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MASTER THESIS

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GLODEP 2024

Quantitative Analysis of the Effects of Floods in Nepal

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DECLARATION

I, Subina Thapaliya, hereby declare that this master's thesis titled "Quantitative Analysis of the Effects of Floods in Nepal" is the outcome of my work. All works related to conducting research and writing the content to prepare this thesis report are my initiatives and efforts.

I confirm that I have duly cited and referenced all sources of datasets and information—different data repositories, academic literature, and other relevant secondary sources—to acknowledge their utility in my research. Additionally, I have acknowledged any intellectual support received throughout the process.

I, therefore, declare my academic integrity and take full responsibility for the content of this thesis.

Subina Thapaliya
Date: 28 May 2024

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Declaration of honour on the use of AI

During the writing of the submitted thesis, I used the following AI tools, ChatGPT and Grammarly to check for grammatical errors. After using this AI tool, I declare that I have reviewed and edited the text and I take full responsibility for the content of the submitted thesis.

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Zásady pro vypracování

Every year monsoon floods and landslides cause immense economic loss and human fatalities in Nepal (Sharma et al., 2023, NDRR Portal, 2024). This research paper aims to study the relationship between damages caused by floods and landslides and factors of marginalization, such as income level and caste/ ethnicity in Nepal. Marginalization refers to the social process of restricting the access of certain groups of people to opportunities, rights, and resources in the society. The enduring social effects of traditional practices like untouchability, along with other caste-based social exclusions, which are now illegal, make caste/ethnicity as equally relevant and important a marginalizing factor as income level in the context of Nepal (Bhattachan et al., 2009). The literature review on floods and landslides-related studies in Nepal shows a gap in the study of heterogeneity in those disasters-related damages across different income levels and caste/ ethnicity. Therefore, this study aims to address the existing gap in the floods and landslides-related literatures in Nepal.

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I dedicate this academic milestone to my late grandfather, Tika Dutta Thapaliya, who would have been the proudest person to celebrate my pursuit of knowledge and my voyage around the world in this process. Thank you for empowering me with your eternal love and blessings.

ABSTRACT

A primary objective of this research is to contribute to addressing the existing gap in the literature related to the assessment of the effects of floods in Nepal. There are very few works of literature on the household-level economic impact assessment of flood events in Nepal, and those that exist are geographically limited to the river basin, municipality, or village level. Using the nationally representative data from the Household Risk and Vulnerability Survey-Panel conducted by the World Bank, I studied the effects of direct exposure to 2017 flood events in Nepal among households in the rural and urbanizing areas of the Terai belt of Nepal. This research employed descriptive statistics, logistic regression analysis, and difference-in-difference methodology as empirical approaches to assess the impacts on economic outcomes related to crop production, income, and assets. I found that effects from direct flood exposure were larger on total paddy production and value, followed by total income compared to the effect on the household assets. The findings from this research imply that households relying on subsistence agriculture were the most affected group by direct exposure to the 2017 flood in rural and urbanizing areas of the Terai belt of Nepal.

Keywords: climate change, Nepal, Terai, monsoon floods, economic effects, household-level assessment

Table of Contents

List of Tables

List of Figures

List of Abbreviations

GDP	Gross Domestic Product
GoN	Government of Nepal
HRVS-Panel	Household Risk and Vulnerability Survey-Panel
ICIMOD	International Centre for Integrated Mountain Development
masl	Meters above sea level
MoHA	Ministry of Home Affairs [Nepal]
NASA	National Aeronautics and Space Administration
NPR	Nepalese Rupees
NPC	National Planning Commission [Nepal]
PSU	Primary Sampling Unit
SAR	Synthetic Aperture Radar
WBG	World Bank Group
USD	United States Dollar

CHAPTER 1: INTRODUCTION

1.1 Background

South Asia, which is already home to some of the world's most vulnerable populations (World Bank, 2012), faces a significant livelihood threat due to climate change. By the end of the century, countries in the South Asian region are estimated to undergo significant losses in GDP per capita from climate change, Bhutan (18%), Nepal (13%), India (10%), and Pakistan (10%) (World Bank, 2021). This loss in GDP per capita is above the anticipated global average of approximately seven percent (Kahn et al., 2021). Climate change-induced weather anomalies are likely to sharply decrease the quality of life of more than 800 million people in the region (Mani et al., 2018). These vulnerable populations are currently living in areas that are mostly disadvantaged and projected to be (moderate or severe) climate hotspots[1] by 2050[2] (Mani et al., 2018).

Floods are among the key climate change hazards affecting lives and livelihoods in the South Asian region (World Bank, 2012). The region is home to 64% of the flood-affected population in the world (World Bank, 2012). From 1970 to 2010, floods accounted for 80 percent of disaster-related economic loss and 82 percent of the disaster-affected population in South Asia (World Bank, 2012). Recently, Pakistan went through a disastrous flood that affected 33 million people, causing 1,730 deaths and economic losses equivalent to USD 15 billion (World Bank, 2022).

Like other countries in the region, every year, Nepal faces immense economic loss and human fatalities caused by monsoon floods (A. P. Sharma et al., 2023). The country has undergone a six-fold increase in flood frequency and a four-fold increase in flood-related human fatalities post-2000s compared to the 1970s (A. P. Sharma et al., 2023). Nepal ranked 10th on the climate change-related flood risk on the Global Climate Risk Index from 2000 to 2019 (Eckstein et al., 2021). During the last decade (2011–2020), an annual average of 196 events, 90 deaths, and 6,500 affected families were recorded for floods on the Nepalese government's disaster risk reduction portal (A. P. Sharma et al., 2023). While these country-level aggregated statistics provide us with an overview of the disaster effect, they lack a comprehensive understanding of the overall impacts on lives and livelihood (Hallegatte et al., 2016).

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[1] In this context, hotspots are the places where people are vulnerable to face a decrease in their living standard due to weather anomalies (Mani et al., 2018)
[2] This projection is under the carbon-intensive scenario.

There are very few existing works of literature on the household-level economic impact assessment of flood events in Nepal. Those assessments have limited geographical coverage i.e., focusing on the river basin, municipality, or village level (Bista, 2022; Pradhan et al., 2007), and none of them have been done using a nationally representative (panel) dataset. Originally, as mentioned in the Thesis assignment (*zadání diplomové práce*) in the preface, I intended to address this gap in the existing literature not only for floods but also for landslides.[3] I also aimed to analyze the heterogeneity of these disasters' effects across different income levels and caste/ethnic groups in Nepal. However, because of the time constraint, I limited my study to the flood events and analyzed the effects across the affected households in general. Another notable gap in flood-related studies in Nepal, particularly on monsoon and riverine floods, is the limited use of remote-sensing data (T. P. P. Sharma et al., 2019).[4] I have used the flood inundation maps prepared by the International Centre for Integrated Mountain Development (ICIMOD) based on satellite data to identify the households located in the flood-affected areas.

A primary objective of this research is to initiate and contribute to addressing the existing gap in the literature related to the assessment of the economic effects of floods in Nepal. This research aims to analyze the direct effect of the 2017 flood events in Nepal on the economic outcomes—related to crop production, income, and assets—at the household level. Given the relevancy and data availability, the focus of this research is on the rural and urbanizing areas in the Terai region of Nepal.

1.2 Research Questions

The guiding question for this research is:

1. What were the household-level effects of the direct exposure to 2017 flood events on the economic outcomes related to production, income, and assets?

The analyzed economic outcomes encompass:

a) Paddy production in the wet season and its value
b) Total income along with different categories of income, such as income from the crop (wet season, dry season, and total), livestock revenue, and income from wage employment (total and from daily wage)

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[3] Every year monsoon rainfall causes several flood events in the Terai region of Nepal and landslides in the Hill region of Nepal, both causing immense economic losses and human fatalities (MoHA, 2024)
[4] Note that in the context of Nepal, the use of satellite data for studies related to Glacial Lakes Outburst Floods is widely prevalent, but its use in monsoon floods-related studies is limited.

c) Value of total assets and their components such as home, land, livestock, financial assets (saving, cash in hand), and durable goods

I have separated the main guiding questions into the following sub-questions:

a. For each economic outcome, what was the share of complete loss among households who faced direct exposure to the 2017 floods? How did those shares vary among the households living in the flood-affected area but not being directly exposed?

b. How did direct flood exposure affect the probability of completely losing the economic outcomes among the flooded households?

c. How did direct flood exposure affect the partial loss of economic outcomes among the flooded households?

1.3 Significance of the Study

This research is an important initiation and addition to the existing body of literature related to flood studies in Nepal, which has been dominated by descriptive statistics. The economic losses incurred due to floods are often aggregated at larger geographical levels, and hence they are not able to provide a comprehensive understanding of the effects of floods on livelihoods (Noy et al., 2021). Particularly, when floods affect poor households, the economic loss they incur tends to be overlooked when data is aggregated at the village, district, or national level. Despite their low significance observed in macroeconomic analyses, the livelihood effects are very severe in such cases (Botzen et al., 2019; Hallegatte et al., 2016). Therefore, for a comprehensive understanding of the effects of floods, it is very crucial to have an understanding of household-level effects. This research adds an important insight into the household-level effects of the 2017 flood events in Nepal. This type of comprehensive understanding enables formulating efficient policy responses and targeting them to the households and sectors that are in most need of support for post-flood recovery.

1.4 Thesis Structure

The rest of the paper is organized as follows. Chapter 2 provides the study context along with a comprehensive literature review of studies related to the economic effects of flood events in Nepal and briefly describes such literature in the global context. Chapter 3 presents the data sources and describes the data and methodologies used for the empirical analysis in this research. Chapter 4 includes the results, presented as both descriptive statistics and causal inferences, along with robustness tests, a discussion of the findings, and the limitations of this research. Finally, Chapter 5 provides the conclusion of the research and suggests the prospects for future studies on the related topics.

CHAPTER 2: CONTEXT AND LITERATURE REVIEW

2.1 Study Context

2.1.1 Country Profile and Development Context

Nepal is about to graduate from the United Nations' least developed country status in 2026 (United Nations, 2024). The country made some notable progress in poverty reduction in the last few decades, reducing the official poverty rate from 46.1 percent in 2003/4 to 15 percent in 2010/11 (World Bank, 2019). With an average GDP growth of 4.9 percent in the 2010s, Nepal attained the lower-middle income country status in 2020 (World Bank, 2021). Despite facing major economic shocks at the country level, such as multiple earthquakes with high magnitudes in 2015 followed by the economic blockage from India in 2016, Nepal reduced its multidimensional poverty rate from 30.1 percent in 2014 to 17.4 percent in 2019 (NPC, 2021). However, natural and climate change-induced disasters are lingering threats to this decade-long progress in poverty reduction (World Bank, 2021). About 80% of the country's population faces the risk of these hazards (MoHA, 2018). Overall, Nepal has improved its disaster risk situation moving from the overall rank of 31st to 65th position (as the at-risk country) among 191 countries from 2019 to 2024 (European Commission, 2024). The overall risk score (on a scale of 10) for Nepal decreased from 5.4 to 4.1, with a reduction in the score for Lack of Coping Capacity from 5.8 to 5.4 and for Vulnerability from 4.7 to 4.1 (ibid). However, the score for the riverine flood increased from 6.7 to 6.9 during the same period (ibid).

2.1.2 Climate Change and Floods in Nepal

Floods are among the frequent as well as destructive hazards in Nepal (World Bank, 2021). Additionally, the global climate change pattern is likely to increase the frequency and intensity of floods (WBG, 2022). Climate change models predict that Nepal will undergo higher warming than average global warming (World Bank, 2021). Under the RCP8.5 emissions pathway, on average there will be a 1.2°C to 4.2°C temperature rise in Nepal by the 2080s compared to the baseline period 1986–2005 (World Bank, 2021). Because of these weather anomalies, studies have anticipated a three-fold increase in the economic effect of riverine flooding, doubling the size of the flood-affected population by 2030 (World Bank, 2021). The floods that were historically 1 in 100-year events are likely to become 1 in 50-year or 1 in 25-year events by 2030 (World Bank, 2021). The existing research results claim that under the RCP8.5 emissions pathway, in the next 20 years, the riverine floodings could annually affect

199,000 population, costing USD 574 million to the country's GDP (World Bank, 2021). These projected consequences are under the isolated effect of climate change, without taking into account population or infrastructural growth. Under this climate change scenario, Nepal will lose 3.5 percent of its GDP and 1.6 percent of its private consumption to flooding by 2050 (WBG, 2022).

