Human Capital Development and Household Welfare in Myanmar

By

Tial Len Par

Dissertation

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

IN PUBLIC POLICY

2020

Human Capital Development and Household Welfare in Myanmar

By

Tial Len Par

Dissertation

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

IN PUBLIC POLICY

2020

Professor Lee, Ju-Ho

Human Capital Development and Household Welfare in Myanmar

By

Tial Len Par

Dissertation

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

IN PUBLIC POLICY

Committee in charge:

Professor Lee, Ju-Ho, Supervisor	Lee Ju Ho
Professor Kim, Taejong	
Professor Wang, Shun	
Professor Kim, Dongseok	김 동 석
Professor Ahn, Sanghoon	

Approval as of August, 2020

ABSTRACT

HUMAN CAPITAL DEVELOPMENT AND HOUSEHOLD WELFARE IN MYANMAR

By

TIAL LEN PAR

Chapter 1 investigates the long-term effect of exposure to earthquake being either in-utero or two years of life on human capital outcomes — types of disability and years of education employing difference in differences strategy. We compare the human capital outcomes across the subpopulations of cohorts exposed to earthquake being either in-utero or two years of life using Myanmar census data. The results indicate that cohorts exposed to the earthquakes being either in-utero or two years of life have a higher probability of being disabled and less years of education. Moreover, the affected cohorts born in rural areas have a higher probability of being disabled than cohorts born in urban areas. Our findings suggest that being exposed to the earthquake in the early years of life negatively impact on human capital outcomes in the long run.

Chapter 2 examines the effect of the cyclone Nargis on household expenditure and crop production in the Ayeyarwady delta region of Myanmar, using the Myanmar Integrated Household Living Conditions Assessment Survey and applying the difference-in-difference (DID) strategy. We compare household expenditure and crop producation across the subsamples between households in the severely cyclone-affected townships and less cyclone-affected townships. The results show that the cyclone significantly reduces cropland, the quantity of crops harvested, monthly non-food expenditure and health expenditure, and the cyclone increases the quantity of food bought as well as monthly food expenditure. Our findings suggest that the cyclone has a negative impact on crop production and household expenditure.

Chapter 3 studies the impact of university expansion through distance education on graduates' job market outcomes using Myanmar Labor Force Survey. To investigate the policy impacts, this study uses Difference-in-Differences (DID) approach exploiting variations in educational attainment and exposure to the policy intervention. Our findings suggest that the education expansion policy lead policy-affected graduates to the higher probability of being under unemployment, and the lower probability of having a formal job and getting a good job. Results also reveal the differential impacts of gender; male graduates have a higher probability of being under unemployment relative to female graduates; however, they have a higher chance to get a formal job and a good job. Estimates from the Difference-in-Differences integrated with Propensity Score Matching (PSM-DID) reassure the validity of the baseline estimates by purging the ability endogeneity.

Keywords: Earthquakes, Human Capital, Cyclone, Household Welfare, Higher Education Expansion Policy, Job Market, Difference-in-Differences, Myanmar

ACKNOWLEDGEMENTS

I thank God for his spiritual guidance, love, strength throughout my doctoral program. I would not have accomplished this study without his presence with me.

I would like to express my greatest gratitude to my academic supervisor, Professor Lee, Ju-Ho for his guidance, motivation and support which contributed greatly to my research. My special gratitude goes to the members of my dissertation committee: Professor Kim, Taejong; Professor Wang, Shun; Professor Kim, Dongseok; Professor Ahn, Sanghoon for their insightful comments and suggestions that have greatly enhanced the quality of this dissertation to its end.

My deepest gratitude goes to the Planning Department, Ministry of Planning, Finance and Industry in Myanmar for granting me study leave for my doctoral program. I would like to express my sincere gratitude to the Korea International Cooperation Agency – Myanmar Development Institute (KOICA-MDI) for the opportunity to receive a scholarship and financial assistant. I am equally grateful to all faculty members of the KDI school who shared their knowledge and experiences with us and all staffs for their responsibilities in facilitating my stay and studies in KDI.

I would like to express my deepest gratitude to all my colleagues and friends for their kindest supports to me during my studies at KDI School. Finally, I am so grateful to my parents and my brothers who always pray for my success, the great love they showed, and support throughout my life.

God bless you all!

TABLE OF CONTENTS

LIST OF TABLES

APPENDIX TABLES

LIST OF FIGURES

CHAPTER 1

EARLY LIFE EXPOSURE TO EARTHQUAKE AND ITS LONG-TERM EFFECTS ON HUMAN CAPITAL OUTCOMES

1.1 Introduction

Natural disasters are increasing in frequency owing to climate change resulting in a host of problems such as damage to properties, loss of lives, and environmental and public health challenges. Developing countries most often suffer from the devastating effects of these disasters. Asia accounts for the highest-burden of natural disasters globally. In 2018, Asia alone accounted for about 45 percent of global disaster events, and 80 percent of disaster deaths (UCLouvain, CRED & USAID, 2018). Earthquake is one of the most devastating natural disasters due to its unpredictable nature (Chen et al., 2007). The earthquake cannot be underestimated because the impact is severe, widespread, and the consequences frequently remain long-term effects on life and property.

Several studies have investigated the adverse effect of the earthquake on human capital. These studies have examined its impact on health outcomes (Chen et al., 2007; Baez, De la Fuente & Santos, 2010), health outcomes, and education (Hermida 2010; Caruso & Miller, 2015; Paudel & Ryu, 2018; Almond, 2006). Other studies have investigated its effect of in-utero and early-life shocks and posit a long-lasting impact on education, health, and socioeconomic outcome at an older age (Weldeegzie, 2017; Lee, 2014; Maluccio et al., 2009; Maccini & Yang, 2009). The effects tend to be grave for individuals exposed to the earthquake during the prenatal period or within 2 years of birth (Wang, et al. 2017; Troche, 2011; Neelsen & Stratmann, 2011). Research on various disciplines establishes that the environmental condition of a child's early life plays a significant role in assessing economic and health conditions at old age. Barker (1992,1994) argues that the disruption of the fetal environment in utero is associated with chronic health outcomes at old age. We contribute to the above literature by investigating the effect of the earthquake on disability and education restricting our study to individuals exposed to earthquakes being either in-utero or in two years of life.

There are different channels through which earthquakes can affect early life's outcomes directly or indirectly. Earthquake incidence destroys a lot of properties including human lives leaving victims in deployable conditions most of which often resort to poor nutrition, dwelling in slums resulting in exposure to infectious disease. Physicians and epidemiological studies have associated many of the deteriorating conditions at later life to exposure to infectious diseases, famine, psychological and socioeconomic stress during in utero and in early years of life. For example, losing a parent can cause children both emotional and physical harm, and may increase vulnerability to future risk (Beegle, De Weerdt, & Dercon, 2006). Poor health in early-life and nutritional deficiency can have lifelong implications for health, education and labor market outcomes in adulthood (Currie & Vogl, 2013; Currie, 2009; Alderman, Hoddinott, & Kinsey, 2006; Silventoinen, 2003; Duflo, 2001; Lucas, Fewtrell, & Cole, 1999; Martorell, 1999). Studies also show that maternal stress after earthquake affects child outcomes as stress alters blood flow to the uterus, and the fetal environment stimulates the tissue, cell and organ system of the fetus structural and functional changes, which results in long-term effects of the child born from stress-burden mothers (Moreno, et al.2010; Entringer, et al. 2011).

This paper investigates the long-term effect of exposure to earthquake being either in-utero or two years of life on human capital outcomes — disability and educational attainment employing difference in differences strategy. We compare the human capital outcomes across the subpopulations of those who were exposed to earthquake being either in-utero or two years of life using Myanmar census data. The results indicate that individuals who were exposed to earthquake being either in-utero or two years of life have a higher probability of being disabled and less years of education. Moreover, affected individuals born in rural areas have a higher probability of disability than born in urban areas. Our findings suggest that those who were exposed to the earthquake in early childhood negatively impacted on human capital outcomes in the long run.

The rest of the paper is structured as follows. An overview of the earthquakes briefly describes in Section 2. Section 3 illustrates the data using in this analysis. Section 4 constructs the identification strategy. Section 5 shows the empirical results and Section 6 present a discussion of the empirical finding and conclusion.

1.2 Background of Earthquakes

Myanmar has been plagued with a series of devastating earthquakes in some parts of the country. In this study, we analyze the effects of three different earthquakes that is Bago earthquake, Phyu earthquake, and Bagan earthquake. Below is a brief background of the earthquakes.

1.2.1 Bago Earthquake

The Pegu (Bago) earthquake occurred on May 5th, 1930 at 13:45:27 hours GMT on the southern part of Sagaing fault. The magnitude scale of the earthquake was at Ms 7.3. The epicenter of the earthquake was at (17.67° N, 96.54° E). The earthquake caused significant loss of life and buildings killing about 500 people in Bago and 50 people in Yangon.

1.2.2 Pyu Earthquake

Pyu earthquake occurred on the 4th December 1930 at 18:51:44 GMT, 1:22 A.M. (Myanmar Standard Time). The magnitude scale of the earthquake was at Ms 7.3 (Engdahl & Villseñor, 2002; NGDC 1972). The epicenter of the earthquake was at (17.97° N, 96.42° E). The earthquake caused major destruction to buildings, masonry buildings, roads, severe buckling of the railway line, and killing 30 people (Aung, 2017).

1.2.3 Bagan Earthquake

Bagan earthquake occurred on 8^{th} July 1975 at 6:34 pm local time (12:04:42 UTC) with a magnitude scale of Ms 7.0. The epicenter of the earthquake was at (21.48° N, 94.70° E). The earthquake damaged many pagodas, temples, the historical-artistic landmark of Asia, and the center of the Burmese national culture.

1.3 Data

The analysis of this paper uses the 10% sample of the 2014 Myanmar Population and Housing Census (MPHC) conducted by Myanmar government with support from the United Nations Population Fund. The dataset contains a large range of information needed for our analysis and has individual-level variables on demographics: gender, marital status, disability, and educational attainment. The census also reports the information on birth's place at the township level and place of residence which enables us to analyze earthquake effects on human capital such as types of disability and educational attainment.

The 2014 MPHC presents that the total population of Myanmar was 51,486,253 persons in March 2014. Among them, 26,661,667 were females and 24,824,586 were males (DPM, 2015). The total observation number of individual samples in this study is 4,791,185 samples because we use the 10% sample of the 2014 Myanmar Population and Housing Census data. In this study, we restrict the sample to individuals aged 25 years and above for our analysis of the long-term effect of the earthquake. We define affected township as the distance from the epicenter because we do not have the information about the Mercalli intensity scale (MM or

MMI) of the township level. We calculate distance from the epicenter using the latitude and longitude of the epicenters and place of birth townships.

Table 1.1 provides descriptive statistics of the main variables used in this analysis. It provides outcome and control variables with the sample means respectively. Among types of disabilities, seeing was the most frequent with a mean percentage of 4 followed by walking 3 percent. The mean of years of education is 6.69. For Marital status, married people are the majority in our sample with a mean of 73 percent, followed by singles. Other variables include age, gender, and grade/level of education completion and household characteristics.

Table 1.1: Summary Statistics

	Obs	Mean	Std.Dev	Min	Max
Types of Disability					
• Seeing	2531524	0.04	0.2	0	1
• Hearing	2531524	0.02	0.15	0	1
• Remembering	2531524	0.02	0.15	0	1
• Walking	2531524	0.03	0.17	0	1
Years of education	2531524	6.69	3.64	0	18
Age of respondent	2531524	44.61	14.37	25	93
Gender (Male==1)	2531524	0.45	0.5	0	1
Marital Status					
• Single	2531524	0.15	0.36	0	1
• Married	2531524	0.73	0.44	0	1
• Widowed	2531524	0.09	0.29	0	1
• Divorced	2531524	0.02	0.14	0	1
• Renounced	2531524	0	0.02	0	1
Educational Level					
• None	2531524	0.17	0.37	0	1
• Grade 1	2531524	0.01	0.11	0	1
• Grade 2	2531524	0.04	0.19	0	1
• Grade 3	2531524	0.07	0.26	0	1
• Grade 4	2531524	0.12	0.32	0	1
• Grade 5	2531524	0.23	0.42	0	1
• Grade 6	2531524	0.05	0.22	0	1
• Grade 7	2531524	0.04	0.19	0	1
• Grade 8	2531524	0.04	0.2	0	1
• Grade 9	2531524	0.05	0.21	0	1
• Grade 10	2531524	0.05	0.21	0	1
• Grade 11	2531524	0.05	0.22	0	1
• College	2531524	0.01	0.11	0	1
• Vocational training	2531524	0	0.04	0	1
• Undergraduate diploma	2531524	0	0.05	0	1
• Graduate	2531524	0.07	0.25	0	1
• Postgraduate diploma	2531524	0	0.04	0	1
• Master	2531524	0	0.04	0	1
• Ph.D.	2531524	0	0.02	0	1
Household Characteristics					
• Ownership of housing	2531524	0.87	0.34	0	1
• Type of housing unit	2531524	0.99	0.11	0	1
• Electricity access	2531524	0.36	0.48	0	1
• Having a toilet	2531524	0.88	0.33	0	1
• Mobile phone access	2531524	0.38	0.49	0	1
Place of residence (Urban==1)	2531524	0.278	0.448	0	1

Source: The 10 % samples of the 2014 Myanmar Population and Housing Census

1.4 Identification Strategy

1.4.1 Model Specification

We estimate the long-term effect of the three incidences of earthquakes exposure in early life on human capital outcomes using the difference in differences strategy (DID). We compare the human capital outcomes across the subpopulations of those who were exposed to earthquake during their early life and those who did not. Following the in-utero and early-life hypothesis, we assume that individuals who were exposed to the earthquake either being in-utero or two years of life will be negatively affected either in their health status or education in later life. To identify the affected cohorts (hereafter Cohort), we calculated the ages of those who were exposed to the earthquake being either in-utero or two years of life at the time of the earthquake using the 2014 Myanmar Population Census. Although we have a distance of over 1000km, we define severely affected township (hereafter Treated) if the distance of the township of birth is 0 to 150 km from epicenter and less affected township (hereafter Control) as the distance of birth township is 151 to 400 km from epicenter relying on a measure by Mileti & Fitzpatrick (2019) and Agrawal (2001).[1] We also use a log of the entire distance of the affected township as a treatment variable in a separate analysis. We estimate the long-term effects of the earthquake on human capital using the following equation:

$$Y_{ijt} = \beta_0 + \beta_1 Cohort_{it} + \beta_2 Treated_j + \beta_3 \left(Cohort_{it} * Treated_j\right) + X'_{ijt}\alpha + a_k + \mathcal{E}_{ijt}, \quad (1)$$

Where Y_{ijt} represents the outcomes of interest of individual *i* who was born in township *j* and cohort *t*. The set of outcomes considered in the paper consists of the types of disability (a

[1] Mileti & Fitzpatrick (2019) report that a magnitude of 7 to 8 earthquakes can severely impact a distance of 50 to 100 km long. Agrawal (2001) several reports that magnitude 7 earthquakes can be felt up to 400 km long and can severely cause damage up to a distance of 80 km.

binary indicator of difficulties with seeing, hearing, remembering, or walking) and years of education. $Cohort_{it}$ is a dummy variable of the affected cohorts which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. $Treated_j$ is a dummy variable of born in affected townships, which equals one if the distance of the township of birth is 0 to 150 km from the epicenter, and zero if the distance of the township of birth is 151 to 400 km from the epicenter. X'_{ijt} represents a set of individual characteristics such as age dummies, sex, marital status, educational attainment, and household characteristics such as ownership of housing, types of housing units, electricity access, having a toilet, and mobile phone access and urban area dummy. Besides, we include region fixed effects. $\mathcal{E}_{ijt}$ is the error term cluster at township level[2].

We also perform the same experiments to investigate the heterogeneous impact of the earthquake by gender and place of residence in order to provide a more detailed picture. The triple DID estimate of exposure to the earthquake is estimated by the following equation:

$$Y_{ijt} = \beta_0 + \beta_1 C_{it} + \beta_2 T_j + \beta_3 M_{ijt} + \beta_4 R_{ijt} + \beta_5 (C_{it} * T_j) + \beta_6 (C_{it} * M_{ijt}) + \beta_7 (T_j * M_{ijt}) + \beta_8 (C_{it} * R_{ijt}) + \beta_9 (T_j * R_{ijt}) + \beta_4 \left(C_{it} * T_j * M_{ijt}\right) + \beta_5 \left(C_{it} * T_j * R_{ijt}\right) + X'_{ijt}\alpha + a_k + \mathcal{E}_{ijt}, \qquad (2)$$

Where, Y_{ijt} represents the outcomes of interest for individual *i* who was born in township *j* and cohort *t*. The set of outcomes considered in the paper consists of the disability type (a binary indicator of difficulties with Seeing, Hearing, Remembering, or Walking) and educational attainment (Years of Education). C_{it} is a dummy variable indicating affected cohorts which equals one for the individuals who were exposed to the earthquake being either

[2] There are (409) townships in our data set and we clustered standard errors at this level to allow the correlation within the township.

in-utero or in two years of life. T_j is a dummy variable of born in affected townships, which equals one if the distance to township of birth is 0 to 150 km from epicenter and equals zero if the distance to township of birth is 151 to 400 km from the epicenter. M_{ijt} is a dummy variable which equals one for males, and zero equals for females. R_{ijt} is a dummy variable which equals one for born in rural, and zero equals for born in urban areas. X'_{ijt} represents a set of individual characteristics such as age dummies, sex, marital status, educational attainment, and household characteristics such as ownership of housing, types of housing units, electricity access, having a toilet, and mobile phone access and urban area dummy. Besides, we include region fixed effects. $\mathcal{E}_{ijt}$ is the error term cluster at township level[3].

1.5. Empirical Results

1.5.1 Main Findings

Table 1.2, 1.3, and 1.4 show the results of our main specification for the three incidences of earthquakes exposure in early life on types of disability and years of education. Columns (1-4) estimate the impact of the earthquake on types of disability and column (5) estimates the impact of the earthquake on years of education. We control individual characteristics and household characteristics such as age dummies, sex, marital status, educational level, ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban areas dummy in all columns.

We find that Bago earthquake has a positive impact on the likelihood of being disabled and a negative impact on years of education in **Table 1.2**. The results show that affected cohorts who were exposed to Bago earthquake have difficulties in seeing, hearing, remembering, and

[3] There are (409) townships in our data set and we clustered standard errors at this level to allow the correlation within the township.

walking by 3.3 percent, 3.7 percent, 3.3 percent, and 3.9 percent respectively. The results also show that cohorts who were exposed to earthquake has a significant reduction in years of education by 0.18 years.

Table (1.3) show that Phyu earthquake has a positive impact on the likelihood of being disabled and a negative impact on years of education. The results show that affected cohorts who were exposed to Phyu earthquake have difficulties in seeing, hearing, remembering, and walking by 2.4 percent, 3.0 percent, 2.2 percent, and 2.1 percent respectively. We find that there is a significant decrease in the years of education by 0.17 years among cohorts who were exposed to an earthquake.

Table 1.2: Effects of Bago Earthquake on Types of Disability and Years of Education

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.234***	0.206***	0.168***	0.250***	-2.404***
	(0.015)	(0.014)	(0.013)	(0.015)	(0.115)
Treated	0.007*	0.001	0.004**	0.004*	0.141***
	(0.004)	(0.001)	(0.002)	(0.002)	(0.006)
Treated*Cohort	0.033**	0.037***	0.033***	0.039***	-0.183*
	(0.014)	(0.013)	(0.012)	(0.013)	(0.100)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1562614	1562614	1562614	1562614	1562614

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$. The dependent variables are types of disability and years of education specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. The affected township is a dummy variable of born in affected townships, which equals one for the distance of born in townships 0 to 150 km from the epicenter, and zero equals for the distance of townships from 151 to 400 km from the epicenter. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.3: Effects of Phyu Earthquake on Types of Disability and Years of Education

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.240***	0.210***	0.174***	0.262***	-2.400***
	(0.013)	(0.013)	(0.012)	(0.014)	(0.105)
Treated	0.001	0.001	0.001	0.001	0.089***
	(0.004)	(0.001)	(0.002)	(0.002)	(0.005)
Treated*Cohort	0.024*	0.030**	0.022*	0.021*	-0.177**
	(0.013)	(0.012)	(0.012)	(0.013)	(0.090)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1666968	1666968	1666968	1666968	1666968

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the types of disability and years of education specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. The affected township is a dummy variable of born in affected townships, which equals one for the distance of born in townships 0 to 150 km from the epicenter, and zero equals for the distance of townships from 151 to 400 km from the epicenter. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.4: Effects of Bagan Earthquake on Types of Disability and Years of Education

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.009***	0.003***	0.006***	0.006***	-0.398***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.052)
Treated	-0.005*	-0.005***	-0.006***	-0.003*	0.075
	(0.002)	(0.001)	(0.002)	(0.001)	(0.132)
Treated*Cohort	0.003*	0.004***	0.003**	0.003**	0.056
	(0.002)	(0.001)	(0.001)	(0.001)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1390959	1390959	1390959	1390959	1390959

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are types of disability and years of education specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. The affected township is a dummy variable of born in affected townships, which equals one for the distance of born in townships 0 to 150 km from the epicenter, and zero equals for the distance of townships from 151 to 400 km from the epicenter. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table (1.4) show that Bagan earthquake has a positive impact on the likelihood of being disabled and a negative impact on years of education. The results show that affected cohorts who were exposed to Bagan earthquake have difficulties in seeing, hearing, remembering, and walking by 0.3 percent, 0.4 percent, 0.3 percent, and 0.3 percent respectively. We find that there is a positive impact on the years of education, but it is statistically insignificant.

1.5.2 Falsification Test

We perform a falsification test to ensure our findings are valid. Our concern is that the effects of earthquakes on types of disability and years of education may reflect differential trends between treated and control at the baseline. To perform this test, we use older cohorts as pseudo-post and using the same model from **Equation (1).**

We test whether disability and years of education of the older cohorts show statistically significant. The placebo test is expected to provide us statistically insignificant estimates. As we expected, **Table 1.5, 1.6, and 1.7** show that the impact is statistically insignificant indicating that there was no differential trend on disability and years of education for cohorts not exposed to the earthquake, thus confirming the validity of our results, except for years of education of Bagan earthquake. The years of education of Bagan earthquake show positive significant but this does not bias our results since we did not find the earthquake significant impact on years of education in our main results.

Table 1.5: Falsification Test of Bago Earthquake

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.288***	0.249***	0.214***	0.302***	-1.455***
	(0.024)	(0.024)	(0.022)	(0.023)	(0.202)
Treated	0.007*	0.001	0.004**	0.004*	0.452***
	(0.004)	(0.001)	(0.002)	(0.002)	(0.006)
Treated*Cohort	0.012	0.023	0.017	0.025	-0.111
	(0.022)	(0.023)	(0.019)	(0.022)	(0.170)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1562614	1562614	1562614	1562614	1562614

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. **p<0.10, **p<0.05, ***p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.6: Falsification Test of Phyu Earthquake

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.284***	0.258***	0.216***	0.303***	-1.754***
	(0.021)	(0.021)	(0.019)	(0.019)	(0.106)
Treated	0.001	0.001	0.001	0.001	0.132**
	(0.004)	(0.001)	(0.002)	(0.002)	(0.063)
Treated*Cohort	0.015	0.020	0.013	0.030	-0.135
	(0.020)	(0.021)	(0.018)	(0.020)	(0.138)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1666968	1666968	1666968	1666968	1666968

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. **p<0.10, **p<0.05, ***p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.7: Falsification Test of Bagan Earthquake

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.029***	-0.013***	0.009***	0.012***	-0.883***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.036)
Treated	-0.004*	-0.004***	-0.006***	-0.002*	0.017
	(0.002)	(0.002)	(0.002)	(0.001)	(0.059)
Treated*Cohort	-0.002	0.001	0.001	0.000	0.118***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1390959	1390959	1390959	1390959	1390959

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. **p<0.10, ***p<0.05, ****p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

1.5.3 Robustness Checks

We also use a different subsample of severely affected townships and non-affected townships for our second robustness checks using **Equation (1)**. **Tables 1.8, 1.9, and 1.10** report the estimate of the effect on disability and years of education using severely affected townships and non-affected townships. Our findings are consistent with our baseline estimates both in sign and significance level confirming the validity of our results.

Table 1.8: Robustness Check of Bago Earthquake

(Severely and Non-affected Townships)

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.240***	0.218***	0.183***	0.258***	-3.139***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.102)
Treated	0.013***	0.002***	0.006***	0.007***	0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
Treated*Cohort	0.029***	0.031***	0.016***	0.030***	-0.146*
	(0.004)	(0.003)	(0.003)	(0.003)	(0.088)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1877871	1877871	1877871	1877871	1877871

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. Treated is a dummy variable of born in severely earthquake-affected townships and born in less earthquake-affected townships. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.9: Robustness Check of Phyu Earthquake

(Severely and Non-affected Townships)

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.244***	0.221***	0.188***	0.262***	-3.122***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.112)
Treated	0.010***	0.002***	0.004***	0.005***	0.099***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
Treated*Cohort	0.026***	0.030***	0.011***	0.025***	-0.205**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.096)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1716695	1716695	1716695	1716695	1716695

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. Treated is a dummy variable of born in severely earthquake-affected townships and born in less earthquake-affected townships. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.10: Robustness Check of Bagan Earthquake

(Severely and Non-affected Townships)

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.014***	0.004***	0.006***	0.005***	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.016)
Treated	-0.021***	-0.007***	-0.012***	-0.012***	-0.092
	(0.003)	(0.001)	(0.002)	(0.002)	(0.056)
Treated*Cohort	0.009***	0.004***	0.005***	0.007***	0.070
	(0.002)	(0.001)	(0.001)	(0.001)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1832174	1832174	1832174	1832174	1832174

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. Treated is a dummy variable of born in severely earthquake-affected townships and born in less earthquake-affected townships. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

1.5.4 Analysis using Natural Logarithm of Distance to Earthquake Epicenter

We also estimate the impact of the earthquake on human capital outcomes using log of entire distance to earthquake epicenter as the treatment variable. The estimated results of the earthquakes are reported in **Table 1.11, 1.12, and 1.13.**

Table 1.11 shows the results of the impact of the Bago earthquake on disability and years of education using log of distance to earthquake epicenter as the treatment variable. The results show that distance to the epicenter increases, disability reduces a significant reduction in hearing and walking. These findings suggest that individuals who were being either in-utero or two years of life and resides farther than the epicenter are less likely to be disabled. The impact of the Phyu and Bagan earthquakes on disability and years of education using log of distance to earthquake epicenter as the treatment variable are reported in **Table 1.12 and Table 1.13**. The findings in Phyu earthquake are similar to Bago earthquake, however, the pagan earthquake shows a significant reduction in all types of disability and years of education.

Table 1.11: Effects of Bago Earthquake Using Log Distance to Earthquake Epicenter

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.296***	0.294***	0.222***	0.340***	-3.776***
	(0.041)	(0.034)	(0.036)	(0.037)	(0.313)
Log of Distance	-0.004***	-0.000	-0.002**	-0.003***	-0.183***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.058)
Interaction Term	-0.007	-0.012*	-0.006	-0.012*	0.052
	(0.007)	(0.006)	(0.007)	(0.007)	(0.057)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	2467420	2467420	2467420	2467420	2467420

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The dependent variables are the disability type and educational attainment specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. Log of distance is the continuous treatment variable which is a log of the distance of born in townships to the earthquake epicenter. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.12: Effects of Phyu Earthquake Using Log Distance to Earthquake Epicenter

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.301***	0.302***	0.217***	0.342***	-3.829***
	(0.043)	(0.037)	(0.038)	(0.038)	(0.341)
Treated	-0.004**	-0.000	-0.002**	-0.003***	-0.225***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.062)
Interaction Term	-0.008	-0.013**	-0.005	-0.013*	0.061
	(0.008)	(0.007)	(0.007)	(0.007)	(0.063)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	2467420	2467420	2467420	2467420	2467420

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. Log of distance is the continuous treatment variable which is a log of the distance of born in townships to the earthquake epicenter. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.13: Effects of Bagan Earthquake Using Log Distance to Earthquake Epicenter

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.042***	0.023***	0.028***	0.030***	0.124
	(0.007)	(0.003)	(0.004)	(0.005)	(0.128)
Treated	0.011***	0.004***	0.007***	0.006***	-0.030
	(0.002)	(0.001)	(0.001)	(0.001)	(0.050)
Interaction Term	-0.005***	-0.003***	-0.003***	-0.004***	-0.131***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	2467420	2467420	2467420	2467420	2467420

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. We define the affected cohort is a dummy variable of years of the affected cohort which equals one for the individuals who were exposed to the earthquake being either in-utero or in two years of life. Log of distance is the continuous treatment variable which is a log of the distance of born in townships to the earthquake epicenter. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

1.5.5 Heterogeneous Effect of the Earthquakes

The effects of earthquake by gender and place of residence can vary. For instance, Paudel & Ryu (2018) show that the effect of earthquake on educational outcomes impacted greatly on females. We investigate the heterogeneous impact of the earthquake by gender and place of residence. The estimates from **Equation (2)** of Bago earthquake are reported in **Table 1.14 and Table 1.15,** show heterogeneous impact of the Bago earthquake on disability and years of education by gender and place of residence. **Table 1.14** results show that there is no differential impact between affected males and affected females.

Table 1.15 show heterogeneous impact of the Bago earthquake on disability and years of education by place of residence. The result shows that the Bago earthquake-affected cohorts born in rural areas have a positive significant effect on disability and positive but insignificant effect on years of education. The result reveals that the affected cohorts born in rural areas have more likely to be disabled than affected cohorts born in urban areas.

The estimates from **Equation (2)** of Phyu earthquake and Bagan earthquakes are reported in **Appendix Table A.1-A.4.** The results show heterogeneous impact of the earthquakes on disability and educational attainment by gender and place of residence**.** The findings show that the affected cohorts born in rural areas have a higher probability of disability than born in urban areas.

Table 1.14: Triple DID: Heterogeneity by Gender (Bago Earthquake)

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.244***	0.207***	0.178***	0.265***	-2.661***
	(0.016)	(0.016)	(0.014)	(0.016)	(0.136)
Treated	0.007*	0.001	0.004**	0.004*	0.069
	(0.004)	(0.001)	(0.002)	(0.002)	(0.066)
Male	0.001	0.002***	0.003***	0.004***	0.499***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.052)
Cohort* Treated	0.033**	0.034**	0.024*	0.040***	-0.155
	(0.016)	(0.015)	(0.014)	(0.015)	(0.159)
Cohort*Male	-0.028*	-0.003	-0.029*	-0.042**	0.586***
	(0.016)	(0.019)	(0.017)	(0.019)	(0.167)
Treated *Male	-0.001	-0.000	-0.001	-0.001	-0.069
	(0.001)	(0.001)	(0.001)	(0.001)	(0.059)
Cohort*Treated *Male	0.003	0.006	0.025	0.000	0.106
	(0.021)	(0.023)	(0.021)	(0.022)	(0.207)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1562614	1562614	1562614	1562614	1562614

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table 1.15: Triple DID: Heterogeneity by Place of Residence (Bago Earthquake)

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.209***	0.197***	0.147***	0.263***	-3.347***
	(0.026)	(0.024)	(0.018)	(0.022)	(0.180)
Treated	-0.007**	-0.001*	0.000	-0.000	0.124
	(0.003)	(0.001)	(0.001)	(0.001)	(0.103)
Rural	-0.008***	-0.001	-0.002	-0.003**	-1.426***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.072)
Cohort* Treated	-0.019	-0.017	-0.004	-0.037*	-0.119
	(0.025)	(0.023)	(0.017)	(0.021)	(0.186)
Cohort*Rural	0.036	0.015	0.030	-0.013	1.434***
	(0.022)	(0.022)	(0.019)	(0.021)	(0.173)
Treated *Rural	0.018***	0.004***	0.005**	0.005**	-0.127
	(0.004)	(0.001)	(0.002)	(0.002)	(0.108)
Cohort*Treated *Rural	0.081***	0.080***	0.059***	0.108***	0.189
	(0.027)	(0.025)	(0.022)	(0.025)	(0.201)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1562614	1562614	1562614	1562614	1562614

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10*, ** *p<0.05*, *** *p<0.01*. The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

1.6 Discussion and Conclusion

This paper investigates the long-term effect of the earthquake exposure being either in-utero or two years of life on human capital outcomes using the difference in difference approach. Our results indicate that earthquakes increase the probability of being disabled in the long term after earthquake exposure and as well reduces the years of education.

Our results on disability are consistent with previous findings by Caruso and Miller (2015), who note an increase in the likelihood of being disabled of 0.001 among cohorts who experienced the 1970 Ancash earthquake in their early life. However, in terms of the magnitude, the coefficients of our estimates are bigger, indicating that the effect of the earthquake in our study is more pronounced. The negative impact of the Bago earthquake and Phyu earthquake on years of education are consistent with previous findings by Caruso and Miller (2015), who report an average reduction of 0.49 to 0.70 years of education among cohorts who experienced the 1970 Ancash earthquake in their early life.

Our results on years of education are also consistent with previous findings by Paudel and Ryu (2018), who show an average reduction of 0.8 years of education among cohorts who experienced Nepal's earthquake in their early life. However, our coefficients are smaller for years of education compare to previous studies. These findings answer our research question on the long-term effect of exposure to earthquake being either in-utero or two years of life on disability and years of education. We have no doubt that our results are valid given that our falsification test shows no differential trend in the outcome variables of interest. Other robustness checks also support our findings.

We also show the impact of the earthquakes on disability and years of education using log of entire distance to earthquake epicenter as the treatment variable. The results show that as the distance to the epicenter increases, the probability of being disabled reduces. These findings suggest that individuals who were being either in-utero or two years of life and resides farther than the epicenters of the earthquakes are less likely to be disabled. The results of the heterogeneity of the earthquake by gender and place of the resident show that there is no differential impact between effected-males and effected-females. Affected cohorts born in rural areas are more likely to have disabilities than affected cohort born in urban areas.

Two of the earthquakes in our study, Bago earthquake and Phyu earthquake occurred in the same year, however in different months. There might be an overlapping impact of both earthquakes since we use the same birth cohorts for our analysis and the distance from the epicenter of the Bago earthquake to the Phyu earthquake is 128km, which is within the 150km use for our analysis. Our data set does not contain date and month of birth thus we could not estimate the impact using the exact age of the affected cohorts. Since the two earthquakes occurred in the same year but different months, we could isolate the affected cohorts with their specific ages using the date and month of birth, which may assist us to solve the issue of overlapping.

To the best of our knowledge, this is the only study that investigates the effect of earthquakes on various types of disability which gives a new insight to policymakers on the types of disability which earthquakes affected cohorts suffer at old age, thus a key contribution to literature. Previous studies only examine earthquake effect on aggregate disability making it difficult to identify the types of disability earthquake cohorts experienced in the long run.

We have shown in this study that earthquakes can have a long-term adverse effect on cohorts exposed to being either in-utero and two years of life. We, therefore, recommend regular screening of persons exposed to earthquakes for early identification, treatment, and setting-up rehabilitation centers for persons with disabilities. Social workers should work with the families of affected cohorts to help them understand the nature of the disability and its outcome, to make the necessary adjustments to assist the disabled person deal with personal and interpersonal concerns related to the disability. We also recommend free provision of disability aids by the government for persons exposed to earthquake diagnosed with disability. Concerning years of education, we encourage a strong policy design to tackle the decline in years of education among persons affected.

REFERENCES

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. Oxford economic papers, 58(3), 450-474.

Almond, D. (2006). Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 US population. *Journal of political Economy*, *114*(4), 672-712.

Agrawal, K. C. (2001). Industrial power engineering handbook. Elsevier.

Aung, H. H. Myanmar Earthquakes History (August, 2017).

Baez, J., De la Fuente, A., & Santos, I. V. (2010). Do natural disasters affect human capital? An assessment based on existing empirical evidence.

Barker, D. J. P. (1992). The fetal and infant origins of adult disease. *BMJ: British Medical Journal*, *301*(6761), 1111.

Barker, D. J. P. (1994). *Mothers, babies and disease in later life*. BMJ publishing group.

Beegle, K., De Weerdt, J., & Dercon, S. (2006). Orphan hood and the long-run impact on children. American journal of agricultural economics, 88(5), 1266-1272.

Caruso, G., & Miller, S. (2015). Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 Ancash Earthquake. *Journal of development economics*, *117*, 134-150.

Chen, C. H., Tan, H. K. L., Liao, L. R., Chen, H. H., Chan, C. C., Chen, C. Y., ... & Lu, M. L. (2007). Long-term psychological outcome of 1999 Taiwan earthquake survivors: a survey of a high-risk sample with property damage. *Comprehensive psychiatry*, *48*(3), 269-275.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. Journal of economic literature, 47(1), 87-122.

Currie, J., & Vogl, T. (2013). Early-life health and adult circumstance in developing countries. Annu. Rev. Econ., 5(1), 1-36.

Department of Population Myanmar. (2015). The 2014 Myanmar Population and Housing Census. The Union Report.

Duflo, E. (2001). Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. American economic review, 91(4), 795-813.

Engdahl, E. R., & Villseñor, A. (2002). Global Seismicity: 1900-1999, in International Handbook of Earthquake and Engineering Seismology. *edited by WH Lee, H Kanamori, PC Jennings, et al. Academic Press, Amsterdam, Boston, New York, Oxford, Paris, San Diego, San Francisco, Singapore*, 665-690.

Entringer, S., Epel, E. S., Kumsta, R., Lin, J., Hellhammer, D. H., Blackburn, E. H., ... & Wadhwa, P. D. (2011). Stress exposure in intrauterine life is associated with shorter telomere length in young adulthood. Proceedings of the National Academy of Sciences, 108(33), E513-E518.

Guha-Sapir, D., Vos, F., Below, R., & Ponserre, S. (2012). Annual Disaster Statistical Review 2011: The Numbers and Trends published by the Centre for Research on the Epidemiology of Disasters (CRED) Brussels.

Hermida, P. (2010). The long-term effect of natural disasters: Health and education in Guatemala after the 1976 earthquake. *Unpublished manuscript*.

Lee, C. (2014). In utero exposure to the Korean War and its long-term effects on socioeconomic and health outcomes. *Journal of health economics*, *33*, 76-93.

Li, N., Wang, Y., Zhao, X., Gao, Y., Song, M., Yu, L., ... & Cai, J. (2015). Long-term effect of early-life stress from earthquake exposure on working memory in adulthood. Neuropsychiatric disease and treatment, 11, 2959.

Lucas, A., Fewtrell, M. S., & Cole, T. J. (1999). Fetal origins of adult disease—the hypothesis revisited. Bmj, 319(7204), 245-249.

Maccini, S., & Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, *99*(3), 1006-26.

Maluccio, J. A., Hoddinott, J., Behrman, J. R., Martorell, R., Quisumbing, A. R., & Stein, A. D. (2009). The impact of improving nutrition during early childhood on education among Guatemalan adults. *The Economic Journal*, *119*(537), 734-763.

Martorell, R. (1999). The nature of child malnutrition and its long-term implications. Food and nutrition Bulletin, 20(3), 288-292.

Moreno, M. A., Briner, L. R., Williams, A., Brockman, L., Walker, L., & Christakis, D. A. (2010). A content analysis of displayed alcohol references on a social networking web site. Journal of adolescent health, 47(2), 168-175.

Mileti, D., & Fitzpatrick, C. (2019). The great earthquake experiment: Risk communication and public action. Routledge.

National Geophysical Data Center / World Data Service (NGDC/WDS) (1972), Significant Earthquake Database (Data Set).

Neelsen, S., & Stratmann, T. (2011). Effects of prenatal and early life malnutrition: Evidence from the Greek famine. *Journal of Health Economics*, *30*(3), 479-488.

Park, A., & Wang, S. (2017). Benefiting from disaster? Public and private responses to the Wenchuan earthquake. World Development, 94, 38-50.

Paudel, J., & Ryu, H. (2018). Natural disasters and human capital: The case of Nepal's earthquake. World Development, 111, 1-12.

Pawar, A. T., Shelke, S., & Kakrani, V. A. (2005). Rapid assessment survey of earthquake affected Bhuj block of Kachchh District, Gujarat, India. Indian journal of medical sciences, 59(11), 488-494.

Peek-Asa, C., Ramirez, M. R., Shoaf, K., Seligson, H., & Kraus, J. F. (2000). GIS mapping of earthquake-related deaths and hospital admissions from the 1994 Northridge, California, earthquake. Annals of Epidemiology, 10(1), 5-13.

Silventoinen, K. (2003). Determinants of variation in adult body height. Journal of biosocial science, 35(2), 263-285.

Takasaki, Y. (2017). Do natural disasters decrease the gender gap in schooling? World Development, 94, 75-89.

Torche, F. (2011). The effect of maternal stress on birth outcomes: exploiting a natural experiment. Demography, 48(4), 1473-1491.

UCLouvain, CRED & USAID, (2018). Natural disasters: An opportunity to prepare.

Wang, R., An, C., Wang, J., Wang, Y., Song, M., Li, N., ... & Wang, X. (2017). Earthquake experience at different trimesters during pregnancy is associated with leukocyte telomere length and long-term health in adulthood. Frontiers in psychiatry, 8, 208.

Weldeegzie, S. G. (2017). Growing-up unfortunate: War and human Capital in Ethiopia. *World Development*, *96*, 474-489.

APPENDIX A

Table A.1: Triple DID: Heterogeneity by Gender (Phyu Earthquake)

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.253***	0.212***	0.183***	0.276***	-2.672***
	(0.014)	(0.015)	(0.013)	(0.015)	(0.133)
Treated	0.001	0.001	0.001	0.001	0.119*
	(0.004)	(0.001)	(0.002)	(0.002)	(0.065)
Male	0.000	0.001***	0.002***	0.003***	0.502***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.043)
Cohort* Treated	0.019	0.023	0.014	0.022	-0.167
	(0.015)	(0.014)	(0.013)	(0.014)	(0.149)
Cohort*Male	-0.035**	-0.004	-0.024	-0.039**	0.667***
	(0.014)	(0.017)	(0.015)	(0.015)	(0.155)
Treated *Male	-0.001	0.000	-0.000	-0.000	-0.064
	(0.001)	(0.001)	(0.001)	(0.001)	(0.052)
Cohort*Treated *Male	0.016	0.020	0.023	0.000	0.003
	(0.020)	(0.021)	(0.019)	(0.020)	(0.195)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1666968	1666968	1666968	1666968	1666968

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. “Individual controls” include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table A.2: Triple DID: Heterogeneity by Place of Residence (Phyu Earthquake)

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.198***	0.189***	0.154***	0.245***	-3.240***
	(0.020)	(0.020)	(0.015)	(0.018)	(0.143)
Treated	-0.006**	-0.001	-0.000	-0.001	0.233**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.103)
Rural	-0.002	-0.000	-0.000	-0.001	-1.379***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.066)
Cohort* Treated	-0.004	-0.012	-0.019	-0.018	-0.283*
	(0.020)	(0.020)	(0.014)	(0.018)	(0.157)
Cohort*Rural	0.058***	0.030*	0.029*	0.025	1.361***
	(0.018)	(0.018)	(0.017)	(0.020)	(0.136)
Treated *Rural	0.009**	0.002*	0.002	0.002	-0.209*
	(0.004)	(0.001)	(0.002)	(0.002)	(0.107)
Cohort*Treated *Rural	0.047*	0.063***	0.062***	0.059**	0.256
	(0.024)	(0.022)	(0.021)	(0.025)	(0.176)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1666968	1666968	1666968	1666968	1666968

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *$p<0.10$*, ** *$p<0.05$*, *** *$p<0.01$*. The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table A.3: Triple DID: Heterogeneity by Gender (Bagan Earthquake)

	Disability				Years of Education
	Seeing	Hearing	Remembering	Walking	
	(1)	(2)	(3)	(4)	(5)
Cohort	0.011***	0.003***	0.005***	0.005***	-0.750***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.045)
Treated	-0.005**	-0.005***	-0.007***	-0.003**	-0.011
	(0.003)	(0.001)	(0.002)	(0.002)	(0.066)
Male	0.001	0.001***	0.001**	0.002***	0.351***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.044)
Cohort* Treated	0.003	0.005***	0.003**	0.002	0.022
	(0.002)	(0.001)	(0.001)	(0.002)	(0.038)
Cohort*Male	-0.002**	0.000	0.002**	0.002*	-0.294***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.029)
Treated *Male	0.001	0.000	0.002***	0.002***	0.302***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.052)
Cohort*Treated *Male	0.001	-0.001	-0.001	0.001	0.134***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1390959	1390959	1390959	1390959	1390959

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

Table A.4: Triple DID: Heterogeneity by Place of Residence (Bagan Earthquake)

	Disability				Years of
	Seeing	Hearing	Remembering	Walking	Education
	(1)	(2)	(3)	(4)	(5)
Cohort	0.014***	0.009***	0.011***	0.010***	-0.640***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.053)
Treated	-0.004	-0.002***	-0.002**	-0.001	-0.211**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.091)
Rural	0.003*	0.004***	0.003***	0.002**	-1.646***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.067)
Cohort* Treated	0.003	0.002*	0.002	0.001	0.058
	(0.002)	(0.001)	(0.001)	(0.001)	(0.065)
Cohort*Rural	-0.006***	-0.007***	-0.006***	-0.005***	-0.093**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.046)
Treated *Rural	-0.002	-0.003**	-0.005***	-0.002	0.307***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.098)
Cohort*Treated *Rural	0.000	0.003**	0.001	0.001	0.057
	(0.002)	(0.001)	(0.002)	(0.002)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1390959	1390959	1390959	1390959	1390959

Notes: Linear probability models. Robust standard errors are clustered at a township level in parentheses. $*p<0.10$, $**p<0.05$, $***p<0.01$. The dependent variables are the disability type and educational attainment specified in the heading of the table. "Individual controls" include sex, age, marital status, education level, and "Household characteristics" ownership of housing, types of housing units, electricity access, having a toilet and mobile phone access, and urban area dummy.

CHAPTER 2

THE EFFECTS OF NATURAL DISASTER ON HOUSEHOLD EXPENDITURES AND CROP PRODUCTION: A CASE STUDY ON CYCLONE NARGIS AFFECTED REGION IN MYANMAR

2.1 Introduction

Over the past few years in Myanmar, the number of natural disasters has increased as well as its severity. Different types of disasters such as earthquakes, floods, landslides, cyclones, and drought occur frequently in Myanmar. Several researches have confirmed that natural disasters have increased and adversely correlates with several dimensions of human life such as human resources, economies, and poverty, especially in developing countries (Linnerooth-Bayer & Mechler, 2008; Moench, Mechler & Stapleton, 2007; Guha-Sapir, Hargitt & Hoyois, 2004). Since 1950s, economic losses owing to natural disasters have risen to 14-folds, which is US$ 67 billion per year (Guha-Sapir et al., 2004). Linnerooth-Bayer and Mechler (2008) report that more than 95 percent of death by cause of natural disasters occurred in developing countries in 1980–2004, with economic losses totaling USD 54 billion annually.

Several studies have investigated the adverse impact of natural disasters on household expenditure and income. These studies show a negative association between natural disasters and household income and expenditure (Arouri, Nguyen & Youssef, 2015; Sulistyaningrum, 2015; Bui et al., 2014; Mottaleb et al., 2013; Thomas et al., 2010; Masozera, Bailey, & Kerchner, 2007; Dercon, 2004). However, much evidence is still needed for policymakers to better understand the devastating effect of natural disasters for appropriate policy designs towards confronting a similar future occurrence. Our study contributes to these literatures on natural disasters and household income and expenditure.

Globally, billions of households rely on farming for jobs and income, however, negative income shocks due to crop failure are becoming almost daily phenomenon among farmers (Zeigler & Barclay, 2008; Khush, 2004). Weather-related natural disasters can bring significant negative income shocks to farmers, as crops harvested, and income significantly corresponds to weather conditions. For instance, the estimated annual loss in rice production is more than 4 million tons in India and Bangladesh alone due to seasonal floods (IRRI, 2010). Natural disasters can result in a 100 percent yield loss in extreme cases. Households in Bangladesh in fully flooded villages lost about 90 percent of their crops, cattle, and poultry during the 1994 flood (Khandker, 2007). Some research explores the effect of a disaster-related crop shock on household consumption and expenditure as millions of households around the world rely on agriculture for jobs and earnings. These researchers note that in the event of a crop failure, households were unable to smooth their consumption, thus they were more likely to cut their expenditure (Cameron & Worswick, 2001; Kochar, 1999). Negative income shocks lead to lower expenditure on health and education, particularly households in developing countries (Sawada and Lokshin, 2009; Duryea et al., 2007; Benson and Clay, 2004).

This paper investigates the effect of the cyclone Nargis on household expenditure and crop production in the Ayeyarwady delta region of Myanmar, using the Myanmar Integrated Household Living Conditions Assessment Survey and applying difference-in-difference (DID) strategy. We compare household expenditure and crop harvested across the subsamples between households in the severely cyclone-affected townships and less cyclone-affected townships.

The results show that the cyclone significantly reduces cropland, the quantity of crops harvested, monthly non-food expenditure, and health expenditure by 35.0 percent, 33.2 percent, 10.7 percent, and 17.8 percent respectively. The cyclone increases the quantity of food bought as well as monthly food expenditure by 10.2 percent and 18.2 percent respectively. We estimate the quantity of food bought to determine what happened to the rising food expenditure. Our findings suggest that the cyclone has a negative impact on crop production and household expenditure. One possible reason could the reduction in cropland which led to reduce quantity crops harvested as a result of the cyclone. As a result of the reduced crops of harvested, households had to channel their income on food for survival thus increased in food expenditure with resultant reduction in non-food expenditure.

The remainder of the paper is organized as follows. Section 2 briefly describes the Cyclone Nargis ad study area. Section 3 presents the data sources and characteristics of sample households. Section 4 describes the identification strategy. Section 5 presents the empirical results and Section 6 presents discussions and conclusion of the paper.

2.2 Background

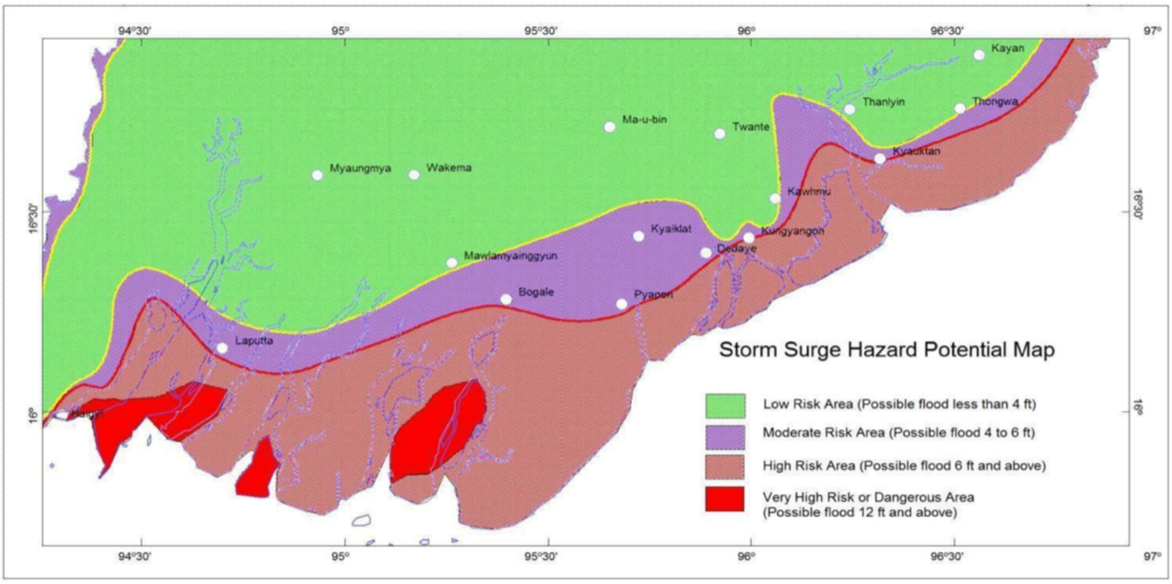
Cyclone Nargis was an extremely damaging and the deadliest natural disaster in the recorded history of Myanmar. The cyclone struck the Ayeyarwady delta region, Myanmar in the late afternoon of 2nd May 2008, and lasted throughout the night and moved towards the southern Yangon region the next day. It brought high-speed winds over 200 kilometers per hour (108 knots) and a tidal storm surged 3.6 meters (12 foot) high. Over the next day, the Cyclone Nargis caused catastrophic damage resulting in loss of life of about 140,000 people in the delta region of the country. Survivors' lives and livelihoods were severely affected with up to 800,000 persons displaced, 450,000 houses damaged, croplands flooded, and significant losses of food stocks, paddy, livelihood related equipment, and infrastructure (Shwe, 2013; TCG, 2009).

Figure 2.1 and Figure 2.2 show a map of Cyclone Nargis affected region and storm surge level.

Figure 2.1: Map of Cyclone Nargis Affected Region

Source: Post-Nargis Periodic Review

Figure 2.2: Map of Storm Surge Level



Source: Storm Surge Hazard Mapping

In our study, we choose Ayeyarwady delta region because it is the most severely affected region and because most people in that region are farmers, we seize the opportunity to examine the cyclone effect on household expenditure and crop production. Although Yangon region was also affected by the cyclone, the severity was not as compared to Ayeyarwady delta region. Ayeyarwady delta region also is known as "The rice bowl of Myanmar", as the country's largest rice producer, consists of 26 townships and it is estimated to be the most populated region in Myanmar. Farming is the main source of income and livelihood in the cyclone-affected areas and rice is the most important crop in the area affected by the cyclone. It is the region with the highest percentage of rural population (88 %) compared to 12% residing in urban areas. Eleven townships were struck by the cyclone Nargis and four of the townships such as Labutta, Bogalay, Mawlamyinegyun, and Pyapon were severely affected (TCG, 2009).

2.3 Data

The paper uses Myanmar Integrated Household Living Conditions Survey (IHLCA) data collected in 2004, 2009, 2010 to investigate the effect of the Cyclone Nargis on household expenditures and crop production. The dataset is collected by the United Nations Children's Fund (UNICEF) jointly with the Planning Department of Ministry of National Planning and Economic Development and Swedish International Development Cooperative Agency. The dataset contains a wide range of information needed for our analysis and have variables on household head information, household size, and region of the resident. These allow us to analyze the effect of the Cyclone Nargis on household expenditures and crop production such as total household food and non-food expenditures, acres of cropland, and quantity of crop harvested.

2.3.1 Descriptive Summary Statistics

Descriptive statistics of the main variables used in this analysis are presented in **Table 2.1**. It presents the outcome and control variables with the sample means respectively.

Table 2.1: Summary Statistics

	Obs	Mean	Std.Dev	Min	Max
Log of plot acre	23166	1.37	1.03	0	6.43
Log of total quantity harvest	18060	5.11	1.81	0	13.46
Log of monthly quantity of food consumec	52422	7.44	1.33	0	12.83
Log of monthly food expenditure	52417	9.84	0.85	3.69	14.97
Log of monthly non-food expenditure	52461	9.59	0.97	1.10	15.77
Log of health expenditure	14226	9.36	1.63	0	17.73
Log of education expenditure	20664	9.49	1.61	0.69	16.46
HH head's gender (Male==1)	49639	0.81	0.39	0	1
Age of HH head	49639	51.73	13.58	16	99
Educational level of HH head					
• KG	49639	0.01	0.09	0	1
• Grade 1	49639	0.02	0.13	0	1
• Grade 2	49639	0.09	0.28	0	1
• Grade 3	49639	0.13	0.34	0	1
• Grade 4	49639	0.27	0.44	0	1
• Grade 5	49639	0.06	0.23	0	1
• Grade 6	49639	0.04	0.21	0	1
• Grade 7	49639	0.06	0.24	0	1
• Grade 8	49639	0.06	0.23	0	1
• Grade 9	49639	0.07	0.26	0	1
• Grade 10	49639	0.04	0.20	0	1
• Undergraduate diploma	49639	0.07	0.26	0	1
• Bachelor degree	49639	0.04	0.20	0	1
• Postgraduate degree	49639	0.04	0.19	0	1
No. of HH member	49639	4.16	2.02	1	23
Landlord (landlord==1)	52499	0.44	0.50	0	1
Place of residence (Rural==1)	49639	0.69	0.46	0	1

Source: Integrated Household Living Condition Survey

The mean of households' head age in our samples is 51 years. Most of the households' heads are male in our sample with a mean percentage of 81 and the majority have completed grade 4 (24.5 percent) followed by undergraduate diplomas. The mean of number of household members is 4 persons in our sample. The mean of the Landlord household is 44 percent in the sample. About 69 percent of the Households in our observation are in rural areas and 31 percent in urban areas.

2.4 Identification Strategy

We estimate the effect of the cyclone Nargis on household expenditure and crop production using the difference in differences strategy. We compare household expenditure and crop production across the subsamples between households in the severely cyclone-affected townships and less cyclone-affected townships. We estimate the following equation:

$$Y_{ijt} = \beta_0 + \beta_1 Post_{it} + \beta_2 Treatment_j + \beta_3 (Post_{it} * Treatment_j) + X'_{ijt}\alpha + \mathcal{E}_{ijt}, \quad (1)$$

Where, i stands for the individual household; j stands for township, and t stands for year. Y represents the outcome variables that include acres of cropland, the quantity of crop harvested, and expenditures on food and nonfood. $Post_{it}$ is a year dummy variable which equals one for year of 2009 and year of 2010 and equals zero for year of 2004. $Treatment_j$ is a binary indicator that indicates one for storm surge 6ft and above areas (hereafter severely affected townships), and zero denotes for storm surge below 6ft areas (hereafter less affected townships). X'_{ijt} represents a set of household head and household characteristics such as age dummies, sex, years of schooling, number of household members, landlord, and household located area dummy. $\mathcal{E}_{ij}$ is the error term. Since our study setting is only 10 townships, using clustered standard errors will bias our results downward. To address this issue, we use bootstrap procedures to obtain valid inference as proposed by Cameron et al., (2010).

The validity of our finding rests on the fact that the outcomes variables of interest did not show a differential trend in the treatment and control regions before the cyclone incidence. However, we could not estimate the parallel trend assumption owing to data unavailability. We perform a balancing test to see the correlation between treatment and control. Significant mean differences indicate treatment and control are unbalanced. However, as we show in table **Table 2.2**, most of our covariates were below the accepted threshold of 5 percent, suggesting that our baseline covariates were balanced at the baseline supporting the parallel path theory.

Table 2.2: Balancing Test

Variable(s)	Mean Control	Mean Treated	| t |	Diff.
HH head gender (Male==1)	0.88	0.86	1.30	-0.02
Age of HH head	50.65	50.72	0.10	0.07
Educational level of HH head	6.92	6.72	1.00	-0.21
No. of HH member	4.18	4.20	0.10	0.01
Landlord (Own==1)	0.92	0.93	0.77	0.01
Place of residence (Rural==1)	0.92	0.90	1.53	-0.02

Notes: Difference = Mean (not affected) − Mean (affected). * *p<0.10,* ** *p<0.05,* *** *p<0.01.*

2.5. Empirical Results

2.5.1 Main Findings

We report our main specification results for the effect of the cyclone on household expenditures and crop production in **Table 2.3**. All dependent variables are in log levels: log of cropland acre, log of quantity of crop harvest, log of quantity of monthly food, log of monthly food expenditure, log of monthly non-food expenditure, log of health expenditure, and log of education expenditure. We control the following covariates: household head and household characteristics such as age dummies, sex, years of schooling, number of household members, landlord dummies, and household located area dummy are included in all columns and coefficients with bootstrap standard error are reported in parentheses.

Table 2.3: The Effect of the Cyclone on Crop Production and Household Expenditure

	Cropland (Acre)	Quantity of Crop Harvested	Quantity of Food Bought	Monthly Food Expenditure	Monthly Nonfood Expenditure	Health Expenditure	Education Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year 2009 & 2010	0.087**	0.048	2.510***	0.810***	1.080***	0.838***	1.056***
	(0.036)	(0.084)	(0.012)	(0.012)	(0.018)	(0.056)	(0.059)
Treatment	0.590***	0.398***	-0.090***	-0.221***	0.042	0.257***	-0.048
	(0.047)	(0.080)	(0.022)	(0.022)	(0.029)	(0.073)	(0.090)
Interaction term	-0.350***	-0.332***	0.102***	0.182***	-0.107***	-0.178*	0.157
	(0.068)	(0.127)	(0.023)	(0.027)	(0.032)	(0.105)	(0.098)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5399	4173	5399	5399	5399	3411	4857

Notes: Coefficients with bootstrap standard errors are reported in parentheses. **p<0.10, ***p<0.05, ****p<0.01.* The dependent variables are log of household expenditure and crop production specified in the heading of the table. We define the year 2009 & 2010 equals to one for the years 2009 and 2010 and equals to zero for the year 2004. The dummy for the cyclone-affected township equals one for severely cyclone-affected townships, and zero denotes for less cyclone-affected townships. Household head and household characteristic controls include sex, age dummies, years of schooling, number of household members, landlord dummies, and household located area dummy.

Table 2.3 shows the estimates of the effect of the cyclone on household expenditures and crop production. The results show that the cyclone significantly reduces cropland, the quantity of crops harvested, monthly non-food expenditure, and health expenditure by 35.0 percent, 33.2 percent, 10.7 percent, and 17.8 percent respectively. The cyclone increases the quantity of food bought as well as monthly food expenditure by 10.2 percent and 18.2 percent respectively. We estimate the quantity of food bought to determine what happened to the rising food expenditure. Our findings suggest that the cyclone has a negative impact on crop production and household expenditure. One possible reason could the reduction in cropland which led to reduce quantity crops harvested as a result of the cyclone. As a result of the reduced crops harvested, households had to channel their income on food for survival thus increased in food expenditure with resultant reduction in non-food expenditure.

2.5.3 Heterogeneous Effect

To explore the differential impact of the cyclone on landlord and rural residence we perform extra experiments. **Table 2.4 reports** the results of the heterogeneity of crop production and household expenditure by landlord.

Table 2.4: Heterogeneity of Crop Production and Household Expenditure by Landlord

	Cropland (Acre)	Quantity of Crop Harvested	Quantity of Food Bought	Monthly Food Expenditure	Monthly Nonfood Expenditure	Health Expenditure	Education Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year 2009 & 2010	0.094***	0.058	2.444***	0.793***	1.129***	0.860***	1.146***
	(0.036)	(0.094)	(0.017)	(0.024)	(0.028)	(0.123)	(0.082)
Treatment	0.594***	0.403***	-0.123***	-0.431***	0.057	0.225	0.065
	(0.070)	(0.092)	(0.034)	(0.055)	(0.053)	(0.149)	(0.138)
Interaction term	-0.358***	-0.337***	0.120***	0.315***	-0.135**	-0.085	0.051
	(0.078)	(0.128)	(0.035)	(0.063)	(0.054)	(0.211)	(0.186)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5246	4081	5246	5246	5246	1370	2115

Notes: Coefficients with bootstrap standard errors are reported in parentheses. * *p<0.10,* ** *p<0.05,* *** *p<0.01.* The dependent variables are log of household expenditure and crop production specified in the heading of the table. We define years of 2009 & 2010 equal one for the years 2009 and 2010 and equals to zero for the year 2004. The dummy for the cyclone-affected township equals one for severely cyclone-affected townships, and zero denotes for less cyclone-affected townships. Household head and household characteristic controls include sex, age dummies, years of schooling, number of household members, landlord dummies, and household located area dummy.

The results of **Table 2.4** show that the cyclone significantly reduces landlord households of cropland, the quantity of crops harvested, and monthly non-food expenditure by 35.8 percent, 33.7 percent and 13.5 percent respectively. The cyclone increases landlord households of the quantity of food bought as well as monthly food expenditure by 12.0 percent and 31.5 percent respectively. Our findings show that landlord households experienced a significant reduction in crop production and an increase in food expenditure but there is no significant impact on health expenditure and education expenditure.

Table 2.5: Heterogeneity of Crop Production and Household Expenditure by Rural Residence

	Cropland (Acre)	Quantity of Crop Harvested	Quantity of Food Bought	Monthly Food Expenditure	Monthly Nonfood Expenditure	Health Expenditure	Education Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year 2009 & 2010	0.081**	0.038	2.515***	0.814***	1.092***	0.856***	1.134***
	(0.038)	(0.082)	(0.010)	(0.021)	(0.024)	(0.088)	(0.067)
Treatment	0.485***	0.388***	-0.100***	-0.246***	0.041	0.248**	0.139
	(0.070)	(0.094)	(0.029)	(0.033)	(0.035)	(0.115)	(0.117)
Interaction term	-0.269***	-0.319**	0.111***	0.196***	-0.126***	-0.173	-0.126
	(0.084)	(0.125)	(0.028)	(0.034)	(0.040)	(0.156)	(0.134)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4979	3895	4979	4979	4979	2233	3317

Notes: Coefficients with bootstrap standard errors are reported in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$. The dependent variables are log of household expenditure and crop production specified in the heading of the table. We define years 2009 & 2010 equals to one for the years 2009 and 2010 and equals to zero for the year 2004. The dummy for the cyclone-affected township equals one for severely cyclone-affected townships, and zero denotes for less cyclone-affected townships. Household head and household characteristic controls include sex, age dummies, years of schooling, number of household members, landlord dummies, and household located area dummy.

Table 2.5 presents the results of the heterogeneous effect of the cyclone by households in rural residences. The results show that the cyclone significantly reduces households in rural residences of cropland, the quantity of crops harvested, and monthly non-food expenditure by 26.9 percent, 31.9 percent, and 12.6 percent respectively. The cyclone increases households in rural residences of the quantity of food bought as well as monthly food expenditure by 11.1 percent and 19.6 percent respectively. Our findings show that households in rural areas experience a significant reduction in crop production and an increase in food expenditure. One of the reasons could be that 88 percent of the population in Ayeyarwady delta region are living in rural areas and only 12 percent are living in urban areas. Thus, the severity of household residence in rural areas is high.

2.5.4 Robustness Checks

We perform robustness checks to strengthen our finding the impact of the cyclone Nargis on crop production and household expenditure is valid. To perform the robustness checks, we compare household expenditure and crop production across the subsamples between household in the severely affected townships and non-affected townships using the same model from **Equation (1).**

Table 2.6 report the estimate of the comparison of the household expenditure and crop production across the subsamples between household in the severely affected townships and nonaffected townships. Our findings are consistent and similar both in sign and significant which support the validity of our baseline estimates.

Table 2.6: Robustness Check (Severely Affected and Non-affected Townships)

	Cropland (Acre)	Quantity of Crop Harvested	Quantity of Food Bought	Monthly Food Expenditure	Monthly Nonfood Expenditure	Health Expenditure	Education Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year 2009 & 2010	-0.096	0.353***	2.520***	0.939***	1.191***	0.921***	1.173***
	(0.063)	(0.086)	(0.018)	(0.024)	(0.023)	(0.097)	(0.105)
Treatment	0.551***	0.525***	-0.090***	-0.064**	0.259***	0.205**	0.295**
	(0.072)	(0.126)	(0.024)	(0.031)	(0.028)	(0.095)	(0.120)
Interaction term	-0.216***	-0.660***	0.085***	0.100***	-0.228***	-0.232*	0.020
	(0.082)	(0.162)	(0.024)	(0.032)	(0.031)	(0.146)	(0.127)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2819	2303	2819	2819	2819	2083	2538

Notes: Coefficients with bootstrap standard errors are reported in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$. The dependent variables are log of household expenditure and crop production specified in the heading of the table. We define the year 2009 & 2010 equals to one for the years 2009 and 2010 and equals to zero for the year 2004. The dummy for the cyclone-affected township equals one for severely cyclone-affected townships, and zero denotes for non-cyclone-affected townships. Household head and household characteristic controls include sex, age dummies, years of schooling, number of household members, landlord dummies, and household located area dummy.

2.6 Discussion and Conclusion

Farming is a major source of livelihood, income, and employment for the majority of households in developing countries. However, farmers most frequently experience crop losses due to weather-related natural disasters and these losses can lead to significant negative income shocks to farmers resulting in reduced expenditure. The reduction of expenditure can affect farm household members' human capital formation in the long run. To ensure the long-term welfare for farm households, it is essential to understand a reduction in expenditure due to negative income shocks, mainly in regions often faced with natural disasters.

In this paper, we investigate the effect of the cyclone Nargis on household expenditure and crop production in the Ayeyarwady delta region of Myanmar, using the Myanmar Integrated Household Living Conditions Assessment Survey and applying difference-in-difference (DID) strategy. We compare household expenditure and crop harvested across the subsamples between households in the severely cyclone-affected townships and less cyclone-affected townships. Our findings suggest that the cyclone has a negative impact on crop production and household expenditure.

The results show that the cyclone significantly reduces cropland, the quantity of crops harvested, monthly non-food expenditure, and health expenditure by 35.0 percent, 33.2 percent, 10.7 percent, and 17.8 percent respectively. The cyclone increases the quantity of food bought as well as monthly food expenditure by 10.2 percent and 18.2 percent respectively. We estimate the quantity of food bought to determine what happened to the rising food expenditure. Our results are consistent with previous findings by Mottaleb et al., (2013), show that cyclone Aila reduced rice land acre, paddy production, own-paddy consumption, the value of paddy sold and household expenditure and increased total food expenditure except for health expenditure. They report that cyclone Aila increased food expenditure among cyclone-affected households by 26 percent since cyclone destroyed households' paddy yields, households were forced to buy foodstuffs from the market which they could have gotten from the farms. In terms of the magnitude of the food expenditure, the coefficients of our estimates are smaller suggesting that our findings are less pronounced. Previous studies by Cameron and Worswick (2001) and Kochar (1999), also note that in the event of a crop failure, households were unable to smooth their consumption, thus they were more likely to cut their expenditure. In our study, one possible reason could be that the reduction of cropland which led to reduce the quantity of crops harvested because of the cyclone. As a result, households channeled their income on food for survival thus food expenditure increased with resultant reduction in non-food expenditure. Before the cyclone, households mostly consume foodstuffs harvested from their farms, however, with the reduction of crops harvested as reveal in this study, households had to purchase the foodstuffs that were previously harvested from farms leading to increase in food expenditure. We do not doubt that our results are valid given that our robustness checks also support our main findings. To the best of our knowledge, this study could be the only study that investigates the effect of the cyclone on household expenditures and crop production in Myanmar.

The findings indicate that natural disasters lead to major declines in the affected households' crop production and expenditure. Thus, these results highlight the role of natural disaster and to ensure food security and income of farm households. Mottaleb et al., (2013) propose that government and international donor agencies expand and improve disaster relief loans for farm households that are frequently impacted by natural disasters. We recommend that government and international donor agencies should provide loans for farm households affected by natural disasters. We also suggest that experts from agricultural research institutes should disseminate information to farmers on high yielding crops that are resilient to climate change and to support them by making these crops available.

REFERENCES

Arouri, M., Nguyen, C., & Youssef, A. B. (2015). Natural disasters, household welfare, and resilience: evidence from rural Vietnam. *World development*, *70*, 59-77.

Benson, C., & Clay, E. (2004). Understanding the economic and financial impacts of natural disasters. The World Bank.

Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Applied Economics*, *46*(15), 1751-1766.

Cameron, A. C., & Miller, D. L. (2010). Robust inference with clustered data. *Handbook of empirical economics and finance*, *106*, 1-28.

Cameron, L. A., & Worswick, C. (2001). Education expenditure responses to crop loss in Indonesia: A gender bias. *Economic development and cultural change*, *49*(2), 351-363.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics*, *74*(2), 309-329.

Duryea, S., Lam, D., & Levison, D. (2007). Effects of economic shocks on children's employment and schooling in Brazil. Journal of development economics, 84(1), 188-214.

Guha-Sapir, D., Hargitt, D., & Hoyois, P. (2004). *Thirty years of natural disasters 1974-2003: The numbers*. Presses univ. de Louvain.

International Rice Research Institute. (2010). Scuba rice: breeding flood tolerance into Asia's local mega rice varieties.

Khandker, S. R. (2007). Coping with flood: role of institutions in Bangladesh. *Agricultural Economics*, *36*(2), 169-180.

Khush, G. S. (2004, February). Harnessing science and technology for sustainable rice-based production systems. In *FAO rice conference* (Vol. 4, p. 13).

Kochar, A. (1999). Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics*, *81*(1), 50-61.

Linnerooth-Bayer, J., & Mechler, R. (2008). Insurance against losses from natural disasters in developing countries. *IIASA, Background paper for UN WESS, July*.

Masozera, M., Bailey, M., & Kerchner, C. (2007). Distribution of impacts of natural disasters across income groups: A case study of New Orleans. *Ecological Economics*, *63*(2-3), 299-306.

Moench, M., Mechler, R., & Stapleton, S. (2007). Guidance note on the costs and benefits of disaster risk reduction. *Paper for ISDR High level Platform on Disaster Risk Reduction*.

Mottaleb, K. A., Mohanty, S., Hoang, H. T. K., & Rejesus, R. M. (2013). The effects of natural disasters on farm household income and expenditures: A study on rice farmers in Bangladesh. *Agricultural Systems*, *121*, 43-52.

Sawada, Y., & Lokshin, M. (2009). Obstacles to school progression in rural Pakistan: An analysis of gender and sibling rivalry using field survey data. Journal of development Economics, 88(2), 335-347.

Shwe, T. A., Zwi, A. B., Roberts, G., & Thompson, L. (2013). *Cyclone Nargis 2008: Human Resourcing Insights from Within the Myanmar Red Cross*. Human Resources for Health Knowledge Hub.

Sulistyaningrum, E. (2015). Household Expenditure in Response to Natural Disasters. *Journal of Indonesian Economy and Business*, *30*(3), 257-272.

Tripartite Core Group (2009). Post-Nargis Periodic Review II.

Thomas, T., Christiaensen, L., Do, Q. T., & Trung, L. D. (2010). *Natural disasters and household welfare: evidence from Vietnam*. The World Bank.

Villa, J. M. (2016). diff: Simplifying the estimation of difference-in-differences treatment effects. *Stata Journal*, *16*(1), 52–71.

Zeigler, R. S., & Barclay, A. (2008). The relevance of rice.

CHAPTER 3

THE IMPACT OF HIGHER EDUCATION EXPANSION THROUGH DISTANCE EDUCATION ON GRADUATE'S JOB MARKET OUTCOMES: EVIDENCE FROM MYANMAR

3.1 Introduction

University education is perceived as one of the crucial forces for modernization and development, and the demand for its access is markedly increasing in developing countries. The modernization and transformation of the market economy in Myanmar have caused tremendous growth in higher education demand. As a result, both the number of universities and student enrollment has gradually increased since 1989 (Chinelone, 2018). To meet the higher demand, higher education expansion through distance education plays a vital role in Myanmar.

In 1998, the University of Distance Education (UDE) had been established by the modernization of the University of Correspondence Courses (UCC). After the establishment of UDE, approximately 60 % of the matriculated students enrolled in the UDE every academic year. In 2012, 60.4 % of graduates are from the UDE and just 39.6% are from conventional universities and colleges (Caraig, 2018). The increase in the number of graduates via higher education expansion has raised many questions and they have been hotly debated. Scholars noted that the lower quality of UDE's graduates as limited interaction between students and teachers, insufficient teaching aids, unlimited enrollment in UDE and unskilled teachers (Chinelone, 2018; Hlah, 2013; JICA, 2013; Labonte, 1993) and as a result, the degree turns just a signaling device to open the door for job opportunities (Thaung, 2015). After the expansion of higher education in China, the quality of higher education has decreased due to limited resources and rapidly increasing student-teacher ratios. (Wu and Zheng, 2008). Education brings prosperity to both individuals and society; however, none of the benefits to education flow automatically from simply attending school; all depend on learning while in school. Besides, if the education system is poorly managed, it can promote social “bads” rather than social “goods” (World Bank, 2018; Livingstone, 1998).

In this paper, we investigate the impact of higher education expansion through distance learning on graduates’ job-market performance using Myanmar data. We exploit the increase in the number of UDE as exogenous policy interventions to address four questions: How has this education expansion policy affected the individual’s educational opportunities? How has this education expansion policy impacted the unemployment of tertiary graduates? How has this education expansion policy impacted having a formal job of employed tertiary graduates? How has this education expansion policy impacted having a good job of employed tertiary graduates? Such questions tend to be basic but often posed in a public debate. Many criticize that the policy of higher education expansion caused high unemployment among tertiary graduates, while some claim that the policy of higher education expansion does not cause unemployment among tertiary graduates but reverses low capability (S. Li, Whalley, & Xing, 2014; Oppedisano, 2014, 2011; Chevalier & Lindley, 2009; Walker & Zhu, 2008). To our knowledge, there are a few empirical researches that address these issues.

This paper shows that the policy of education expansion has increased the probability of tertiary graduates, but that the same policy of expansion has also clearly increased unemployment for tertiary graduates and has decreased having a formal job and having a good job of tertiary graduates who are employed. We use the difference-in-differences strategy and integrated it with a propensity score matching (PSM) to estimate our results. We compare the job market outcomes of policy-affected graduates relative to those not affected by the policy.

Generally, the college entrance age in Myanmar is at the age of 16; therefore, we assume that the UDE expansion in 1998 will affect individuals born in 1982 and after will not affect individuals born before 1982.

We perform the same experiments to examine the differential impact of the expansion policy between males and females to provide a more detailed picture. We find that unemployment for policy-affected male graduates experienced higher unemployment while female graduates experienced lower unemployment. Our findings are consistent with the traditions of the community because females normally do not actively search for jobs. The results also suggest that males have more chance to get a formal job and a good job while females have less chance to get a formal job and a good job. Our findings support the results of previous studies (S. Li et al., 2014; Knight, Deng, & Li, 2017; Chi, Freeman, & Li (2012); S. Li & Xing, 2010; Y. A. Li, Whalley, Zhang, & Zhao, 2011; Meng, Shen & Xue, 2009) that examined the impact of China's rapid expansion of higher education, in the period of 1998–2008, when enrolments almost six-folds. They found out that the expansion policy increased the probability of attending college, the unemployment rate, and has reduced the relative wages and the proportion of good jobs.

The remainder of the paper is organized as follows. Section 2 briefly describes the higher education expansion in Myanmar. Section 3 illustrates the data using in this paper. Section 4 describes the identification strategy. Section 5 presents the empirical results and Section 6 concludes the paper.

3.2 Institution Background

The first-ever distance education institution in Myanmar, the University Correspondence Courses (UCC) were initiated in 1970s to offer higher education to those who are not able to pursue it at conventional universities for various reasons. UCC has been designed to conform with normal university degree courses and to be conducted on the same level as full-time courses (Caraig, 2018).

In 1975-76 academic year, a Bachelor's degree in UCC in Arts, Science, Law, and Economics was first offered at Yangon University and served the whole country. Beginning from the academic year 1985-86, the UCC has been extended to all universities, degree colleges, and colleges, each of which has become a center for student registration in the region. The teaching-learning process at that time was based on printed materials and radio lessons (Caraig, 2018).

In 1998, Yangon University of Distance Education (YUDE) and Mandalay University of Distance Education (MUDE) were established to modernize the UCC. YUDE affiliates to regional branches in Lower Myanmar and MUDE affiliates to regional branches in Upper Myanmar. Before 1998, there were twenty-two regional branches. After the establishment of YUDE and MUDE, regional branches rise to thirty-three.

The main purpose of the establishment of the two universities of distance education is to provide access to higher education to the people of Myanmar at a minimum cost and without having to leave their homes and jobs, particularly for students living in border areas. Students can take any course of study within a set of criteria set by the Department of Higher Education. The main mode of delivery of courses included printed materials, laboratories, assignments, and intensive classes. Students must attend their respective universities for the laboratory and final examination. Students completed successfully their course studies over 60% of intake.

We assume that the increase in the number of graduates due to the expansion policy in 1998 will have a consequence on the job market especially for the individuals who have tertiary education. This paper investigates how this higher education expansion policy affects individual graduates' job market performance in the remaining sections.

3.3 Data Source and Description

We use Myanmar Labour Force - 2015, Child Labour and School-to-Work Transition Survey (2015-LF-CL-SWTS) to investigate the impact of higher education expansion and graduates' job market performance. The dataset is collected by the Ministry of Labour, Employment and Social Security jointly with the Central Statistical Organization and International Labour Organization. The dataset contains a wide range of information needed for our analysis and has the variable of each household member: individual characteristics, family background, household characteristics, educational level, employment status, occupational level, and the region of the resident. Therefore, the survey allows us to analyze the effects of the expansion policy on the graduates' job market performance such as unemployment, having a formal job, and having a good job.

In this data, the numbers of individual-level observations are 101,278 before cleaning and the sample size of the households is 24,000. This sample survey was based on the 2014 Myanmar Population and Housing Census which include 80,557 enumeration areas. A sample of 1,500 was chosen from enumeration areas and 24,000 households were selected from selected enumeration areas for the survey. We restrict the samples only for individuals who are secondary and tertiary graduates since our emphasis is on the effects of the education expansion policy on higher education, but due to data limitations, tertiary graduates cannot be distinguished as graduates from UDE or graduates from Conventional University.

In Myanmar, children normally enter primary school at the age of five and graduate secondary education at the age of sixteen right after they graduate from secondary school, they proceed to College after successful college entrance examination normally at age 16. As a result, we assume that the UDE expansion policy in 1998 will affect individuals born in 1982 and after and those individuals born before 1982. In this study, we restrict samples only for individuals who are aged 15-64 (working age group). **Table 3.1** report summary statistics of the main variables used in this study.

Table 3.1: Summary Statistics

	Obs	Mean	Std.Dev	Min	Max
Dummy for unemployment (yes=1)	11110	0.314	0.464	0	1
Dummy for having a formal job (yes=1)	7353	0.364	0.481	0	1
Dummy for having a good job (yes=1)	7532	0.299	0.458	0	1
Age of respondent	11175	33.561	12.085	15	64
Gender of respondent (male=1)	11175	0.444	0.497	0	1
Household head's gender (male=1)	11175	0.761	0.427	0	1
Urban household (yes=1)	11175	0.668	0.471	0	1
# of household member	11175	5.032	2.195	1	25
Dummy for house ownership (Own=1)	11175	0.856	0.351	0	1
Dummy for having access to take loan (yes=1)	11175	0.242	0.429	0	1
Dummy for having a vocational training (yes=1)	11175	0.083	0.275	0	1
Household head's education (year of schooling)	10590	4.139	2.090	0	11
Household head's occupation					
• Managers	9666	0.027	0.161	0	1
• Professionals	9666	0.057	0.232	0	1
• Technicians	9666	0.056	0.230	0	1
• Clerical support workers	9666	0.028	0.165	0	1
• Service and sale workers	9666	0.153	0.360	0	1
• Skilled agricultural workers	9666	0.165	0.372	0	1
• Trade workers	9666	0.071	0.256	0	1
• Machine operators	9666	0.046	0.209	0	1
• Elementary occupation	9666	0.048	0.213	0	1
• Unemployed	9666	0.347	0.476	0	1
• Retired	9666	0.003	0.053	0	1
Types of dwelling					
• Concrete roof (yes=1)	11175	0.049	0.216	0	1
• Tin roof (yes=1)	11175	0.843	0.364	0	1
• Tile roof (yes=1)	11175	0.012	0.110	0	1
• Thatches (yes=1)	11175	0.083	0.276	0	1
• Bamboo roof (yes=1)	11175	0.012	0.108	0	1
• Other roof (yes=1)	11175	0.000	0.016	0	1
Marital Status					
• Single (yes=1)	11175	0.508	0.500	0	1
• Married (yes=1)	11175	0.451	0.498	0	1
• Separated (yes=1)	11175	0.013	0.113	0	1
• Divorced (yes=1)	11175	0.006	0.080	0	1
• Widowed (yes=1)	11175	0.021	0.145	0	1

Sources: 2015 Myanmar Labour Force Survey

3.4 Identification Strategy

To estimate the impact of Higher Education Expansion on the job market outcomes of policy-affected graduates, we use the difference-in-differences approach with propensity score matching (PSM). We compare the outcome variables – unemployment, having a formal job, and having a job in a good position between policy-affected graduates and graduates not affected by the policy using job market outcomes of non-graduates as a counterfactual. The college entrance age in Myanmar; generally, is at the age of sixteen. We assume that the UDE expansion in 1998 will affect individuals born in 1982 and after and will not affect individuals born before 1982.

To estimate the effects of UDE expansion on the graduates' job market outcomes, we use the following equation:

$$Y_{ij} = \beta_0 + \beta_1 T_{Age} + \beta_1 T_{edu} + \beta_3 T_{Age} * T_{edu} + X'_{ij}\beta_4 + Z'_{ij}\beta_4 + a_j + \mathcal{E}_{ij}, \quad (1)$$

where, Y_{ij} represents outcome variables – unemployment, having a formal job, and having a good job. "Unemployment"[4] is a dummy variable, which equals one for the unemployed individual, and zero equals for the individual who is employed. In unemployment, we restrict the individual who is attending training or school, sickness, injury or disability, and too young or too old to find a job. "Having a formal job" is an indicator, which takes one for the individual who is employed in the formal sector (hereafter Formal Job), and zero takes an individual who is employed in the informal sector[5]. The informal employment is classified as working family members, self-employed in the informal sector, employees with no social security contribution

[4] Unemployment is defined as all those of working age who were not in employment, engaged in job-seeking activities during a specified recent period, and were currently available for job seeker with an opportunity to work (ILO, 2016).
[5] The informal sector is defined as unregistered private enterprises under any ministry and small privately-owned companies involved producing goods or services for sale or exchange.

from the employer, employees with social security contributions from the employer but no paid annual leave, and no paid sick leave (ILO, 2016). “Having a good job” indicates one for the individual who has a good job, zero indicates the other job. We define jobs in a good position (hereafter Good Job) as managers, professionals, technicians, and associate professionals (Knight et al., 2017). The occupational level is divided into nine categories following the ILO's International Standard Classification of Occupations. Out of nine categories of occupational level, "Good Job" is defined as managers, professionals, technicians and associate professionals, and nine other categories as other jobs. T_{Age} is a dummy variable which equals one for the individuals born in 1982 and after (policy-affected groups), and zero takes individuals born before 1982 (not affected groups by the policy). T_{edu} is an indicator that indicates one for tertiary graduates, and zero denotes for secondary graduates. X'_{ij} represents individual characteristics such as age, sex, and marital status. Z'_{ij} denotes household-level characteristics such as gender of household head, the education level of household head, household size, types of dwelling, ownership status of dwelling, household take any loan, and attending vocational training. In all regressions, we control for dummies for fifteen regions, "a_j”. $\mathcal{E}_{ij}$ is the error term. Since the number of our regions are few (only 16 regions) using clustered standard errors will bias the standard errors downwards over-rejecting our null hypotheses. To address this issue, we use bootstrap procedures to obtain valid inference as proposed by Cameron et al., (2010).

One of the possible threats to the identification strategy of conventional Difference-in-Differences setting is the change in the composition of the control group. After the expansion policy, a certain portion of individuals who have the same ability with the individuals who did not have a tertiary education before the expansion will have a chance to graduates. In other words, a certain group of individuals who are not as smart as the individuals who would have a tertiary education even if there exists no expansion policy will have a tertiary education. So, the adverse effect of graduates' job market performance may be associated with individuals' abilities. If we could control for individual abilities such as IQ test score, and proxies for cognitive ability, the ability endogeneity problem would be able to solve. Nevertheless, the LFS does not support the required information. To mitigate the ability endogeneity problem, we use a propensity score matching approach in the Difference-in-Differences setting.

To have a proper counterfactual of policy-affected individuals and to control the potential endogeneity in the individual's abilities in a conventional Difference-in-Difference setting, we use a Propensity Score Matching (PSM) method and apply Kernel matching, to select graduates who were born before 1982 (not affected by the policy) with a weighted predicted probability based on the covariates: parents' characteristics, father's education, and father's occupations; place of residence, rural or urban, regions; households' socio-economic conditions, types of dwellings, house ownership, access to the loan that we believe which are the most important conditions to the decision of going college. We use a Probit model to predict the probability of having a college degree as follows:

$$P_i = \Pr(Degree_i | X_i) = \Phi \, (X_i' \, \beta + \, \mathcal{E}_i), \qquad (2)$$

Where $Degree_i$ is a binary variable which equals one for an individual with a college degree, zero takes otherwise. X_i is a vector of covariates such as parents' characteristics, father's education, and father's occupations; place of residence, rural or urban, regions; households' socio-economic conditions, types of dwellings, house ownership, access to the loan that are important to the decision of going College, and Φ is standard normal cumulative distribution function. Then we calculate the predicted probability of having a degree (propensity score) of individuals who were not affected by the policy, and then we create matched individuals who do have a degree and born before 1982 by using a Kernel propensity-score weight. Then, we use the predicted probability to implement a suitable counterfactual of policy-affected graduates born in 1982 and after.

Then, we compare the job market outcomes between individuals who have a tertiary degree and who do not have and individuals who were born before 1982 and born in 1982 and after. To estimate the effects of UDE expansion, in other words, to obtain a kernel propensity-score matching DID treatment effect, we use the following equation:

$$DID = \{E(Y_{id=1}|D_{i=1} = 1, YOUNG_i = 1) - \ w^{Y}_{id=0} \times E(Y_{id=0}|D_{i=0} = 0, YOUNG_i = 1) - w^{O}_{id=1} \times E(Y_{id=1}|D_{i=1} = 1, YOUNG_i = 0) - \ w^{O}_{id=0} \times E(Y_{id=0}|D_{i=0} = 0, YOUNG_i = 0), \qquad (3)$$

$Y_{id=1}$ represents the job market outcomes of graduates and $Y_{id=0}$ indicates the outcomes of non-graduates. $w^{O}_{id=1}$, $w^{O}_{id=0}$ are the Kernel weights for the individuals born before 1982, who have a tertiary degree and who do not have, respectively. $w^{Y}_{id=0}$ is the Kernel weight for individuals born in 1982 and after and do not have a degree. Three sets of Kernel weights are calculated by using the estimated propensity-score and do not require the panel structure of the units of the samples (Villa, 2016).

3.5 Empirical Results

We first estimate the probability of having a degree of individuals born before 1982 by using a Probit model. The estimates of equation (1) are described in **Table 3.2**. Coefficients indicate that the variables we used are important determinants of the decision for going to the University. Most of the covariates are significant at 1%, supporting the assumption that household heads' gender, household head's education, place of residence, and the household socio-economic conditions influence the probability of having a college degree. PSM provides a robust and reliable control sample for estimating the effects of expansion policy on graduates' job market outcomes if the household socio-economic conditions are balanced between graduates and non-graduates.

Table 3.2: Probit model: Probability of Having a College Degree

Variables	Coefficients	Standard error
Household head's Education	0.169***	(0.013)
Respondent's gender (male=1)	-0.570***	(0.047)
Respondent's age	-0.024***	(0.002)
Urban (yes=1)	0.161***	(0.056)
Dummy for house ownership (Own=1)	0.126*	(0.066)
Household head's Occupation (Omitted = Manager)		
• Professionals	-0.041	(0.157)
• Technicians	-0.474***	(0.161)
• Clerical support workers	-0.592***	(0.183)
• Service and sale workers	-0.690***	(0.143)
• Skilled agricultural workers	-0.875***	(0.155)
• Trade workers	-0.896***	(0.164)
• Machine operators	-0.822***	(0.171)
• Elementary occupation	-1.174***	(0.184)
• Unemployed	-0.459***	(0.138)
• Retired	-0.523	(0.424)
Type of Dwelling (Omitted=Concrete roof)		
• Tin roof	-0.191*	(0.100)
• Tile roof	-0.272	(0.209)
• Thatches roof	-0.396***	(0.142)
• Bamboo roof	-0.669**	(0.263)
Region (Omitted=Kachin)		
• Kayah	1.001***	(0.236)
• Kayin	0.030	(0.158)
• Chin	-0.292*	(0.169)
• Sagaing	0.284**	(0.111)
• Thanintharyi	1.290***	(0.189)
• Bago	0.231**	(0.115)
• Magway	0.485***	(0.116)
• Mandalay	0.784***	(0.105)
• Mon	0.492***	(0.120)
• Rakhine	0.205*	(0.124)
• Yangon	0.504***	(0.098)
• Shan	0.337**	(0.133)
• Ayeyawady	0.383***	(0.123)
• Nay Pyi Taw	1.106***	(0.134)
Observations	3908	

Notes: Coefficients with bootstrap standard errors are reported in parentheses. The dependent variable is a dummy variable that equals one for the individuals who have a bachelor's degree and zero otherwise. * *p<0.10*, ** *p<0.05*, *** *p<0.01*.

We also show the results of balancing test in **Tabel 3.3**, in the 'pre-matching', the mean differences most of the characteristics exceeds 5 percent – the recommended threshold for balance between treatment and control (Caliendo and Kopeinig, 2008) indicating imbalances at baseline covariates which may make our estimates bias, hence the need for propensity score matching approach to ensure both control and treatment similarly. Applying the kernel matching as we present in the same table 'post-matching' the results showing success in matching as the mean differences of most covariates are 5 percent and below.

Tables 3.3: Balancing test

	Before Matching			Post Matching		
Weighted Variable(s)	Mean Control	Mean Treated	Diff.	Mean Control	Mean Treated	Diff.
HH head's education	4.45	5.36	0.905***	4.80	5.36	0.56***
HH head's occupation	7.44	6.72	-0.72***	6.98	6.62	-0.36***
Loan access	0.22	0.17	-0.05***	0.16	0.16	0.00
House own (Own=1)	0.86	0.83	-0.04***	0.86	0.84	-0.03**
Type of Dwelling	2.19	2.04	-0.15***	2.03	2.02	-0.01
Urban (Urban=1)	0.69	0.80	0.11***	0.81	0.82	0.01
Region	8.50	9.55	1.05***	9.46	9.54	0.08

3.5.1 DID and PSM-DID Estimates

The estimates of Equation (1) using DID without propensity-score-matching are reported in Panel A of Table (4). Column (1) reports the policy effect on unemployment of policy-affected graduates and column (2) and (3) estimates the impact of expansion on unemployment of policy-affected female graduates and policy-affected male graduates. Control covariates such as individual characteristics, family background, household characteristics, and region fixed effects are included in all columns. The coefficient of the policy affected age in all columns are positive and statistically significant at the 1 percent level in the first and second column and the coefficient of policy-affected graduates in all columns are negative and statistically significant at the 1 percent level in all column. The DID estimator is estimated to be positive in column (1), in all samples and male sample in column (3), both statistically significant with the probability of being under unemployment of policy-affected graduates increase by 4 percent and the probability of policy-affected male graduates increase by 11.3 percent respectively. The policy-affected female graduates are estimated to be negative with the probability of unemployment by 2.4 percent, but not statistically significant. The result shows that policy-affected males are more likely to be unemployed while policy-affected females are less likely to be unemployed. One reason for this difference between genders is that females were not actively searching for jobs and working informally at home. But males are more likely to be employed in a professional job with higher salaries.

The estimates of DID with PSM (propensity-score-matching) are reported in Panel B of **Table 3.4**. The dependent variable and control covariates are same as in Panel A. The coefficient of the policy-affected age in all column are positive and statistically significant at the 1 percent level and the coefficient of the policy-affected graduates in all column are negative and statistically significant at the 1 percent level. The coefficient of the interaction term in Column (1) of Panel B indicates that the probability of being unemployment of policy-affected graduates increase by 9.2 percent, in Column (2) suggests that policy-affected male graduates have 22.9 percent higher probability of unemployment but we find no evidence in policy-affected female graduates after the expansion policy. The magnitude of the estimates in PSM-DID and traditional DID are different. The coefficients in traditional DD might be underestimated when we investigate the policy impacts on graduates' job market outcomes because we cannot control the ability of graduates. To mitigate the problem of ability endogeneity in policy-affected graduates and graduates who are not affected by the policy, in the PSM-DD setting, we match graduates and non-graduates in both pre-policy intervention and post-policy intervention by using father's occupation and education, place of residence, and other socio-economic conditions that are assumed to be important to the decision of going College. After purging the ability endogeneity in the PSM-DD setting, the size of coefficients is more pronounced than in the traditional DD setting.

Table 3.4: Effects on Graduates' Unemployment: DID with Matching

Dummy for Unemployment (Yes=1)	All samples (1)	Female (2)	Male (3)
Panel A: DID without Matching			
Individual who was born after 1982 (yes=1)	0.106***	0.163***	0.001
	(0.014)	(0.027)	(0.016)
Tertiary graduates (yes=1)	-0.137***	-0.155***	-0.119***
	(0.014)	(0.026)	(0.015)
Interaction terms	0.040**	-0.024	0.113***
	(0.018)	(0.031)	(0.023)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	9406	4534	4872
Panel B: DID with PSM			
Individual who was born after 1982 (yes=1)	0.061***	0.099***	-0.069***
	(0.014)	(0.021)	(0.018)
Tertiary graduates (yes=1)	-0.214***	-0.215***	-0.251***
	(0.015)	(0.023)	(0.018)
Interaction terms	0.092***	0.028	0.229***
	(0.019)	(0.029)	(0.025)
Observations	9406	4534	4872

Notes: Coefficients with bootstrap standard errors are reported in parentheses. We use all samples in column (1), and in column (2) and (3), we restrict sample as female and male respectively. Dependent variables, "Unemployment", in all columns are a dummy variable that equals one for the individual who is not employed, and zero equals for the individual who is employed. We define one as a policy-affected individual who was born after 1982, and zero takes otherwise. The dummy for tertiary graduates equals one for individuals who have a tertiary degree, and zero denotes for individuals who have a secondary degree. "Individual controls" include age, gender, marital status, and having vocational training. "Household controls" include household head's education, household head's occupation, house ownership, types of dwelling, having access to take a loan, place of residence, and region. * *p<0.10,* ** *p<0.05,* *** *p<0.01.*

The policy impacts on having a formal job for the graduates that we estimate with a conventional DID is in Panel A of **Table 3.5**. The DID estimator is negative in all columns but only column (1), all samples, and column (2), policy-affected female graduates are statistically significant. Policy-affected graduates have decreased the probability of having a formal job by

4.0 percent at the 5 percent statistically significant level and policy-affected female graduates have decreased the probability of having a formal job by 7.2 percent at 10 percent statistically significant level. The DID estimator of policy-affected male graduates is negative with the probability of having a job by 0.2 percent, but not statistically significant. The result shows that policy-affected female graduates are less likely to have a formal job while the policy-affected male graduates are more likely to have a formal job.

The estimates of DID with PSM are reported in Panel B of **Table 3.5**. The dependent variable and control covariates are same as in Panel A. The coefficient of the interaction term in Column (1) of Panel B indicates that the probability of having a formal job of policy-affected graduates has decreased by 7.0 percent and Column (2) shows that the probability of having a formal job of policy-affected female graduates has decreased by 6.2 percent. The probability of having a formal job of policy-affected male graduates is estimated to be negative and there is no significant impact after the expansion policy. The magnitude of the estimates in the PSM-DID setting is more pronounced compared to the estimates of DID without matching.

Table 3.5: Effects on Having a Formal Job: DID with Matching

Dummy for Having a Formal Job (Yes=1)	All samples (1)	Female (2)	Male (3)
Panel A: DID without Matching			
Individual who was born after 1982 (yes=1)	0.005	0.059	-0.040
	(0.022)	(0.042)	(0.029)
Tertiary graduates (yes=1)	0.268***	0.330***	0.150***
	(0.016)	(0.032)	(0.024)
Interaction terms	-0.045**	-0.072*	-0.002
	(0.021)	(0.037)	(0.030)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	7426	2706	3558
Panel B: DID with PSM			
Individual who was born after 1982 (yes=1)	0.000	-0.109***	-0.140***
	(0.029)	(0.025)	(0.022)
Tertiary graduates (yes=1)	0.279***	0.331***	0.190***
	(0.035)	(0.027)	(0.021)
Interaction terms	-0.070*	-0.062*	-0.018
	(0.040)	(0.035)	(0.031)
Observations	7426	2706	3558

Notes: Coefficients with bootstrap standard errors are reported in parentheses. We use all samples in column (1), and in column (2) and (3), we restrict sample as female and male respectively. The dependent variables, "Having a formal job", in all columns are a dummy variable that equals one for the individual who is employed in the formal sector, and zero equals for the individual who is employed in the informal sector. We define one as policy-affected individuals who were born after 1982, and zero takes otherwise. The dummy for tertiary graduates equals one for individuals who have a tertiary degree, and zero denotes for individuals who have a secondary degree. "Individual controls" include age, gender, marital status, and having vocational training. "Household controls" include household head's education, household head's occupation, house ownership, types of dwelling, having access to take a loan, place of residence, and region. ** $p<0.10$, ** $p<0.05$, *** $p<0.01$.*

The impact of policy on having a good job for the graduates that we estimate with a conventional DID is in Panel A of **Table 3.6**. The interaction terms are negative in all columns but only column (1), all samples, and column (2), policy-affected female graduates who have a formal job are statistically significant. The probability of the policy-affected graduates who are employed decrease having a good job by 5.1 percent at the 1 percent statistically significant level and the probability of the policy-affected female graduates who have a formal job decrease having a good job by 6.7 percent at 10 percent statistically significant level. The policy-affected male graduates who have a formal job is negative with the probability of having a good job by 1.4 percent and policy-affected male graduates who have an informal job is positive with the probability of having a good job by 4.4 percent but not statistically significant. The result shows that policy-affected male graduates who have a formal job are more likely to have a good job while policy-affected female graduates who have a formal job is less likely to have a good job. In general, policy-affected graduates are less likely to have a good job.

We report the estimates of DID with PSM in Panel B of **Table 3.6**. The dependent variables and control covariates are same as in Panel A. The coefficient of the interaction term in Column (1) of Panel B indicates that the probability of having a good job of policy-affected graduates who are employed decreased by 10.1 percent and Column (2) shows that the probability of having a good job of policy-affected female graduates who have a formal job decrease by 8.4 percent but we find no significant impact on Column (3-5) after the expansion policy. The magnitude of the estimates in the PSM-DID setting is more pronounced compared to the estimates of conventional DD.

Table 3.6: Effects on Having a Good Job: DID with Matching

Dummy for Good Job (Yes=1)	All samples	**Female**		**Male**	
		Formal	Informal	Formal	Informal
	(1)	(2)	(3)	(4)	(5)
Panel A: DID without Matching					
Individual in 1982 and after	-0.069***	-0.023	-0.032	-0.048***	-0.062
(yes=1)	(0.013)	(0.023)	(0.066)	(0.013)	(0.043)
Tertiary graduates (yes=1)	0.316***	0.258***	0.389***	0.133***	0.226***
	(0.016)	(0.033)	(0.050)	(0.019)	(0.038)
Interaction terms	-0.051***	-0.067*	-0.004	-0.014	0.044
	(0.020)	(0.039)	(0.070)	(0.027)	(0.056)
Individual Controls	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	6431	1592	1108	2404	1145
Panel B: DID with PSM					
Individual born after 1982	-0.019	-0.015	-0.007	-0.100***	0.008
(yes=1)	(0.015)	(0.030)	(0.039)	(0.024)	(0.040)
Tertiary graduates (yes=1)	0.385***	0.242***	0.483***	0.188***	0.331***
	(0.015)	(0.035)	(0.038)	(0.024)	(0.033)
Interaction terms	-0.101***	-0.084**	-0.054	-0.021	-0.063
	(0.021)	(0.041)	(0.053)	(0.033)	(0.057)
Observations	6431	1592	1108	2404	1145

Notes: Coefficients with bootstrap standard errors are reported in parentheses. We use all samples in column (1), and in column (2) to (5), we restrict sample as female and male respectively. The dependent variables, "Having a good job", in all columns are a dummy variable that equals one for the individual who has a good job, and which equals zero for the individual who has another job. We define one as policy-affected individuals who were born after 1982, and zero takes otherwise. The dummy for tertiary graduates equals one for individuals who have a tertiary degree, and zero denotes for individuals who have a secondary degree. "Individual controls" include age, gender, marital status, and having vocational training. "Household controls" include household head's education, household head's occupation, house ownership, types of dwelling, having access to take a loan, place of residence, and region. * *p<0.10,* ** *p<0.05,* *** *p<0.01*

3.5.2 Complimentary Analysis

We also estimate the narrowing sample within 3 years cohort and 5 years cohort nearby 1982 using the same model from **Eq (1).** The estimates of the impact of the higher education expansion policy on graduate's job market outcomes by 3 years birth cohort and 5 years birth cohort after 1982 are reported in **Appendix Table C.1 and C.2.**

3.6 Conclusion

This paper explores the changes that have taken place in Myanmar's higher education system since 1998 and particularly in the University of Distance Education which we label as Myanmar's higher educational transformation. We attempt to track these changes and analyze their consequences; it is believed that it has a huge impact on the labour market of Myanmar.

This study used one-period cross-sectional data from Myanmar Labour Force Survey - 2015. Difference-in-Differences strategy, which is integrated with a propensity score matching (PSM) is employed to examine the effects of education expansion policy on job market outcomes – unemployment, having a formal job, and having a good job by comparing between policy-affected graduates and graduates not affected by the policy.

We find that the education expansion policy has increased the probability of tertiary graduates, but that the same policy of expansion has increased unemployment of policy-affected graduates and has decreased having a formal job and having a good job of policy-affected graduates in overall estimations. We show that unemployment was higher among policy-affected males graduates while policy-affected female's graduates experienced lower unemployment. We also show that males have more chance to get a formal job and a good job while females have less chance to get a formal job and a good job.

Overall estimations of our results indicate that the expansion policy have a negative impact on the job market. JICA (2013) noted that the excess supply in Myanmar's industrial labor force is due to the fact that the increase in the number of new university graduates is larger than the increase in employment which is linked with our findings that the expansion policy has a negative impact on employment and a decrease in having a formal and a good job.

Our limitation in this study is that; we do not have data set that contains graduates from the university of distance education in Myanmar and we use a data set that has overall graduates. The reason is that 60 percent of graduates in every academic year are from the university of distance education and our findings may reflect the job market of distance education graduates. However, we are cautious to conclude that the distance education expansion policy in Myanmar generally has a negative impact on university graduates' job market, in that, our findings include graduates not affected by the policy.

REFERENCES

Cameron, A. C., & Miller, D. L. (2010). Robust inference with clustered data. *Handbook of empirical economics and finance*, *106*, 1-28.

Caraig, B. (2018). Southeast Asian Massive Open Online Courses. *Journal of Southeast Asian Education*, *1*.

Chevalier, A., & Lindley, J. (2009). Overeducation and the skills of UK graduates. *Journal of the Royal Statistical Society. Series A: Statistics in Society*, *172*(2), 307–337.

Chi, W., Freeman, R. B., & Li, H. (2012). Adjusting to really big changes in the labor market in China, 1989–2009. *National Bureau of Economic Research, working paper 17721, January.*

Chinelone. (2018). *Myanmar's Higher Education Reform: Which Way Forward?*

Hlah, T. (2013). Present Situation of Distance Education in Myanmar.

ILO. (2016). Report on Myanmar Labour Force Survey - 2015. *Ministry of Labour , Immigration and Population In collaboration with International Labour Organization*.

JICA. (2013). *Data Collection Survey on Education Sector in Myanmar*.

Knight, J., Deng, Q., & Li, S. (2017). China's expansion of higher education: The labour market consequences of a supply shock. *China Economic Review*, *43*, 127–141.

Labonte, J. (1993). *Distance Education In ASIA And The Pacific: Country Papers*. *Australia - Republic of Korea, Volume I.*

Livingstone, D.W., 1998. The Education-Jobs Gap: Underemployment or Economic Democracy. *Westview Press, Boulder, Colo*.

Li, S., Whalley, J., & Xing, C. (2014). China's higher education expansion and unemployment of college graduates. *China Economic Review*, *30*(71103019), 567–582.

Li, S., & Xing, C. (2010). China's Higher Education Expansion and its Labor Market Consequences. *IZA Discussion Paper Series Paper No. 4974, May*, (4974), Discussion paper 4974.

Li, Y. A., Whalley, J., Zhang, S., & Zhao, X. (2011). The Higher Educational Transformation of China and Its Global Implications. *World Economy*, *34*(4), 516–545.

Meng, X., Shen, K., & Xue, S. (2009). Economic Reform, Education Expansion, and Earnings Inequality for Urban Males in China, 1988-2007 (Preliminary). *IZA Discussion Papers*, (4919), 1988–2007.

Oppedisano, V. (2011). The (adverse) effects of expanding higher education: Evidence from Italy. *Economics of Education Review*, *30*(5), 997–1008.

Oppedisano, V. (2014). Higher education expansion and unskilled labour market outcomes. *Economics of Education Review*, *40*, 205.

Thaung, W. P. P. (2015). *An Overview of Higher Education Reform In Myanmar*.

Villa, J. M. (2016). diff: Simplifying the estimation of difference-in-differences treatment effects. *Stata Journal*, *16*(1), 52–71.

Walker, I., & Zhu, Y. (2008). The college wage premium and the expansion of higher education in the UK. *Scandinavian Journal of Economics*, *110*(4), 695–709.

World Bank. (2018). Learning To Realize Education's Promise. A World Bank Group Flagship Report.

Wu, F., Zhang, D., & Zhang, J. (2008). Unequal education, poverty and low growth—A theoretical framework for rural education of China. Economics of Education Review, 27(3), 308-318.

APPENDIX C

Table C.1: The Impact of Expansion Policy on Job Market Outcomes by 3 Years Birth Cohort

	Unemployment (1)	Formal Job (2)	Good Job (3)
3 Years birth cohort (yes=1)	0.061*	-0.027	-0.04
	-0.033	-0.04	-0.05
Tertiary graduates (yes=1)	-0.055*	0.187***	0.251***
	-0.029	-0.037	-0.061
Interaction terms	0.009	-0.052	-0.049
	-0.028	-0.052	-0.061
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1389	1134	1171

Notes: Linear probability models. Coefficients with bootstrap standard error are reported in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$. The dependent variables are unemployment, having a formal job and having a good job. We define one as policy-affected individuals who was 3 years birth cohort after 1982, and zero takes zero takes 3 years birth cohort before 1982. The dummy for tertiary graduates equals one for individuals who have tertiary degree, and zero denotes for individuals who have a secondary degree. "Individual controls" include age, gender, marital status, and having vocational training. "Household controls" include household head's education, household head's occupation, house ownership, types of dwelling, having access to take loan, place of residence and region. *$p<0.10$, **$p<0.05$, ***$p<0.01$

Table C.2: The Impact of Expansion Policy on Job Market Outcomes by 5 Years Birth Cohort

	Unemployment (1)	Formal Job (2)	Good Job (3)
5 Years birth cohort (yes=1)	0.026	-0.022	0.009
	(0.020)	(0.051)	(0.053)
Tertiary graduates (yes=1)	-0.098***	0.239***	0.284***
	(0.020)	(0.042)	(0.025)
Interaction terms	0.034	-0.002	-0.036*
	(0.026)	(0.048)	(0.020)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	3094	1945	1985

Notes: Linear probability models. Coefficients with bootstrap standard error are reported in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$. The dependent variables are unemployment, having a formal job and having a good job. We define one as policy-affected individuals who was 5 years birth cohort after 1982, and zero takes 5 years birth cohort before 1982. The dummy for tertiary graduates equals one for individuals who have tertiary degree, and zero denotes for individuals who have a secondary degree. "Individual controls" include age, gender, marital status, and having vocational training. "Household controls" include household head's education, household head's occupation, house ownership, types of dwelling, having access to take loan, place of residence and region. *$p<0.10$, **$p<0.05$, ***$p<0.$