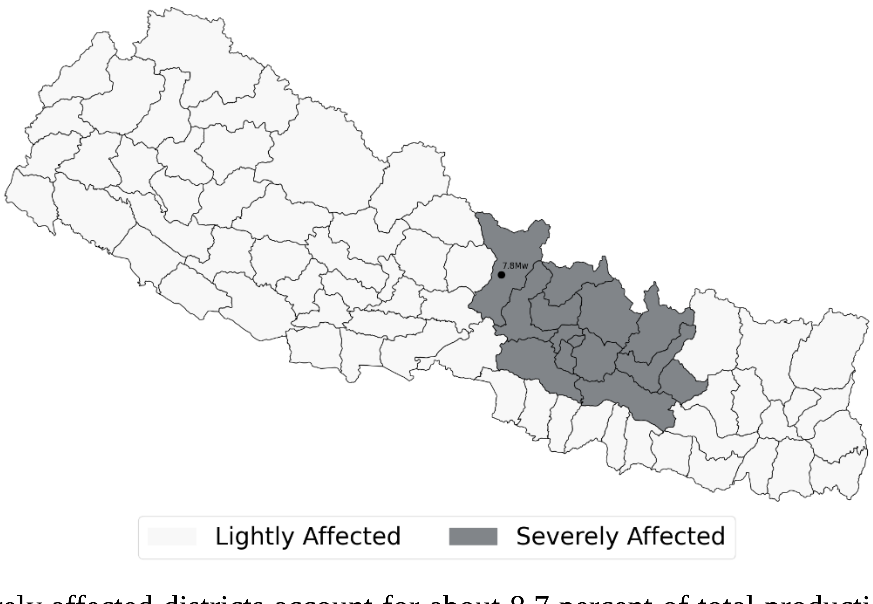
There are three major potential threats to identification, (i) soil quality and access to irrigation facilities, (ii) distance from the epicenter, and (iii) population as the additional control variable. To resolve this issue, the study conducted several robustness checks, including redefining the control group by excluding districts of Terai region, redefining the treatment group by excluding inner Terai districts, and including interpolated population data as the additional control variable in the baseline model.

IV. EMPIRICAL RESULTS

4.1. Descriptive analysis

The descriptive analysis begins by presenting the severely affected and lightly affected districts on the map (Figure 1). NPC (2015a) has identified 14 districts, namely, Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga, as severely affected. These 14 districts are either Himalayan or Hilly districts, of Gandaki, Bagmati, and Koshi Province.

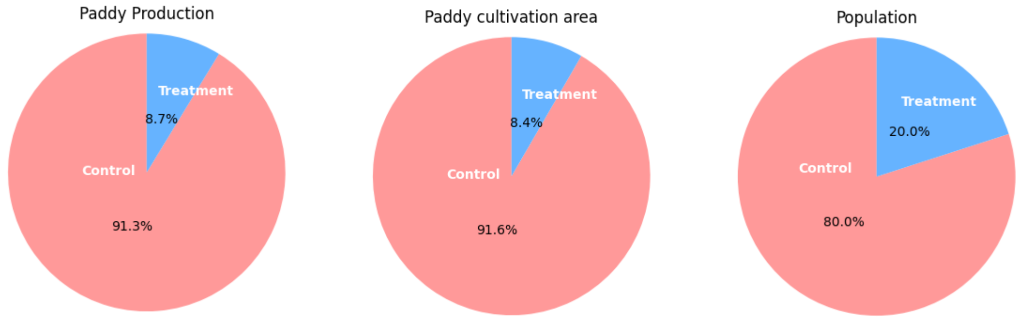
Figure 1: Earthquake-affected districts



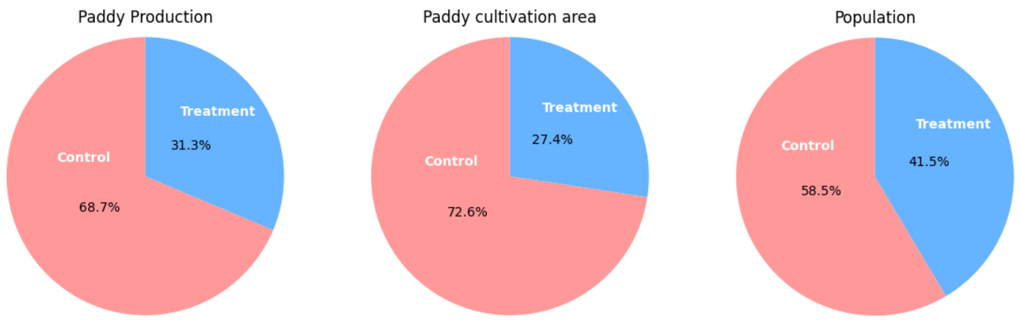
The 14 severely affected districts account for about 8.7 percent of total production and about 8.4 percent of total paddy cultivation area. However, about 20 percent of the total population reside in these districts (Figure 2A). The contribution of these districts substantially increases when we exclude districts of Terai region (Figure 2B). These districts contribute one-third of total paddy production and two-fifth of total population when considering the Hilly and Himalayan region (Figure 2B).