Nepal faces different categories of floods depending on the triggering mechanisms associated with a) continuous rainfall and cloudburst b) glacial lakes outburst c) landslide dam outburst d) infrastructure failure e) obstructed flow of the water bodies (Khanal et al., 2007; NPC, 2017). Glacial Lakes Outburst Floods (GLOFs) and riverine floods triggered by heavy monsoon rainfall are the major flood categories that are at risk of worsening because of climate change-induced weather anomalies (Bajracharya et al., 2020; Mool et al., 2011; A. P. Sharma et al., 2023; World Bank, 2021). Although the historical and present share of GLOFs on flood-related loss and damages in Nepal has been low (MoHA, 2024), GLOFs pose a significant threat to lives and livelihoods in the future (A. P. Sharma et al., 2023). This prediction is supported by scientific models showing that Himalayan glaciers will undergo 29% mass loss by 2035 and between 15% and 78% mass loss by 2100 (T. P. P. Sharma et al., 2019) (Jiménez Cisneros et al., 2014). The scope of this research, however, is limited to the monsoon floods in the Terai region of Nepal, which so far comprise the majority of flood occurrences as well as damages in Nepal (MoHA, 2024; T. P. P. Sharma et al., 2019).

Nepal faces most of the flood events in the monsoon months of July and August when the rainfall exceeds 45% of annual precipitation (T. P. P. Sharma et al., 2019). Nepal also receives 80% of its total annual precipitation between June and September (T. P. P. Sharma et al., 2019). This percentage share is even greater (84%) for the southern Terai belt than the national average (Jacoby & Walker, 2019). Terai region, the northern extension of the Indo-Gangetic plain, extends between the altitude of 60 m to 300 m above sea level and covers 13% of the country's total territory (Khanal et al., 2007). Monsoon—an important factor for agricultural productivity when it brings rainfall in the right amount—often comes in a destructive form in this region (NPC, 2017). Between 2011 and 2020, the districts in the Terai region were the most flood-affected in the country (A. P. Sharma et al., 2023).

2.1.3 Nepal Flood 2017

The torrential monsoon precipitation from August 11th to August 14th of 2017 caused flooding across the Terai belt of Nepal as seen in Appendix 1 (NPC, 2017). The rainfall was the heaviest precipitation recorded in the last six decades for most of the affected districts (NPC, 2017) Thirty-five out of the country's seventy-seven districts were affected by this flood (T. P. P. Sharma et al., 2019), resulting in the inundation of 80% of the Terai region (NPC, 2017). The 2017 flood damaged more than 190,000 houses, leaving 1.7 million people affected (ibid). 179 people died (T. P. P. Sharma et al., 2019) and tens of thousands of people were displaced (NPC, 2017). Excluding the household-level losses, the country faced economic damages worth USD 584 million (NPR 60,716 million), amounting to 3% of Nepal's GDP (ibid). The sector with the highest share of economic loss was housing (USD 375. 8 million) followed by irrigation (USD 168.1 million) and agriculture (USD 61.6 million) (ibid). Despite households bearing the most important share of economic losses (ibid), the existing literature has not assessed the household-level impact. The damage assessment related to the 2017 flood has been limited to descriptive statistics, aggregated at the district, provincial, or national level (T. P. P. Sharma et al., 2019; NPC, 2017).

The 2017 flood was an additional economic shock for the affected areas, amid the recovery phase of the entire country from two major economic shocks i.e., earthquakes in 2015 and the 2016 blockade from India (Walker et al., 2019). Indeed, Nepal experienced multiple earthquakes in April and May 2015, the largest magnitude (7.6 Richter scale) of which was the strongest since 1934 (NPC, 2015). The earthquakes resulted in around 9,000 human deaths along with economic losses worth NPR 706 (USD 7) billion (ibid). Following the earthquake, at the end of 2015 and early 2016, India imposed an economic blockade, stopping the supply of commodities, most importantly, food and fuel, across the border (Walker et al., 2019). For a landlocked country, with India being only one major gateway for import, the blockade had a huge economic impact nationwide. Hence, the 2017 flood was an added burden while households were still recovering from those major shocks.

2.1.4 Flood-related Vulnerability

In the context of Nepal, the economically disadvantaged people who are engaged in subsistence agriculture and living in rural and remote areas are among the most vulnerable populations to disasters (World Bank, 2021). In 2015, about 69% of the country's workforce was employed in subsistence and small-scale agriculture (World Bank, 2021), however, agriculture accounted for only 30% of the country's GDP (NPC, 2017). Rural populations face economic hardship due to less diversified livelihood options (Dixit et al., 2007). Therefore, poverty in Nepal is concentrated in rural areas, where around 33% of people face multidimensional poverty (World Bank, 2021).

Rural agricultural households relying on subsistence farming in the lowlands of Terai are among the most vulnerable populations exposed to floods in Nepal (Amadio et al., 2023). The Terai region, where 70% of the population is dependent on subsistence farming, hosts a large share of the country's population living below the poverty line (NPC, 2017). Given the low elevation i.e., below 300 masl of land, this region is also more susceptible to flooding than the Hill and the mountain region. Indeed, Terai is home to the majority of flood-exposed households in the country (Shreevastav et al., 2021; World Bank, 2021). Some 2017 flood-affected districts in the Terai belt are ranking particularly low on the Human Development Index (NPC, 2017). These households that are already facing issues such as food insecurity and poor nutrition are vulnerable to any damage to livelihood from floods (NPC, 2017). Given that the Terai region of Nepal was the most affected area by the 2017 floods and is home to the most vulnerable populations, I have focused this research on the Terai region.

2.2 Literature Review

2.2.1 Economic Effects of Floods in Nepal

This study used the scoping methodology for a literature review to find the existing scope and findings from the literature related to the economic effect of floods in Nepal. I used Google Scholar and SCOPUS as the two primary search databases, inserting keywords such as 'Flood Nepal Economic Effect.' The search in these databases was limited to peer-reviewed articles. Additionally, the Google search engine was used with the same keywords, and some of the reports from the World Bank and the United Nations Development Program (UNDP) were also used for a comprehensive literature review.

The articles sorted in Google Scholar and SCOPUS were first screened for relevancy based on their titles. Then a thorough review of the abstracts and conclusions was done for the shortlisted articles. Then, I used the selected articles to find other relevant articles, using the forward and backward citation tracking processes. Google Scholar was used to track the articles citing the selected papers, and the reference sections of the papers were used for the backward citation analysis. Few more relevant articles were obtained through this process.

The selected papers were then categorized based on the types or scopes of flood impact assessment such as future impact assessment, assessment of past floods using descriptive statistics, assessment at the national level, provincial level, or household level, assessment at the national level in the South Asian regional context, and so on. The literature review table below (Table 1) consists of the articles representing all the categories found during the review process. Thus, following the above-mentioned methodology, a comprehensive literature review was completed to find the scope of the existing literature and detect the literature gap.

Table 1: Literature review on economic effects of floods in Nepal

Author, Date	Period	Cases of study	Method	Findings
(Bista, 2022)	2009–2015	Sot Khola water basin, Nepal	Gini coefficient method to determine the income distribution effects of floods and landslides in the affected community	Natural disaster further exacerbates income inequality and poverty as disaster loss and damages disproportionately affect the socio-economically vulnerable groups.
(Delalay et al., 2020)	N/A (Future potential impact assessment)	A section of the Koshi (River) basin in Sindhupalchowk district, Nepal	Flood risk assessment model under low-exposure and high-exposure scenarios	In both high and low exposure scenarios, the economic loss emerges from the loss of income and customs revenue due to damage to the road, and high exposure will also lead to substantial damage to planned hydropower projects.
(Perera et al., 2015)	2007 and Future	West Rapti River, Nepal	Future damage assessment through flood inundation simulation, hydrological modeling, and field survey data	Compared to the flood damages from the baseline period of 2007, the model predicts an increase in the intensities and frequencies of floods. Furthermore, the flood-related potential damages on household livelihood and agriculture are projected to increase respectively by 1.80 and 1.95 times at "Present" and by 2.40 and 2.27 times between 2075-2099.
(Shrestha, 2019)	1971-2016	Provincial and country-level, Nepal	Aggregated summary statistics of damages from natural and human-induced hazards at the national and provincial level	The frequency and the economic losses from disasters showed an increasing trend for the study period. Floods were among the top disasters in terms of the occurrence and also economic damages.
(& Adhikary, 2019)	1971 to 2017	Country-level, Nepal	Summary statistics on damages and loss aggregated at the national level	On average the economic damages from natural disasters as a percentage of GDP remained at 0.85% between 1981 to 1991, 5.07% between 1992 to 2002, and 3.91% between 2003 to 2013. Disasters combined with political disruptions lead to a negative effect on the economy of the country.
(Yogacharya & Gautam, 2008)	1983 to 2006	Country-level, Nepal	Summary statistics on damages and loss aggregated at the national level	Within the study period, the decreasing trend in human casualties and the increasing trend in economic damages were found. The 1993 flood event causing the death of 1336 people accounted for 87% of total deaths for the year and was the most destructive flood.
(Parajuli et al., 2023)	2021	Melamchi Municipality and Helambu Rural Municipality, Nepal	Descriptive statistics on the loss and damages faced by households and also aggregated at the municipality level	The recovery needs for the affected population exceed 10 folds of the flood-affected municipalities' annual budget.

(A. P. Sharma et al., 2023)	1971–2020	District level, Nepal	District-wise summary statistics and data visualization on the flood loss	After the 2000s, there has been an increase in flood events by six times and flood-related deaths by four times compared to the 1970s.
(Pradhan et al., 2007)	1993	Sarlahi district, Nepal	Descriptive statistics comparing the pre and post-flood data from around 7000 households	Flood-related fatalities were higher among the socio-economically marginalized population groups i.e., children and poor households that have thatched roofs.
(National Planning Commission, 2017)	2017	Country-level, Nepal	Summary statistics on the aggregated loss and damages	2017 flood events incurred economic loss worth USD 584.7 million, which comprises 3% of the country's GDP. The sector with the highest share of economic loss was housing (USD 375. 8 million) followed by irrigation (USD 168.1 million) and agriculture (USD 61.6 million).
(Dixit et al., 2007)	1950 to 2007	Nawalparasi and Rautahat district, Nepal	Ethnographic and historical assessment of flood-related damages along with assessment of disaster risk reduction and adaptation programs	Inadequate measures from the government and concerned parties for flood risk and damage reduction.
(Kafle, 2020)	1983 to Present	Koshi, Kamala, Narayani, West Rapti rivers, Nepal	Multi-criteria decision-making (MCDM) model and Shannon Entropy Method for comparative study on loss and damages among the studied river basins	Floods in the Koshi River had undergone the most economic losses and damages in comparison to other studied rivers.
(Dewan, 2015)	1984 to 2007	Nepal and Bangladesh	Review of secondary resources to synthesize the vulnerability, damages, and resilience, along with policy recommendation	Nepal and Bangladesh have historically faced huge economic and livelihood losses from floods. The existing efforts on disaster preparedness and mitigation in both countries are not enough, and there is a need to integrate traditional and indigenous knowledge and practices to cope with the disaster.
(Elalem & Pal, 2015)	1981 to 2013	Hindu-Kush Himalaya region	Macroeconomic descriptive statistics on loss	In the Hindu-Kush Himalaya region, Pakistan, Afghanistan, and Nepal face high economic losses from floods, and Bangladesh, Pakistan, Bhutan, and India face the most human impacts.

Source: Author's compilation based on the literature review

As noted above in the literature review table, the existing literature on the assessment of the flood-induced effects in Nepal is concentrated on summary statistics of aggregated loss at the district, provincial, or national level. While such statistics estimate the economic cost in general, they can neither capture the comprehensive effects on livelihoods nor inform how the effects are distributed across different groups of populations based on income level and other socio-economic aspects (Noy et al., 2021). Although few studies in Nepal have conducted household-level flood impact assessment (Bista, 2022; Pradhan et al., 2007), the geographical coverage is limited to the river basin, municipality, or village level. Furthermore, the studies analyzing the causal impact of the flood are almost non-existent.

