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KHAN, Rida Ali

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KDI School of Public Policy and Management

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The long-term impact of in-utero exposure to natural disasters: Evidence from the 2010 Pakistan flood

Rida Ali Khan*

Abstract

This paper utilizes the Pakistan 2010 flood as a natural experiment, to examine the long-term effects of prenatal stress exposure. The flood began in late July, resulting in the brunt of the damages and loss. It affected more than 20 million people, caused between 1,800 and 2,000 causalities, damaged or destroyed approximately 1.7 million houses and economic loss of US$43 billion, making it the worst flood in the history of Pakistan. Microdata from the years 2019 and 2020 indicate that cohorts in utero during the flood displayed reduced rates of health and cognitive development outcomes compared with unaffected birth cohorts and unaffected districts. However, I did not find any significant effect on functional development such as hearing, listening and walking.

Keywords: Flood 2010, Natural Disaster, In-Utero Exposure, Children Development
JEL: Q54, I25, O15

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1 Introduction

In recent years, scholarly interest has expanded around the complicated and unexplored relationship between environmental stressors and human development as global climatic challenges become more pronounced. Natural and man-made disasters such as floods, famines, cyclones, conflicts, and terrorism affect the mass populations in developing countries and natural disasters are considered exogenous shocks among scholars. However, among such shocks, natural disasters such as earthquakes, cyclones, and floods have been very few studied and are most likely to continue affecting people's lives. (Caruso and Miller, 2015). This study contributes to this growing body of knowledge by rigorously investigating the repercussions of the 2010 flood during the in-utero period on cognitive development and functional disabilities.

Recent research suggests that early childhood shocks have long-term effects on health. (Almond, 2006) compared to the shocks during a young age. The fact is, such consequences are more pronounced when these shocks affect while in-utero or in early childhood like the first two or three years after birth compared to those who are affected in later ages (Neelsen and Stratmann, 2011). The majority of studies have utilized infrequent and extreme incidents, such as the 1944 Dutch Famine and the 1918 Spanish Influenza, as natural experiments to evaluate the Fetal Origins Hypothesis (FOH). (Almond, 2006; Chen and Zhou, 2007). This hypothesis posits a strong association between the health status of infants during gestation and the initial two years of life, and their subsequent physical and cognitive development (Barker, 1994). Chung et al. (2014); Rana et al. (2023) examined the impact of the 2010 flood on children's disaster resilience and the prevalence of stress disorders in individuals. However, the Pakistan 2010 flood's long-term effect remains unanswered, particularly regarding in-utero exposure. Therefore, this study represents a single effort to investigate the long-term causal impact on children's development.

This study explores the long-term causal effects of exposure to the 2010 flood in Pakistan during pregnancy, aiming to determine if these effects persist into postnatal development. Flood 2010 started in late July and ended in late August. It was considered the worst flood in Pakistan's history, affecting 20 million people, destroying homes, crops, and infrastructure, and leaving millions vulnerable to malnutrition and waterborne diseases. To date, a couple of studies have focused on the short-term effects of Floods and other natural disasters, largely overlooking the long-term effects. However, this study specifically assesses the impact of the 2010 flood, an exogenous shock, on the cognitive and functional disabilities of affected cohorts. To estimate this, the research focuses on the 2010 flood in Pakistan and evaluates its consequences by using the micro-data collected ten years after the flood.

The main datasets for this study are sourced from two important sources. For the precise measurement of the flood I utilize satellite data sourced from Fair et al. (2017). To measure the disabilities and health impairments I utilize the Pakistan Social Living and Measurement Survey (PSLM) collected by the Pakistan Board of Statistics (PBS) in the year 2019 and 2020. This data is nationally representative at the district level. It covers a number of socioeconomic modules including health, disabilities, and migration.

Throughout the specifications, the treatment variables are formed through interaction terms. Specifically combining birth cohorts and a flood dummy variable. In addition to the flood dummy, I utilize more precise measures including continuous flood intensity, the proportion of the population affected, and proportion of are affected. Birth cohorts represent groups of children born in different time frames before, during & after the flood, and the flood dummy variable indicates whether the districts were exposed to the 2010 flood. The control group includes neighboring cohorts from the flood-affected region as well as all cohorts from the unaffected region, ensuring a comprehensive analysis by comparing both directly impacted and proximate cohorts and districts for a contextual understanding of in-utero groups. To account for potential age-related influences on outcome variables, age-fixed effects are introduced at the levels of months and years, allowing for a detailed examination of age-related variations within the dataset. To control for the unobserved time-invariant group variation, I utilize the district and province fixed effects as birthplace.

Control variables in the study encompass a range of demographic and socioeconomic factors. I specifically control for gender, age, and education as main demographic controls, ensuring a critical examination of outcomes. Migration and displacement factors are controlled to partially out the effect due to population movements and potential disruptions caused by the flood. The variable "flood risk" is an important factor that is attributable to the regions and represented as a potential predictor of flood that ultimately can cause a selection bias, therefore, I control for the flood risk which is observed at the district level. These control variables collectively allow for a more rigorous and robust exploration of the long-term impacts of the 2010 flood on various dimensions of human capital. The control variables for each of the regression models are given in the table notes.

I find that the flood, on average significantly increases the health impairments or the adverse health outcomes by 0.16 sigma. The cognitive disabilities have been increased by 0.07 sigma. However, I find a marginally significant effect on functional disabilities. The results are robust and more pronounced when I use the precise measure of the flood i.e. proportion of population and area affected in Table 3, 4 and 5. The main mechanism in an underlying relationship is the fetal origin hypothesis which indicates that the shock during the pregnancy can significantly affect the baby's development, particularly the cognitive development and the effect persists in the long run.

In addition to the main findings, I conducted a sub-group analysis based on household income and gender. I find that the health impairments and cognitive abilities of boys are more affected compared to girls. However, there is no significant effect on the functional abilities of boys and girls. The effect on health impairments by gender is presented in Table B5, effect on cognitive abilities is presented in Table B6. As with the main findings, the insignificant effects for both genders are reported in Table B7.

I find that the flood has significantly affected the low-income groups compared to high income. Using the median value of the income I divide the sample and estimate the effect on health, cognitive, and functional development. Findings for the health outcome are detailed in Table B2, for cognitive development in Table B3, and for functional development in Table B4. The effects on health and cognitive abilities are pronounced and significant for the low-income groups compared to the high-income group. While the functional abilities are not affected in both groups.

This study contributes to the body of growing knowledge that examines the long-term effects of natural disasters as well as the studies evaluating the effect of shocks during pregnancy. This research can potentially inform policymakers about health impairments and cognitive disabilities. The government can use this research in designing their policies, particularly for vulnerable populations and while developing policies on health and education. The affected cohorts can easily be identified and targeted for interventions through the data from the NADRA which is a national database of the population in Pakistan.

Background of the study and details on flood and caused damages are provided in Section 2. The potential data sources and their details are given in Section 3. The rest of the study includes the empirical strategy in Section 4 and results in 5. Finally the conclusion is provided in Section 6.

2 Background

In a study by Alderman et al. (2012), it was found that floods are the most common type of disaster, causing significant human and economic losses globally.. They are also likely to occur more frequently in the future. In fact, floods account for nearly half of all losses from natural disasters. The health effects of floods vary based on geographical and socioeconomic factors and the inherent vulnerability of affected populations (Ahern et al., 2005; Du et al., 2010). Existing research suggests that exposure to any type of shock in utero has a lasting impact on health and livelihood, even in older ages (Lee, 2014). In addition to health consequences, the in-utero shocks and health at birth affect other socioeconomic outcomes such as education, income, and life expectancy. It is therefore economists, particularly health economists, are interested in estimating such effects caused by the in-utero or at-birth exposures (Black et al., 2007; Currie, 2011) migration is one of the key exposures that is measured by many scholars.

The mechanism behind the underlying relationships is the stress during the pregnancy. Depression and/or stress during the pregnancy potentially affect the fetus following the neuroendocrine, immune function, and behavioral channels (Dunkel Schetter, 2011). The fetal programming hypothesis explains such a relation between the stressor during pregnancy and its potential and long-lasting effect on outcomes at birth (Laplante et al., 2018; Barker, 1992). In addition to the fetal programming hypothesis, other potential mechanisms are prenatal depression and poor pregnancy outcome that affect the postnatal health of children, preterm birth and also cause stunting in children such as height for age or weight for age (Mallett and Etzel, 2018). However, the effect on health including mental and physical varies according to the exposure to stress (Reynolds et al., 2013).

