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Impact of 2015 Earthquake on Educational Attainment of Children in Nepal

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Abstract

Background: Natural disaster has far-reaching consequences on the economic development of low-income economies due to the damage to physical and human capital and their poor resilience toward such damages. Nepal faces such disasters at frequent intervals without much effort to account for its consequences, particularly on human capital.

Objective: This study assesses the short-term impact of Nepal's 2015 earthquake on children's educational attainment. The study also conducts heterogeneous analysis to understand how the impact varies by gender. Secondary school completion is chosen as a measure of educational attainment.

Method: The study utilizes second and third rounds of household survey data taken from the Nepal Risk and Vulnerability Survey (NHRVS) conducted by the World Bank. The study uses child fixed effects combined with the difference-in-difference method to account for issues relating to identifying the earthquake's impact on educational attainment.

Results: The study finds that the cohorts exposed to the earthquake had an adverse effect on the probability of secondary school completion. A heterogeneous analysis by gender further reveals that the male children experienced a significant drop in their secondary school completion probability while female children essentially had no impact.

Implication: The quality of human resources depends upon the quality of health and education in any country. The findings of this research draw the attention of the policymakers to the serious consequences that natural disaster has on human capital and help make informed policy decisions not only during the recovery process but also during the planning and policy formulation stage.

Originality: This paper is original and has not been published anywhere else.

Keywords: Natural disaster, earthquake, education, Nepal

Paper Type: Research Paper

JEL Classification: *I20, Q54, R20*

Introduction

Natural disasters take several forms like drought, flood, earthquakes, and hurricanes and have effects on a wide range of domains such as economic, social, psychological and demographic, among others. It is a normal phenomenon everywhere but has disproportionate adverse effects in developing countries where democracy and quality of institutions are relatively weaker (Kahn, 2005; Loayza et al., 2012; Toya & Skidmore, 2007). While a large body of literature has shown negative effects of natural disasters on economic growth, several others have found small or no effect or even positive effects (Loayza et al., 2012). For example, Skidmore & Toya (2002) have empirically shown that frequencies of natural disasters are positively correlated with rates of human capital accumulation, total factor productivity and economic growth. However, physical capital investment may fall, and substitution toward human capital investment may increase. Therefore, this macro-evidence about the effects of natural disasters is inadequate to provide a clear picture of the true effects unless otherwise supported by evidence at the micro-level.

At the micro-level, natural disasters have primarily two effects: short-term effects where households experience loss of physical capital and long-term effects where households loose human capital. Human capital comprises health and education that are both indicators and instruments of human development (Bloom, 2007; Sen, 1999).[1]

Human capital is more important since they are the key driver of economic growth (Raut, 2017). In this study, we assess the microeconomic consequences of natural disasters on one of the major indicators of human capital: education.

It is essential to empirically understand the effects of natural disasters on children's education. Millions of children worldwide are forced to leave the school at the onset of extreme climatic conditions mainly because the schools are damaged or destroyed. Hence, children not going to school are more likely to risk child labor, early marriage, exploitation and recruitment into the armed forces. Save the Children warns that any delay in putting these children back to school would increase the risk of being permanently dropped out of school (Watt, 2017).

Educational figures show positive trends in enrollment rates at each level of education system in Nepal. However, drop-out statistics paints rather a bleak picture as compared to the progress in school enrollment. About 50 percent of the children drop out before they reach the lower secondary level (UNESCO, 2012). Since the 2015 earthquake in Nepal severely disrupted the educational services, a report released by National Planning Commission/Government of Nepal (2015) also expects that this will deteriorate the learning outcomes of children in the short to medium term. Earthquake has imposed a major setback with the likely increase in the drop-out rates. As discussed above, children are forced to leave the school when school buildings and access infrastructures are damaged due to natural disaster leaving them highly vulnerable to child labor, child marriage, trafficking and recruitment into armed forces. When they remain away from school for a prolonged period of time, it is highly likely that they may never return to schools. UNICEF (2015) expects that nearly 1 million children in Nepal are at the point of no return to school. Hence, natural disaster may have severe human capital consequences affecting the long term economic growth of a nation. Realizing the importance of education for human resource development, this study uses robust econometric method to analyze the effects of the earthquake on educational attainment of children.

This study analyzes the short-term impact of natural disasters on one measure of children's educational attainment: secondary school completion. Here, the study exploits the variation in the intensity of the earthquake at the community level for identification. The micro-level data obtained from the nationally representative household survey data is combined with self-reported variation in the measure of earthquake intensity at the community level.

[1] See the section on Literature review for the related studies on microeconomic consequences of natural disasters.