2.2.2 Relevant Literature in the Global Context

There is long-standing literature that has studied the effect of natural disasters on economic outcomes using theoretical and empirical models (Botzen et al., 2019). However, the studies using macroeconomic data such as GDP to study the disaster's effect at the country level dominate the literature (Botzen et al., 2019; Felbermayr & Gröschl, 2014; Noy, 2009). Results from the recent literature have shown the importance of studying the economic impact of disasters at the disaggregated level to understand the localized impacts (Felbermayr et al., 2022). Particularly, such disaggregated household-level impact assessment is important for low-income countries, as they experience 90% of natural disaster events (Klomp, 2016), and the effects on household-level livelihood effect are very severe (Hallegatte et al., 2020). Poor people are disproportionately exposed to floods within countries in the Global South (Patankar, 2015; Winsemius et al., 2018). Although the livelihood, income, and assets of these households are severely affected, the economic share of such effects barely gains any weight in aggregated statistics (Botzen et al., 2019; Hallegatte et al., 2016). Hence, to assess the true livelihood impact of floods, it is crucial to study the effect on economic outcomes at the household level in low-income countries.

While there is little existing literature on the household-level impact assessment of floods, studies have mostly found an overall negative effect on economic outcomes such as crop production (Del Ninno et al., 2001; Djoumessi Tiague, 2023; McCarthy et al., 2018), income (Erman et al., 2020; Patnaik et al., 2019), and assets (Del Ninno et al., 2001) at the household level. However, as the localized flood impact is highly context-specific, the findings when compared across different flood events are rather nuanced. For example, Djoumessi Tiague (2023) analyzed the effects of two different floods in 2009 in Tanzania and found a 34% decrease in the value of crop production for households in flood-affected areas. This finding by Djoumessi Tiague (2023) implies a significant effect on income for agricultural households relying on farm income. Whereas Noy et al. (2021) found that the negative effect on the income among the flood-affected households was driven by the loss in business income while analyzing the effects of Thailand's 2011 floods. In the case of this flood event in Thailand, middle and high-income households faced significant negative effects, whereas the effect was statistically insignificant among poor households (Poapongsakorn & Meethom, 2013). Additionally, the findings are not only nuanced for different flood events but also for the same flood event when analysed at different disaggregated economic outcomes and for different timeframes. For example, McCarthy et al. (2018), during their study of the effects of the 2015 flood events in Malawi, found an increase in per capita calorie intake, but a decrease in dietary diversity. Additionally, Patnaik et al. (2019) found that food consumption sharply increased immediately after the flood event in Chennai, India but the effect reversed a year later. These nuanced findings in the global context further emphasize the importance of filling in the existing research gap in the studies on the economic effect of floods in Nepal to get a comprehensive understanding of the impact at the household level.

This research has been conducted with inspiration from the existing literature on the effects of floods on economic outcomes at the household level in the global context. It aims to build on the research done by Noy et al. (2021) and Djoumessi Tiague (2023) along with other similar literature by (Bangalore (Forthcoming), Morshed et al. (2022), McCarthy et al. (2018), Karim (2018), and Poapongsakorn & Meethom (2013). Like in the rest of these papers except for Karim (2018) and Morshed et al., (2022), this research paper uses panel data, which is yet to be well represented among the existing literature on this type of study (McCarthy et al., 2018). Two of the mentioned studies closely related to this research are the flood impact assessment in Thailand (Noy et al., 2021), and Tanzania (Djoumessi Tiague, 2023).

CHAPTER 3: METHODOLOGY

3.1 Data

3.1.1 Household Risk and Vulnerability Survey-Panel

3.1.1.1 Survey Description

I used the Household Risk and Vulnerability Survey-Panel (HRVS-Panel) for economic outcome variables such as income, assets, and production, along with the socio-economic characteristics of households (World Bank, n.d.a). The survey was nationally representative and conducted in 50 out of the 77 randomly selected districts of Nepal (WBG, 2016). A random cluster of 400 Primary Sampling Units (PSUs) was selected to represent the rural and urbanizing Village Development Committees (ibid).[5] The sample size is 6000 households, 15 households per PSU (ibid). The same households were surveyed across three waves: Wave 1 in 2016, Wave 2 in 2017, and Wave 3 in 2018. The interviews were conducted between June and August for all three waves.

The survey timing coincided with the period of seasonal monsoon rainfall i.e., June to September. The field visit for the Wave 2 Survey was between 12th June to 14th August 2017. Following the completion of the Wave 2 survey—in the week of 11th August 2017—Nepal experienced the heaviest rainfall of the last 15 years, causing floods in the Terai belt (WBG, 2018). The mean rainfall for 2017 was 1800 mm, exceeding the average of 1200 mm for the recent past years (NPC, 2017). Although the flood damaged 190,000 houses and affected 1.7 million people (NPC, 2017), the surveyed households did not include much of the 2017 flood-affected households. The additional inquiry from the survey team concluded that the sampled areas did not cover the flood-affected area (Walker et al., 2019). However, 105 households out of 6051 households surveyed in the Wave 3 reported being flooded in 2017. Although several households faced displacement from the 2017 floods, the survey for sample households used in this research did not have the issue of attrition, as described in section 3.2.[6] Most of the households that reported being flooded experienced flooding in August, followed by that in September, and quite a few households reported being flooded, in the months before and after this period as well.

[5] The HRVS-panel survey excluded urban areas and no locations from the Kathmandu Valley (Kathmandu, Bhaktapur, and Latipur) were included in the survey cluster selection.
[6] Additionally, for an overall 6000 households, the retention rate across all three waves was 94% (Walker et al., 2019).

Despite the limitation of not having the majority of flood-affected households in the survey sample, this research is relevant and important for the following reasons: 1) the existing research gap studying the household-level economic effects of floods in Nepal 2) very rare availability of nationally representative panel dataset for household surveys 3) rare coincidence of the availability of panel dataset that has data right before and after the major flood event in the country 4) a survey including data on economic outcomes such as production and income for one year recall period 5) the number of flood-affected households still being considerable to allow the use of econometric analyses.

3.1.1.2 Flood Measure

Section 15 of the HRVS-panel household questionnaire asks, "In the past 24 months, has your household experienced any of the following shocks?" (World Bank, n.d.b). The module consists of a list of 21 different economic shocks (Appendix 2). All shocks reported in wave 3 were within the past 12-month period. Since wave 2 survey interviews ended in August 2017 and wave 3 survey interviews started in June 2018, wave 3 captured the households who reported being flooded by the 2017 monsoon flood. The shock module also contains other relevant questions providing further details such as the loss in income or assets from the shock, coping mechanisms used by households to deal with the shock, and so on.

3.1.1.3 Data Cleaning and Variables Construction

The data from the HRVS-panel survey were not readily present in the form that could be used for the analysis (i.e., at the household level). I used STATA to clean up and prepare the dataset for the analysis. The cleaning of the dataset was done for all the observations i.e., 6000 households, before extracting the sample used in the analysis. All the relevant datasets and the codes used for the data cleaning and analysis are published as supplemental materials along with this thesis report.

To construct the outcome and interest variables, the following stated processes were completed using STATA. The variable measuring income from crops in the wet season, which was initially disaggregated by types of crops, was aggregated at the household level. A similar process was followed for the income from crops during the dry season. Then, the two variables were summed up to construct the total annual household income made from selling the crops.

For calculating the household income made from the daily wage jobs, the observations for income from different jobs for each household member were aggregated. Then this variable was summed up with the household level income made from long-term jobs, and contracts, together with the bonus and other extra income—all of which were made by aggregating the values initially disaggregated by jobs—to construct a variable measuring the overall household income from the wage employment. These two variables, income from crop and wage employment, were then combined with the rental income and revenue from livestock and non-agricultural enterprises to construct total household income generated from all sources.

In the case of assets, I aggregated cash, savings in banks and cooperatives, fixed deposits, stocks, shares, treasury bills, employee provident fund/citizen investment fund, and life insurance, to form a total financial asset variable. Then, the financial asset variable was merged with the variables measuring values aggregated at the household level for land (initially disaggregated by plots), home, owned livestock (initially disaggregated by livestock IDs), and durable goods (initially at disaggregated form), to create the variable for the total household assets.

In the case of the production, I only selected paddy production in the wet season for the analysis. The scope of this research is limited to the Terai region of Nepal, where the wet season cultivation is paddy intensive. During the wet season, 95% of the total land area cultivated by the surveyed households in the Terai region was used for paddy production (Jacoby & Walker, 2019). This high dominance of paddy cultivation in the wet season is due to the high dependency of paddy cultivation on monsoon rainfall (Jacoby & Walker, 2019). The quantity of paddy harvest in the dataset was recorded in different units of measurement such as Maund, Muri, and Pathi, as local units vary across different parts of the country. I converted the measuring units to kilograms based on the unit conversion method mentioned in the survey report (WBG, 2016). In the case of the unit selling price of paddy, there were a few missing and unrealistic values. For example, in the case of survey wave 2, the range of paddy price per kg was NPR 14 to NPR 102, except for two values one in the lower end (NPR 0.36) and another in the higher end (NPR 2000). Those values may be because of errors in data entry or data records. Given that other geographical locations near these two PSUs had the unit price of paddy within the range, it is unlikely that those observations were true. The unit selling price of the crop was presented at the PSU level so few missing values would create a significant number of missing values at the household level. Therefore, these values were replaced by the mean value. The mean value was calculated at the district level since it was the next greater geographical aggregation reported in the survey, and within the district, the unit price for paddy can be assumed to be quite similar. For generating the variable on the production value, the product of the quantity and selling price per kg was calculated.

Just like for the unit selling price for paddy, all the values in the dataset used for constructing the outcome and interest variables were checked for unrealistic values[7], starting from its most disaggregated form to the final household-level aggregated values. In most of the cases, the unrealistic observations were simply omitted by household IDs[8]. This is because the observations of such values were rare, with less than 10 observations even at the disaggregated levels in the overall dataset of 6000 households. In the sample households of this research, very few observations were missing. The highest number of missing observations was 13 for the variable total income out of 2,166 observations, across all three survey waves. Only for two variables, the value of livestock and the price of paddy per kg (as explained above), the unrealistic and missing values were replaced with the mean values. For the value of livestock, the mean price per unit of livestock was generated by livestock type and district. Then, the product of that unit value and the number of livestock was used to replace the unrealistic values. The definitions of all the variables used in the analysis are presented in a table in Appendix 3.

3.1.2 Flood Inundation Map

Another data source used in the paper is the flood inundation map for the 2017 flood in Nepal. The data has been generated by the International Centre for Integrated Mountain Development (ICIMOD)[9], using Sentinel-1 synthetic aperture radar (SAR) images for 2017, and made openly available for public use (ICIMOD, 2017a, 2017b, 2017c, 2017d). ICIMOD has leveraged the availability of the European Space Agency's (ESA) Sentinel-1 C-band SAR, which is open access data, to monitor the extent of floodings in South Asian countries (Uddin et al., 2019). Unlike optical images from MODIS or Landsat, SAR data is not dependent on solar illumination or atmospheric conditions and hence, it is possible to collect data at night or with cloud coverage (NASA, 2021). This feature is very important for inundation mapping in Nepal as the cloud coverage is high during the monsoon months or flooding season in the South Asian region (Uddin et al., 2019). The limitation of SAR data, however, is that it cannot differentiate well between water and snow/ice (NASA, 2021). In this case, the inundation mapping is done

[7] Note that unrealistic value does not mean extreme values or "outliers". Just like in the case of the unit selling price of paddy, the value that is very far from what could exist (given the context of the country) and is possibly a result of a data entry error is treated as an unrealistic value. Also, I cleaned the data for the entire sample of 6000 households and given that there were very few values across all three survey waves that had to be discarded, none of them might have been part of the sample households used for this research. It was the initial part of the data quality check.

[8] If one value for the household was detected as unrealistic, all the observations for the household for that variable were omitted.