According to Barker (2002); Glover (2011); Gluckman et al. (2005), social, behavioral, and health outcomes in older age can be traced back to the prenatal period, where stress can potentially influence body and brain development. Many human studies have shown that mothers' exposure to disaster and stress alters the structure and function of offspring's brain (Babenko et al., 2015; Glover, 2011; Buss et al., 2010). Laplante et al. (2018), results suggest that prenatal maternal stress was related to lower cognitive abilities in two and half year olds who were exposed to Lowa Flood in utero. Rosales-Rueda (2018), finds that children in utero during the 1997–1998 El Niño floods exposure during the first trimester results in cognitive deficits. Chang et al. (2022), exposure to rainfall shocks in-utero is linked to lower cognitive skills at ages 5 and 15 in children. Majid (2015) studies have shown that children in Indonesia who were exposed to Ramadan while in the womb scored 7.8 percent lower on cognitive tests. Many studies in medical sciences and psychology suggest that low birth weight and early malnutrition may lead to impaired cognitive development (Linnet et al., 2006; Mara, 2003; Shenkin et al., 2004). Research indicates that stress experienced by mothers during pregnancy, known as prenatal maternal stress (PNMS), is linked to less-than-optimal development in children (Van den Bergh et al., 2020). High levels of stress can have various negative effects on birth outcomes, such as increasing the risk of preterm birth and low birth weight. Additionally, stress can impact pregnancy health by raising the chances of gestational hypertension and preeclampsia, and also contribute to mental health issues (Dunkel Schetter, 2011; Leeners et al., 2007). Low birth weight and preterm birth are linked to higher risks of significant physical and mental impairments (Saigal et al., 1991; Reichman et al., 2008; Goosby and Cheadle, 2009).

On the other hand, the literature on the correlation between natural disasters and birth outcomes presents mixed findings (Hetherington et al., 2021). Several smaller convenience sample studies have revealed rises in preterm birth or low birthweight rates in connection with natural disasters, including Hurricane Katrina and multiple earthquakes (Glynn et al., 2001; Xiong et al., 2008). When a mother experienced a 1 standard deviation reduction in rainfall before pregnancy, her child was 0.17 standard deviations shorter (0.53 cms) by age four. Though some compensation occurred, by age 13, the child still measured 0.12 standard deviations shorter (0.83 cms) on average(Ahmed, 2016). On the other hand, larger studies like Glynn et al. (2001); Torche and Kleinhaus (2012); King et al. (2012) found that earlier in-utero exposure to disaster may result in adverse outcomes. Almond (2006) found that Birth cohorts who were in utero at the peak of the pandemic are estimated to experience a 20% higher disability rate by the age of 61 as a consequence of fetal exposure to influenza.

2.1 Climate Change

Floods are generally considered natural disasters, but the causes and consequences of floods are not entirely natural. Human activities contribute to the causes of floods by destroying the climate and exacerbating losses by not implementing mitigation strategies. Climate change is a multiplier of danger, affecting individuals unequally. The poorest and those least able to withstand climate shocks suffer the most. Low-income nations suffer the most when climate change is not addressed. Pakistan, which contributes 0.9 percent of global greenhouse gas emissions, is vulnerable to climate change. The consequences include severe floods, sudden changes in rainfall patterns, melting Himalayan glaciers, and an increase in vector-borne illnesses such as dengue. The 2010 Pakistan flood is a prominent example of heavy rainfall and melting glaciers. The data from the World Bank's Climate Risk Report of Pakistan indicates that the floods caused highest economic and human losses among all kind of natural disasters. Table A1 provides details on the aggregate losses caused by different disasters. In addition, the flood of 2010 started in July which is the rainy season in Pakistan. Figure A1 indicates that the predictions of heavy rains are not difficult which ultimately suggests that this kind of disaster has a human contribution by not following mitigation strategies.

2.2 Flood 2010 Pakistan

The flood in Pakistan began in late July, resulting in the brunt of the damage and loss. Fair et al. (2017) documented the human and economic losses of the 2010 flood. Their findings indicate that the 2010 flood caused a significant loss by destroying around 1.7 million houses, 2000 causalities, and more than 20 million population was affected. The 2010 flood was the worst natural disaster in the history of Pakistan. Although, the 2005 earthquake caused a significant loss that loss was concentrated in one region and the total loss was significantly smaller than the caused by the flood.

Since the pregnancies and births are considered random, the most affected population were the pregnant women who lost their houses and economic support (Nasir, 2021). A survey was conducted in 2010 fall which covered approximately 1,769 households in 29 most affected districts. The survey results indicate that 55 percent of households reported their house was damaged by the flood, 77 percent people responded that at least one of their household members had worst health outcome following the flood and 88 percent reported their economic capacity was severely affected (Kirsch, 2012).

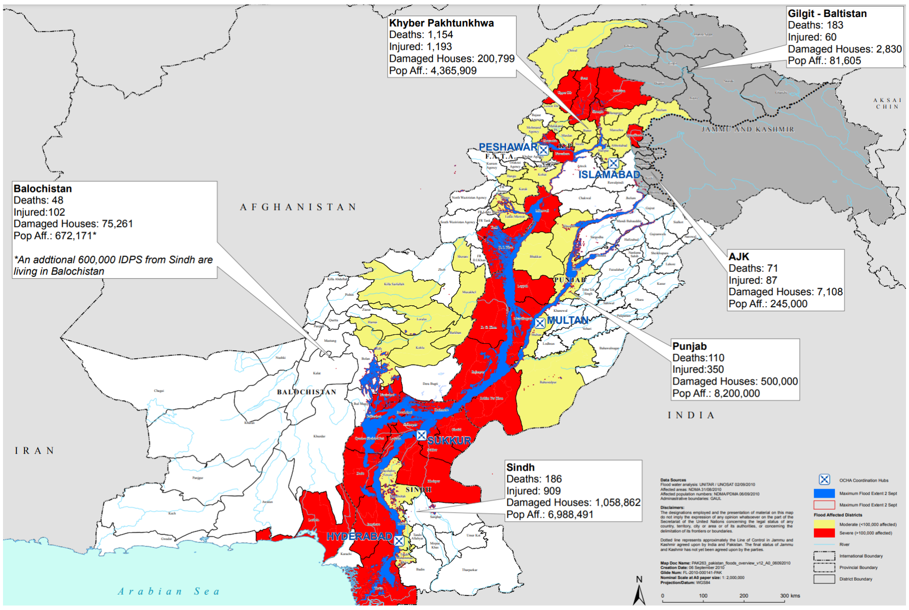
I reported the affected region and extent of flood by district in Figure 1. This figure was sourced from the United Nations (UN) Office for the Coordination of Humanitarian Affairs (OCHA)[1], illustrates the flood-affected regions as of August 27, 2010.

The 2010 flood was the worst in the history of Pakistan as figured out in Figure 2. Until the 15th of August, after the 15 days of flood, the reported number of deaths was more than 1600. the Economist reported on August 21, that the number of causalities dramatically increased due to short-term after-effects and argued that "it is no more than the plain truth that the worst is yet to come–in terms of hunger, disease, looting, and violence as victims scramble to save themselves and their families.".

The flood was considered an outlier in the history of natural disasters in Pakistan. I report the standardized values of the population affected and the standardized value of deaths in Figure 2 over the last couple of decades. The used in the upper panel of Figure 2 consists of years from 1975 to 2012 and is sourced from the International Disaster

[1]Source: UN OCHA (https://www.unocha.org/publications/map/pakistan/pakistan-flood-extent-27-aug-2010-and-flood-affected-districts-26-aug-2010)

Figure 1: Pakistan 2010 Flood



Notes: The affected area encompasses the 64 districts out of 130 of Pakistan, consist of Abbottabad, Bahawalpur, Bannu, Barkhan, Batagram, Bhakhar, Bunair, Chitral, Hangu, Haripur, Harnai, Hyderabad, Jhang, Karak, Khushab, Kohat, Kohlu, Lakki Marwat, Larkana, Loralai, Malakand, Mansehra, Matiari, Mohmand, Multan, Musa Khel, Nawabshah, Nowshero, Feroze, Qilla Saifullah, Sherani, Sibbi, Swabi, Tando Muhammad Khan, Charsada, D. G. Khan, D. I. Khan, Ghotki, Jacobabad, Jaffarabad, Jamshoro, Kashmore, Kohistan, Layyah, Mardan, Khairpur, Mianwali, Muzaffargarh, Nasirabad, Tamboo, Nowshera, Peshawar, Qambar Shahdad Kot, Quetta, Rajanpur, Shangla, Shikarpur, Sukkur, Swat, Tank, Thatta, Upper Dir.