Figure 2: Profile of treatment districts

Panel A: All districts included

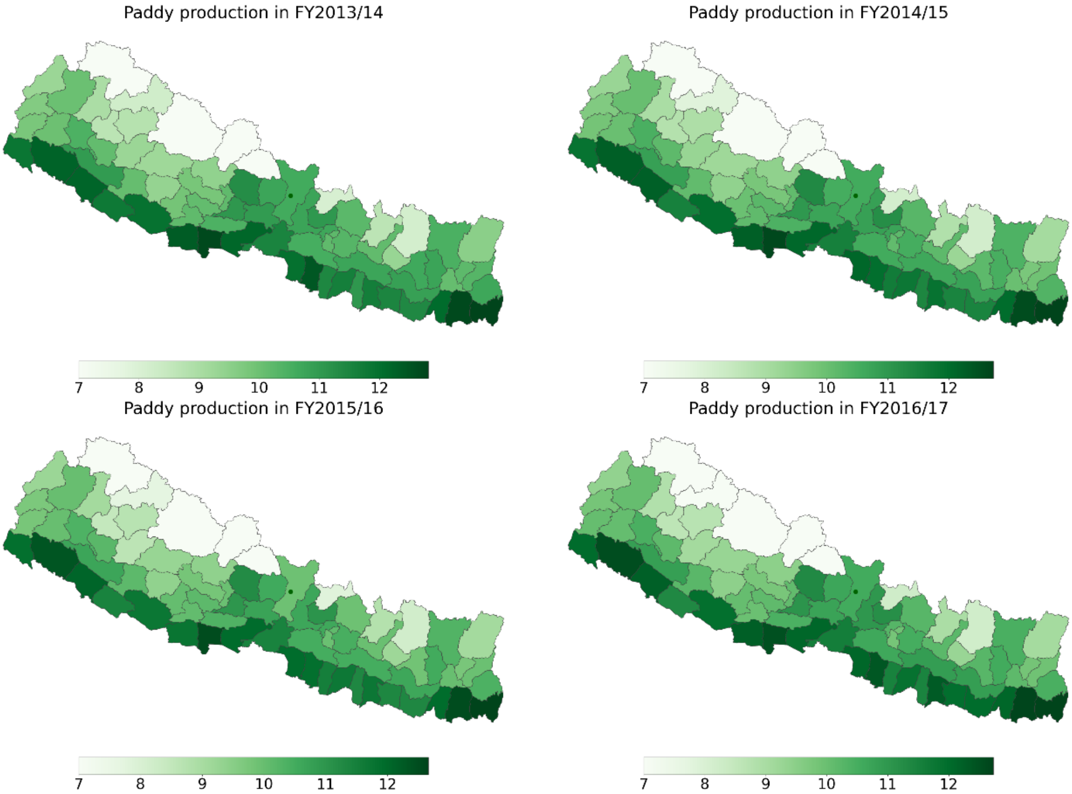


Panel B: Districts of Terai region excluded



The spatial-temporal variation in paddy production illustrates district-level trends of paddy production on a logarithmic scale from 2014 to 2017. Terai region accounts for three-quarters of paddy production, as indicated by the darker color in districts of this region (Figure 3). The paddy production in severely affected districts decreased in 2015/16, but swiftly bounced back in 2016/17 (Figure 3). Paddy farming is a process that lasts for half a year. Initially, farmers prepare nursery beds to grow paddy plants in the pre-monsoon period, which falls in April, and cultivate the new paddy plants in the monsoon, which falls in June and July. Finally, the paddy is harvested in autumn, which falls in October. The devastating earthquake crumbled houses and farmhouses where farmers store seeds for sowing. Consequently, farmers were unable to prepare nursery beds to produce seedlings, which resulted in an immediate decline in paddy production (MoALD, 2016; NPC, 2015a, 2015b). However, various coping strategies, including mutual and community support, and years of experience in coping with natural hazards, inherent to the mountainous region, have played a pivotal role in quick recovery (Epstein et al., 2017).

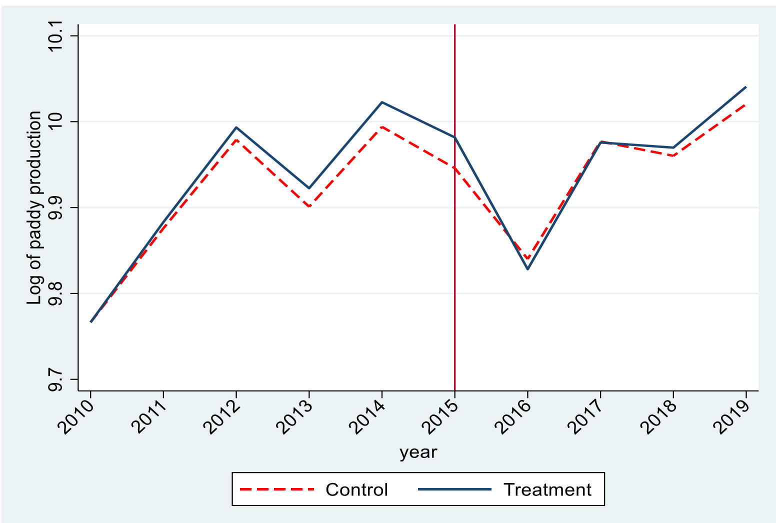
Figure 3: Spatio-Temporal Variation in Paddy Production



Note: Dot represents Epicenter

The linear trend of paddy production depicts that the paddy production in severely affected districts (treatment group) and least affected districts (control groups) has evolved in parallel (Figure 4). Summer drought affected paddy production in FY2012/13 (Bagale et al., 2021; Hamal et al., 2021) and reduced paddy production all over Nepal. Figure 4 exhibits a parallel trend of paddy production for treatment and control groups during pre-earthquake periods. The divergence in the trend is apparent immediately after the earthquake. However, the paddy production seems to follow the pre-earthquake trend in FY2017/18.