[9] ICIMOD is an intergovernmental research organization in Hindu Kush Himalaya region–Afghanistan, Bangladesh, Bhutan, China, India, Myanmar, Nepal, and Pakistan. It is one of the leading organizations, contributing to research on the livelihoods, environment, and culture in the region.

for the Terai belt which does not have snow or ice coverage. I obtained four raster files that mapped the inundated area on the 11th, 13th, 16th, and 21st of August 2017 from the ICIMOD data repository (ICIMOD, 2017a, 2017b, 2017c, 2017d). The data has been used to construct the counterfactual for the treatment group. A detailed approach to the construction of the control group is explained in the following section.

3.2 Treatment and Control Groups Construction

I used the self-reported shock data from HRVS-panel wave 3 to construct the treatment group, i.e., the households who reported experiencing the 2017 flood. The research on the economic impact assessment of floods often uses either self-reported flood exposure (Karim, 2018; Morshed et al., 2022; Patankar, 2015) or satellite data on flood inundation intersected with the household GPS (Djoumessi Tiague, 2023; McCarthy et al., 2018; Poapongsakorn & Meethom, 2013) to measure a flood exposure. There are pros and cons associated with both of these methods.

Some concerns expressed in the literature on the flood measure using self-reported data are questionnaire framing or wording, recall bias, and strategic (false) reporting (Bangalore, Forthcoming). In the case of this research, the question asked in the survey is clear and explicit to determine if the households have experienced the flood shock or not (refer to Appendix 2). Since the period to recall the exposure to the 2017 flood events was less than a year, we can also eliminate the second bias. The third bias about false reporting refers to a situation in which households strategically report being flooded to receive potential relief funds or other benefits directly tied to the flood. This misperception is less likely to happen as the households had gone through Wave 1 and Wave 2 surveys in the preceding two years. Furthermore, given the extensive[10] scope of the survey with hundreds of inquiries on diverse topics, as well as 21 different types of shocks listed in the module, the strategic false reporting is unlikely (Bangalore, Forthcoming).

In the case of satellite data, although it can be a reliable objective way to identify flood-affected areas, its accuracy and reliability are questionable when it comes to identifying household-level exposure. First, within the same neighborhood, a household might be directly affected by a flood event while the neighboring household remains unaffected (Patankar, 2015). Therefore, the polygon of flooded areas, created by using satellite data, might not accurately reflect the

[10] The questionnaires comprise 16 sections categorized as education, health, housing and access to facilities, wage jobs, farming and livestock, credit, savings, financial assets, shocks, and so on (WBG, 2016).

flood experiences at the household level. Additionally, the self-reported measure can capture a wider range of ways households might have experienced the effects of a flood than simply by having inundation inside or near their houses (Erman et al., 2020). For example, a household might have agricultural land in the flood-affected area but might be living in a neighbourhood that was not inundated. In this case, the satellite data will not capture this household despite facing a direct flood effect as a flood-affected household. Second, the inundated area mapped using different satellite data sources can produce different results (Tellman et al., 2022) and consequently, identify different households as flooded and non-flooded depending on what data source has been used.

The above-mentioned demerits of the satellite data are not applicable when determining the flood-affected areas or neighbourhoods. Therefore, I used the data prepared by ICIMOD from satellite sources to identify the flood-affected areas instead of flood-exposed households. This approach is important to create comparable control groups for methodology applied in this research. Otherwise, flood-prone households are likely to reside in different areas, and hence have different geo-climatic and socioeconomic characteristics, compared to non-flood-prone households (Hallegatte et al., 2020).

At first, the four raster datasets of the inundated areas (i.e., areas affected by flooding in August 2017) that were collected from the ICIMOD open data repository were converted to polygons. The polygons then were merged to create a single polygon of inundated areas. Simultaneously, I obtained the dataset on the GPS locations of the center points of the HRVS-panel survey clusters (PSUs) from the World Bank. Initially, a request to access the GPS locations of the surveyed households was sent to the contact person from the World Bank. Due to the need to maintain the anonymity and confidentiality of the surveyed households, the data on household-level GPS was not revealed. Instead, the dataset on the GPS locations at the PSU level was provided, which was sufficient to fulfill the need for this research. This is because, in this research, the satellite data was not used as the flood measure for households and was rather used to determine the flood-affected survey clusters (or PSUs).

Then, using ArcGIS Pro software[11], I created a circular buffer of a 3 km radius around each PSU's centre point. This buffer should incorporate all households within a PSU. Note that the survey clusters for the HRVS-panel survey were generated before federalism in Nepal when there was an old administrative division with Village Development Committees (VDCs). Under

[11] Note that I have attached the datasets used in this process—along with the detailed steps that I followed in ArcGIS pro software, illustrated using module builder—in the supplemental materials.

that system, the average size of the local body (VDC ward) in Nepal used to be 20 square kilometers (Devkota, 2022). Therefore, the selected buffer size was appropriate for this study. The inundated area polygon was then intersected with these buffers. Only the PSUs with greater than 5% of their buffer areas intersecting with the inundated area were selected. Setting a threshold of 5% ensures that PSUs that were not affected by the floods were discarded from the list to construct the control group. For example, in the list of all PSUs with their buffers intersecting with the inundated area, there were PSUs whose buffers' boundary lines barely touched the inundated polygon. Please refer to Appendix 4 to see the examples of selected and discarded PSUs at above mentioned 5% threshold.

Then the households within those selected PSUs were merged with 105 households that self-reported being flooded in 2017 (treatment group) to create a sample of 749 households. There were a few overlaps (46 households) between households in flood-affected PSUs and households who reported being flooded.[12] Those overlapping households remained part of the treatment group, leaving 644 households in the control group. I further limited the sample to the Terai region. The Terai region is the hub for the monsoon floods in general, and in particular, it was the most affected region for the 2017 flood (Appendix 1). So, any households in the dataset with an elevation above 300 masl were discarded. As households in both treatment and control groups were dominantly in the Terai belt, this process discarded only 11 households from the sample (five from the treatment (T) group and six from the control (C) group). Furthermore, seven more households (1 T and 6 C) that reported experiencing a flood in the wave 2 survey were dropped from the sample since wave 2 is used as a pre-flood period. Finally, nine households (2 T and 7 C) that were not present in either wave 2 or wave 3 were dropped to ensure that the panel dataset was balanced. This means the attrition rate within the sample households for this research was very low. At last, the sample is left with 97 households in the treatment group and 625 households in the control group.

The above-mentioned approach selects the households for the comparison group from the areas that were affected by the 2017 flood. It means that the households who are in the control group had a probability of being directly exposed to the flood, but they were not. Therefore, this approach of the treatment and control groups' construction helps us to somehow balance

[12] Note that the inundation maps from ICIMOD only cover the areas flooded during certain days in mid-August so it is expected not to have all households that self-reported being flooded in the flood-affected households' list that is prepared based on those maps.

geographical, climatic, and socioeconomic characteristics across households in both groups, which is crucial for the empirical strategy applied in this research.

3.3 Empirical Strategy

I start with a general overview of the households facing the severe effects on economic outcomes during the post-flood period. The first sub-question is on the percentage of directly-flood-exposed households who completely lost their economic outcomes related to production, income, and assets in the post-flood year. And those shares of the complete loss across different outcome variables are also calculated for the control group. It is because there were many zero values in some economic outcomes i.e., crop production, income from the crop, saving, income from wage employment, and so on (refer to Table 4). Either a considerable number of households in the sample did not have those economic outcomes due to the nature of their livelihood, or they lost those economic outcomes completely due to the flood or other economic shock in the post-flood period. The descriptive statistics, following a few required calculations, can address this question. For this, I first created the dummy variables for those economic outcomes, assigning 0 to observations with zero values, and 1 otherwise. Then, households with 0 dummy values post-flood and 1 pre-flood shall be assigned with value of 1 for the complete loss dummy for those outcomes. Then, descriptive statistics on the number and percentage of households with values of 1 for complete loss dummy variables in control and treatment groups answer the above question.

The answer to the first question will help us understand the overview picture of severely affected households during the post-flood period. However, we cannot infer from those descriptive statistics that the observed effects on the economic outcomes are caused by direct exposure to flooding. A complete loss of economic outcome can also occur due to the indirect effects of the flood on the market operations and other factors such as any overlapping economic shocks or other disasters affecting the households. We can observe indeed that is the case as a considerable percentage of households in the control group had a complete loss across different economic outcomes as observed in Table 5. Therefore, I applied the causal inference strategy to answer the subsequent questions on the isolated effect of direct exposure to flood faced by the affected households.

I divided the causal inference into two stages. At first, in model specification 1, I used the logit regression to find the influence of direct exposure to flood on a complete loss of an economic outcome.

Equation 1: Model specification for stage 1 logit regression

$$Logit\ (Pr(Y_i = 1)|Flooded_i, X_i) = \beta_0 + \delta * Flooded_i + \beta X_i \qquad (1)$$

In the above equation, Y_i is the dummy variable for a complete loss of an economic outcome such as paddy production, total income, income from crops, and so on for a household (i)[13]. $Flooded_i$ is the dummy that takes the value 1 for households that self-reported being flooded in 2017 and 0 for the households who lived in the flooded area based on the inundation map but did not self-report as being flooded. δ is the main coefficient of interest, which captures the effect of direct exposure to flooding on (the log-odds of) a complete loss in the economic outcomes.

The explanatory variables (X_i) used in the model are number of working-age members, education status of household head, gender of household head, distance from the nearest market (km), elevation (masl), total cultivated land in the wet season (km^2), and binary variable on any economic shock experienced by the households. The pre-flood values of those variables have been used in the analysis. These explanatory variables along with a few others (which were removed from the model due to high correlation with the current explanatory variables) were carefully considered based on their relevancy described in the literature (McCarthy et al., 2018; Morshed et al., 2022; Noy et al., 2021). Additionally, I performed the goodness of fit test (Hosmer–Lemeshow chi-square test) to verify that the model fits the data.

Secondly, in stage 2, I focused on the households that experienced a partial loss in an economic outcome. Given that the dataset has two levels of difference—based on the treatment status (direct flood exposure) and the time–I have used the difference-in-difference setup. In model specification 2, outcome variables $ln(Y_{it})$ are the logarithmic transformed value of an economic outcome of household (i) in time (t). I have chosen the logarithmic transformations to normalize the distribution of the variables and stabilize their variances as the economic outcomes tend to have positively skewed[14] and heteroskedastic[15] distribution. Furthermore, the log-transformed observations eliminate all zero values. It means households facing no effect at all or complete loss of economic outcomes are both eliminated from the analysis. Therefore, we can then analyze the effect of direct flood exposure on the partial loss of an economic outcome.

[13] Only households with non-zero and non-missing values to the economic outcomes in the pre-flood period are included in the analysis.
[14] Economic outcomes such as income and assets tend to have a high number of observations on low-end and long-tail distribution with few high values.
[15] Economic outcomes tend to have a higher magnitude of variance at the high end compared to low-end values.

Equation 2: Model Specification for stage 2 difference-in-difference analysis

$$ln(Y_{it}) = \beta_0 + \lambda * Post_F + \gamma_i + \delta(Post_F * Flooded_i) + \varepsilon_{it} \qquad (2)$$

$Post_F$ is the time dummy with the value 1 for the post-flood period i.e., for survey wave 3, and 0 for the pre-flood period, i.e., survey wave 2. γ_i is the household-fixed effects, which controls for the time-invariant household characteristics. δ is the main coefficient of interest, which is the change in the logged outcome variable due to the direct flood exposure. For the robustness of the result, I have clustered the standard errors at the household level. In the main model specification, no control variables have been added, however, they are included in the analysis used for the robustness check. The covariates control for the time-varying household characteristics and confounding variables that can influence both exposures to flood and economic outcomes (refer to section 4.3).

The difference-in-difference analysis makes the causal inference by isolating the effect of flood from other factors that can influence the outcome variables. The post-flood ($Post_F$) dummy in the model specification absorbs the effect attributed to time trends that are common in both treatment and control groups (Cunningham, 2021). There might not be a big effect arising from the time trend such as inflation or the change in agricultural productivity from technological advancement given that there is only one year gap between the pre-flood and post-flood observations. However, there could be some confounding factors such as deviation in rainfall, temperature variation, and other similar observed and unobserved time-specific factors that are likely to influence the outcome variables.