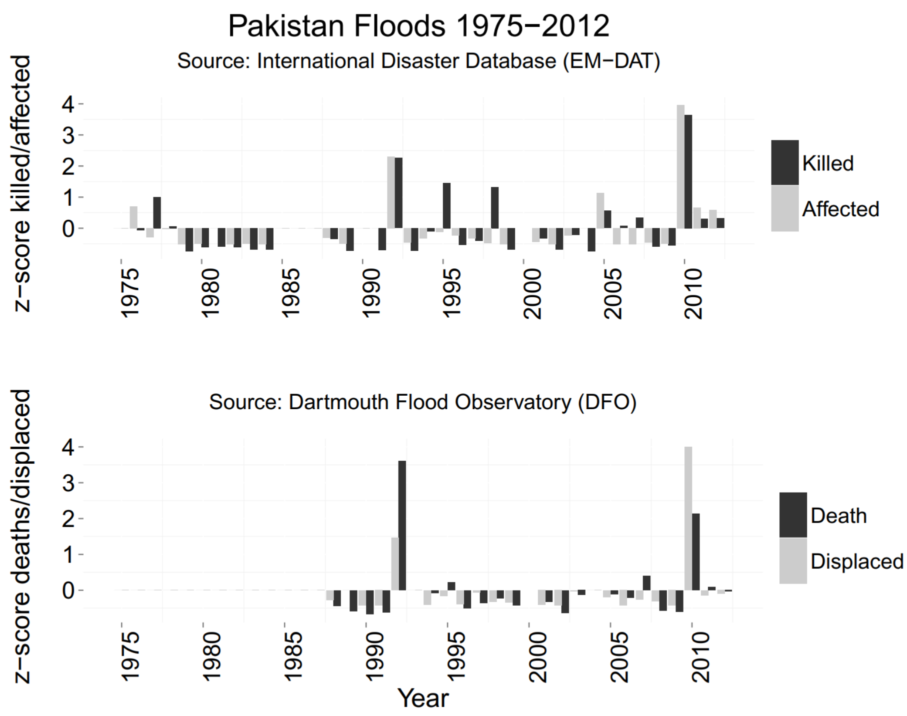
Database (EM-DAT) hosted by the Center for Research on the Epidemiology of Disasters (2013). The lower panel of Figure 2 represents the z-score of the same variable covering the period from 1988 to 2012 but the data is sourced from the Global Active Archive of Large Flood Events of the Dartmouth Flood Observatory (DFO) (2013).

The 2010 flood in Pakistan was the largest in the country's history in terms of the number of people affected and temporarily displaced. It was several times more devastating than the next largest flood, according to the EM-DAT[2]. In terms of infrastructure, 78 out of 141 districts were severely damaged by this natural disaster. Former UN Secretary-General Ban Ki-moon highlighted the devastation caused by the 2010 flood by saying that, *"In the past, I have witnessed many natural disasters around the world, but nothing like this."*

Despite extensive and concerted efforts at local, national, and global levels to address the aftermath of the 2010–11 floods, their lasting impact on various socioeconomic indicators

[2] The next largest flood was in 1992, which affected 12.8 million people, temporarily displaced 4.3 million, and resulted in at least 1,446 fatalities.

Figure 2: Trend of Floods and Affected People



persists. In response to the unprecedented devastation, the Pakistani government, civil society, and the international community rallied together to coordinate relief efforts. The National Disaster Management Agency (NDMA) played a pivotal role in directing these initiatives, collaborating closely with federal ministries, armed forces, and donors (Ahmed, 2010; Khan and Mughal, 2010; UN OCHA, 2010). By impacting the physical and mental health of pregnant women and their access to health services, floods can affect the health of newborns. (Tong et al., 2011).

3 Data

In my analysis, I utilized three data sources: (1) geocoded data on the floods, (2) nationally representative microdata collected by the Pakistan Bureau of Statistics as part of the Pakistan Social and Living Standards Measurement Survey 2019-20, and (3) a variety of geospatial variables used to predict flood risk in advance.

Disabilities: The PSLM data is a main resource in our study, offering a comprehensive examination of various socioeconomic aspects across the country. Conducted by the

Pakistan Board of Statistics (PBS), this nationally representative survey captures a wide array of indicators related to household demographics, income, employment, education, health, and housing conditions. With an annual frequency, the PSLM provides a valuable snapshot of living standards, allowing for the exploration of trends and changes over time. Particularly pertinent to our study, the education module of PSLM contributes critical insights into educational attainment, learning outcomes, and other factors for cohorts affected by the 2010 flood.

Flood: United Nations Institute for Training and Research's (UNITAR) Operational Satellite Applications Program (UNOSAT) documents the data on natural disasters worldwide. UNITAR also documented the geo-spatial data of the 2010 and 2011 floods of Pakistan (United Nations Institute for Training and Research, 2003). Their geospatial flood data is observed at 100m m resolution of the affected area thereby providing a very detailed exposure of flood at a geographically disaggregated level. of their data is I have utilized their data in this research. I adopted the same data from Fair et al. (2017) and I used the UNOSAT observatory data in the following years to generate a maximal flood extent. I also utilized the data from Oak Ridge National Laboratory (2008), which provides the land-scan grid data observed at 5km km resolution consisting of population. The above-mentioned datasets were used to calculate the percentage of population and areas affected within each district. This approach uses the continuous or staggered nature of a difference-in-differences type estimator instead of the binary variable. As a result the findings and robust and valid. The summary statistics are given below in Table 1.

4 Empirical Strategy

4.1 Estimation

To estimate the effect of flood on health outcomes, and cognitive and functional disabilities, I employ Equation 1. This main estimation specification quantifies flood exposure using four different measures. First I use the flood dummy defined at the district level, second, the flood exposure represents the continuous exposure to flood as detailed in Figure 1. The other two are the more precise measures defined as the proportion of pop-

Table 1: Summary Statistics

Variables	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
Age in Years	24.1180	18.5230	0	99	870,171
=1 if Female	0.4857	0.4998	0	1	870,171
=1 if belongs to Rural	0.7071	0.4551	0	1	871,852
=1 if Migrated	0.0553	0.2285	0	1	871,841
Adverse Health	0.2609	1.1130	0	18	871,852
Cognitive Disability	0.1073	0.6768	0	9	871,852
Functional Disability	0.1536	0.6101	0	9	871,852
Memory Disability Index	0.0375	0.2559	0	3	871,841
Caring Disability Index	0.0397	0.2732	0	3	871,841
Speaking Disability Index	0.0301	0.2471	0	3	871,841
Seeing Disability Index	0.0393	0.2400	0	3	871,841
Hearing Disability Index	0.0318	0.2345	0	3	871,841
Walking Disability Index	0.0824	0.3739	0	3	871,841

Notes: The table provides an overview of the Pakistan Social Living Measurement (PSLM) survey data. The survey period is 2019-2020 representing whole country. For each variable, the table presents the mean in column (1), standard deviations (SD) in column (2), minimum value (Min) in column (3), maximum value (Max) in column (4) and the number of observations in column (5).

ulation and area affected at the district level using the data presented in Section 3. These four measures enable me to estimate its causal effects on disabilities using the following equation in Table 3,4 & 5:

$$Y_{ijt} = \phi(Flood_j \times Cohort_t) + \gamma_j + \tau_t + \epsilon_{ijt} \tag{1}$$

where Y_{ijt} is an outcome variable, health impairment, cognitive or functional disability of child i from district j born in month-year t. The variable $Flood_j$ represents a dummy variable if a district j is exposed to flood. $Cohort_t$ is a binary variable indicating the children who were born within 9 months starting from the flood. For example, consider the flood months of late July, August, and September of 2010, if a child is born between August 2010 and March 2011, the term is =1, otherwise 0. The interaction term $Flood_j \times Cohort_t$ identifies the children who were exposed to flood in utero. However, I used different flood measures in the analysis. The γ_j accounts for the district fixed effect and τ_t accounts for the cohort fixed effect. To estimate the causal effect, the empirical strategy given in Equation 1 requires holding a parallel trend assumption before the flood and strict independence of the flood from the baseline disabilities.