The first section introduces the study; the second section reviews the relevant literature and identifies research gaps. The third section describes the research methodology, data collection, and analysis process. Then in section four, we present the results, interpret and discuss them. The fifth section provides the conclusion of the study.

Review of Literature

Several studies have investigated on the effects of natural disasters on health, both physical and mental. Torche (2011) uses the 2005 Chilean earthquake as a natural experiment to look into the effect of prenatal earthquake-induced maternal stress on the birth weight of newborns. The study, employing a difference-in-difference method, finds that maternal exposure negatively affects birth weight, confirming that in utero exposure may have consequential effects on individual outcomes throughout the life cycle. Almond (2006) exploits the 1918 influenza pandemic as a natural experiment to show that in-utero exposure to influenza would significantly reduce the probability of the children graduating from high school and earning less and being more likely to be poor. On the other hand, Gørgens, Meng, & Vaithianathan (2012) show that China's great famine in 1959-61 reduced the number of survivors exposed to food shortages in the first five years of life stunted by 1 to 2 cm.

Although several anecdotes are available, only limited empirical evidence is available to assess the microeconomic consequences of natural disasters on education. De Vreyer, Guilbert, & Mesple-Somps (2015) estimates the long-run impact of a large income shock-induced from 1987-89 locust plague in Mali on the educational outcomes of children. They use data from the population census survey in 1998 and exploit spatial and temporal variation to construct birth cohorts of affected individuals and compare them with the unaffected ones. The study, using the difference-in-difference method as an estimation strategy, finds that the education of boys who were just born or were aged less than four during the period of shock was severely affected by the plague. Likewise, girls' education in rural areas was also the hardest hit. Other evidence suggests that the households cut back on education expenditure. The children's probability of working is more likely to increase (For details on related literature, see Baez, Fuente, & Santos, 2010). For example, Santos (2007) shows that the school attendance decline for the households hardest hit by the earthquakes and their children are more likely to be engaged in child labor. There is evidence on similar lines about the effects of rainfall shock on school attendance in India (Jacoby & Skoufias, 1997).

Another study by Shah & Steinberg (2017) shows that rainfall shocks during school years have an adverse long-term impact on children's total years of schooling, particularly of aged 11 to 13. The likelihood of dropout of this age group increases significantly due to such positive rainfall shocks. Similarly, a study of children aged 12 to 15 years in four countries: Ethiopia, India, Peru, and Vietnam, shows that poor children are more vulnerable to natural disasters. The study also shows the differential impact of various disasters such as droughts, floods, frosts, and hailstorms. The flood had the worst consequence; it reduced the number of completed grades of children aged 12 to 15 and increased their exposure to work and responsibilities. Likewise, Jensen (2000) shows that the extreme weather shocks between 1986 and 1987 in Ivory Coast reduce enrolment rates by 20 percentage points.

Using primary data and exploiting the difference-in-difference strategy, Di Pietro (2018) examined the effect of the L'Aquila earthquake on the academic performance of the local university students. He found that the earthquake reduced the probability of graduating on time by 6.6 percentage points. Using a similar estimation strategy, Hermida (2011) also estimates the long-term effects of Guatemala's 1976 earthquake on the educational attainment and adult height of Guatemalan children. The results show long-term detrimental effects on the education of school children with severe impacts on children of unskilled workers and educated mothers. One interesting study suggests that the intensity of deaths vis-a-vis physical damages has a more significant effect on secondary school attainment (Onigbinde 2018).

Literature also discusses channels about the relationship between natural disasters and educational attainment. Most studies identify loss in income, poor health of the children exposed to vulnerability, and destruction of education-related infrastructure (such as schools and classrooms). These studies also noted the reduction in consumption expenditure as an essential channel (see, for example, Baez & Santos, 2007; Nguyen & Minh Pham, 2018; Raut, 2021). Both income and substitution effects (e.g. child labour, psychological effects) jointly work to reduce the quantity of education demanded—the marginal utility of a child's income increases when family income declines. In addition, the substitution effect is likely when reconstruction efforts during post-disaster periods increase child wage, which raises the opportunity cost of attending school. Jensen (2000) further argues that the natural shocks cause liquidity constrained households to cut down health, education, and physical capital investments.

In Nepal, few studies look into the effect of natural disasters on school outcomes. Brewer et al. (2016) analyze the long term impact of natural disasters on school attendance and enrollment of the children. The survey questionnaire was used to collect data administered to school-aged children in twelve schools located in six districts of Nepal. The double difference framework utilized before-after and treatment-control design for identification. The finding shows that earthquakes reduce school enrollment and attendance among children aged 5 to 18, and heterogeneity analysis further suggests variation in impact by age, gender, and caste.