Due to the panel structure of the data, I have also included the household-fixed effect (γ_i) in the model. This modification made the treatment dummy in the usual difference-in-difference setup useless. The household-fixed effect absorbs the time-invariant characteristics (both observables and unobservables) of the households (Cunningham, 2021). Although the observables could have been controlled for by including them in the model, the unobservable effects could cause a biased result. Therefore, this approach controls for omitted variables bias, increasing the robustness of the results. A similar approach has been adopted in the research by Noy et al. (2021).

The key assumption for the difference-in-difference framework is the parallel trend assumption between the control and treatment groups. The treatment and control groups may initially have differences in economic outcomes. However, in the absence of treatment, the change in the economic outcomes for the treatment group should have been the same as the change in the control group (Cunningham, 2021). The parallel trend is unobservable. However, given the method used for the construction of the control group, as explained in section 3.2, the parallel trend assumption is likely to be valid. Due to the similarities in the socioeconomic and geoclimatic characteristics, the factors influencing the change in economic outcomes can be assumed to have more or less similar effects among treatment and control groups. Additionally, in section 4.3, I have included tests for parallel pre-trends for economic outcomes to add more confidence to the parallel trend assumption.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Initially, I compared the households in the treatment and control groups using some proxy variables to see if they have on average similar or comparable socio-economic status and geo-climatic features. The variables in Table 2 have been chosen based on the data relevancy and availability and following their use in previous research papers *(McCarthy et al., 2018; Morshed et al., 2022; Noy et al., 2021)*. These characteristics can influence the households' economic outcomes and their probability of being affected by flood events. As seen in Table 2, the treatment and control groups are similar in most of those characteristics, except for the number of working-age members, distance to the nearest market and bank, total area of cultivated land in the wet season, and elevation. The average number of working-age members is slightly higher for the treatment group compared to the control group. The households in the treatment group are approximately 2.5 km further away from the nearest bank and market and have cultivated more land during the wet season than households in the control group. Furthermore, the households in the treatment group are located in higher elevations, 10 masl more than in the control group. Although it might appear surprising that the flooded households are in higher elevations, it is possible due to the methodology used to construct the control group[16].

The empirical strategies used in the research have considered the concerns over the above-mentioned differences. In the logit model analyzing a complete loss in an economic outcome, the variables in Table 2 are added to the model as explanatory variables[17]. For difference-in-difference analysis on partial loss assessment, an additional robustness test has been conducted including these variables[18] as covariates.

[16] In the case of the control group, all the households are selected from the areas that were significantly flooded as explained in section 3.2. In contrast, for the treatment group, there is more heterogeneity across households in the elevation because among all households reported being flooded, some are in significantly flooded areas while some are not. Therefore, on average the elevation for the treatment group is higher.
[17] Only a few variables that are presented in the baseline characteristics table are removed from the list of explanatory variables in the logistic regression model due to their high correlation with other variables, and hence the issue of multicollinearity.
[18] Same case as mentioned in the above footnote i.e., the discard of some of the variables from the list of covariates due to multicollinearity issue.

Table 2: Comparison of baseline household characteristics between control and treatment groups

	Mean (Treatment)	No. HH (Treatment)	Mean (Control)	No. HH (Control)	T-stat	P-value
Working Age Members	3.51	97	3.17	622	-2.024	**0.043**
Education HH Head[a]	1.60	96	1.54	619	-1.183	0.237
Gender HH Head	0.15	97	0.20	622	0.967	0.334
Slope[b]	1.01	97	1.01	625	-0.233	0.816
Home Ownership	1.00	97	1.00	625	-0.557	0.578
Distance Market*	5.51	97	2.99	625	-7.335	**0.000**
Distance Bank*	8.44	97	5.82	625	-4.490	**0.000**
Distance Motor Road*	1.30	97	1.24	623	-0.349	0.727
Distance Health Post*	2.08	97	1.89	625	-1.699	0.090
Elevation[c]	105.00	97	95.38	625	-2.418	**0.016**
Total Assets[d]	14.63	97	14.55	623	-0.746	0.456
Other shocks[e]	0.13	97	0.11	625	-0.632	0.528
Total cultivated land (Wet Season)[f]	5498.4	97	3945.75	625	-2,772	**0.006**

Source: Author's calculation based on HRVS-panel survey data

Note: The data for the baseline year is taken from Survey Wave 2. The null hypothesis for t-test is that the mean values of the economic outcome are the same for the treatment and the control group. The p-values for working-age members, distance bank, distance market and elevations indicate that the null hypothesis is rejected for all those variables at a 5% significance level. No. HH means the number of households.

*All distance-related variables are reported in kilometers.

[a] Education of HH Head takes value 1 for never attending school, 2 for attending school in the past, 3 for attending school at present (no observations for 3 in the sample)

[b] Slope takes the value 1 for flat, 2 for moderate and 3 for steep (no observations for 3 in the sample)

[c] Elevation is reported in meters above sea level (masl) unit

[d] Values for Total assets have been transformed to log(x+1) form to get normal distribution without losing the zero values.

[e] Other shocks is a dummy variable of whether or not the households reported exposure to any economic shock other than floods. No households with self-reported flood shock in Wave 2 are included in the sample.

[f] Total cultivated land is measured in km^2.

Another important concern in the dataset was the presence of a high number of zero values for some of the economic outcome variables. Table 3 presents the summary statistics on the economic outcomes, and Table 4 presents the percentage share of zero values in those economic outcomes. Especially for the variables related to income, the zero values represent more than 50% of the data. To avoid the potential biases in the estimates, I divided the inference into two stages—one for complete loss in the economic outcomes which is mainly related to zero values, and another for partial loss, without zero and missing values —as discussed in the empirical strategy.

Table 3: Summary statistics on the economic outcome variables

	Survey Wave	Mean (Treat)	SD (Treat)	No. HH (Treat)	Mean (Control)	SD (Control)	No. HH (Control)
Paddy Production (Wet Season)[a]							
	Wave2	2128.1	2434.7	97	1393.6	1674.5	625
	Wave3	1505.4	2029.6	97	1460.0	2258.0	625
Production value							
	Wave2	57274.4	70240.5	97	30535.9	36876.6	625
	Wave3	33792.8	45696.5	97	32496.4	53091.0	625
Total Income							
	Wave2	191853.4	211463.4	96	233152.9	393248.3	620
	Wave3	197472.6	267627.0	97	326381.4	1550259	621
Crop Income Wet Season							
	Wave2	21558.0	42435.1	97	8293.1	22476.5	624
	Wave3	9150.9	21242.3	97	10500.1	24784.3	625
Crop Income Dry Season							
	Wave2	20719.8	43300.0	96	11222.0	34843.5	625
	Wave3	24325.3	64133.6	97	10725.2	42124.4	624
Total Crop Income							
	Wave2	42502.3	71577.0	96	19533.1	49100.8	624
	Wave3	33476.2	76049.1	97	21242.1	57443.7	624
Income from Daily Wage							
	Wave2	57649.5	113132.6	97	68068.1	121862.7	625
	Wave3	54498.5	98451.5	97	70910.3	114505.6	624
Income from Wage Employment							
	Wave2	89966.0	122540.9	97	111165.5	148194.3	623
	Wave3	79333.5	117990.3	97	108999.1	143654.9	623
Income from Livestock							
	Wave2	10876.3	18389.9	97	7663.7	20423.4	625
	Wave3	1425.8	6007.7	97	11119.6	38746.1	624
Total Assets Value							
	Wave2	3320669.6	3220060	97	3530651	5738714	623
	Wave3	3127820.6	3042613	97	3559346	6494371	625
Financial Asset Value							
	Wave2	24767.0	40962.7	97	29367.7	69190.8	623
	Wave3	35112.4	77715.9	97	52451.4	156324.5	625
Cash in Hand							
	Wave2	1822.7	4478.6	97	1312.3	3838.4	625
	Wave3	4417.5	6700.3	97	5551.8	9340.4	625
Saving							
	Wave2	20882.5	36880	97	26510.3	67658.4	623
	Wave3	21313.4	38946	97	34383.5	90228.3	625
Livestock Value							
	Wave2	36801.5	38716.2	97	38632.0	51046.3	625
	Wave3	26319.6	37407.2	97	39349.3	60403.5	625

Land Value							
	Wave2	1950237.1	2661913	97	1768493	4690333	625
	Wave3	1968020.6	2668539	97	1824949	4716286	625
Home Value							
	Wave2	1203938.1	1049844	97	1558601	1808990	625
	Wave3	994618.6	1033179	97	1483752	2472390	625
Durable Goods Value							
	Wave2	104925.8	96431.3	97	132295.4	210787.1	625
	Wave3	103749.5	99007.1	97	158844.6	323512.9	625

Source: Author's calculation based on HRVS-panel survey data
Note: All the outcome variables except for the paddy production are monetary value with Nepalese Rupees (NPR) currency.
[a]The unit of measurement for paddy production is kilogram (kg). Treat means treatment group and No. HH means the number of households.

Table 4: Percentage of zero values by economic outcome variables

	Wave 2 Treatment (%)	Wave 2 Control (%)	Wave 3 Treatment (%)	Wave 3 Control (%)
Paddy Production (Wet season)	18.6	33.6	34.0	35.2
Total Income	5.2	9.3	15.5	6.9
Income Crop (Wet Season)	54.6	75.4	70.1	69.8
Income Crop (Dry Season)	48.5	67.2	59.8	60.6
Total Crop Income	46.4	62.1	55.7	54.9
Income from Daily Wage	62.9	53.4	60.8	56.2
Income from Wage Employment	45.4	38.1	51.5	42.9
Income from Livestock	67.0	76.2	88.7	71.0
Cash in Hand	78.4	78.2	6.2	5.0
Saving	34.0	39.0	32.0	33.3
Land Value	13.4	32.0	14.4	32.3
Livestock value	25.8	21.0	42.3	29.0
Total Assets	0.0	0.3	0.0	0.0
Total Financial Asset	22.7	26.1	0.0	1.3
Home Value	0.0	0.5	0.0	4.6
Durable goods value	1.0	0.6	0.0	0.0