4.2 Exogeneity of Flood

In the context of this study, whether floods can be considered exogenous depends on various factors. Generally, floods are viewed as natural disasters influenced by unpredictable weather patterns, which allows them to be treated as exogenous events (Sodhi, 2016; Osberghaus, 2019). However, the local context can violate this assumption. For instance, factors such as area type, and socioeconomic conditions may influence both flood risk and health outcomes, potentially introducing endogeneity. To address this corner, I have used a couple of control variables such as area type, socioeconomic characteristics income level, and migration. In addition, if districts that are more vulnerable to flooding differ systematically in other relevant characteristics—such as access to healthcare or economic resources—this can further bias the estimation. However, the balance test before the flood is provided in Table 2 indicating no difference in health before the flood. Further, it can be argued that flood-prone areas, particularly districts with low elevation elevation to sea level, are not only susceptible to flooding but also vulnerable to income shocks that may affect the disabilities. To address this, my analysis controls for the mean elevation of each district above sea level across all specifications. This allows me to account for geographical vulnerabilities that may influence health outcomes. Further, since births are independent of flooding events, this introduces a degree of randomness within the cohorts, enhancing the robustness of the findings.

4.3 Balance Test

To estimate the causal effect of flood on health outcomes and disabilities, affected and unaffected districts must share the same characteristics as before the flood. This assumption is more important, particularly for the outcome variables. The balanced characteristics before the flood provide a solid ground for my estimation provided in Equation 1. In doing so, I provide the balance test before the flood in Table 2.

Table 2: Mean Difference Before Flood

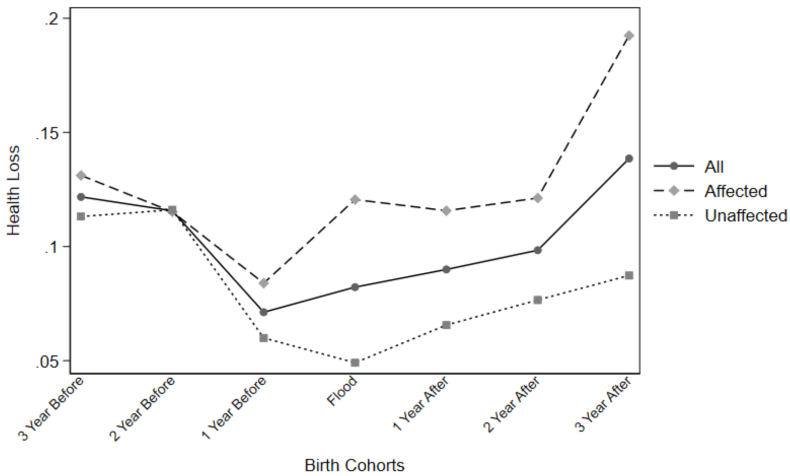
Variable	Affected (1)	Non-Affected (2)	Difference (3)	p-value (4)
Age in Years	9.3639	9.3821	0.0182	0.2529
	(0.4824)	(0.4932)	[0.0159]	
=1 if Female	0.4541	0.4695	0.0154	0.3420
	(0.4980)	(0.4992)	[0.0163]	
=1 if belongs to Rural	0.8079	0.6034	-0.2045	0.0000
	(0.3941)	(0.4893)	[0.0144]	
=1 if Migrated	0.0090	0.0205	0.0115	0.0032
	(0.0945)	(0.1417)	[0.0039]	
Adverse Health	0.0839	0.0599	-0.0240	0.2015
	(0.6018)	(0.5461)	[0.0188]	
Cognitive Disability	0.0428	0.0320	-0.0108	0.3918
	(0.4020)	(0.3727)	[0.0127]	
Functional Disability	0.0411	0.0280	-0.0132	0.1419
	(0.2908)	(0.2553)	[0.0090]	
Memory Disability Index	0.0113	0.0090	-0.0023	0.6280
	(0.1497)	(0.1375)	[0.0047]	
Caring Disability Index	0.0175	0.0100	-0.0075	0.1397
	(0.1720)	(0.1338)	[0.0051]	
Speaking Disability Index	0.0141	0.0130	-0.0011	0.8440
	(0.1723)	(0.1698)	[0.0056]	
Seeing Disability Index	0.0051	0.0090	0.0039	0.2166
	(0.0855)	(0.1091)	[0.0032]	
Hearing Disability Index	0.0096	0.0085	-0.0011	0.8165
	(0.1441)	(0.1429)	[0.0047]	
Walking Disability Index	0.0265	0.0105	-0.0160	0.0128
	(0.2347)	(0.1428)	[0.0064]	
Observations	1775	2002		

Notes: This table employs a t-test between affected and un-affected regions before and after the flood.The result as presented in the table, highlight statistically insignificant differences between both groups before the treatmnet.The first two columns (1-2) display means and standard deviations in paranteses within treatment and control groups, repectively.Column (3) indicates mean differences coupled with standard errors in brackets between treatment and control groups, while column (4) shows the p-value from a two-sided t-test assessing the equivalences of mean.

4.4 Parallel Trend

As outlined in Section 4.1, the assumption of parallel trends in outcome variables is critical when employing the difference-in-differences approach. To validate this assumption, I present Figure 3, which indicates the parallel trends in health impairments between affected and unaffected regions. The data shows a significant increase in health impairments among the affected cohort during the flood, highlighting the impact of flooding on health outcomes. This observation reinforces the validity of my analysis and the necessity of the assumption of parallel trends for our causal inferences.

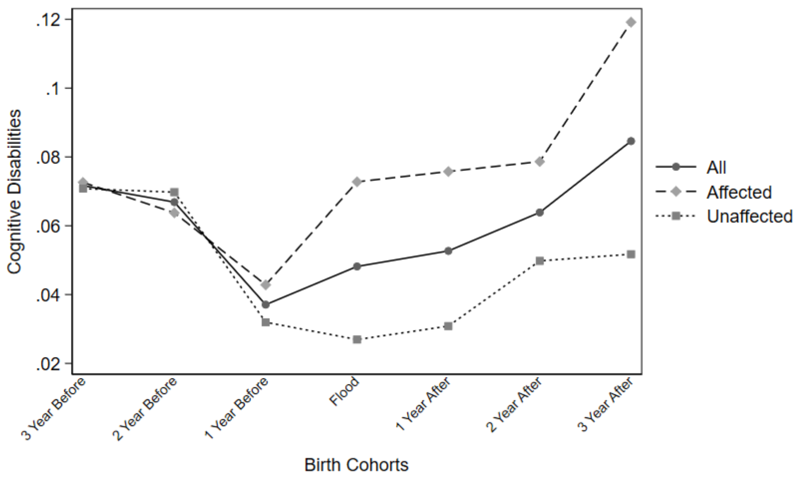
Figure 3: Trend of Children Health Loss



This figure depicts the average health loss among children, drawing upon data extracted from the 2019-20 Pakistan Social and Living Standards Measurement survey. The study segregates individuals based on their birth timing relative to flood occurrences, distinguishing between those born pre-flood, during, and post-flood periods. It also discerns between districts impacted by the floods and those that remained unaffected. The trend lines illustrate a parallel trajectory in average health loss rates before the flood, juxtaposed with a significant increase in health loss among children born during and after flood events.