Paudel and Ryu (2018) assess the long term impact of the 1988 earthquake in eastern Nepal on the educational attainment of affected children. This study compares the children's educational attainment before, during and immediately after the earthquake in both affected and unaffected districts. The empirical results indicated that the cohort of infants born in earthquake-affected districts experienced a significant loss in educational attainment compared to the unaffected ones (i.e. on average, 0.8 grades less schooling). They are 13.8 and 20 per cent less likely to complete middle and high school, respectively while belonging to a high caste household or being a male works to offset the adverse effects of natural disasters.

This study fills the following research gaps in the literature: First, we contribute to the limited literature on the effects of natural disasters on education in South Asia. Second, the outcome used in the study is a school level completion which is a comprehensive measure of educational attainment than school attendance. For example, children, who have not been able to complete secondary level education, have either dropped out or not performed well because of disaster-induced poor classroom conditions, teacher's absence, access to school problems, etc. Third, we use panel data from a nationally representative household survey where, unlike earlier studies, we account for child fixed effects in regression analysis. This study validates the findings of the studies conducted earlier. Fourth, most of the earlier studies identify the long-term impact of natural disasters by utilizing the data collected after a reasonably long period. On the contrary, this study utilizes data collected shortly after the earthquake, identifying the short-term impact. It is also essential to understand the short term impact to assess and compare whether the degree of impact varies over time. For example, it may be possible that the short term impact may be higher while the impact recedes in the long term. Finally, earthquakes as natural disasters are more exogenous than other natural disasters such as floods and famine. Literature using flood and famine has started treating them as endogenous because they are somehow predetermined, unlike an earthquake, which is largely exogenous. Hence, we can consistently estimate the causal impact of an earthquake without worrying about its endogeneity.

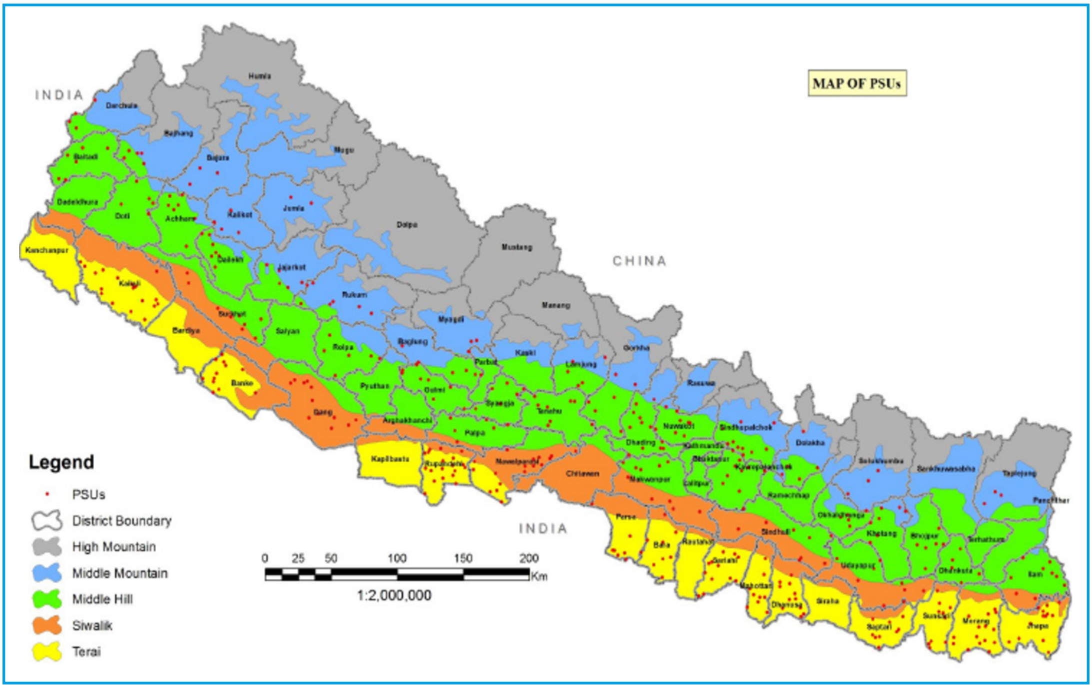
Research methods

Research Design, Data and Variables

We used the treatment-control design in this study. In this study, treatment areas are the communities affected by the 2015 earthquake, while control areas are the communities that were not affected by the earthquake. Since we are interested in analyzing the impact of 2015 earthquake on secondary school completion of students,[2] our eligible population are essentially those who were enrolled in school during the earthquake and were expected to complete secondary level by the time of the survey. In other words, our affected cohort encompassed students aged 14 to 16 during the 2015 earthquake, and were expected to complete secondary level either in 2017 or in 2018. This implies that the affected cohort will fall into 17 to 18 age-group during 2017 and 17 to 19 during 2018. Likewise, for comparison purposes, we utilize the information of students who had already completed secondary level before the earthquake. Our unaffected cohort of students was aged 23 to 26 in 2017 and 24 to 27 in 2018 (See Table 1). This gives us a total sample size of 5085 students at secondary levels.