Source: Author's calculation based on HRVS-panel survey data

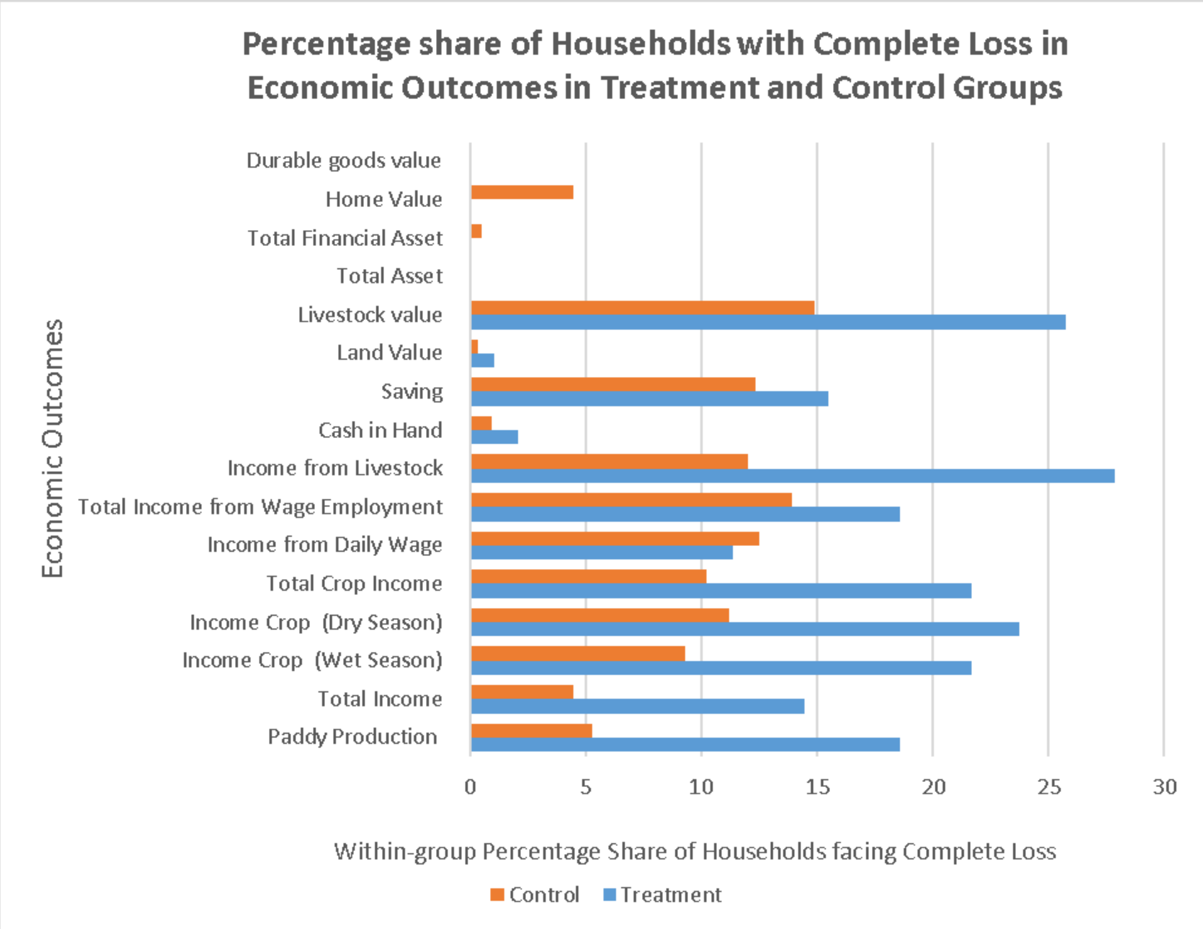
Table 5 presents the frequency distribution of the households facing complete loss in economic outcomes in the treatment and control groups, and Figure 1 presents the graph on the percentage shares of those households and compares across the treatment and control groups. We can see that the share of households facing a complete loss is larger for the treatment group than the control group for many economic outcomes. The variables with a considerably larger share in the treatment group are mainly related to agriculture and farming activities, such as crop production, income from crops (wet season, dry season, and total), income from livestock, and livestock value. In contrast, for some economic outcomes such as income from daily wage, home value, and total financial asset, the share of households facing a complete loss is smaller in the treatment group than in the control group. For assets, almost no households experienced a complete loss in economic outcomes, except for livestock value and savings, across both the control and treatment groups. In the next section, I will present the results from the logit regression analysis to figure out the causal effect of direct flood exposure on the above-mentioned complete losses across different economic outcomes.

Table 5: Frequency distribution of households facing complete losses by economic outcomes

	Number HHs (Treatment)	Number HHs (Control)	Difference in percent share (%)
Paddy Production (Wet Season)	18	33	13.28
Total Income	14	28	9.95
Income Crop (Wet Season)	21	58	12.37
Income Crop (Dry Season)	23	70	12.51
Total Crop Income	21	64	11.41
Income from Daily Wage	11	78	-1.14
Total Income from Wage Employment	18	87	4.64
Income from Livestock	27	75	15.84
Cash in Hand	2	6	1.10
Saving	15	77	3.14
Land Value	1	2	0.71
Livestock value	25	93	10.89
Total Assets	0	0	0.00
Total Financial Asset	0	3	-0.48
Home Value	0	28	-4.48
Durable goods value	0	0	0.00
Total No. of HH (Treatment Group)	97		
Total No. of HH (Control Group)	625		

Source: Author's calculation based on HRVS-panel survey data

Figure 1: Distribution of percentage share of households with complete loss in economic outcomes (treatment vs. control groups)



Source: Author's creation based on HRVS-panel survey data
Note: Percent share is within a group

4.2 Causal Inference

4.2.1 Complete Loss in Economic Outcomes

The logit regression results in Table 6 show the effect of direct exposure to flooding on the complete loss of an economic outcome. The coefficient for $Flooded_i$ is the log odds of facing a complete loss in an economic outcome. Only the economic outcomes that were relevant to assess the complete loss have been included for this causal inference. The variables related to household assets with no or very few observations facing a complete loss have been discarded from the assessment (Figure 1 and Table 5). The analysis results for paddy production, income from livestock, total income and livestock value were statistically significant. These results imply a high influence of direct flood exposure on the complete loss of those economic outcomes among flooded households. The economic outcomes mentioned above are ordered based on the respective strengths of their effects, i.e., paddy production with the most substantial effect and the livestock value with the least.

Table 6: Logit regression results for the relationship between complete loss in economic outcomes and direct flood exposure

	Production	Income						Assets	
	Paddy Production (Wet Season)	Total income	Crop Income Wet Season	Crop Income Dry Season	Total Crop Income	Income from Wage Employment	Income from Livestock	Saving	Livestock value
Flooded$_i$	1.587***	1.421***	0.211	0.396	0.508	0.531	1.683***	0.335	0.885***
	(0.374)	(0.402)	(0.384)	(0.366)	(0.367)	(0.348)	(0.547)	(0.352)	(0.298)
Obs	492	652	197	254	288	435	181	440	561
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HL test p-value[a]	0.7274	0.3197	0.4588	0.1825	0.8606	0.4326	0.1935	0.7998	0.4218

Source: Author's calculation based on HRVS-panel survey data

Note: Paddy production here is a dummy variable for complete loss in post-flood economic outcome. It takes the value 1 if there was no harvest at all in the post-flood period and some harvest in the pre-flood period. All other possible scenarios take the value 0. Only households with non-zero and non-missing values to the economic outcome in the pre-flood period are included in the analysis. The standard errors are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

[a]Hosmer–Lemeshow chi-square goodness-of-fit test (with 10 groups) does not reject the null hypothesis that the logistic model fits the data adequately.

The paddy cultivation practice in the lowlands of Terai is water-intensive (Jacoby & Walker, 2019). Hence, the paddy-cultivated plots are likely to be closer to water bodies or even in flood-prone areas for easy access to irrigation. Therefore, out of all economic outcomes, paddy production is likely to incur the most substantial effect from direct flood exposure as verified by the analysis result.

The results related to income and its components are interesting. Despite having statistically insignificant results for most of its components, the effect on the total income is significant. Although paddy production in the wet season faced the most significant direct effect, the income from the wet season crop did not have a statistically significant effect.[19] The result can imply the subsistence nature of the paddy production among the households who experienced direct flood exposure. The significant effect on the total income seems to be driven by the complete loss in income from livestock. It could be because households might have sold livestock to smooth their consumption, which was affected by the loss in crop production. During their empirical analysis of surveys from 16 developing countries on household-level

[19] Paddy is the dominant crop comprising more than 95% of the cultivated land area in the sample population.

shock exposure, Heltberg et al. (2015) found that the affected households sold livestock for short-term consumption smoothing in the post-shock period. The literature additionally found that the sale of livestock (and other productive assets in general) reduced the households' income generation capacity in the long run. The significant effect on the complete loss of livestock value further confirms the alignment of the analysis results from this research with the findings by Heltberg et al. (2015).

4.2.2 Partial Loss in Economic Outcomes

This section presents the difference-in-difference analysis results on the effects of direct flood exposure for households facing partial losses on economic outcomes.

The direct flood exposure significantly affected the partial loss of paddy production and its value as seen in Table 7. The results from the robustness tests confirm the validity of the model specification used for the analysis of those effects (Appendix 5 and Appendix 6). On average, there was a 30% decrease in the production quantity and a 38% decrease in the production value. The effect on the production value is greater than on the production quantity, which implies the possibility of reduced market price for paddy in areas where households reported direct flood exposure.

Table 7: Difference-in-difference analysis results for the effect of direct flood exposure on the partial loss of paddy production and its value

	Paddy Production (Wet Season)	Paddy Value
$Post_F$	0.056*	0.066*
	(0.032)	(0.034)
$Post_F$*$Flooded_i$	-0.357***	-0.485***
	(0.086)	(0.100)
Observations	963	963
N of HH	520	520
Within R^2	0.04	0.06
HH FE	Yes	Yes
Cluster	hhid	hhid

Source: Author's Computation

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

The households also faced significant effects in the partial loss of income (Table 8). The decrease in total income (28%) seems to be driven particularly by the decrease in income from livestock (77%), wet season crops (57%), and daily wage jobs (20%).[20]

Table 8: Difference-in-difference analysis results for the effect of direct flood exposure on the partial loss of economic outcomes related to household income

	Total income	Crop Income Wet Season	Crop Income Dry Season	Total Crop Income	Income from Daily Wage	Income from Wage Employment	Income from Livestock
$Post_F$	0.130***	0.228**	-0.176*	0.056	0.097	0.064	0.298**
	(0.048)	(0.100)	(0.090)	(0.089)	(0.060)	(0.046)	(0.148)
$Post_F$*$Flooded_i$	-0.334***	-0.852***	0.196	-0.351*	-0.230**	-0.148	-1.470***
	(0.118)	(0.183)	(0.258)	(0.203)	(0.113)	(0.104)	(0.245)
Observations	1323	416	540	614	639	844	373
N of HH	706	297	378	410	401	509	294
Within R^2	0.02	0.12	0.02	0.01	0.01	0.01	0.10
Cluster	hhid	hhid	hhid	hhid	hhid	hhid	hhid
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Author's Computation
Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The analysis result with covariates for total crop income is not statistically significant (refer to Appendix 5).

For assets, as seen in the main analysis results in Table 9, financial assets, cash in hand, and durable goods had significant effects. Based on the parallel pre-trend tests, only the results for financial assets and durable goods are valid (Appendix 6). The value of durable goods was reduced on average by 18.6% and that of financial assets by 38.8%. In cases of cash in hand and other economic outcomes, such as total assets, livestock value, and land value, they did not show parallel pre-trends. Therefore, it is difficult to draw conclusive findings for these economic outcomes.

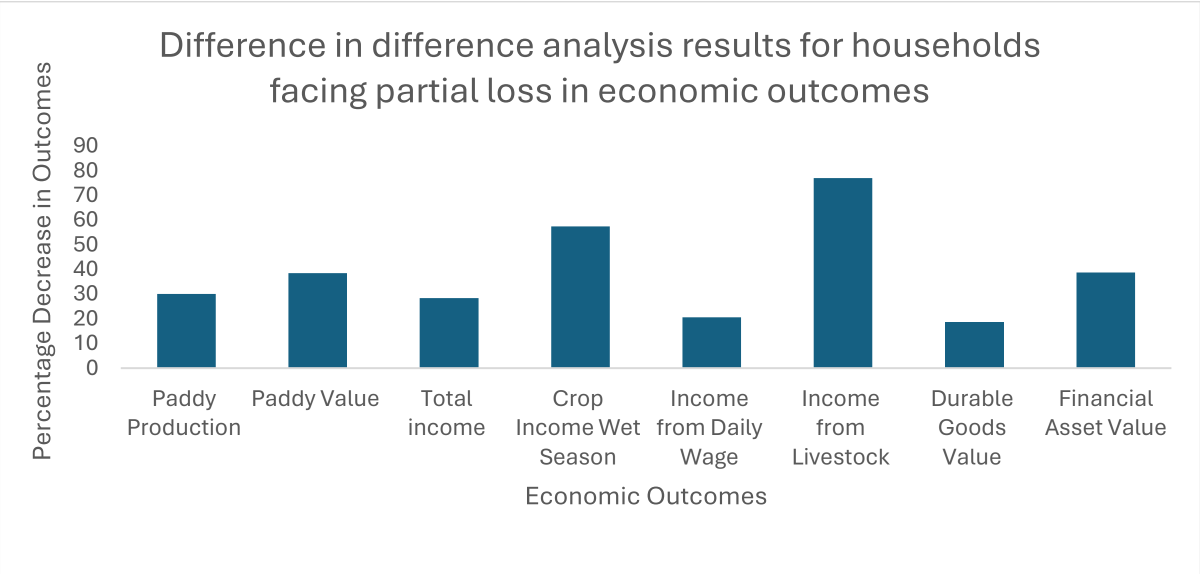
[20] The figures in parenthesis show the percentage decreases in respective economic outcomes.