Figure 4: Trend of paddy production



4.2. Impact evaluation

Table 1 comprises of two panels, each presenting the estimates of the short-run (Panel A) and long-run (Panel B) impact of the 2015 Nepal earthquake on paddy production. Each panel depicts two different models, a canonical difference-in-differences in column (1) and difference-in-differences with controls in column (2). The standard errors have been clustered at the district level to account for serial correlation within districts. The standard errors are robust to heteroscedasticity for all models.

The DiD in Panel A column (1) provides a treatment effect of -0.096. This suggests that paddy production decreased by 9.15 percent[2] in the year following the earthquake. The DiD with controls in Panel A column (2) yields a treatment effect of -0.076, which translates to a contraction in paddy production by 7.32 percent in the subsequent year of the earthquake, after controlling for potential variables that may influence paddy production. The estimates of DiD with controls are robust, as they account for the possible omitted variable bias. The paddy area and rainfall are significant as expected, while chemical fertilizers seem not to influence paddy production in Nepal probably due to a persistent inadequate supply of fertilizers.

Table 2: Impact of earthquake on paddy production

Variables	Panel A Short Run		Panel B Long Run	
	DiD	DiDC	DiD	DiDC
	(1)	(2)	(1)	(2)
$post$	-0.097***	-0.048***	0.009	0.063***
	(0.019)	(0.016)	(0.024)	(0.019)
$treat$	0.236	0.213**	0.185	0.183**
	(0.491)	(0.091)	(0.484)	(0.092)
$post \times treat$	-0.096**	-0.076***	-0.013	-0.026
	(0.045)	(0.028)	(0.060)	(0.044)
Paddy area		1.073***		1.073***
		(0.004)		(0.006)
Rainfall		0.302***		0.078**
		(0.116)		(0.037)
Fertilizer		0.001		
		(0.006)		

[2] $(e^{-0.096} - 1) \times 100 \approx 9.15\ percent$

Constant	9.908***	-1.741**	9.909***	-0.200
	(0.440)	(0.843)	(0.437)	(0.284)
Observations	150	128	675	576
Number of districts	75	64	75	64
Number of years				
Pre-earthquake	1	1	5	5
Post-earthquake	1	1	4	4
Clustered SE	✓	✓	✓	✓
Robust SE	✓	✓	✓	✓

Note: NPC (2015a) identifies 14 out of 75 districts (Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga) as severely affected by the earthquake. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0. $after$ takes value 1 for years after earthquake, 0 otherwise. Data for annual rainfall is available for all 14 treated districts and 50 control districts. Standard errors are presented in parentheses. ***,**,* denotes significance level at 1, 5, and 10 percent respectively. The dependent variable is in log scale, so the coefficients shall be interpreted as $\%\Delta y = (e^{\Gamma} - 1) \times 100$ for categorical variables.

Panel B presents the long-run estimates. The treatment effect produced by both DiD and DiD with controls is insignificant, signifying that the earthquake has no impact on paddy production in the long run. Therefore, we observe an immediate impact of paddy production on the earthquake, but such impact is not prolonged.

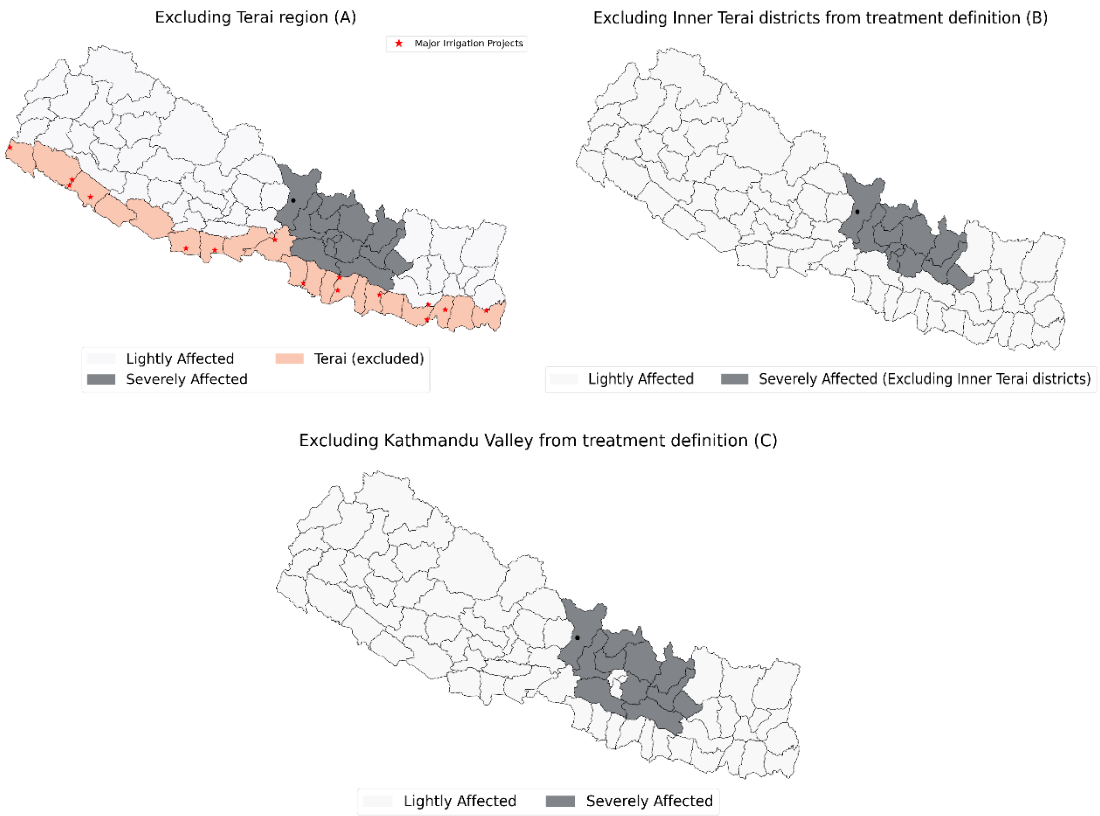
4.3. Robustness checks

The six sets of robustness checks have been performed to corroborate the baseline estimates. The strategies for robustness checks include redefinition control group, redefinition treatment group, including additional control variables, and performing a placebo test using a fake treatment group.

First, districts in the Terai region were the least affected by the earthquake. Excluding Terai region produces a unique advantage by controlling irrigation system and soil quality (Figure 5A). Terai region has the most fertile lands, with irrigation facilities expanded to up to 80 percent of the total irrigable lands of this region (DWRI, 2019). So, the model has been re-estimated by excluding 20 districts of Terai region to justify that the land structure and availability of irrigation facilities do not affect the baseline estimates. The treatment coefficient is significant and negative for the short run, while it is insignificant for the long run.

Second, the damages may differ within these districts due to the geographical differences and shaking intensity. Among 14 severely affected districts, Sindhuli and Makwanpur are inner Terai districts and relatively distant from the epicenter. These districts are less vulnerable to subsequent landslides after the earthquake compared to other hilly counterparts (Figure 5B). So, we replicated the analysis with a new definition of the treatment variable. This allows to control potential selection bias created by including districts with less vulnerable geographical structures (Shakya et al., 2022). The treatment estimate is negative and significant for the short-run, while the long-run treatment estimate is insignificant. This further substantiates the baseline estimate.

Figure 5: Strategies for robustness checks

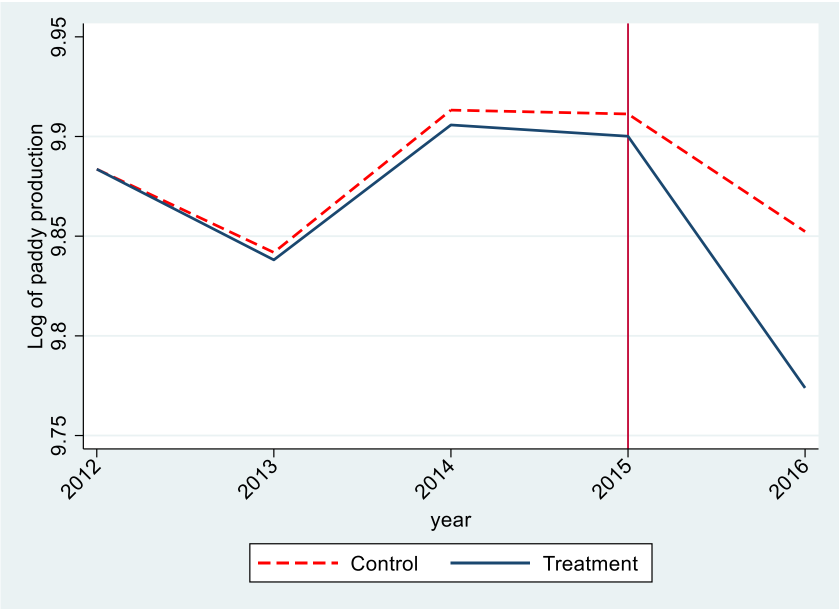


Third, the earthquake destroyed much of the Kathmandu Valley, which comprises three districts namely, Kathmandu, Bhaktapur, and Lalitpur. However, the rapidly increasing urbanization has reduced agricultural activity drastically in this area. So, the study alters the definition of the treatment variable by excluding the three districts of Kathmandu Valley (Figure 5C) and re-estimates the model to investigate the robustness of baseline estimates. The results are parallel to that of baseline estimates that corroborate the baseline estimate.

Fourth, the baseline models include potential control variables but do not include population. The traditional farming techniques are labor-intensive, so it is plausible to add population to the baseline model. Population data for each district is only available for the census years. Thus, the study exploits the district-wise population data of the 2011 and 2021 censuses to interpolate the district-level population for the remaining years. The model estimates are unaltered even after including population as the additional control variable.

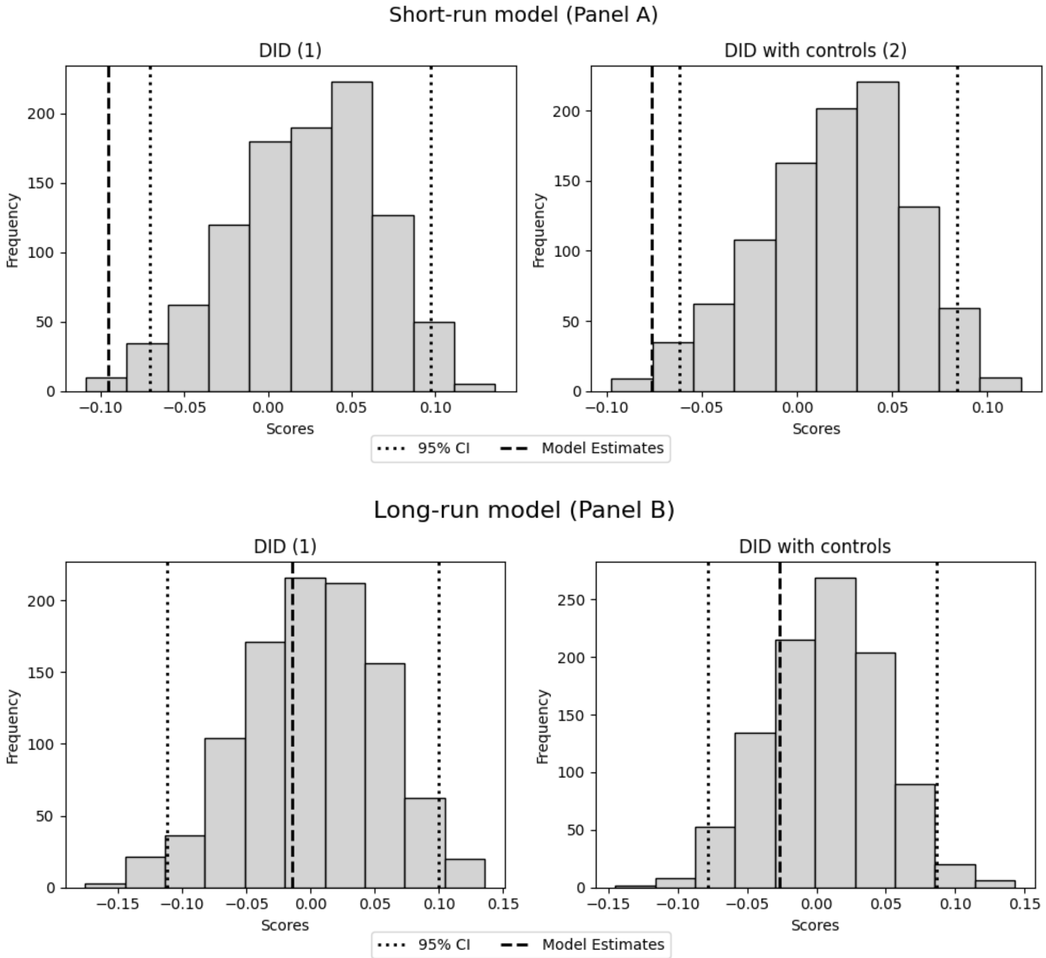
Fifth, we extend the pre-treatment periods to assess the short-run impact. Egami and Yamauchi (2023) propose this approach for assessing the parallel trend assumption. The article extends the pre-treatment to FY2011/12 and also incorporates important control variables, paddy area, rainfall and population, as suggested by Egami and Yamauchi (2023). The conditional parallel trend assumption holds for pre-treatment periods (Figure 6) and the results are parallel to the baseline model. This corroborates our baseline estimates.

Figure 6: Conditional parallel trend assumption



Finally, literature, including Shakya et al. (2022) and Paudel (2022), suggests applying placebo tests using a fake treatment group to validate the credibility of the treatment effect. The study iterates the baseline model on 1000 fake treatment groups that comprise of districts unaffected by the earthquake. The short-run treatment effect lies outside the 95 percent confidence band (Figure 7A), while the long-run treatment effect lies within the 95 percent confidence band as expected (Figure 7B). This implies that the baseline treatment estimates are unlikely to have occurred by random chance. The result of the placebo test further strengthened the validity of the estimates.

Figure 7: Placebo test



V. DISCUSSION

The 2015 Nepal Earthquake was a natural catastrophe that claimed the lives of thousands of people, collapsed thousands of houses and farmhouses, and buried stored seeds, edibles, and cereals. Farmers prepare nursery beds to produce paddy seedlings in April. The devastating earthquake occurred in April 2015 that disrupted the entire paddy cultivation cycle, which resulted in a noticeable decline in paddy production in the subsequent year. The empirical results suggest a short-term decline in paddy production, but pronounced insignificant negative impact in the long-run. Mohan (2017) and Ray et al. (2018) find that natural disaster has a short-term impact on agriculture, while Israel and Briones (2013) find no significant relationship between natural disasters and crop production. Moreover, Spencer and Polachek (2015) imply that natural disaster has varying impact on agriculture depending upon the nature of the crop. The study scrutinizes the probable reasons for the negative short-run impact and insignificant long-run impact of an earthquake on paddy production in this section.

Nepalese people were not prepared to withstand a natural catastrophe of such scale. The major aftershock of 7.4 magnitude with an epicenter in Sindhupalchok occurred in mid-May 2015. The persistent powerful aftershocks caused distraught and precluded the day-to-day operations for a couple of months after the earthquake. Moreover, people were busy managing family crises and clearing the rubble that limited agricultural activities (NPC, 2015b).

The study finds an insignificant impact of the 2015 Nepal earthquake when considering a longer time horizon. Prior literature, except Liou et al. (2012), concludes that natural disasters do not have a prolonged effect on agriculture. Liou et al. (2012) conclude that the tsunami, triggered by the 2011 Japan earthquake, contaminated arable fields with salty ocean water that may erode soil quality, affecting cultivation for a longer time period. The study further finds the insignificant impact of the 2015 Nepal earthquake on paddy production in the long run, some explanations for this result are as follows.

First, Nepal's agriculture counts on monsoon, and the irrigation facility is limited to only 35 percent of total cultivable land. Earthquakes and subsequent landslides caused widespread damage to infrastructure and houses and claimed thousands of lives. However, damages to the irrigation system were comparatively less intense, affecting less than 10 percent of total irrigated land in severely affected districts (NPC, 2015b). This translates to a direct impact on less than 4 percent of cultivable land.

Second, people living in mountainous regions have a unique community experience in tackling unforeseen catastrophes, as they have adapted to the hazards inherent to mountainous regions, including landslides and avalanches. Generations of community experiences in conjunction with strong social bonds and community support may have bolstered the swift bounce back of the agriculture sector (Epstein et al., 2017).

Third, many individuals who went abroad for employment returned and reunited with their family members in the severely affected districts to cope with the disaster and subsequent losses (MOLESS, 2016). Shakya et al. (2022) conclude that international labor migration declined in severely affected districts by about 37 percent. The returning workers may have filled the deficit of the young labor force in agriculture. Additionally, these workers returned with technical skills learned on the job, widening their exposures, and exploiting their knowledge to initiate business ventures (Maria & Wassink, 2016). Hence, increased labor supply may be one of the potential channels contributing to the subsequent recovery of the agriculture sector.

VI. CONCLUSION

This article examines the short-run and long-run impact of the 2015 Nepal Earthquake on paddy production. The study exploits the difference-in-differences model to investigate the impact of the unanticipated and plausibly exogenous shock of the 2015 Nepal earthquake on paddy production. Five different sets of robustness checks have been conducted to substantiate the baseline estimates.

The findings suggest that the earthquake has a negative impact on paddy production in the short-run, but the effect is not quite pronounced when considering a longer time horizon. The 2015 Nepal earthquake occurred in April and farmers prepare nursery beds to produce paddy seedlings in the same month. Thus, the earthquake severely disrupted the preparation of paddy seedlings which may have hindered the entire paddy cultivation process of that year.

Likewise, the less pronounced long-run effect is plausible considering several key factors: first, Nepal's agriculture heavily relies on monsoon. Second, Nepalese people residing on mountainous terrain are accustomed to hazards inherent to rocky mountainous landscapes that may have cushioned the prolonged negative impact of the earthquake. Third, strong social bonds, and mutual and community support aid in overcoming adversaries, and lastly, the returning of migrant workers may have contributed to mitigating potential disruptions to agricultural activities.

Since Nepal is in earthquake zone, it is necessary to manage enough food stock to avoid the likely food insecurity in the short run. Moreover, this type of research work can also be carried out to assess the impact of other natural disaster on agricultural production.

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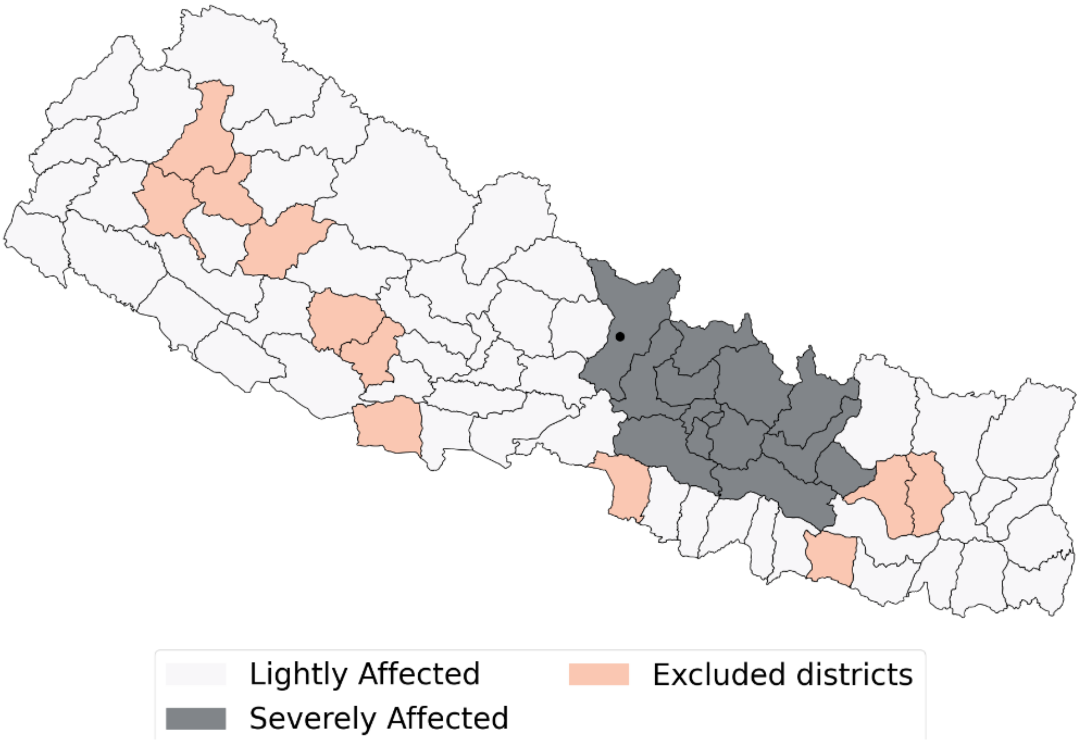
APPENDIX

Table A1: List of districts with treatment status

Districts	Status	Districts	Status	Districts	Status
Taplejung	0	Nuwakot	1	Kapilbastu	0
Sankhuwasabha	0	Dhading	1	Dolpa	0
Solukhumbu	0	Makwanpur	1	Mugu	0
Panchthar	0	Dhanusha	0	Humla	0
Illam	0	Mahottari	0	Jumla	0
Terhathum	0	Sarlahi	0	Kalikot	0
Dhankuta	0	Rautahat	0	Rukum	0
Bhojpur	0	Bara	0	Rolpa	0
Khotang	0	Parsa	0	Pyuthan	0
Okhaldhunga	1	Chitwan	0	Salyan	0
Udayapur	0	Manang	0	Jajarkot	0
Jhapa	0	Mustang	0	Dailekh	0
Morang	0	Gorkha	1	Surkhet	0
Sunsari	0	Lamjung	0	Dang	0
Saptari	0	Tanahu	0	Banke	0
Siraha	0	Kaski	0	Bardiya	0
Dolakha	1	Parbat	0	Bajura	0
Sindhupalchok	1	Syangja	0	Bajhang	0
Rasuwa	1	Palpa	0	Darchula	0
Ramechap	1	Myagdi	0	Achham	0
Sindhuli	1	Baglung	0	Doti	0
Kavre	1	Gulmi	0	Baitadi	0
Bhaktapur	1	Arghakhanchi	0	Dadeldhura	0
Lalitpur	1	Nawalparasi	0	Kailali	0
Kathmandu	1	Rupandehi	0	Kanchanpur	0

Note: NPC (2015a) identifies 14 out of 75 districts (Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga) as severely affected by the earthquake. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0.

Figure A1: Excluded districts due to unavailability of rainfall data



Note: Rainfall data from 11 districts (Bhojpur, Khotang, Siraha, Parsa, Kapilbastu, Kalikot, Rolpa, Pyuthan, Jajarkot, Bajura, and Achham) is not available. But this shall not preclude our analysis as rainfall data for all 14 treatment districts is available.

Table A2: Excluding districts of Terai region

Variables	Panel A Short Run		Panel B Long Run	
	DiD	DiDC	DiD	DiDC
	(1)	(2)	(1)	(2)
$post$	-0.087***	-0.044**	-0.029	0.060**
	(0.026)	(0.020)	(0.030)	(0.025)
$treat$	1.241*	0.243**	1.187*	0.215**
	(0.634)	(0.099)	(0.625)	(0.094)
$post \times treat$	-0.106**	-0.080***	0.026	-0.023
	(0.049)	(0.030)	(0.062)	(0.047)
Paddy area		1.072***		1.067***
		(0.004)		(0.004)
Rainfall		0.344***		0.109**
		(0.131)		(0.043)
Fertilizer		-0.004		
		(0.005)		
Constant	8.903***	-2.026**	8.907***	-0.395
	(0.594)	(0.944)	(0.589)	(0.319)
Observations	110	94	495	423
Number of districts	55	47	55	47
Clustered SE	✓	✓	✓	✓
Robust SE	✓	✓	✓	✓

Note: NPC (2015a) identifies 14 out of 75 districts (Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga) as severely affected by the earthquake. The 20 districts of Terai region have been excluded from the control group. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0. $after$ takes value 1 for years after the earthquake, 0 otherwise. Data for annual rainfall is available for all 14 treated districts and 50 control districts. Standard errors are presented in parentheses. ***,**,* denotes significance level at 1, 5, and 10 percent respectively.

Table A3: New treatment definition: Excluding Inner Terai districts

Variables	Panel A Short Run		Panel B Long Run	
	DiD	DiDC	DiD	DiDC
	(1)	(2)	(1)	(2)
$post$	-0.098***	-0.050***	0.016	0.065***
	(0.019)	(0.016)	(0.024)	(0.018)
$treat$	0.138	0.226**	0.103	0.190*
	(0.493)	(0.104)	(0.486)	(0.106)
$post \times treat$	-0.107**	-0.076***	-0.056	-0.038
	(0.050)	(0.030)	(0.060)	(0.049)
Paddy area		1.073***		1.073***
		(0.004)		(0.006)
Rainfall		0.304***		0.079**
		(0.115)		(0.037)
Fertilizer		0.001		
		(0.006)		
Constant	9.931***	-1.762**	9.927***	-0.202
	(0.426)	(0.835)	(0.423)	(0.283)
Observations	150	128	675	576
Number of districts	75	64	75	64
Clustered SE	✓	✓	✓	✓
Robust SE	✓	✓	✓	✓

Note: The new treatment variable has been defined by excluding two inner Terai districts from the baseline treatment definition. Now, the treatment group includes only 12 out of 75 districts (Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Dolakha, and Okhuldhunga) as severely affected by the earthquake. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0. $after$ takes value 1 for years after the earthquake, 0 otherwise. Data for annual rainfall is available for all 14 treated districts and 50 control districts. Standard errors are presented in parentheses. ***,**,* denotes significance level at 1, 5, and 10 percent respectively.

Table A4: New treatment definition: Excluding districts of Kathmandu Valley

Variables	Panel A Short Run		Panel B Long Run	
	DiD	DiDC	DiD	DiDC
	(1)	(2)	(1)	(2)
$post$	-0.098***	-0.052***	-0.004	0.048**
	(0.019)	(0.016)	(0.024)	(0.019)
$treat$	0.162	0.030	0.102	-0.014
	(0.501)	(0.069)	(0.491)	(0.058)
$post \times treat$	-0.114**	-0.080**	0.075	0.053
	(0.053)	(0.031)	(0.053)	(0.033)
Paddy area		1.072***		1.073***
		(0.004)		(0.005)
Rainfall		0.285**		0.064*
		(0.118)		(0.037)
Fertilizer		0.003		
		(0.008)		
Constant	9.929***	-1.592*	9.928***	-0.058
	(0.420)	(0.855)	(0.416)	(0.285)
Observations	150	128	675	576
Number of districts	75	64	75	64
Clustered SE	✓	✓	✓	✓
Robust SE	✓	✓	✓	✓

Note: The new treatment variable has been defined by excluding three districts of Kathmandu Valley from the baseline treatment definition. Now, the treatment group includes only 12 out of 75 districts ((Gorkha, Nuwakot, Dhading, Rasuwa, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga) as severely affected by the earthquake. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0. $after$ takes value 1 for years after the earthquake, 0 otherwise. Data for annual rainfall is available for all 14 treated districts and 50 control districts. Standard errors are presented in parenthesis. ***,**,* denotes significance level at 1, 5, and 10 percent respectively.

Table A5: Including population as additional control variable

Variables	Short-run	Long run
	DiDC	DiDC
	(1)	(2)
$post$	-0.052**	0.058***
	(0.020)	(0.020)
$treat$	0.180**	0.175**
	(0.079)	(0.074)
$post \times treat$	-0.074**	-0.024
	(0.030)	(0.045)
Paddy area	1.027***	1.028***
	(0.011)	(0.009)
Rainfall	0.184**	0.184***
	(0.078)	(0.062)
Fertilizer	0.005	
	(0.013)	
Population	0.168***	0.167***
	(0.044)	(0.030)
Constant	9.929***	-1.592*
	(0.420)	(0.855)
Observations	128	576
Number of districts	64	75
Clustered SE	✓	✓
Robust SE	✓	✓

Note: NPC (2015a) identifies 14 out of 75 districts (Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga) as severely affected by the earthquake. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0. $after$ takes value 1 for years after the earthquake, 0 otherwise. Data for annual rainfall is available for all 14 treated districts and 50 control districts. Standard errors are presented in parentheses. ***,**,* denotes significance level at 1, 5, and 10 percent respectively.

Table A5: Extending pre-treatment period

Variables	Short-run
	DiDC
	(1)
$post$	-0.029
	(0.023)
$treat$	0.164**
	(0.073)
$post \times treat$	-0.067*
	(0.038)
Paddy area	1.014***
	(0.011)
Rainfall	0.031
	(0.038)
Population	0.214***
	(0.036)
Constant	-1.975***
	(0.454)
Observations	320
Number of districts	64
Number of Years	
Pre-treatment	4
Post-treatment	1
Clustered SE	✓
Robust SE	✓

Note: NPC (2015a) identifies 14 out of 75 districts (Gorkha, Nuwakot, Dhading, Rasuwa, Kathmandu, Bhaktapur, Lalitpur, Sindhupalchok, Kavrepalanchok, Ramechhap, Sindhuli, Makwanpur, Dolakha, and Okhuldhunga) as severely affected by the earthquake. These districts are treated districts and assigned value 1; the remaining 61 districts are control districts and assigned value 0. $after$ takes value 1 for years after the earthquake, 0 otherwise. Data for annual rainfall is available for all 14 treated districts and 50 control districts. Standard errors are presented in parentheses. ***,**,* denotes significance level at 1, 5, and 10 percent respectively.