This study uses two rounds of panel data from a nationally representative household survey: Nepal Household Risk and Vulnerability Survey (NHRVS). The World Bank conduced this survey in 2016, 2017, and 2018. This study utilizes the second and third waves conducted in 2017 and 2018 (NHRVS2 and NHRVS3) respectively. Both surveys were conducted from June to August in their respective years. Altogether 6000 households were sampled from randomly selected 400 primary sampling units (PSUs) based on population distribution from rural and urbanizing VDCs, excluding the municipal areas, across 50 districts (See Figure 2). However, only 97.25% and 94.93% of the 6000 households interviewed in NHRVS1 could be located in NHRVS2 and NHRVS3, yielding an attrition rate of 2.75% and 5.07%, respectively.

Figure 2: Map of survey districts and PSUs



Source: NHRVS 2018

[2] We use the terms students and children interchangeably.

Table 1: Choice of affected and unaffected cohorts

Secondary School Completion (SSC)			
	Completed Age		
	April 2015	NHRVS 2017	NHRVS 2018
Affected Cohort (SSC)	14		17
	15	17	18
	16	18	19
Unaffected Cohort (SSC)	21	23	24
	22	24	25
	23	25	26
	24	26	27

Source: Author's calculation

Next, we divide our total PSUs into treatment and control areas based on the self-reported shocks reported at the community levels. The NHRVS asks the community leaders and other community members separately, among other things, about various types of shocks (both covariate and idiosyncratic) experienced at the community levels. Although household surveys also ask households questions relating to the shocks, we choose the shocks reported at community levels in order to avoid endogeneity bias by choosing shocks reported at household levels. Out of 262 PSUs used in the study, 89 PSUs (34%) were affected by the 2015 earthquake, while 173 PSUs (66%) were not. Table 2 presents the definition and expected sign of all the variables used in the regression analysis. In contrast, Table 3 provides the summary statistics of the variables chosen in the study by treatment and control areas.

Table 2: Definition of variables used in the regression analysis and their expected sign

Variables	Working definition	Expected sign
Dependent variable		
Secondary level completed (=1)	This is a dummy variable for the student who have already completed the secondary level of education (Class 10 or SLC) by the time of the survey	
Independent variables		
Affected cohort (=1)	This is a dummy variable for the student who were aged 14 to 16 during the 2015 earthquake and were expected to complete secondary level either in 2017 or in 2018.	?
Treatment area (=1)	Dummy for the community affected by earthquake	-
Age	Completed Age of student in years	+
Age squared	Squared of completed age of student	-
Male (=1)	Dummy for male student	?
No education (=1)	Dummy for the household head without any formal education	Reference category
Less than primary completed (=1)	Dummy for the household head who has completed less than primary level of education (under class 5)	+
Primary completed (=1)	Dummy for the household head having completed primary level of education	+

Variables	Working definition	Expected sign
Secondary completed (=1)	Dummy for the household head having completed secondary level of education	+
Brahmin and Chettri (=1)	Dummy for the *Brahmin* and *chettri* household	Reference category
Adibasi and janajati	Dummy for the *Adibasi* and *janajati* household	-
Dalit	Dummy for the *Dalit* household	-
Madhesi	Dummy for the *Madhesi* household	-
Cultural Groups	Dummy for the *Cultural groups* household	-
Other castes	Dummy for the *other castes* household	-
Head age	Completed age of household head in years	?
Head age squared	Square of completed age of household head in years	?
Head marital status (=1)	Dummy for married household head	?
Head Male (=1)	Dummy if the household head is a male	?