Table 9: Difference-in-difference analysis results for the effect of direct flood exposure on the partial loss of economic outcomes related to household assets

	Total Asset Value	Financial Asset Value	Cash in Hand	Saving	Livestock Value	Land Value	Home Value	Durable Goods Value
Post_F	-0.130***	0.285***	-0.461***	0.200**	0.136***	0.047***	-0.128***	0.145***
	(0.033)	(0.082)	(0.107)	(0.093)	(0.049)	(0.016)	(0.044)	(0.035)
*Post_F*Flooded_i*	0.022	-0.491**	-0.596**	-0.122	-0.161	-0.022	-0.165	-0.206**
	(0.056)	(0.213)	(0.262)	(0.221)	(0.150)	(0.020)	(0.117)	(0.093)
Observations	1442	1251	842	928	1066	1015	1412	1439
N of HH	722	717	693	575	618	509	721	722
Within R^2	0.03	0.02	0.19	0.01	0.02	0.02	0.02	0.02
Cluster	hhid	hhid	hhid	hhid	hhid	hhid	hhid	hhid
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Author's computation
Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Figure 2: Percentage decrease in economic outcomes for households facing partial loss due to direct flood exposure



Source: Author's creation based on the results of the difference in difference analysis

Figure 2 summarizes the results for partial loss in economic outcomes that were statistically significant. Among the aggregated outcomes (i.e., total production, total income, and total assets), paddy production value faced the highest percentage decrease, followed by total income. No statistically significant effect was seen in the total assets. Out of all the disaggregated economic outcomes, income from livestock faced the highest decrease.

Assessing aggregated results from the complete loss and partial loss analyses, we can see that the effects of direct flood exposure were worse for income from livestock, paddy production (both quantity and value), and total income. The results for these economic outcomes are large and significant in both cases. For livestock value, the flood-exposed households faced a significant effect on complete loss, but the effect was insignificant for partial loss.[21] Overall, I found that the effects were larger on total paddy production and its value, followed by total income, compared to the effect on the assets. These results imply that agricultural households relying on subsistence agriculture, as the only source of livelihood, were the most affected group by direct exposure to the 2017 floods in Nepal.

Given the existing gap in the literature on flood-related economic impact assessment in Nepal at the household level, the findings from this research are difficult to compare with other research conducted in the national context. However, the results from this research are comparable to the context literature at the global level. For instance, Del Ninno (2001) also found greater effects on crop production and income compared to assets among flood-affected households in Bangladesh. Similarly, crop production faced the most significant effect, out of all other economic outcomes, in household-level flood impact assessment in Tanzania by Djoumessi Tiague (2023).

4.3 Robustness Check

The robustness of the main results has been ensured by using several tests. In the case of the logistic regression model (for the analysis of the effects on complete loss of economic outcomes), the robustness of results is ensured by the non-significance of the Hosmer–Lemeshow goodness-of-fit test (with 10 groups). The p-values from the test results are included in the main analysis result table. Based on the test results, the null hypothesis that the logistic model fits the data adequately for all the economic outcomes remains unrejected.

For the difference-in-difference methods to assess the effect on the partial loss of economic outcomes, the robustness and validity of the results were tested using two approaches. First, I added the covariates in the main model specification, such as the number of working-age

[21] This result can imply that households owned very few livestock and hence, either they do not have to sell anything or get rid of all (of the few they own).

members, education of household head, gender of household head, distance from the nearest market (in km), elevation (in masl), total cultivated land in the wet season (in km^2) and dummy variable on whether or not households face any other economic shocks. These covariates control for the time-varying household characteristics and confounding variables that can influence both exposures to flood and economic outcomes. They were carefully considered based on their relevancy described in the literature (McCarthy et al., 2018; Morshed et al., 2022; Noy et al., 2021). The results from the analysis with covariates (refer to Appendix 5) are almost similar to the results in the main analysis (refer to section 4.2.2) for all the economic outcomes. Second, I conducted the test for the validity of the underlying parallel trend assumption of the difference-in-difference model. As we cannot test for the parallel trend directly, I checked if the economic outcomes show the parallel pre-trend[22]. I replaced the post-flood dummy in the main analysis with the time dummy. Here the time dummy is 1 for survey wave 2 and 0 for survey wave 1, both are the periods before the 2017 flood. All the economic outcomes related to production and income showed parallel pre-trends (refer to Appendix 6). Among economic outcomes related to assets, total assets, cash in hand, livestock value, and land value did not pass the parallel pre-trend test.

4.4 Limitations of the Study

While interpreting the results from this research, it should be carefully noted that the causal inferences (logistic regression and difference-in-difference method) in this research capture only the isolated effects of direct flood exposure. A disaster shock such as a flood can affect the local economy in such a way that all households, whether or not directly affected by the flood, can face a substantial loss in their income and other economic outcomes (Morshed et al., 2022; Noy et al., 2021; Poapongsakorn & Meethom, 2013). Morshed et al. (2022) analyzed the spillover[23] effect of floods in Bangladesh and found that the decrease in income for the spillover group was more significant than the directly affected group. Additionally, Poapongsakorn & Meethom (2013) and Noy et al. (2021) found a significant spillover effect of the 2011 flood in Thailand even among the households that were not located in the flood-affected areas. This is consistent with the analysis results from this research as we can see that, in addition to households in the treatment group, significant percentages of households in the control group

[22] Note that parallel pre-trends do not confirm the parallel trends in the variables. Indeed, a parallel pre-trend is neither a necessary nor a sufficient condition for the parallel trend, however, it is a commonly used methodology in research using difference-in-difference method (Cunningham, 2021)

[23] The spillover group in research by Morshed et al. (2022) has the exact same construction as the control group in this research i.e., households residing in the flood-affected areas but did not self-report as being flooded.

also faced complete losses in economic outcomes associated with income such as crop income during the wet season (9.28%), crop income during the dry season (11.2%), total crop income (10.24%), and income from the wage employment (13.92%) as well as savings (12.3%) (refer to Table 5). The complete losses in those economic outcomes among households in the control group may be (partly if not entirely) due to the spillover effect of floods as those households were in flood-affected areas. The statistically insignificant results for those economic outcomes cannot imply that they remain completely unaffected by the flood exposure. Indeed, the statistical insignificance of those effects can also be due to the high spillover effects, as found by the above-referred research. Note that the empirical analysis methods used in this research deduct the effects experienced by the comparison group (the households who did not report being flooded) to isolate the effect of direct flood exposure. Given the time limitation for conducting this research, I could not extend the study to analyze the spillover effects faced by households. Therefore, the scope of this research is limited to the isolated effects of direct flood exposure on economic outcomes among the households self-reporting the exposure to the 2017 floods in Nepal.

Additionally, the findings from this research only capture the short-term effects. The post-flood period used for the assessment of flood effects was one year after the 2017 flood. I could not look at the long-term effect due to data unavailability after the 2018 survey wave for the HRVS-panel survey. Also, the data from the HRVS-panel survey is nationally representative only for rural and urbanizing areas so the results from this study cannot be generalized to the urban areas of Nepal. Furthermore, some of the economic outcomes related to assets did not pass the parallel pre-trend test. Therefore, additional robustness tests need to be done to verify the validity of the difference in difference analysis results to determine the effect of partial loss for those economic outcomes.

CHAPTER 5: CONCLUSION

The findings from this research imply that households relying on subsistence agriculture were the most affected group by direct exposure to the 2017 floods in rural and urbanizing areas of the Terai belt of Nepal. The empirical analysis of the complete loss of an economic outcome showed that paddy production, income from livestock, total income, and livestock value were the outcomes with the most substantial effect. For households facing only the partial loss, the most severe effect was on the income from livestock, which decreased by 77%. Additionally, among the aggregated economic outcomes, with a 38% decrease, paddy production value faced the most substantial effect on the partial loss, followed by the total income, which faced a 28% decrease. Overall, this research found that effects from direct flood exposure were larger on total paddy production and value, followed by total income compared to the effect on the assets. Practically, the findings of this research emphasize the urgent need for targeted interventions to support subsistence agricultural households in the Terai region, particularly in enhancing flood resilience through improved agricultural practices, financial support, and infrastructure development.

As mentioned above, this research adds important insights into the household-level effects of the 2017 flood events in Nepal. The prior studies on impact assessments for 2017 floods have only presented the summary statistics of aggregated loss at the district, provincial, or national level. More importantly, this research is among very few existing works of literature on the household-level economic impact assessment of any flood events in Nepal. Furthermore, there was no prior literature on household-level flood impact assessment done for Nepal by using the nationally representative panel dataset. Therefore, this research is an important initiation and addition to the existing body of literature related to flood studies in Nepal.

A comprehensive understanding of past flood events and their effects can play a crucial role in formulating efficient adaptation and recovery plans targeted to the population and sectors that are prone to severe effects. Nepal faces a significant threat of exacerbated effects on lives and economy because of the increased riverine floodings attributed to climate change (World Bank, 2021; WBG 2022).[24] Therefore, the research on the household-level impact assessment of floods in Nepal is very important for future disaster preparedness. Policymakers can use the

[24] In the next 20 years, the riverine floodings could annually affect 199,000 population, costing USD 574 million to the country's GDP (WBG & ADB, 2021).

insights from this type of research to design and implement more effective disaster risk reduction strategies, focusing on the most vulnerable populations.

Further research should be done to gain a comprehensive understanding of the effect of the 2017 floods in Nepal, building on the findings of this research. As noted in section 4.4, one limitation of this research is that the analysis results from causal inferences only capture the isolated effects of direct flood exposure. But other studies have found the spillover effect to be equally (if not more) significant in comparison to the direct effects of the flood (Morshed et al., 2022; Noy et al., 2021). Therefore, first and foremost, future studies can look at the spillover effect faced by the households living in the flood-affected area but not directly exposed to the flood. The findings on the spillover effect can complement the isolated effects among the directly flood-exposed households to assess the overall effects of the flood. Second, the heterogeneity of the effects across different groups such as income level, caste and ethnicity, and households living in historically flood-prone or historically non-exposed areas can deepen the understanding of the flood-related effects. These heterogenous impact assessments can identify the groups that are facing the most severe effects of floods and hence, prioritize the support on disaster preparedness and post-disaster relief among them. Third, supplemental qualitative research can be conducted in the flood-affected areas to increase the understanding of the findings from the empirical analysis.

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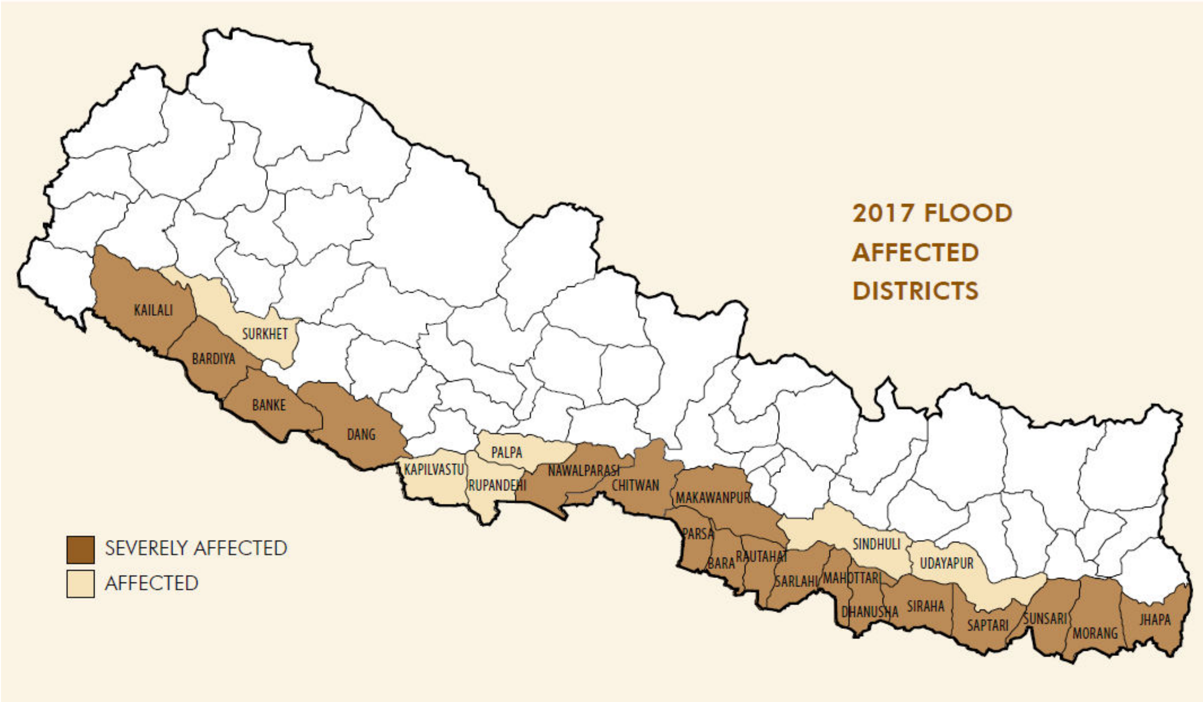
Appendices