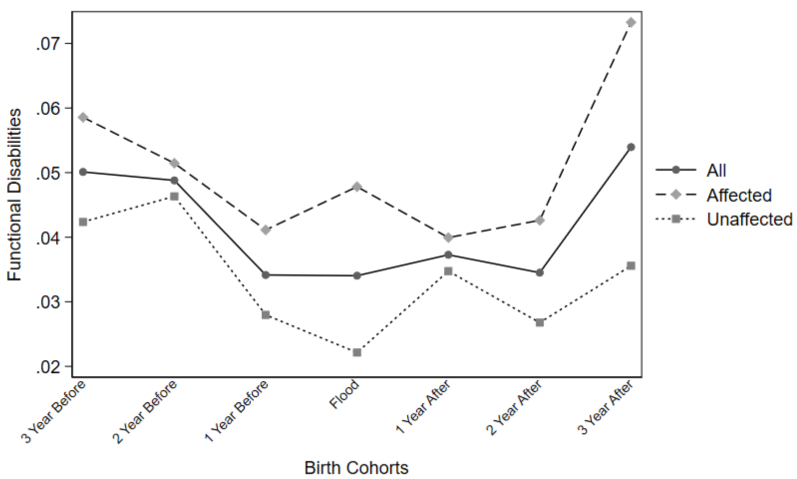
In addition to health impairments, I analyze cognitive and functional disabilities to further assess the validity of the parallel trends assumption. Figures 4 and 5 present the trends for cognitive disabilities and functional disabilities, respectively. The data supports the parallel trends assumption for cognitive disabilities, indicating comparable trajectories between the affected and unaffected groups. However, in the case of functional disabilities, there is a slight violation of this assumption two years before the flood, suggesting that the trends may not be entirely comparable before the flood.

Figure 4: Trend of Cognitive Disabilities



This figure depicts the average cognitive disabilities among children, drawing upon data extracted from the 2019-20 Pakistan Social and Living Standards Measurement survey. The study segregates individuals based on their birth timing relative to flood occurrences, distinguishing between those born pre-flood, during, and post-flood periods. It also discerns between districts impacted by the floods and those that remained unaffected. The trend lines illustrate a parallel trajectory in cognitive disability rates before the flood, juxtaposed with a notable increase in cognitive disabilities among children born during and after flood events.

Figure 5: Trend of Functional Disabilities



This figure depicts the average functional disabilities among children, drawing upon data extracted from the 2019-20 Pakistan Social and Living Standards Measurement survey. The study segregates individuals based on their birth timing relative to flood occurrences, distinguishing between those born pre-flood, during the flood, and post-flood periods. It also discerns between districts impacted by the floods and those that remained unaffected. The trend lines illustrate a parallel trajectory in functional disability rates prior to the flood, juxtaposed with a notable increase in cognitive disabilities among children born during and after flood events.

5 Findings

This section explores the effects of flood by using the difference-in-difference estimator using Equation 1 where the flood is measured with four different types of estimators.

5.1 Effect on Health Impairments

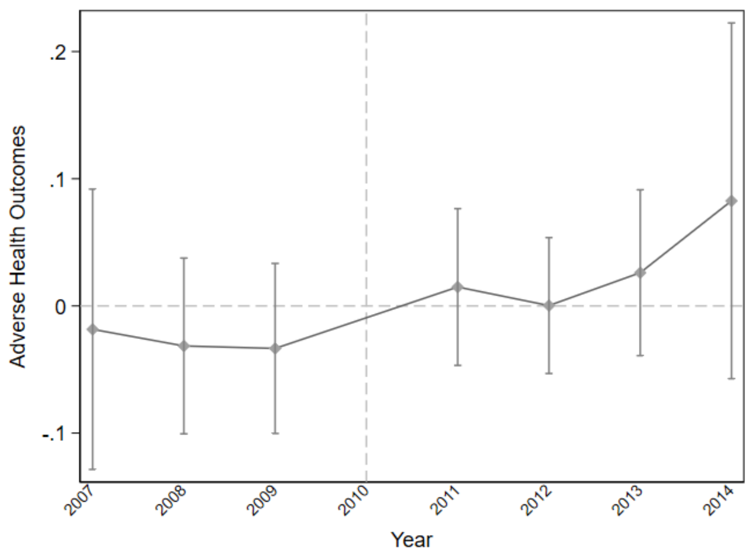
Table 3 explores the impact of the flood on health outcomes. I employ the difference-in-differences estimation as detailed in Equation 1. The flood is measured at four difference estimators i.e. flood dummy, flood intensity, the proportion of population affected, and proportion of area affected. The proportions are measured by dividing the affected population and area by the district population. On average the flood has significantly increased the adverse health outcomes or the health impairments. Column 1 indicates the flood has statistically significantly increased health impairments by 0.0621 points on the health index. It is a 60 percent increase in health impairments relative to the mean of the dependent variable as $(0.0621/0.1054 \times 100) \approx 59.9184\%$. In order to better interpret the effect size, it can be calculated in standard deviation which is 0.05 sigma increase as $(0.0621 \times 0.7629) \approx 0.0473$. The results are consistent throughout the column 1 to 4. However, while using the precise measures of the flood such as the proportion of population and area affected, the effect size is precise as relatively large. For instance, as indicated in column 3, the one percent increase in the affected population increases the health impairments by 200 percent as $(0.2102/0.1054 \times 100) \approx 199.43\%$ and 0.16 standard deviations as $(0.2102 \times 0.7629) \approx 0.1603$. Similarly, column 4 shows an increase of 167 percent which is 0.13 standard deviations. Figure 6 represents the event study of health impairments indicating a significant increase in adverse health outcomes right after the flood. The omitted cohort is the most affected one, however, the effect can be observed in the later cohorts.

Table 3: Impact of Flood on Adverse Health Outcomes

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
	0.0621	0.0337	0.2102	0.1759
	(0.0269)	(0.0154)	(0.0920)	(0.0750)
	[0.0229]	[0.0309]	[0.0246]	[0.0210]
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	27,393	27,393	27,393	27,393
Dep. Var. Mean	0.1054	0.1054	0.1054	0.1054
Dep. Var. SD	0.7629	0.7629	0.7629	0.7629

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Adverse Health Outcomes' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Figure 6: Impact of Flood on Health Impairments



5.2 Effect on Cognitive Disabilities

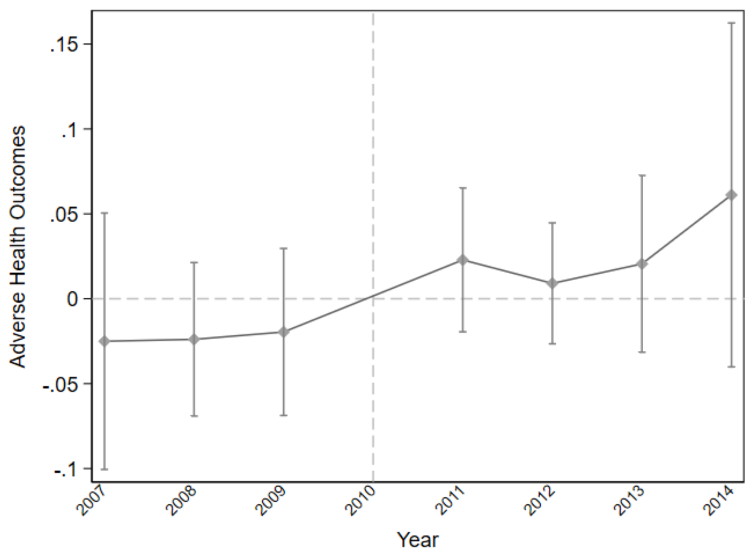
Table 4 explores the impact of the flood on cognitive disabilities. I employ the difference-in-differences estimation as detailed in Equation 1. The flood is measured at four difference estimators i.e. flood dummy, flood intensity, the proportion of population affected, and proportion of area affected. The proportions are measured by dividing the affected population and area by the district population. On average the flood has significantly increased cognitive disabilities. Column 1 indicates the flood has statistically significantly increased cognitive disabilities by 0.0424 points on the index. It is a 71 percent increase in cognitive disabilities relative to the mean of the dependent variable as $(0.0424/0.0594 \times 100) \approx 71.380\%$. In order to better interpret the effect size, it can be calculated in standard deviation which is 0.01 sigma increase as $(0.0424 \times 0.5075) \approx 0.01218$. The results are consistent throughout the column 1 to 4. However, while using the precise measures of the flood such as the proportion of population and area affected, the effect size is precise as relatively large. For instance, as indicated in column 3, the one percent increase in the affected population increases the cognitive disabilities by 242 percent as $(0.1438/0.0594 \times 100) \approx 242.08\%$ and 0.07 standard deviations as $(0.1438 \times 0.5075) \approx 0.0729$. Similarly, column 4 shows an increase of 217 percent which is 0.7 standard deviations. Figure 7 represents the event study of cognitive disabilities indicating a significant increase in cognitive disabilities right after the flood. The omitted cohort is the most affected one, however, the effect can be observed in the later cohorts.

Table 4: Impact of Flood on Cognitive Disabilities

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
	0.0424	0.0240	0.1438	0.1294
	(0.0177)	(0.0110)	(0.0610)	(0.0517)
	[0.0186]	[0.0314]	[0.0205]	[0.0140]
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	27,393	27,393	27,393	27,393
Dep. Var. Mean	0.0594	0.0594	0.0594	0.0594
Dep. Var. SD	0.5075	0.5075	0.5075	0.5075

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Cognitive Disabilities' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Figure 7: Impact of Flood on Cognitive Disabilities



5.3 Effect on Functional Disabilities

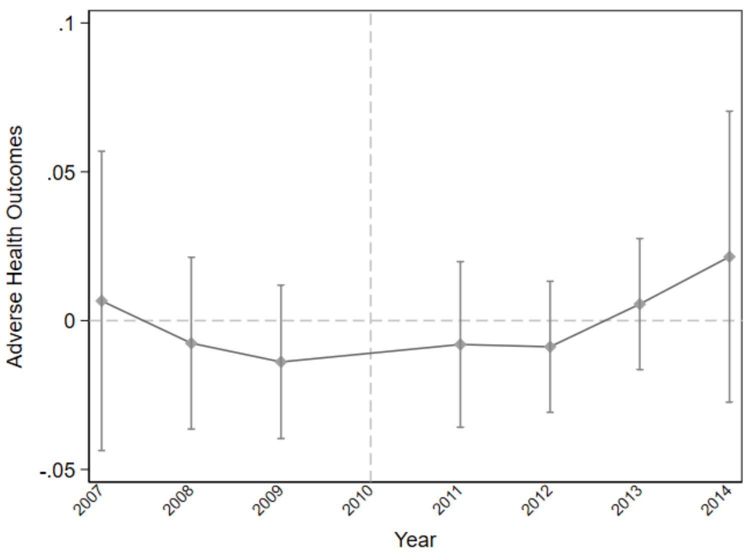
Table 5 explores the impact of the flood on functional disabilities. I employ the difference-in-differences estimation as detailed in Equation 1. The flood is measured at four difference estimators i.e. flood dummy, flood intensity, the proportion of population affected, and proportion of area affected. The proportions are measured by dividing the affected population and area by the district population. On average the flood has marginally increased functional disabilities. Column 1 indicates the flood has statistically significantly increased functional disabilities by 0.0196 points on the index. It is a 42 percent increase in cognitive disabilities relative to the mean of the dependent variable as $(0.0196/0.0460 \times 100) \approx 42.60\%$. In order to better interpret the effect size, it can be calculated in standard deviation which is 0.01 sigma increase as $(0.0196 \times 0.3435) \approx 0.0067$. The results are consistent throughout the column 1 to 4. However, while using the precise measures of the flood such as the proportion of population and area affected, the effect size is precise as relatively large. For instance, as indicated in column 3, the one percent increase in the affected population increases the functional disabilities by 144 percent as $(0.0664/0.0460 \times 100) \approx 144.34\%$ and 0.02 standard deviations as $(0.0664 \times 0.3435) \approx 0.0228$. Similarly, column 4 shows an increase of 101 percent which is 0.015 standard deviations. Figure 8 represents the event study of functional disabilities indicating a marginally increased in functional disabilities right after the flood. The omitted cohort is the most affected one, however, the effect can be observed in the later cohorts.

Table 5: Impact of Flood on Functional Disabilities

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
	0.0196	0.0097	0.0664	0.0465
	(0.0113)	(0.0056)	(0.0364)	(0.0304)
	[0.0865]	[0.0850]	[0.0715]	[0.1295]
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	27,393	27,393	27,393	27,393
Dep. Var. Mean	0.0460	0.0460	0.0460	0.0460
Dep. Var. SD	0.3435	0.3435	0.3435	0.3435

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Functional Disabilities' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Figure 8: Impact of Flood on Functional Disabilities



6 Conclusion

This paper contributes to the growing body of literature examining the long-term effects of prenatal stress exposure induced by natural disasters on child development outcomes. By leveraging the Pakistan 2010 flood as a natural experiment, the study investigates the long-term repercussions of in-utero exposure to the disaster on health outcomes, and cognitive and functional disabilities of affected cohorts.

The findings presented in this paper offer evidence of a significant negative association between flood exposure during the in-utero period and subsequent health and cognitive development of children. I, however, haven't find any significant effect on the functional development of children.

Structured across multiple cross-section panels, our analysis scrutinizes various dimensions, beginning with child development indices. Consistent with the findings of (Lee, 2014; Black et al., 2007; Currie, 2011; Dunkel Schetter, 2011; Du et al., 2010; Ahern et al., 2005), our results reveal a significant negative association between flood exposure during the in-utero period and indices of overall child development and cognitive development. This underscores the growing body of literature indicating the susceptibility of early-life developmental trajectories to environmental perturbations (Mallett and Etzel, 2018; Reynolds et al., 2013; Tong et al., 2011; Barker, 1992).

These results shed light on the long-term consequences of natural disasters on human development, particularly during critical periods of fetal development. The implications of these findings extend beyond academic discourse, informing policy and intervention strategies aimed at mitigating the long-term effects of prenatal stress exposure and improving resilience in vulnerable populations facing similar environmental adversities.

Finally, research exploring the mechanisms underlying the observed associations and examining the effectiveness of targeted interventions to overcome the adverse effects of prenatal stress exposure remains imperative. By deepening our understanding of the interplay between environmental stressors and human development, we can better equip societies to confront the challenges posed by natural disasters and safeguard the well-being of future generations.

Some limitations are associated with this study. Having enough statistical power by clustering the standard errors at the district level considering the identification level of microdata, the more granular data at the tehsil or village level can provide more accurate estimates. This study addresses the flood of 2010 and its longer-term effects on disabilities, however, future studies can focus on other natural disasters such as the 2005 earthquake, and can also estimate other socioeconomic outcomes for the 2010 flood. I compared two differences, one by exposed districts and the second by cohorts considering their in-utero exposure. One can consider the second difference by survey year and compare short-term disabilities.

References

Ahern, M., R. S. Kovats, P. Wilkinson, R. Few, and F. Matthies (2005). Global health impacts of floods: epidemiologic evidence. *Epidemiologic reviews 27*(1), 36–46.

Ahmed, H. (2016). Rainfall shocks and child health in rural pakistanγ.

Ahmed, I. (2010). Pakistan floods: How new networks of pakistanis are mobilizing to help. *Christian Science Monitor*.

Alderman, K., L. R. Turner, and S. Tong (2012). Floods and human health: a systematic review. *Environment international 47*, 37–47.

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.

Babenko, O., I. Kovalchuk, and G. A. Metz (2015). Stress-induced perinatal and transgenerational epigenetic programming of brain development and mental health. *Neuroscience & Biobehavioral Reviews 48*, 70–91.

Barker, D. J. (2002). Fetal programming of coronary heart disease. *Trends in Endocrinology & Metabolism 13*(9), 364–368.

Barker, D. J. P. (1992). Fetal and infant origins of adult disease. *Bmj*.

Barker, D. J. P. (1994). *Mothers, Babies, and Disease in Later Life.* London: BMJ Publishing Group.

Black, S. E., P. J. Devereux, and K. G. Salvanes (2007). From the cradle to the labor market? the effect of birth weight on adult outcomes. *The Quarterly Journal of Economics 122*(1), 409–439.

Buss, C., E. P. Davis, L. T. Muftuler, K. Head, and C. A. Sandman (2010). High pregnancy anxiety during mid-gestation is associated with decreased gray matter density in 6–9-year-old children. *Psychoneuroendocrinology 35*(1), 141–153.

Caruso, G. and S. Miller (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.

Chang, G., M. Favara, and R. Novella (2022). The origins of cognitive skills and non-cognitive skills: The long-term effect of in-utero rainfall shocks in india. *Economics & Human Biology 44*, 101089.

Chen, Y. and L.-A. Zhou (2007). The long-term health and economic consequences of the 1959–1961 famine in china. *Journal of Health Economics 26*(4), 659–681.

Chung, M. C., S. Jalal, and N. U. Khan (2014). Posttraumatic stress disorder and psychiatric comorbidity following the 2010 flood in pakistan: Exposure characteristics, cognitive distortions, and emotional suppression. *Psychiatry 77*(3), 289–304.

Currie, J. (2011). Inequality at birth: Some causes and consequences. *American Economic Review 101*(3), 1–22.

Du, W., G. J. FitzGerald, M. Clark, and X.-Y. Hou (2010). Health impacts of floods. *Prehospital and disaster medicine 25*(3), 265–272.

Dunkel Schetter, C. (2011). Psychological science on pregnancy: stress processes, biopsychosocial models, and emerging research issues. *Annual review of psychology 62*, 531–558.

Fair, C. C., P. Kuhn, N. A. Malhotra, and J. Shapiro (2017). Natural disasters and political engagement: evidence from the 2010–11 pakistani floods.

Glover, V. (2011). Annual research review: prenatal stress and the origins of psychopathology: an evolutionary perspective. *Journal of Child Psychology and Psychiatry 52*(4), 356–367.

Gluckman, P. D., M. A. Hanson, and H. G. Spencer (2005). Predictive adaptive responses and human evolution. *Trends in ecology & evolution 20*(10), 527–533.

Glynn, L. M., P. D. Wadhwa, C. Dunkel-Schetter, A. Chicz-DeMet, and C. A. Sandman (2001). When stress happens matters: effects of earthquake timing on stress responsivity in pregnancy. *American journal of obstetrics and gynecology 184*(4), 637–642.

Goosby, B. J. and J. E. Cheadle (2009). Birth weight, math and reading achievement growth: A multilevel between-sibling, between-families approach. *Social Forces 87*(3), 1291–1320.

Hetherington, E., K. Adhikari, L. Tomfohr-Madsen, S. Patten, and A. Metcalfe (2021). Birth outcomes, pregnancy complications, and postpartum mental health after the 2013 calgary flood: A difference in difference analysis. *PLoS One 16*(2), e0246670.

Khan, R. and R. Mughal (2010). Floods ravage nw pakistan, kill 430 people. *Associated Press (AP)*.

King, S., K. Dancause, A.-M. Turcotte-Tremblay, F. Veru, and D. P. Laplante (2012). Using natural disasters to study the effects of prenatal maternal stress on child health and development. *Birth Defects Research Part C: Embryo Today: Reviews 96*(4), 273–288.

Kirsch, U. (2012). *Structural optimization: fundamentals and applications*. Springer Science & Business Media.

Laplante, D. P., K. J. Hart, M. W. O'Hara, A. Brunet, and S. King (2018). Prenatal maternal stress is associated with toddler cognitive functioning: The iowa flood study. *Early human development 116*, 84–92.

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.

Leeners, B., P. Neumaier-Wagner, S. Kuse, R. Stiller, and W. Rath (2007). Emotional stress and the risk to develop hypertensive diseases in pregnancy. *Hypertension in Pregnancy 26*(2), 211–226.

Linnet, K. M., K. Wisborg, E. Agerbo, N.-J. Secher, P. H. Thomsen, and T. B. Henriksen (2006). Gestational age, birthweight and the risk of hyperkinetic disorder. *Archives of disease in childhood*.

Majid, M. F. (2015). The persistent effects of in utero nutrition shocks over the life cycle: Evidence from ramadan fasting. *Journal of Development Economics 117*, 48–57.

Mallett, L. H. and R. A. Etzel (2018). Flooding: what is the impact on pregnancy and child health? *Disasters 42*(3), 432–458.

Mara, D. D. (2003). Water, sanitation and hygiene for the health of developing nations. *Public health 117*(6), 452–456.

Nasir, M. (2021). Prenatal exposure to shocks and early-life health: Impact of terrorism and flood on birth outcomes in pakistan. *Defence and Peace Economics 32*(5), 572–587.

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

Oak Ridge National Laboratory (2008). LandScan Global Population Database. Electronic Resource.

Osberghaus, D. (2019). The effects of natural disasters and weather variations on international trade and financial flows: a review of the empirical literature. *Economics of Disasters and Climate Change 3*(3), 305–325.

Rana, I. A., I. U. H. K. Niazi, Z. Khalid, A. Nawaz, and F. A. Najam (2023). A novel framework to assess multidimensional disaster resilience of children: from conceptualization to quantification. *International journal of disaster risk reduction 96*, 103914.

Reichman, N. E., H. Corman, and K. Noonan (2008). Impact of child disability on the family. *Maternal and Child Health Journal 12*, 679–683.

Reynolds, R. M., J. Labad, C. Buss, P. Ghaemmaghami, and K. Räikkönen (2013). Transmitting biological effects of stress in utero: implications for mother and offspring. *Psychoneuroendocrinology 38*(9), 1843–1849.

Rosales-Rueda, M. (2018). The impact of early life shocks on human capital formation: Evidence from el niño floods in ecuador. *Journal of health economics 62*, 13–44.

Saigal, S., P. Rosenbaum, P. Szatmari, and D. Campbell (1991). Learning disabilities and school problems in a regional cohort of extremely low birth weight (< 1000 g) children: A comparison with term controls. *Journal of Developmental & Behavioral Pediatrics 12*(5), 294–300.

Shenkin, S. D., J. M. Starr, and I. J. Deary (2004). Birth weight and cognitive ability in childhood: a systematic review. *Psychological bulletin 130*(6), 989.

Sodhi, M. S. (2016). Natural disasters, the economy and population vulnerability as a vicious cycle with exogenous hazards. *Journal of Operations Management 45*, 101–113.

Tong, V. T., M. E. Zotti, and J. Hsia (2011). Impact of the red river catastrophic flood on women giving birth in north dakota, 1994–2000. *Maternal and child health journal 15*, 281–288.

Torche, F. and K. Kleinhaus (2012). Prenatal stress, gestational age and secondary sex ratio: the sex-specific effects of exposure to a natural disaster in early pregnancy. *Human reproduction 27*(2), 558–567.

UN OCHA (2010). Pakistan — Flood — July 2010 Table B: Total Humanitarian Assistance per Donor – United Nations Office for the Coordination of Humanitarian Affairs. Technical Report. http://fts.unocha.org.

United Nations Institute for Training and Research (2003). UNITAR's Operational Satellite Applications Programme (UNOSAT). Electronic resource.

Van den Bergh, B. R., M. I. van den Heuvel, M. Lahti, M. Braeken, S. R. de Rooij, S. Entringer, D. Hoyer, T. Roseboom, K. Räikkönen, S. King, et al. (2020). Prenatal developmental origins of behavior and mental health: The influence of maternal stress in pregnancy. *Neuroscience & Biobehavioral Reviews 117*, 26–64.

Xiong, X., E. W. Harville, P. Buekens, D. R. Mattison, K. Elkind-Hirsch, and G. Pridjian (2008). Exposure to hurricane katrina, post-traumatic stress disorder and birth outcomes. *The American journal of the medical sciences 336*(2), 111–115.

A Appendix

Figure A1: Monthly Rainfall and Temperature (Average 1991-2020)

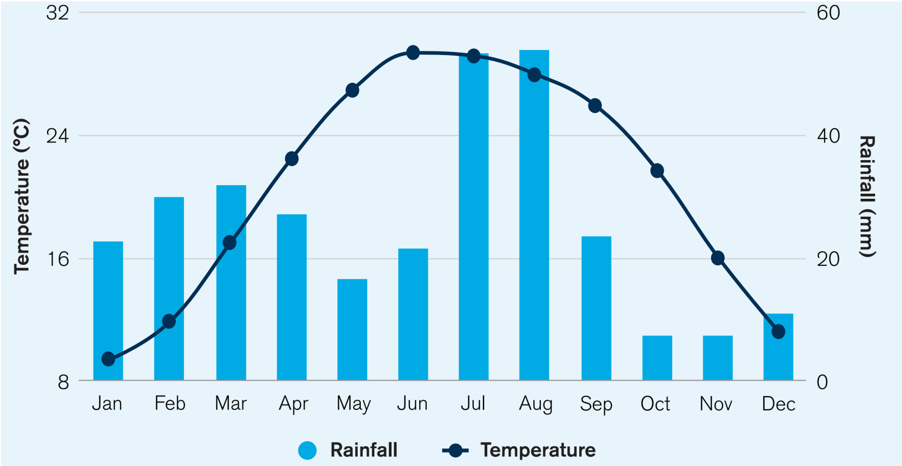


Table A1: Natural Hazards in Pakistan from 1900 to 2020

Disaster Type	Disaster Subtype	Events Count	Total Deaths	Total Affected	Total Damage ('000 US$)
Drought	Drought	1	143	2,200,000	247,000
Earthquake	Ground movement	35	144,116	7,435,786	5,376,755
Epidemic	Bacterial disease	3	142	11,103	0
	Parasitic disease	1	0	5,000	0
	Viral disease	2	130	56,338	0
	Others	5	131	371	0
Extreme temperature	Cold wave	3	18	0	0
	Heat wave	15	2,936	80,574	18,000
Flood	Flash flood	24	3,590	22,114,253	10,184,118
	Riverine flood	43	9,229	34,967,357	9,727,030
	Others	39	5,286	23,863,294	2,670,030
Landslide	Avalanche	12	567	4,435	0
	Landslide	9	222	29,707	18,000
	Mudslide	2	16	12	0
Storm	Convective storm	15	402	1,906	0
	Tropical cyclone	7	11,555	2,599,940	1,715,036
	Others	7	184	2,988	0

B Heterogenous Effects

2.1 Effect by Income

Table B2: Impact of Flood on Adverse Health Outcomes by Income

	Flood Dummy	Flood Exposure	% Population Affected	% Area Affected
	(1)	(2)	(3)	(4)
		Panel A: High Income		
	0.0371	0.0099	0.0260	0.0671
	(0.0360)	(0.0139)	(0.0911)	(0.0867)
	[0.3045]	[0.4789]	[0.7760]	[0.4410]
Observations	9,508	9,508	9,508	9,508
Dep. Var. Mean	0.0943	0.0943	0.0943	0.0943
Dep. Var. SD	0.6970	0.6970	0.6970	0.6970
		Panel A: Low Income		
	0.0753	0.0447	0.2364	0.1997
	(0.0319)	(0.0188)	(0.1083)	(0.0946)
	[0.0202]	[0.0191]	[0.0314]	[0.0374]
Observations	17,885	17,885	17,885	17,885
Dep. Var. Mean	0.1097	0.1097	0.1097	0.1097
Dep. Var. SD	0.7825	0.7825	0.7825	0.7825
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Adverse Health Outcomes' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Table B3: Impact of Flood on Cognitive Disabilities by Income

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
		Panel A: High Income		
	0.0271	0.0054	-0.0043	0.0298
	(0.0405)	(0.0201)	(0.0938)	(0.1023)
	[0.5049]	[0.7872]	[0.9635]	[0.7718]
Observations	9,540	9,540	9,540	9,540
Dep. Var. Mean	0.0546	0.0546	0.0546	0.0546
Dep. Var. SD	0.4977	0.4977	0.4977	0.4977
		Panel A: Low Income		
	0.0433	0.0221	0.0472	0.1105
	(0.0198)	(0.0124)	(0.0568)	(0.0495)
	[0.0314]	[0.0779]	[0.4082]	[0.0281]
Observations	17,910	17,910	17,910	17,910
Dep. Var. Mean	0.0611	0.0611	0.0611	0.0611
Dep. Var. SD	0.5081	0.5081	0.5081	0.5081
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Cognitive Disabilities' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Table B4: Impact of Flood on Functional Disabilities by Income

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
		Panel A: High Income		
	-0.0051	0.0028	-0.0426	-0.0712
	(0.0158)	(0.0108)	(0.0519)	(0.0449)
	[0.7500]	[0.7952]	[0.4145]	[0.1166]
Observations	9,469	9,469	9,469	9,469
Dep. Var. Mean	0.0446	0.0446	0.0446	0.0446
Dep. Var. SD	0.3386	0.3386	0.3386	0.3386
		Panel A: Low Income		
	0.0106	0.0037	0.0401	0.0078
	(0.0153)	(0.0086)	(0.0539)	(0.0439)
	[0.4891]	[0.6716]	[0.4592]	[0.8587]
Observations	17,857	17,857	17,857	17,857
Dep. Var. Mean	0.0469	0.0469	0.0469	0.0469
Dep. Var. SD	0.3553	0.3553	0.3553	0.3553
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Functional Disabilities' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

2.2 Effect by Gender

Table B5: Impact of Flood on Adverse Health Outcomes by Gender

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
		Panel A: Girls		
	0.0615	0.0347	0.1917	0.0431
	(0.0467)	(0.0324)	(0.2812)	(0.1658)
	[0.1913]	[0.2862]	[0.4972]	[0.7954]
Observations	12,626	12,626	12,626	12,626
Dep. Var. Mean	0.0911	0.0911	0.0911	0.0911
Dep. Var. SD	0.7155	0.7155	0.7155	0.7155
		Panel A: Boys		
	0.0689	0.0387	0.2452	0.3040
	(0.0319)	(0.0187)	(0.1354)	(0.1050)
	[0.0334]	[0.0415]	[0.0733]	[0.0047]
Observations	14,765	14,765	14,765	14,765
Dep. Var. Mean	0.1177	0.1177	0.1177	0.1177
Dep. Var. SD	0.8010	0.8010	0.8010	0.8010
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Adverse Health Outcomes' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Table B6: Impact of Flood on Cognitive Disabilities by Gender

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
		Panel A: Girls		
	0.0363	0.0199	0.1106	0.0291
	(0.0316)	(0.0219)	(0.1775)	(0.1171)
	[0.2536]	[0.3660]	[0.5346]	[0.8041]
Observations	12,626	12,626	12,626	12,626
Dep. Var. Mean	0.0515	0.0515	0.0515	0.0515
Dep. Var. SD	0.4742	0.4742	0.4742	0.4742
		Panel A: Boys		
	0.0509	0.0304	0.1779	0.2174
	(0.0212)	(0.0135)	(0.0928)	(0.0789)
	[0.0183]	[0.0263]	[0.0581]	[0.0070]
Observations	14,765	14,765	14,765	14,765
Dep. Var. Mean	0.0662	0.0662	0.0662	0.0662
Dep. Var. SD	0.5343	0.5343	0.5343	0.5343
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Cognitive Disabilities' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.

Table B7: Impact of Flood on Functional Disabilities by Gender

	Flood Dummy (1)	Flood Exposure (2)	% Population Affected (3)	% Area Affected (4)
	Panel A: Girls			
	0.0252	0.0148	0.0811	0.0140
	(0.0185)	(0.0123)	(0.1100)	(0.0612)
	[0.1778]	[0.2324]	[0.4631]	[0.8198]
Observations	12,626	12,626	12,626	12,626
Dep. Var. Mean	0.0396	0.0396	0.0396	0.0396
Dep. Var. SD	0.3221	0.3221	0.3221	0.3221
	Panel A: Boys			
	0.0180	0.0083	0.0673	0.0866
	(0.0142)	(0.0065)	(0.0546)	(0.0382)
	[0.2063]	[0.2074]	[0.2210]	[0.0258]
Observations	14,765	14,765	14,765	14,765
Dep. Var. Mean	0.0515	0.0515	0.0515	0.0515
Dep. Var. SD	0.3607	0.3607	0.3607	0.3607
Controls	Yes	Yes	Yes	Yes
Birth Place Fixed Effects	Yes	Yes	Yes	Yes
Birth Time Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents estimates of difference-in-differences using the outcome variable 'Functional Disabilities' based on data from births between 2005 and 2012. Column (1) represents the effect of binary treatment variables, while column (2) depicts flood extent categorized as 0, 1, and 2. Column (3) uses the proportion of the population affected within a district and column (4) employs the proportion of the area affected within the district. Control variables include gender, area (urban/rural), migration, the interaction of the 2011 flood with affected districts, flood risk to the districts, and mean elevation in kilometers. The regression model includes time-fixed effects consisting of month- and year-fixed effects, and area-fixed effects accounting for province, division, and district-fixed effects. Standard errors, reported in parentheses, are clustered at the district level, and p-values testing the null hypothesis of a zero treatment effect are presented in brackets.