Table 3: Descriptive statistics of the main variables used in the study

	Secondary Level		
	Treatment Area (T)	Control Area (C)	Difference (T-C)
Secondary level completed (=1)	0.418	0.429	-0.011
Affected cohort (=1)	0.462	0.460	
Age	21.646	21.63	
Age squared	482.596	482.023	
Male (=1)	0.467	0.442	
Son/Daughter of Household head (=1)	0.668	0.629	
No education (=1)	0.066	0.067	
Less than primary completed	0.124	0.123	
Primary completed	0.316	0.315	
Secondary Completed	0.493	0.495	
Brahmin and Chettri	0.118	0.304	
Adibasi and janajati	0.505	0.387	
Dalit	0.156	0.149	
Madhesi	0.170	0.116	
Cultural Groups	0.017	0.029	
Other castes	0.034	0.014	
Head age	49.84	50.129	
Head age squared	2619.966	2660.012	
Head marital status	0.889	0.883	
Head Male	0.812	0.802	
Observations	1838	3247	

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3 shows that 41.8 and 42.9 percent of the students have completed secondary levels in treatment and control areas respectively. The difference is negative in case of secondary level but t-test shows that it is not statistically significant. In order to confirm that these results hold when we control for bunch of other students and households' characteristics, we further employ the fixed effects model as specified in equation 1 below. The results of the same are presented in succeeding sections. So far as other variables are concerned, Table 2 shows that there is only marginal difference between treatment and control areas both in case of primary and secondary levels.

Identification Strategy

Our empirical strategy is based on Paudel & Ryu (2018) that looked into the impact of the 1988 earthquake on children's schooling outcomes in Nepal. Several studies use a similar strategy to identify the impact of civil conflict on educational attainment in various developing economies (see, for example, Pivovarova & Swee, 2015 & Valente, 2014). The difference-in-difference specification is as follows:

$$Y^t_{ij} = \beta_1 (treatment_j * affected^t_i) + \beta_2\, treatment_j + \beta_3\, affected^t_i + \beta_4 X_i + s_i + \varepsilon^t_{ij} \text{ ....} (1)$$

Where Y^t_{ij} is a schooling outcome of children *i* in cluster *j* born at time *t*. It represents a dummy for secondary school completion. $treatment_j$ is a dummy for community *j* affected by earthquake and $affected^t_i$ is a dummy variable for affected cohorts during the earthquake. X_i is a vector of controls for student's and household head's characteristics. s_i is a child's fixed effects and ε^t_{ij} is the error term. The error term is clustered at district levels. The β_1 coefficient term on the interaction between $treatment_j$ and $affected^t_i$ i.e. $treatment_j * affected^t_i$ gives the effect on schooling of cohort of children exposed to earthquake.

Here, our affected cohort is represented by $affected^t_i$. In other word, $affected^t_i$ is a dummy for a student who were aged 14 to 16 years old during 2015 earthquake and are expected to complete her secondary education during the survey either in 2016 or in 2018. We choose an unaffected cohort who were aged 21 to 24 years during the earthquake and have completed their secondary education quite earlier from the period of earthquake.[1] Hence, essentially we utilize linear probability model as an estimation method where we control for child fixed effects.

The estimated results may, therefore not report coefficients for treatment area and affected cohorts. This is because child fixed effects may absorb the effects of these entities. This is also the reason we cannot control for birth cohort b_t. Child fixed effects is expected to take into account for unobserved heterogeneity of the children. For example, a child may be systematically different in abilities from other children. In such a case, the estimated coefficient of the impact of earthquake (as reported as β_1 in equation 1) will be biased.

Although we intend to exploit natural experiment setting to argue that our $treatment_j$ variable is exogenous, it may be possible that it may be endogenous. Since this is self-reported at community levels, it may be reported based on the level of damage sustained due to earthquake at household and community levels. In regression equation above, the economic damage may confound the effects of $treatment_j$ variable (as an omitted variable bias) thus the β_1 coefficient may be downward biased.

Ideally, we can employ random effects model if we presume that our variables of interest ($treatment_j$ & $treatment_j * affected^t_i$) in equation (1) are not correlated with the error term ε^t_{ij}. Otherwise, we need to employ fixed effects model. In order to confirm the choice of the model, we run a Hausman test. The null hypothesis is that there is no systematic difference in coefficients i.e., random effects model is best fit. In other words, if we fail to accept null hypotheses, we choose fixed effects model. The test

[1] We use data from third round of Nepal Living Standard survey to delineate the schooling age of children. Generally, the children start secondary school at the age of 12 and are expected to complete it by 16. Here, completion of secondary school means completion of class 10 (Central Bureau of Statistics, 2011).

rejects the null hypotheses indicating that the *treatment*$_j$ & *treatment*$_j$ * *affected*^t_i are endogenous and therefore fixed effect model is the best fit in our setting. Results from the Hausman test are reported in Appendix 1.

Data Analysis and Results

Table 4 presents the results of the regression analysis. In the case of regression results in Table 4 for secondary school completion, the coefficients on the interaction term between the treatment area and affected cohort are positive and significant when the district, VDC and household fixed effects are accounted for. However, the coefficient becomes negative and significant when child fixed effects are controlled. This control shows that the child's unobserved heterogeneity (for example, children's innate ability) is important, and the results may be misleading if this is not accounted for. Our preferred specification is the regression result that accounts for the child fixed effects reported in column (4) of Table 4. The coefficient is -0.376, indicating that the affected cohort in the treatment area was 37.6 per cent less likely to complete secondary level schooling. These suggest that the earthquake adversely affected the probability of completing secondary levels.

As far as other control variables are concerned, results show a non-linear relationship between the age of the children and the probability of completion of schooling. In other words, the likelihood of completion increases up to certain age and then the probability declines. The probability of completing secondary levels decreases after the students are 25 years old. The gender of the children has no effect.

In terms of the effects of caste, the probability of completion is lower for Adibasi and janajati, Dalit, Madhesi, cultural groups, and other castes than the Brahmin and Chhetri. The cultural groups report the lowest probability, followed by Madhesi, Dalits, other castes, and Adibasi and janajatis in the case of primary school. The same is true in the case of the secondary level, except that the other castes have the lowest probability of completion after cultural groups, followed by Dalits, Madhesi, and Adibasi and janajatis. The household head's education is also positively associated with the probability of school completion; the higher the level of the household head's education, the higher is the probability. The household head's age also exhibits a non-linear relationship; however, the association is first negative and then positive. This means that the probability of completion first declines and then increases after the head attains a certain age. The household head's marital status and gender have no role.

Table 4: Regression results for the effect of earthquake on secondary school completion

	(1)	(2)	(3)	(4)
	District fixed effects	Village fixed effects	Household fixed effects	Student's fixed effects
VARIABLES		Secondary level completed (=1)		
Treatment area (=1)	-0.0393	-0.0265		0.0760
	(0.0369)	(0.0707)		(0.109)
Affected Cohort (=1)	0.192***	0.233***	0.360***	
	(0.0422)	(0.0453)	(0.0943)	
Affected Cohort*Treatment area (=1)	0.0742**	0.0639**	0.168**	-0.376**
	(0.0291)	(0.0316)	(0.0700)	(0.146)
Age of student	0.370***	0.398***	0.593***	0.721***
	(0.0394)	(0.0429)	(0.0787)	(0.104)
Age of student squared	-0.00775***	-0.00829***	-0.0122***	-0.0146***
	(0.000870)	(0.000954)	(0.00166)	(0.00215)

	(1)	(2)	(3)	(4)
	District fixed effects	Village fixed effects	Household fixed effects	Student's fixed effects
VARIABLES		Secondary level completed (=1)		
Male (=1)	0.0112	0.0125	0.0493	
	(0.0142)	(0.0152)	(0.0309)	
Adibasi and janajati	-0.112***	-0.0674**		
	(0.0209)	(0.0267)		
Dalit	-0.153***	-0.163***		
	(0.0290)	(0.0387)		
Madhesi	-0.142***	-0.104**		
	(0.0284)	(0.0440)		
Cultural Groups	-0.269***	-0.193***		
	(0.0284)	(0.0462)		
Other castes	-0.185***	-0.141***		
	(0.0306)	(0.0518)		
Son/Daughter of household head (=1)	-0.000353	0.0129	0.0242	-0.225
	(0.0234)	(0.0243)	(0.0383)	(0.228)
Household head less than primary level completed (=1)	-0.0193	-0.0408	0.0587	0.0490
	(0.0248)	(0.0324)	(0.0372)	(0.0476)
Household head primary level completed (=1)	-0.0373	-0.0720**	0.0178	0.0191
	(0.0278)	(0.0347)	(0.0606)	(0.0754)
Household head secondary level completed (=1)	0.579***	0.519***	0.530***	0.524***
	(0.0322)	(0.0380)	(0.0790)	(0.103)
Household head age	-0.0218***	-0.0202***	-0.0102	-0.00619
	(0.00519)	(0.00639)	(0.0218)	(0.0196)
Household head age squared	0.000189***	0.000179***	7.90e-05	1.16e-05
	(4.98e-05)	(6.03e-05)	(0.000219)	(0.000176)
Household Head Marital status (=1)	-0.00796	-0.0150	0.0133	-0.0147
	(0.0224)	(0.0221)	(0.112)	(0.131)
Household Head Male (=1)	0.0142	0.0207	0.100*	0.112
	(0.0185)	(0.0175)	(0.0562)	(0.0711)
Constant	-3.523***	-3.936***	-6.817***	-7.998***
	(0.441)	(0.478)	(1.108)	(1.188)
Observations	5,085	5,085	5,085	5,085
R-squared	0.446	0.505	0.791	0.917

Robust standard errors in parentheses

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

Analysis by Gender

We also explored whether the impact differs by gender of the children. We primarily conducted a t-test to show whether the difference in secondary school completion is significant by gender. As carried out earlier, the regression analysis does not report the coefficients on the interaction term between the treatment area and the affected cohort due to the lack of sufficient observations when the sample is restricted by gender. We, therefore, reported t-test results in Tables 5 and 6 separately for treatment area, affected cohort and interaction term between the two.

Table 5: t-test results for the effect of earthquake on secondary level completion by gender (male)

	Treatment area		**Difference**	**Affected cohort**		**Difference**	**Treatment area*Affected cohort**		**Difference**
	(=1)	(=0)		(=1)	(=0)		(=1)	(=0)	
Secondary School Completion (=1)	0.403	0.450	-0.047**	0.369	0.492	-0.123***	0.366	0.447	-0.081***
Observations	858	1436		1108	1186		402	1892	

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

Table 6: t-test results for the effect of earthquake on secondary level completion by gender (female)

	Treatment area		**Difference**	**Affected cohort**		**Difference**	**Treatment area*Affected cohort**		**Difference**
	(=1)	(=0)		(=1)	(=0)		(=1)	(=0)	
Secondary School Completion (=1)	0.431	0.412	0.019	0.403	0.431	-0.028	0.457	0.411	0.046*
Observations	980	1811		1237	1554		448	2343	

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

The results in Tables 5 & 6 show that the male children are adversely affected while female children are not affected. They show that fewer children in the treatment area have completed secondary school vis-à-vis the children in the control area. Likewise, fewer children in the affected cohort have completed secondary school. The t-test shows that these differences are also significant. Also, the difference in the proportion of interaction terms between the treatment area and the affected cohort is negative and significant. On the contrary, these differences are insignificant for female children except for the interaction term between the treatment area and the affected cohort, as shown in Table 6. The difference in the interaction term is positive and significant; however, we consider not rejecting the null hypotheses of no difference since this is significant at the 10 per cent level.

Discussion

Essentially, we find a negative impact of the earthquake on secondary school completion. In terms of impact by gender, the study finds that male students suffered while female students had no impact. These findings echo the findings of several other studies identifying the impact of natural disasters and exposure to conflict on educational attainment. For example, Swee (2015) assesses the impact of the 1992-1995 Bosnian war and finds that the cohorts exposed to war are less likely to complete secondary schooling. Further, the study also finds that the male cohort experienced the brunt of the war more than the female ones. Although findings are very similar to ours, it might be surprising to observe a negative effect on the male than the female cohort in a developing economy context where parental investments are usually male-biased. In the current study, we can reason the same; Nepal is also a patriarchal society where sons are preferred while prioritizing parental investment on human capital. While a study by Paudel & Ryu (2018) confirms that earthquake has adverse effects on secondary school completion, the findings differ when analyzed by gender. This study analyzes the impact of the 1988 earthquake in Nepal on the educational attainment of affected children and finds female cohorts are affected more than male ones. The author puts forward the male-biased story to justify the findings. This difference in findings may be emanating from the fact that we assess the short-term impact while the study by Paudel & Ryu (2018) looks into the long-term impact of the Nepal earthquake. In the short term and the immediate aftermath of the earthquake, it may be possible that the male member is more likely to extend strong support towards the recovery process. For example, they are more likely to engage in paid work for income support or contribute to rebuilding the damaged house. However, in the long term, this may not be the case; the households will recover both in terms of physical assets and livelihood. Consequently, male children get back from the paid work and house rebuilding and the investment in the human capital is increased, as suggested by the male-biased story discussed above.

It is not unusual to expect that child labor would increase in the aftermath of natural disasters. They may need to support the household either by assisting in recovering/rebuilding the damaged physical assets or by engaging as a paid worker. A study in the case of primary school education (grades 1 – 7) in Zambia concluded that the school children partly met the rising demands of child labor in flood plains. Most children in these areas are over 14 in class 7 and are expected to support the family by engaging in income-generating activities and sometimes by shifting gender norms in the role of breadwinner (Khalil Conteh, 2015). A recent study on the impact of the COVID-19 pandemic on child education in Nepal by Dawadi et al. (2020) also reasons that the parents were no longer able to send their children to school due to job loss and the worsening economic crisis. Further, the children may need to work to provide economic support to their families. It is estimated that the situation is worse in rural areas.

Now let us discuss additional channels explaining why earthquakes may adversely affect school completion. First, poor health and human loss from natural disasters directly affect child's education. Several studies show adverse long-term effects of natural disasters on their health (Alderman et al., 2006; Hoddinott & Kinsey, 2001). Second, the cost of education increases while access to schools becomes difficult when natural disasters destroy education-related infrastructures such as schools and classrooms. Likewise, extreme events such as long droughts and heavy floods also pose difficulties for children to access schools (Baez & Santos, 2007b; Javier Baez et al., 2010; Stein et al., 2003). Third, economic loss due to natural disasters decreases household income, which may further reduce education expenditure and may also need to turn to children's labor for additional income. (de Janvry et al., 2006; Grootaert & Kanbur, 1995). Further, natural disasters may damage the rural household's major source of livelihood, such as farm assets and livestock. This will impair the household's ability to invest in health and education since the households reprioritize their expenses to recover physical assets and consumption smoothing.

Conclusion

This study assesses the short-term impact of Nepal's 2015 earthquake on children's educational attainment, primarily secondary school completion. Essentially, the study is interested in knowing whether the children, at their secondary levels during the earthquake, completed their schooling and whether the earthquake had any role to play in that. The study uses a novel nationally representative household survey data set, Nepal Household Risk and Vulnerability Survey, collected by the World Bank from 2016 to 2018. This study uses the second and third waves of NHRVS collected in 2017 and 2018. After accounting for missing observations, the study could identify 5085 students at secondary levels. As far as the econometric model is concerned, the study uses the difference-in-difference method to identify earthquake's impact on educational attainment. The model combines variation in two variables for identification: treatment area and affected cohorts. The former is a measure of earthquake intensity at the community level (PSU) and is based on whether the community was affected by the 2015 earthquake. The latter measures whether a student belongs to the cohort exposed to the earthquake in 2015 and ideally would have completed their secondary level by the survey. Hence, the interaction of these two separate variables would yield a proper measure of the effect of the earthquake on educational attainment.

Furthermore, the model accounts for child fixed effects so that any unobserved heterogeneity on the part of the children and its effects can be cancelled out for cleaner identification of the impact. The study finds that the earthquake had a significant negative impact on secondary school completion probability. Further, disaggregation of the analysis by gender reveals that the educational attainment of male children was adversely affected, while this study does not observe any effect in the case of female children.

Nepal is a country prone to natural disasters. The number of natural disasters has increased in Nepal; on average, about 539 disaster events occur annually (Shrestha, 2019). This growing number of natural disaster events indicates that it severely impacted human lives, properties, and infrastructure. While the government's concern in the immediate aftermath of the disaster is more on recovery of the lost infrastructure and economic activities, less attention is given to its impact on health and education. Since the quality of health and education determines the quality of the economy's human capital, it is important to understand the impact of natural disaster on these important dimensions. This will help make informed policy decisions during the recovery process and during the planning and policy formulation stage.

This study points out the serious consequences of the natural disaster on the educational attainment of children exposed to such disasters. It may be noteworthy that any adverse consequences in the short term will have long term consequences on the human capital formation of the country. This will also determine the quality of human resources and thus the wages it can command in national and international labor markets. This, therefore, urges policymakers to show seriousness and design policies and strategies related to disaster risk reduction, health and education that are responsive to the effects of natural calamities.

Finally, the findings are not conclusive but indicative. More research using rich data and robust methods is required to validate these findings. Similarly, several tests of robustness could be performed to test the sensitivity of the model as well as the results obtained in the study. . For example, one can use an alternative measure of treatment variable (whether affected by earthquake), both of extensive and intensive margins (such as measures of earthquake intensity itself). Also, one may choose different outcome variables for educational attainments, such as graduation (if, for example, one could graduate to a higher class or levels) and test/exam scores.

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Conflict of Interest

There was no conflict of interest while preparing this article.

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Annex

	Coefficients (b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
treatment	-.2431938	-.0455206	-.1976732	.3790944
age	.3931533	.3458785	.0472748	.0140403
agesq	-.0080024	-.0071721	-.0008303	.0003462
male	1.114947	-.0116726	1.12662	.3913509
rel_hhd	-.1464654	.0104598	-.1569252	.0943865
hhd_educat~d				
1	.1189063	-.0363846	.1552909	.0419149
2	.1016566	-.049778	.1514346	.0517728
3	.5785101	.5385882	.0399219	.0533044
hhd_age	-.0292934	-.0253663	-.0039271	.0106508
hhd_agesq	.0002409	.0002249	.0000159	.0001026
hhd_mstatus	.0426394	.0038316	.0388078	.0522166
hhd_male	.0516437	.0088588	.0427849	.029791

```
                        b = consistent under Ho and Ha; obtained from xtreg
         B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           =       97.01
                Prob>chi2 =      0.0000
```