Appendix 1: 2017 Flood-affected Area Map

Map of Nepal displaying the districts affected by the 2017 flood events



Source: National Planning Commission [GoN] (2017)

Appendix 2: HRVS-Panel Question on Household Shocks

Question on household shock experience and list of household shocks from section 15 of HRVS-panel survey (household) questionnaire

SECTION 15: SHOCKS

No.	15.01		15.02	15.03	15.04
	In the past 24 months, has your household experienced any of the following shocks 1. Yes 2. No		Did the shock result in a decrease or loss of income or assets? 1. Income Loss 2. Assets Loss 3. Both income and assets loss 4. The event didnot result in any loss	What was the monetary value of the loss?	How long ago (in months) did this shock take place?
01	Earthquake				
02	Flood				
03	Landslide				
04	Drought				
05	Fire				
06	Hail/Lightening				
07	Pests and Plant Diseases				
08	Post Harvest Loss				
09	Forced Displacement				
10	Riots/Blockage				
11	Death of a family member				
12	Diseases or injury of family member				
13	Loss of a regular job of a household member				
14	Failure or bankruptcy				
15	Theft				
16	Break upof a family (Abandonment, separation				
17	Loss of contract or default by creditor				
18	W ithdraw al of government assistance				
19	Fuel shortage,				
20	Unexpected Higher Prices				
21	Livestock loss				

Source: (World Bank, n.d.b)

Appendix 3: Definitions of Variables

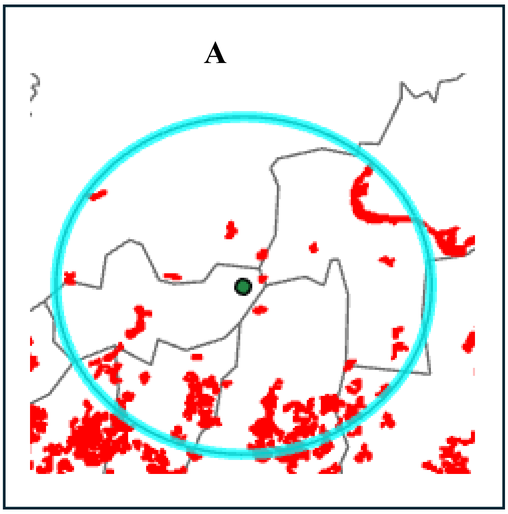
Variables	Definition of Variables
Economic Outcome Variables	
Paddy Production (Wet Season)	Quantity (kilograms) of total paddy harvested by the household in wet season
Production value	The product of paddy harvest quantity (kilograms) in the wet season and the price per kilograms of paddy at the level of primary sampling units
Total Income	Yearly sum of household income (in Nepalese Rupees currency) generated from selling of crops, wage employment, rent, selling of livestock products, selling of products from non-agricultural enterprises
Crop Income Wet Season	Income generated by selling crops grown in wet season
Crop Income Dry Season	Income generated by selling crops grown in dry season
Total Crop Income	Total income by selling wet and dry season crops
Income from Daily Wage	Income generated by the household from wage employment with daily contract in a year
Income from Wage Employment	Income generated by the household from wage employment with daily contract, long-term contract, and task-based contract work in a year
Income from Livestock	Income generated by the household by selling products from livestock in a year
Total Asset Value	Sum of self-estimated monetary values of land, home, livestock, financial assets, and durable goods owned by household
Financial Asset Value	Sum of the assets owned by households in the form of Cash in hand, saving in bank and cooperatives, Fixed Deposit, Stocks, Shares, Treasury Bills, Employee Provident Fund/Citizen Investment Fund, Life Insurance
Cash in Hand	Amount of cash in hand
Saving	Total sum of savings of the household in bank and cooperatives
Livestock Value	Self-estimated monetary value of all livestock owned by the household
Land Value	Self-estimated monetary value of all plots owned by households
Home Value	Self-estimated monetary value of the residency owned by the household
Durable Goods Value	Self-estimated monetary value of all durable goods owned by the household
Other Variables	
Working Age Members	Number of household members in working age group of 15 to 64 years old
Education HH Head	Categorical variable indicating whether the head of the household attended school or not, Never Attended School (1), Attended school in the past (2)
Gender HH Head	Binary variable on gender of household head, male (0), female (1)
Slope	Categorical variable on slope of housing plot, Flat (1), Moderate (2)
Home Ownership	Binary variable on whether or not household own the house they reside on: No (0), Yes (1)
Distance Market	Distance of the house from nearest daily market in kilometers
Distance Bank	Distance of the house from the nearest bank in kilometers
Distance Motor Road	Distance of the house from the nearest motorable road in kilometers
Distance Health Post	Distance of the house from the nearest health post in kilometers
Elevation	Elevation of the household location measured in meters above sea level unit

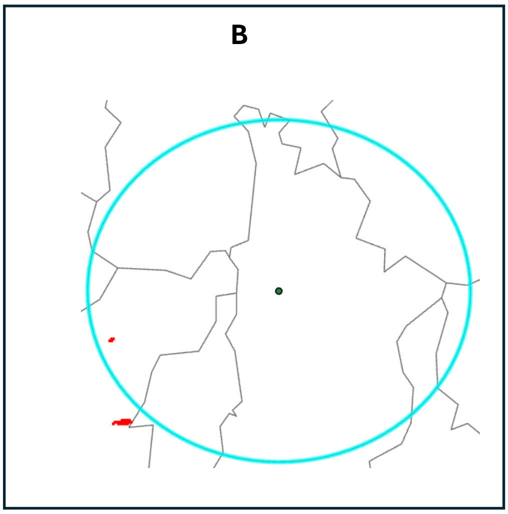
Note: All the variables are constructed based on the data from Household Risk and Vulnerability Survey (HRVS). All monetary values are in Nepalese Rupees currency and all the distances are measured in kilometers.

Source: Author's creation based on the computation used in the research

Appendix 4: PSU selection criteria

Selection criteria of the PSUs based on buffer intersection with inundated area





Source: Author's creation using data from HRVS-panel survey, ICIMOD inundation map in ArcGIS software
Note: The red mosaic is the inundated area. The green dot in the middle is the Primary Sampling Unit Center point and the blue circle is the 3km buffer around the PSU center point. The PSU in image A has passed the threshold of the inundated area covering 5% of the buffer and hence included in the control group construction. The PSU in image B on the left was also among the list of PSUs whose buffer intersected with the inundated area but was later removed from the list for control group construction for not passing the 5% threshold requirement.

Appendix 5: Results of difference-in-difference analysis with covariates

Regression results with covariates for robustness check on difference-in-difference analysis for economic outcomes on paddy production.

	Paddy Production	Paddy Value
$Post_F$	0.045	0.051
	(0.031)	(0.032)
$Post_F$*$Flooded_i$	-0.332***	-0.448***
	(0.085)	(0.099)
Observations	961	961
N of HH	519	519
Within R^2	0.11	0.13
Cluster	hhid	hhid
HH FE	fe	fe
Controls	Yes	Yes

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation

Regression results with covariates for robustness check on difference in difference analysis for economic outcomes on household income and its components.

	Total income	Crop Income Wet Season	Crop Income Dry Season	Total Crop Income	Income from Daily Wage	Income from Wage Employment	Income from Livestock
$Post_F$	0.119**	0.219**	-0.188**	0.044	0.075	0.058	0.289*
	(0.047)	(0.097)	(0.092)	(0.092)	(0.061)	(0.046)	(0.160)
*$Post_F$*$Flooded_i$*	-0.262**	-0.710***	0.299	-0.200	-0.207*	-0.138	-1.336***
	(0.111)	(0.200)	(0.253)	(0.201)	(0.121)	(0.106)	(0.428)
Observations	1315	415	539	613	634	838	373
N of HH	704	296	377	409	400	508	294
Within R^2	0.07	0.18	0.09	0.09	0.06	0.06	0.14
Cluster	hhid	hhid	hhid	hhid	hhid	hhid	hhid
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation

Regression results with covariates for robustness check on difference in difference analysis for economic outcomes on household assets and its components.

	Total Asset Value	Financial Asset Value	Cash in Hand	Saving	Livestock Value	Land Value	Home Value	Durable Goods Value
$Post_F$	-0.123***	0.261***	-0.488***	0.213**	0.112**	0.044***	-0.135***	0.144***
	(0.033)	(0.084)	(0.125)	(0.096)	(0.050)	(0.016)	(0.045)	(0.035)
*$Post_F$*$Flooded_i$*	0.022	-0.464**	-0.538**	-0.133	-0.119	-0.018	-0.102	-0.183*
	(0.057)	(0.213)	(0.242)	(0.227)	(0.148)	(0.021)	(0.104)	(0.097)
Observations	1433	1243	839	921	1060	1012	1403	1430
N of HH	722	716	691	574	616	509	719	722
Within R^2	0.03	0.03	0.22	0.02	0.05	0.03	0.02	0.03
Cluster	hhid	hhid	hhid	hhid	hhid	hhid	hhid	hhid
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation

Appendix 6: Results of parallel pre-trend tests

Regression results for parallel pre-trend test on difference in difference analysis for economic outcomes on paddy production.

	Paddy Production (Wet Season)	Paddy Value
Time	0.264***	0.302***
	(0.041)	(0.042)
*Time*Flooded$_i$*	-0.074	0.077
	(0.095)	(0.097)
Observations	961	961
N of HH	530	530
Within R^2	0.10	0.14
Cluster	hhid	hhid
HH FE	Yes	Yes

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation

Regression results for parallel pre-trend test on difference in difference analysis for economic outcomes on household income and its components.

	Total income	Crop Income Wet Season	Crop Income Dry Season	Total Crop Income	Income from Daily Wage	Income from Wage Employment	Income from Livestock
Time	0.536***	0.206	0.589***	0.255***	0.379***	0.385***	0.402***
	(0.057)	(0.126)	(0.106)	(0.097)	(0.073)	(0.057)	(0.154)
*Time*Flooded$_i$*	0.115	-0.063	-0.314	0.074	0.239	0.067	0.070
	(0.166)	(0.257)	(0.299)	(0.250)	(0.167)	(0.150)	(0.542)
Observations	1275	416	492	564	583	806	378
N of HH	698	297	341	378	387	514	298
Within R^2	0.16	0.03	0.16	0.05	0.16	0.16	0.09
Cluster	hhid	hhid	hhid	hhid	hhid	hhid	hhid
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation

Regression results for parallel pre-trend test on difference in difference analysis for economic outcomes on household income and its components.

	Total Asset Value	Financial Asset Value	Cash in Hand	Saving	Livestock Value	Land Value	Home Value	Durable Goods Value
Time	0.336***	-0.162*	-0.393***	-0.659***	-0.333***	-0.105**	0.382***	0.721***
	(0.037)	(0.086)	(0.111)	(0.121)	(0.057)	(0.051)	(0.045)	(0.047)
*Time*Flooded$_i$*	-0.240**	-0.224	0.664***	-0.315	0.677***	-0.204*	0.044	-0.075
	(0.102)	(0.221)	(0.219)	(0.349)	(0.145)	(0.119)	(0.116)	(0.124)
Observations	1441	1194	707	726	1052	1011	1406	1428
N of HH	722	698	594	516	622	513	721	722
Within R^2	0.10	0.01	0.11	0.16	0.09	0.02	0.12	0.27
Cluster	hhid	hhid	hhid	hhid	hhid	hhid	hhid	hhid
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The economic outcomes are logarithmic transformed values. All zero values are omitted, which means only the effect on households facing the partial loss is analyzed. Results include household fixed effect. The standard errors are clustered at the household level and are included in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation