(Im)balance in the household balance sheet in the aftermath of a natural disaster

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Abstract

This study examines the long-run impact of a flood on the household balance sheet in coastal India. Considering multiple rounds of large-scale household surveys and employing a difference-in-difference methodology, the paper finds that flood affects the assets holdings and liabilities of the affected households. The flood-affected households are less likely to invest in illiquid assets and are more likely to hold liquid financial assets in the post-flood period, pointing towards a substitution in the asset side of the household balance sheet. On the other hand, we find that flood adversely impacts the liabilities of the affected households as proxied by their likelihood of being indebted and the extent of indebtedness. Additional evidence indicates that the increased indebtedness is driven by loans taken to meet household expenditures. The affected households also end up paying higher interest rates on borrowings. Hence, our findings draw significant policy implications for disaster-affected households.

Keywords: Climate, floods, illiquid assets, financial assets, debt, India

JEL Codes: D15, G11, G51, Q54

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1. Introduction

Climate change can be thought of as one of the leading risks facing the world population in the coming years. Global warming has increased the surface temperature by over one-degree celsius from 1850-1900 to 2011-2020 (IPCC Report, 2023[3]). The report highlights that a further increase in global temperature is likely to result in high levels of risk of climate hazards, including higher frequency and intensity of floods in coastal regions, droughts, landslides, and heat waves, among others. These catastrophic events cause sudden disruption in everyday life and widespread damage to property and livelihoods. Existing studies highlight that natural disasters are related to substantial economic losses (Khan et al.,2019) and environmental damages (Parida et al., 2021; Sangha et al.,2020; Botzen et al.,2019). Few studies at the household level also examine the effect of natural disasters on income and consumption (Patnaik et al.,2019), loss of assets (Baez et al.,2016), and adverse health impacts (Paterson et al.,2018).

Unfortunately, few regions and sub-populations are more vulnerable to these disasters compared to others. Given the geographical location, the Asia Pacific Region experiences over 60% of the world's natural disasters (Asia Pacific Disaster Report,2019). Emerging evidence suggests that the poor residing in less developed economies are more vulnerable to natural disasters even though they contribute the least towards climate change (Arouri et al., 2015; De Haen and Hemrich, 2007). It is important to note that the absolute impact of a natural disaster is higher in developed countries than in less developed economies; however, the relative share of loss to overall GDP can be substantially higher in less developed countries (Bui et al.,2014; Noy and Vu,2010; Albala-Bertrand,1993). For instance, the World Disaster Report (2015) documents that the total amount of estimated damage during 2005-2014 due to natural disasters in Asian countries (mainly developing) amounts to 749,690 million US dollars, whereas for European countries (mainly developed), it stands around 145,767 million US dollars. Noy (2009) documents that disasters appear to be costlier in developing countries than in developed ones because of higher population density. One possible reason might be the ability of developed countries to pursue public policies following adverse shocks that lower-income countries do not seem to enjoy and often end up in worse conditions. Studies (Thurlow et al.,2012; Jury,2002) argue that the economic footprint of climate variability is specifically significant for developing countries since they are less able to cope-up with environmental challenges.

[3] Sixth Assessment Report, Intergovernmental Panel on Climate Change. Visit https://www.ipcc.ch/report/ar6/syr/ for more details. (Accessed on March 31, 2023).

Given this backdrop, the objective of this study is to primarily assess the impact of coastal flooding on household balance sheets in India several years after the flood. Specifically, we ask two important questions in this regard using the Tamil Nadu flood of 2015 in the southern part of the country as a case study. First, the question deals with the asset allocation decision of the affected households and the extent to which coastal flood affects households' holdings of liquid and illiquid assets several years after the advent of a flood. Next, we assess what happens to the liabilities of the households. For this, we consider the indebtedness and extent of indebtedness years after the flood as proxies of liability side indicators.

Floods can have short-term as well as long-term impacts on household balance sheets. In the long run, floods can affect household balance sheets in several ways. First, in the absence of flood insurance, households may have to incur large expenditures to cover flood damage, and it may take years to recover from this financial shock induced by flood, especially for vulnerable households. Second, if the flood is severe, there could be potential damage to property and immovable assets. This can permanently reduce the worth of the fixed assets and also force households to borrow to repair the affected property. Third, loss of income in the aftermath of the flood may cause households to dis-save and borrow to meet household expenditures. Next, flood-affected households may become wary of investing in immovable property as these assets are severely affected by floods. Finally, on the positive side, households may start saving for emergencies by investing more in liquid assets because of floods.

Several studies have examined the impact of natural disasters on household behavior. For instance, Beyer et al. (2022) find decreased outstanding borrowing for household consumption and increased debt for housing and medical purposes in the short run after the Kerala flood in May 2018. They also observe a reduction in income and expenditure of the households and an increase in post office savings, and a decrease in other savings instruments like bank deposits and gold. Similarly, Patnaik et al. (2019) highlight an overall reduction in income from two months to the one year after the Chennai flood. However, in contrast, it finds that household expenditure exhibits a sharp increase till six months and then registers a significant fall. In the long run, there is evidence of a decline in consumption and income post-flood period (Baez et al.,2016; Arouri et al.,2015). Further, Gopalakrishnan et al. (2019) show that investment in both real estate and financial assets increases after a rainfall shock though the change in real estate is insignificant. Additionally, they provide evidence that households that experienced two shocks in consecutive periods are likely to decrease investment in financial assets and increase investment in real estate. Their study also reveals that housheholds use financial assets as the transitory asset class for adjusting the huge cost of real estate. Bui et al. (2014) report a substantial reduction in per capita income and expenditure of the households which have faced any natural disaster within the last five years in Vietnam. Masiero and Santarossa (2020) provide evidence of a sharp increase in household expenditure after twelve years of flood shock. On the other hand, a recent study by Johar et al. (2022) find no impact on household income but a substantial impact on the financial hardship of Australian households in the post-disaster period. Using high-frequency data from India for 2001-12, Tamuly and Mukhopadhay (2022) find that natural disaster negatively impacts household consumption but positively impacts the value of Innin China, substantially reduce the likelihood of households participating in stock markets and other risky asset markets.

We consider India for this study for several reasons. First, in India, the occurrences of heavy rainfall resulting in floods, landslides, and crop damage are rising (Roxy et al.,2017). Eckstein et al. (2021) identify India as one of the most vulnerable countries that are likely to witness a rise in sea levels and increased river flooding. From the perspective of urban flooding, India is the second most vulnerable country after China (Bandopadhay et al., 2021). Second, in 2015, Tamil Nadu, a southern state of India, witnessed incessant rainfall during November-December due to the formation of a depression over the southwest Bay of Bengal and owing to a strong El Nino, which led to a devastating flood in the Coromandel coastal districts of Tamil Nadu. In the aftermath of this flood, more than 400 people died while all the hospitals stopped performing,18 lakhs were displaced, and all the power supplies were suspended (Bandyopadhyay et al.,2021). Moreover, economic losses of about 3 billion USD made this flood the costliest disaster of 2015 in India and eight most expensive all over the world (Narasimham, 2015). This extreme (exogenous) flood allows to study the effect of flood on household balance sheet using appropriate methodological tools. Third, the availability of large reliable household level datasets tracking the assets and liabilities at regular intervals allows us to study the effect of floods on household's balance sheet in the Indian context in a reliable manner and comment on the implications for other country settings with some confidence.

Using the exogenous Tamil Nadu flood of 2015 we identify the treated districts as the districts of Tamil Nadu that were affected by the flood and the rest of the districts as control districts. We make use of the three rounds of the large-scale All India Debt and Investment Survey datasets, and using a standard difference in difference set; our study finds that flood leads to a change in asset allocation of the treated households. Specifically, we find that the treated households were less likely to hold illiquid assets and more likely to hold liquid financial assets. This could be either attributed to the loss of property and/or value erosion due to the flood, or a change in perception towards physical assets due to floods disproportionately causing damage to illiquid immovable assets. On exploring further, we find that the likelihood of holding both real estate and ornaments fall in the post flood period, whereas among financial assets, only the likelihood of investments in retirement funds increases. Interestingly, we also find that among those holding illiquid assets, the amount of assets held by the treated households fell on average after the flood which is mainly driven by the fall in the value of real estate. Together, the asset side findings point towards households substituting liquid assets for illiquid assets in the aftermath of disasters like a flood. Broadly, it aligns with the idea that exposure to climate hazards induces households to reassess the probability of facing future natural disasters and change their preferences and behavior in light of the same.

Our analysis for the liability side indicates that flood-affected households are more likely to be indebted more than three years after the flood and have a greater extent of indebtedness. Further, our result suggests that higher borrowing by the affected households is mostly for meeting household expenditures. Lastly, we find that the average interest rate paid by the affected households in the aftermath of the flood is also higher; however, we do not find any evidence that the increased cost of borrowing is because of higher share of informal borrowing. The liability side analysis highlights the vulnerability of Indian households due to exposure to climate hazards like floods.

Our paper makes key contributions to three strands of literature. Firstly, this study contributes to the literature on studies on climate change and household behavior (Zhang et al.,2021; Zhang,2016). We extend this literature by providing evidence on how high-frequency natural disasters like floods can impact the assets and liabilities of households in high-risk coastal regions. Secondly, our study also contributes to the literature on the long-run effects of climate change. Even though studies have focused on the short-run impact of floods on household financial behavior (Beyer et al.,2022; Patnaik et al., 2019), our study is among the early ones to assess the long-term impact of a flood on both sides of the balance sheet of the affected households. Thirdly, the study also contributes to the growing household finance literature in emerging economies (Beyer et al.,2022; Patnaik et al.,2019; Bui et al.,2014) and underscores their vulnerabilities, especially in the aftermath of natural disasters.

Our paper is organized as follows. Section 2 presents the research questions. Section 3 elaborates on the Tamil Nadu flood of 2015, whereas Section 4 presents the data and variables. Section 5 presents the methodology, and Section 6 discusses the findings of the paper and finally Section 7 concludes the study.

2. Research question

Experiential learning theory suggests that the best way to learn lessons is by actually having experiences. Henceforth, the experience of natural disasters is expected to influence the attitude of the households toward their financial activity. Earlier studies infer that catastrophe experience affects an individual's attitude to risk. For example, a household experiencing a natural hazard may attach a higher probability of experiencing another disaster in the future (Brown et al.,2018; Gallagher,2014). For example, using the case study of Australian flood of 2011, Page et al. (2014) find a change in the risk-taking behavior of flood-affected homeowners just after the disaster. Further, the Precautionary savings theory suggests that expected risk and a household's precautionary savings are positively correlated. In fact, the savings rate depends on risk expectation and the households' risk preference (Gunning et al.,2010). Hence, we expect that a change in the risk perception of the households due to the flood may lead them to save more and invest in financial assets. Given that the portfolio of Indian households is concentrated in illiquid assets like land and gold, we hypothesize that the flood leads to a change in portfolio allocation by reducing investments in illiquid assets and increasing investments in liquid financial assets.

However, severe economic loss and income shock in the short run may have a long term impact on liability side of the household balance sheet. First, the extent of economic loss owing to the devastating flood may prohibit households from paying back the debt outstanding at the time of the disaster in a timely manner. Additionally, studies exhibit that natural disaster leads to a decrease in income and an increase in expenditure creates a lot of financial pressure on households to meet both ends, and households end up with borrowing to handle the distressed situation (Bhattacharjee and Behera, 2018). Moreover, disaster induced damage to property, diseases and loss of income may induce the affected households to borrow further. Hence, even though the asset side of the balance sheet is likely to show improvement in terms of composition, the affected households are likely to remain indebted even in the longer term.

3. Tamil Nadu Flood of 2015

The Tamil Nadu flood of 2015 (TN flood) brought about by northeast monsoon was one of the most severe floods that took place in the country. A leading daily, Times of India[4] reported "*With estimates of damages and losses ranging from nearly Rs 200 billion to over Rs 1 trillion, the floods were the costliest to have occurred in 2015, and were among the costliest natural disasters of the year*." Chennai Metropolitan City, the capital of Tamil Nadu witnessed heavy rainfall of above 1000 mm in November 2015, coupled with a high-speed storm, which led to the fall of more than 900 trees (GCC, 2017[5]). Moreover, another depression

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[4]https://timesofindia.indiatimes.com/topic/chennai-floods (Accessed on May 5, 2023)

[5] GCC(2017). GCC Disaster management plan. Greater Chennai Corporation (https://www.scribd.com/document/543240186/Chennai-Gcc-Disaster-Management-Plan-2017#).

was formed over Tamil Nadu triggered by El Nino at the end of November, which resulted in additional rainfall. Studies suggest that the gradual increase in temperature might have resulted in incessant rainfall in the coastal area of Tamil Nadu and Pondicherry during November 2015. In Chennai itself, 165 out of 200 wards went underwater. During the period, power supply, schools, airports, and railway services were disrupted. Even the emergency services like hospitals also ceased functioning. The prolonged period of torrential rain led to overflowing of waterbodies. Government of India announced Chennai as disaster zone (Bremner,2015). About 30% of the Chennai households went through an economic loss of Rs.2 lakhs to Rs.20 lakhs (Narasimhan et al.,2016), and industrial sector faced a loss of around 14,000 crores (Express News Service,2015[6]).

According to the National Institute of Disaster Management report, Tiruvallur, Chennai, Kancheepuram, Villupuram, Cuddalore, and Nagapattinam in the state of Tamil Nadu; Puducherry and Karaikal in the union territory of Pondicherry were severely affected by the flood[7] (Figure 1) and over 400 deaths were reported in the affected districts. Due to power cuts, 18 patients were reported dead in hospital ventilation. Further, around 3 million flood-affected families experienced partial or complete damage to their residences, and 1.8 million people were shifted elsewhere.

<<Figure 1>>

4. Data and variables

The All-India Debt and Investment Surveys (AIDIS) are periodically conducted by the National Statistics (NSS) Office under the Ministry of Statistics and Program Implementation to assess the state of investments and debt of households in India. The survey provides the basic information on the assets and liabilities of the households along with its other socio-demographic features, including educational attainment, occupation, and across all the states and union territories of India. We employ the last three rounds of the AIDIS which were implemented as a part of the 59th, 70th and 77th NSS rounds in the years 2003, 2013 and 2019, respectively. AIDIS-2019 surveyed 1,16,461, whereas AIDIS-2013 and AIDIS 2003 covered 1,10,800 households and 1,43,285 households across all major states and union territories in India, respectively. We consider the households surveyed in the state of Tamil Nadu and Pondicherry in the three rounds for our study which yields a sample of 26,629 households. The sample includes 7,434

[6]https://www.newindianexpress.com/cities/chennai/2015/dec/27/Flood-hit-Industrial-Belts-Clamour-for-Aid-861032.html

[7] According to the report on Chennai flood,2015 by the Disaster Management Support Division under ISRO, we consider 8 districts with highest rainfall during the period 1.10.2015 to 9.12.2015 as our treatment group. See Table A1 in Appendix for the rainfall details.

households from AIDIS-2019, 7,290 households from AIDIS-2013, and 11,905 households from AIDIS-2003. All the values partaing to debts and assets of the hosuheolds are reffered to 30th June of respective years. However, the values are adjusted in our pooled cross-sectional database with respect to the price level given by CPI (Source: World Bank) of given years taking the base as 2010.

In the study both asset and liability side variables as considered as the outcomes. For the asset side, we use two illiquid and financial assets measures. Illiquid1 is an indicator variable that takes the value one if the household owns land, buildings, and jewellery and zero otherwise. Illiquid2 is a continuous variable defined as the natural logarithm of the amount of money invested in land, buildings and jewellery by the household on the survey date. Similarly, Financial1 is an indicator variable that takes the value one if the household owns financial assets, including deposits, retirement savings, mutual funds, bonds, shares, etc., and zero otherwise. Financial2 is the logarithm of the value of deposits, retirement savings, mutual funds, bonds, shares, etc., held by households. Again, for the liability side of the household balance sheet, we consider two measures. Indebtedness is the indicator variable that takes the value one if the household has any loan outstanding on the day of the survey and zero otherwise and captures the participation of the household in the debt market, whereas the extent of indebtedness (EOI) is the logarithm of the value of the loan.

Additionally, we define a variable 'flood' that takes the value one if the districts in TN and Pondicherry were affected by the TN flood of 2015 and zero otherwise (refer Figure 1). These affected districts form our treatment group and the unaffected districts of Tamil Nadu and Pondicherry forms the control group for the study. Note we exclude the districts bordering the treated districts from our analysis as these districts may be argued to be exposed to the flood as they may have social ties with households of the affected districts or the flood may change the risk perception of neighboring districts and hence may confound our results. Further, we define a variable 'post' that takes the value of one for 2018 i.e. for all the households surveyed from AIDIS-2018-19 and zero otherwise i.e. those surveyed in AIDIS-2012-13 and AIDIS-2002-03. In other words, this variable represents the households few years after the flood.

In line with the literature, we also control for various socioeconomic factors that are likely to affect the financial outcomes of the household. Studies indicate that the household head's age, marital status, employment status, family income, and the number of dependent children in the family influence the financial behavior of households (Tamuly and Mukhopadhyay,2022; Beyer et al.,2022). Additionally, in the Indian context, studies find that the household head's gender, caste, religion, and residential area are essential predictors of household asset ownership (Rampal and Biswas, 2022; Lahiri and Biswas, 2022).

Likewise, we control for the dependency ratio, age, educational status, gender of the household head, caste, religion, and area of residence, in our framework. Table 1 describes the variables used in the study along with the mean of the variables.

<<Table 1>>

5. Methodology

We rely on a difference-in-difference (DD) approach to examine the causal effect of TN flood of 2015 on household balance sheet and estimate the following regression model. DD approach is widely used in economics and finance literature to tease out the causal effect of exogenous shocks/policy (Beyer et al., 2022; Tamuly and Mukhopadhyay, 2022).

$$y_{hdt} = \beta_0 + \beta_1 Flood_d + \beta_2 Post_t + \beta_3 Flood_d * Post_t + \beta_4 X_{hdt} + District_d + \varepsilon_{hdt} \quad (1)$$

Where y_{hdt} denotes the asset and liability side outcome variables discussed above. As mentioned earlier, flood captures whether the districts were affected by the flood in 2015, post variable captures if the household is surveyed post the TN flood of 2015, i.e., in the year 2018, and is the treatment variable. Finally, Flood*Post takes the value one if the surveyed household is from the flood-affected districts and whether the household was surveyed as a part of AIDIS-2018-19 and zero otherwise. These households constitute the treated group post-treatment and β_3 will capture the impact of the flood on outcome variables after partialling out the effect of being located in flood affected districts (given by β_1) as well as surveyed in 2019 (β_2). β_3 gives the effect of flood on the flood-affected households in the aftermath of the flood relative to those not affected by the flood. X_{hdt} gives the set of control variables, $District_d$ are the district-fixed and ε_{hdt} captures household-level idiosyncratic shocks.

We employ probit regression method when the outcome variables are given by the indicator variables – Illiquid1, Financial1, and Indebtedness. On the other hand, when we use the continuous variables – Illiquid2, Financial2, and EOI as outcome variables for the analysis, we estimate a linear regression model using the ordinary least squares method.

6. Result

6.1. Descriptive statistics

Table 2 indicates a higher proportion of the treated and control groups held illiquid as well as financial assets in the post period than in the pre-treatment period. However, the increase in illiquid asset holding for the treated group is lower by 0.1 percentage points than for the control group, whereas, for financial assets the increase is much higher for the treated group than the control group. Further, the value of illiquid assets is higher in the pre-treatment period for the treated households and the reverse is observed for the control group. On the other hand, the value of financial assets is lower for the treated group in the aftermath of the flood compared to control households. Even the indebtedness of treated households decreased by around 5.3 percentage points between pre and post treatment period and during the same period the indebtedness of control group households decreased by a 4.9 percentage points. Further, the outstanding loan of treated households increased in the post period whereas the opposite is observed for control households.

<<Table 2>>

6.2. Difference-in-difference results

Table 3 presents the DD regression marginal effects, which give the effect of the flood on the asset side of the balance sheet. Column 1 indicates that the flood led to a fall in the likelihood of holding illiquid assets IIlliquid1) by 1.6 percentage points. On the other hand, the coefficient of the interaction term is significant and positive for Financial1 indicator (Column 3). From the asset side, it appears that the households are 9.5 percentage points more likely to hold liquid financial assets years after the flood. On turning to value of assets, we again observe a similar pattern (Columns 2 and 4), wherein the average value of illiquid assets is lower by 7% for treated households post flood and the value of financial assets held by treated households increased on average by 25.3% in the aftermath of the flood. These results are largely in line with the experiential as well as the predictions of the precautionary savings theories. Experiencing flood and the possible damage to physical assets and an increase in awareness regarding the usefulness of financial assets at the time of need may explain these results.

<<Table 3>>

Table 4 presents the results for the liability side of the household balance sheet. Column 1 indicates a positive and significant result for the interaction term between flood and post variables, suggesting that the incidence of indebtedness has increased by 7.5 percentage points among treated households compared to the control group in the post flood period. Further, column 2 indicates that even the EOI for the affected households in the post-flood period is statistically higher than the control households. The increased indebtedness and higher EOI can be due to the severe flood-induced economic loss negatively impacting the debt-repaying ability of the affected households. Further, these indebted households are likely to be forced to take additional loans to sustain consumption in the post flood period. These findings related to the impact of the flood on a household balance sheet, to an extent, in line with the findings of Beyer et al. (2022), where they found that Kerala floods led to a fall in gold investments and a rise in post office savings by the treated households after the flood.

<<Table 4>>

A critical assumption while using the DD framework is that the difference in outcomes between the treated and the control groups does not change over time in the pre-flood period, also known as the parallel trends assumption. To ascertain the validity of this assumption, we consider a sample that constitutes the unaffected households i.e., households belonging to Tamil Nadu and Pondicherry but in the pre-flood years. In other words, we restrict our sample only to AIDIS 59th and 70th rounds and estimate the below equation:

$$y_{hdt} = \partial_0 + \partial_1 Flood_d + \partial_2\ Year_t + \partial_3\ Flood_d * Year_t + \partial_4\ X_{hdt}\ + District_d\ +\ \varepsilon_{hdt} \tag{2}$$

In the above specification, if the estimate ∂_3 turns out to be insignificant, we argue that the outcomes of households in the flood-affected districts are not statistically different from those from the flood-unaffected districts in the pre-flood years. The other variables are the same as those in equation (1). Table A2 in the Appendix shows the test result suggesting a statistically insignificant interaction term for the Illiquid1, Illiquid2, Financial2, Indebtedness, and EOI but not for the Financial1 variable. It is worthwhile to mention that though the estimates can be interpreted largely as causal, one should be careful for inferring the results of impact of flood and the likelihood of holding financial assets.

6.3. Robustness checks

6.3.1. *Alternate treatment group*

We redefine our treatment group by considering only the highly affected districts (Tiruvallur, Chennai, Kancheepuram, Villupuram), keeping control group districts intact and re-estimate our model. Apendix Table A3 presents the result for this alternate sample. We find that for the asset variables, the households in the highly affected reduced their participation in illiquid asset (Column 1) and increased participation in financial assets (Column 3) after the flood. The results remain unchanged on considering the value of illiquid and liquid assets (Column 2 and 4). Even for indebtedness and EOI we find that the coefficient of interaction term is positive and significant (Column 5-6), reinforcing the robustness of our findings.

6.3.2. *Alternate control group*

Next, we consider the alternate control group by including the districts that share borders with the affected districts and re-estimate the model. Again, as expected, we do not find any qualitative change in our results for both asset and liability variables (Appendix Table A4), again ensuring that the main findings are not sensitive to the selection of control groups.

6.4. Portfolio rebalancing

Our main analysis suggests that possibly flood-affected households are rebalancing their asset portfolio after the flood. To explore this further, we consider the sub-sample of households holding both liquid and illiquid assets. In our sample, 77% of households participate in both physical as well financial asset markets. Re-estimating the results for this sub-sample, we find that the amount of illiquid assets held by affected households decreased by 2.9% (Column 1 of Table 5), and the value of financial assets held increased by 23.7% in the post flood period (Column 2 of Table 5). Hence, as predicted we conclude that the flood indeed led to the rebalancing of the asset portfolio by the affected households after the shock. As per the experiential theory, these households, after experiencing a flood, may reduce illiquid assets holdings and increase investments in financial assets given their lower transaction costs, higher liquidity, and usefulness during the crisis period. Lower value in illiquid assets can be explained, given the vulnerability of land and buildings in the wake of natural disasters.

<<Table 5>>

6.5. Types of assets

Our main analysis suggests that households are less likely to hold illiquid assets and more likely to hold financial assets in the post-flood period. In this section, we explore the asset types that primarily drive the result. For illiquid assets, we consider two categories, i.e., real estate (land and buildings) and ornaments. We define real estate1 and real estate2 variables, where the former captures the ownership of real estate, and the latter gives the value of the real estate, respectively. Likewise, ornaments uptake is defined by the dummy variable ornaments1, whereas the value of ornaments is given by the ornaments2 variable. We re-estimate the effect of the flood by considering the types of illiquid assets for the subsample of households holding illiquid assets. The results presented in Table 6 suggest that the treated households are less likely to hold both real estate (Column 1) and ornaments (Column 3) in the post flood period by over 2 percentage points. Whereas we find that the value of real estate falls for the treated households (column 2); however, the value of ornaments held by the treated households remains unchanged after the flood. Therefore, the fall in the value of illiquid assets appears to be driven by the fall in real estate value among treated households.

Further, for financial assets, we consider two types of assets, i.e., deposits and retirement funds. The variable deposit includes all the savings and term deposits in commercial banks, post-office, cooperative banks, other financial fixed income sources (NSC, KVP, savings bond), deposits with non-banking finance companies, micro-finance institutions and self-help groups, and other financial savings. On the other hand, retirement funds include provident funds, pension funds, and other types of contributory funds and annuity schemes. We define deposit1 and deposit2 to capture whether households have deposits and the value of deposits, respectively. Similarly, we define retirement fund1 and retirement fund2 variables and re-estimate the results. Note this regression is estimated for the households owning financial assets (80.2% of households). Column 5 of Table 6 suggests that households in the treated group are not more likely to hold deposits in the post flood period. This result is not surprising as the post flood period is almost five years after the implementation of the Government of India's flagship financial inclusion program Pradhan Mantri Jan Dhan Yojana (PMJDY), which targeted universal bank account ownership. Interestingly, the uptake of retirement funds for treated households increased by almost 8 percentage points (column 7) in the post flood period. Hence, the higher likelihood of owing financial assets in the post flood period by the treated households appears to be driven by a higher likelihood of having retirement funds. It also provides suggestive evidence that in the aftermath of a natural disaster, households' financial behaviour may improve, and they may start investing in long term financial assets instead of investing in illiquid assets. We observe that the value of deposits as well as retirement funds held by treated households after the flood is higher on average (columns 6 and 8).

<<Table 6>>

6.6. Purpose of debt

Our main analysis indicates that the indebtedness of affected households increased in the post flood period. In this section, we explore the purpose of debt that drives this increase in indebtedness. AIDIS provides information on whether the households took a loan for business purposes, for meeting household expenditure, for housing, for meeting education and health expenditure, for investment in financial instruments, and for repaying existing debt. The summary of the proportion of households taking loan for each of these purposes is given in column 3 of Table 1. Since, in our sample, only 0.14% of households have taken loans for financial investment, we do not consider this as a separate category as debt for financial investments is unlikely to drive our indebtedness results. We define six binary variables – Business, Household expenditure, Education and Health expenditure, Housing, and Repaying debt- and re-estimate equation (1) wherein these dummies are our outcome variables. The definition of these variables are given in Table 1. Note that the Housing and Education and health dummy is defined only for households surveyed in AIDIS-2012-13 and AIDIS-2018-19 as these questions were not administered as part of AIDIS-2002-03. Further, this analysis excludes all non-indebted households.

Results tabulated in Table 7 suggest that the treated households are not more likely to take loan for business purposes or for meeting health and education purposes. Even though the disaster is likely to permanently damage houses and property, we do not observe any significant increase in indebtedness for housing by among the treated households after the flood. This ties in with our asset side results that the affected households are likely to reduce their investments in illiquid assets that include land and housing. The likelihood of taking a loan to repay earlier debt falls after the flood among the affected households, whereas we observe a 7 percentage points jump in borrowing by treated households for meeting household expenditure in the post-flood period. These results highlight the vulnerability of affected households several years after the flood and as the likelihood of taking loan for productive purposes like starting and expanding businesses and investments in education does not change, and on the other hand, the households are taking loans for sustaining consumption. However, these results are in contrast to the findings of Beyer et al. (2022) in the context of Kerala floods, wherein they find that outstanding debt for meeting housing expenditure falls, whereas debt outstanding for housing and medical expenses increases just after the flood. The contrary findings highlight that the long-term effect of flood events can be different from the immediate impact of a disaster on household behavior.

<<Table 7>>

6.7. Rate of interest

In this section, we examine whether the cost of debt given by the interest rate of the outstanding debt is different across the treated and control households in the post-flood period. For this, we consider the average interest rate on outstanding debt for indebted households as the outcome variable and re-estimate equation (1). Note that this analysis is only restricted to the set of indebted households. Column 1 of Table 8 suggests that the interest rate increased by almost 1.68 percentage points for the treated households in the post-flood period. What can explain this higher borrowing rate for the treated households? There are several possible reasons for this observation. First, land and house are often used as collateral for borrowing purposes, and the disaster may affect the treated household’s ability to post collateral which in turn may affect the rate of interest. Second, the inability to repay an earlier loan just after the disaster may also reduce the borrower's creditworthiness (Ratcliffe et al.,2020), which may, in turn, lead to an increased interest rate. Third, due to a lack of sufficient/ quality collateral, households may be forced to borrow from informal sources instead of taking loans from formal institutions, which can again increase the rate of interest. We formally test the effect of flood on the share of formal borrowings of the households. We define the share of formal borrowing as the outstanding loan from formal institutions divided by the total outstanding loan for the indebted households as the dependent variable and re-estimate the equation (1). Column 2 of Table 8 indicates that the share of formal borrowing did not fall in the post flood period for the treated household since the coefficient of interaction is insignificant. Therefore, we conclude that higher informal borrowing is not driving the higher interest rates paid by the treated households in the aftermath of the flood.

<<Table 8>>

7. Discussion and Conclusion

This study investigates the long-term impact of the Tamil Nadu flood in 2015 on household balance sheet. Using multiple rounds of largescale household surveys, we find that the flood affected the asset as well as the liability side of the household's balance sheet. In the aftermath of the flood the treated households are less likely to hold illiquid assets and more likely to hold liquid financial assets. Among illiquid assets, treated households were less likely to hold both real estate as well as ornaments. On the other hand, the higher likelihood of holding financial assets among treated households is driven by retirement funds. Further, we find that the value of illiquid assets fell, whereas the value of the liquid financial assets held by the treated households increased in the post flood period. The fall in value of illiquid assets are driven by the fall in the value of real estate, whereas the increased value of financial assets held by treated households in the post flood period is due to increased deposits as well as the value of retirement funds. The results are largely in line with the experiential learning theory.

On the liability side, we observe that the treated households are more likely to be indebtedness in the post flood period, along with a rise in the extent of indebtedness. On exploring further, we find that the treated households are more likely to take a loan to meet household expenditure in the post flood period. Additionally, the treated households had to pay a higher interest rate on debt in the period after the flood. However, we do not find any evidence that the floods led to a fall in the share of formal borrowings of the households. The liability side results underscore the long run vulnerabilities of the households in flood affected regions.

The findings are important from a policy perspective. First, a full or partial debt waiver for disaster affected households can address the issue of increased indebtedness after the flood and reduce financial vulnerability. Additionally, the temporary provision of collateral-free loans and reduced interest rates may help the affected households to cope up in the aftermath of a disaster. Finally, improving financial awareness by nudging households to invest in liquid financial assets and reducing investments in illiquid assets may improve the financial resilience of households and partially shield them from future crisis events.

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List of Figures and Tables

Figure 1: Regions affected by Tamil Nadu flood of 2015

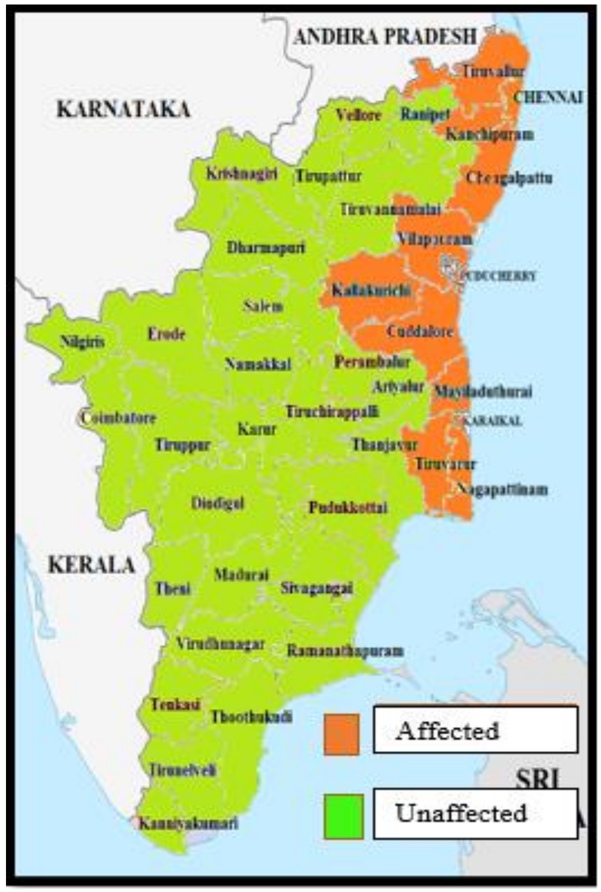

Table 1: Definition of variables

Variables	Descriptions	Means
Post	Dummy variable,1 if the year is 2018,0 for 2003 and 2013.	-
Year	Dummy variable,1 if year is 2013,0 for 2003	-
Flood	Dummy variable, 1 for the flood affected districts of Tamil Nadu and Pondicherry,0 for other districts of Tamil Nadu except the districts which are sharing border Tamil Nadu with the districts of the treatment group. Affected districts of: Tamil Nadu: Tiruvallur, Chennai, Kancheepuram, Villupuram, Cuddalore, Nagapattinam Pondicherry: Puducherry, Karaikal	-
High	Dummy variable, 1 for the highly affected districts of Tamil Nadu,0 for other districts of Tamil Nadu except the districts which are sharing border Tamil Nadu with the districts of the treatment group. Tamil Nadu: Tiruvallur, Chennai, Kancheepuram, Villupuram.	-
Alternative Flood Dummy	Dummy variable, 1 for the flood affected districts of Tamil Nadu and Pondicherry,0 for other districts of Tamil Nadu. Affected districts of: Tamil Nadu: Tiruvallur, Chennai, Kancheepuram, Villupuram, Cuddalore, Nagapattinam Pondicherry: Puducherry, Karaikal	-
Illiquid assets		
Illiquid1	Dummy variable, 1 for having illiquid assets (asset-land, buildings and ornaments),0 otherwise	0.956
Illiquid2	Logarithm of Illiquid asset value	8.049
Types of illiquid assets (Households for which Illiquid1 takes value 1)		
Immovable asset1	Dummy variable, 1 for the households owning immovable assets e.g., land and buildings and 0 otherwise.	0.755
Immovable asset2	Logarithm of amount invested in land and building.	8.496
Ornaments1	Dummy variable, 1 for the households owning ornaments and 0 otherwise.	0.952
Ornaments2	Logarithm of amount invested in ornaments.	4.692
Financial assets:		
Financial1	Dummy variable, 1 for having financial assets (deposit, PF, shares, bonds, mutual funds etc.),0 otherwise	0.802

Financial2	Logarithm of financial assets value.	3.722
Types of financial assets		
(Households for which financial1 takes 1)		
Deposit1	Dummy variable,1 for households participating in following types of deposits and 0 otherwise. Deposits: savings and term deposits in commercial bank, post-office and cooperative bank, other financial fixed income sources (NSC, KVP, savings bond), deposits with non-banking finance companies, micro-finance institutions and self-help groups and other financial savings	0.957
Deposit2	Logarithm of amount invested in all types of deposits.	3.258
Retirement fund1	Dummy variable,1 for households participating in following types of retirement planning fund and 0 otherwise. Retirement planning fund: Provident fund, Pension fund, and other types of contributories and annuity scheme.	0.139
Retirementdun2	Logarithm of amount invested in all types of retirement funds.	5.698
Indebtedness	Dummy variable, 1 for having outstanding debt, 0 otherwise	0.355
Extent of indebtedness (EOI)	Logarithm of outstanding debt amount	7.148
Purpose of loan		
(Households for which indebtedness takes 1)		
Business	Dummy variable 1, if the indebted household has borrowed for business purpose and 0 otherwise.	0.258
Housing	Dummy variable 1, if the indebted household has borrowed for housing purpose and 0 otherwise.	0.549
Household expenditure	Dummy variable 1, if the indebted household has borrowed for household expenditure purpose and 0 otherwise.	0.242
Repayment of debt	Dummy variable 1, if the indebted household has borrowed for debt repayment purpose and 0 otherwise.	0.251
Health and medical	Dummy variable 1, if the indebted household has borrowed for health and medical expenditure purpose and 0 otherwise.	0.062
Financial investment purpose	Dummy variable 1, if the indebted household has borrowed for financial investment purpose and 0 otherwise.	0.001
Others	Dummy variable 1, if the indebted household has borrowed for the purposes other than the mentioned categories and 0 otherwise.	0.076
Rate of interest	The average cost of borrowing of the households.	17.919
Share of formal borrowing	Proportionate amount of outstanding debt borrowed from formal institutions like banks etc.	0.326

Control variables		
Total assets	Logarithm of total value of the assets (physical assets and financial assets). Physical assets: All illiquid assets along with livestock and poultry, transport equipment, agricultural machinery and implements owned, non-farm business equipment owned	7.957
Age	Logarithm of age of the head of the household.	3.817
Dependent ratio	Standardised value of dependency ratio (old and child) in the households	0.339
Gender: Male	Dummy variable,1 for male head of the household and 0 otherwise.	0.822
Religion:		
Hindu	Dummy variable,1 for Hindu, 0 for others	0.882
Muslims	Dummy variable,1 for Muslim, 0 for others	0.061
Others	Dummy variable,1 for Christians,0 for others	0.057
Caste:		
General	Dummy variable,1 for general,0 for others.	0.046
SC-ST	Dummy variable,1 for SC-ST, 0 for others.	0.226
OBC	Dummy variable,1 for other backward class, 0 for others.	0.727
Education (educational attainment of head of the household)		
Illiterate	Dummy variable, 1 for illerterate,0 for others.	0.260
Primary	Dummy variable, 1 for primary educated,0 for others	0.294
Secondary and above	Dummy variables, 1 for secondary educated,0 for others	0.445
Occupation (household type)		
Self-employed	Dummy variable, 1 if the household is self-employed,0 for others.	0.285
Salaried	Dummy variable, 1 if the household is salaried,0 for others	0.279
Casual labour	Dummy variables, 1 if the household is casual labour,0 for others	0.313
Others	Dummy variables, 1 if the household is casual labour,0 for others	0.123
Sector: Urban	Dummy variable, 1 for urban sector and 0 for rural areas.	0.509

Table 2: Descriptive statistics

	Treatment		Control	
	Pre	Post	Pre	Post
Illiquid1	0.928	0.933	0.961	0.967***
	(0.260)	(0.250)	(0.193)	(0.179)
Illiquid2	8.256***	7.899	8.059***	7.900
	(1.991)	(1.862)	(1.550)	(1.587)
Financial1	0.674	0.958***	0.744	0.969***
	(0.469)	(0.200)	(0.436)	(0.171)
Financial2	4.519***	4.518	3.796***	3.247
	(1.989)	(1.884)	(2.035)	(1.408)
Indebtedness	0.359***	0.306	0.344***	0.295
	(0.479)	(0.461)	(0.475)	(0.456)
EOI	7.389***	7.236	7.197***	6.911
	(1.600)	(1.461)	(1.305)	(1.110)
No. of observations	5,564	2,317	9,943	3,663

The above table presents the mean of the variables for treatment and control groups in both the pre-treatment and post-treatment periods. Standard deviations are in parenthesis. The level of significance mentioned in the table is based on the t-test done to check the equality of means for pre and post-flood for each group. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Main result-Asset side

	(1)	(2)	(3)	(4)
Dependent variables	Illiquid1	Illiquid2	Financial1	Financial2
*Flood*Post*	-0.016***	-0.070***	0.095***	0.253***
	(0.005)	(0.012)	(0.016)	(0.054)
Flood	0.007	-0.088***	-0.042**	0.201**
	(0.005)	(0.016)	(0.018)	(0.097)
Post	-0.022***	-0.027***	0.298***	-0.630***
	(0.004)	(0.007)	(0.007)	(0.036)
Total assets	0.019***	1.054***	0.057***	0.369***
	(0.001)	(0.002)	(0.001)	(0.008)
Age	0.008***	0.016*	0.012	0.030
	(0.002)	(0.009)	(0.009)	(0.048)
Dependent ratio	0.004***	0.017***	-0.014***	-0.096***
	(0.001)	(0.002)	(0.003)	(0.014)
Gender: Male	-0.011***	-0.053***	0.022***	0.142***
	(0.002)	(0.006)	(0.007)	(0.037)
Religion: Base: Hindu				
Muslims	0.002	0.028**	-0.019*	-0.179***
	(0.002)	(0.012)	(0.011)	(0.054)
Others	-0.011***	-0.008	0.022**	0.044
	(0.004)	(0.011)	(0.011)	(0.054)
Caste: Base: General				
SC-ST	0.009**	0.084***	-0.074***	-0.438***
	(0.004)	(0.017)	(0.013)	(0.069)
Others	0.007*	0.076***	-0.054***	-0.375***
	(0.004)	(0.016)	(0.012)	(0.062)
Education: Base: Illiterate				
Primary education	0.003*	-0.019***	0.064***	0.197***
	(0.002)	(0.006)	(0.007)	(0.036)
Secondary education and above	-0.005**	-0.086***	0.117***	0.724***
	(0.002)	(0.007)	(0.008)	(0.039)
Occupation: Self employed				
Salaried	0.001	0.014*	0.035***	0.660***
	(0.003)	(0.007)	(0.006)	(0.034)
Casual labor	0.011***	0.107***	-0.006	-0.099***
	(0.002)	(0.006)	(0.007)	(0.034)
Others	0.000	0.069***	-0.015	0.330***
	(0.004)	(0.009)	(0.010)	(0.053)
Sector: Urban	0.000	-0.091***	0.053***	0.520***
	(0.002)	(0.005)	(0.006)	(0.030)
Year FE	-0.026***	0.014**	0.082***	-0.374***
	(0.004)	(0.006)	(0.006)	(0.036)
District fixed effects	Yes	Yes	Yes	Yes
Observations	20,976	20,230	20,976	15,224

The above table presents the marginal effects from probit (columns 1 and 3) and OLS(columns 2 and 4) regression. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Main result- Liability side

	(1)	(2)
Dependent variables	Indebtedness	EOI
*Flood*Post*	0.075***	0.330***
	(0.015)	(0.061)
Flood	0.006	0.198*
	(0.024)	(0.105)
Post	0.084***	1.074***
	(0.010)	(0.041)
Total assets	0.036***	0.288***
	(0.002)	(0.010)
Age	-0.038***	-0.018
	(0.012)	(0.054)
Dependent ratio	-0.025***	-0.081***
	(0.003)	(0.016)
Gender: Male	0.068***	0.109***
	(0.009)	(0.042)
Religion: Base: Hindu		
Muslims	-0.050***	-0.084
	(0.014)	(0.060)
Others	-0.005	-0.004
	(0.014)	(0.060)
Caste: Base: General		
SC-ST	0.020	-0.555***
	(0.017)	(0.077)
Others	0.016	-0.284***
	(0.016)	(0.072)
Education: Base: Illiterate		
Primary education	0.034***	0.065*
	(0.009)	(0.038)
Secondary education and above	0.015	0.355***
	(0.010)	(0.041)
Occupation: Self employed		
Salaried	-0.003	-0.010
	(0.009)	(0.035)
Casual labor	-0.011	-0.274***
	(0.009)	(0.036)
Others	-0.140***	0.052
	(0.012)	(0.069)
Sector: Urban	0.005	0.305***
	(0.007)	(0.031)
Year FE	0.091***	1.193***
	(0.008)	(0.035)
District fixed effects	Yes	Yes
Observations	20,976	7,861

The above table presents the marginal effects from probit and OLS regression of indebtedness of the households (column 1) and its amount (column 2) after the flood experience. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Additional analysis -Rebalancing of the portfolio

	(1)	(2)
Dependent variables	Illiquid2	Financial2
*Flood*Post*	-0.029**	0.237***
	(0.014)	(0.055)
Flood	-0.106***	0.221**
	(0.021)	(0.099)
Post	0.026***	-0.645***
	(0.008)	(0.036)
Other control variables	Yes	Yes
District fixed effects	Yes	Yes
Observations	14,897	14,897

The table above presents the marginal effects of OLS regression in the subsample of two types of asset holders to check the rebalancing of the portfolio. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Types of assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	Real estate1	Real estate2	Ornaments1	Ornaments2	Deposits1	Deposits2	Retirement Fund1	Retirement Fund2
*Flood*Post*	-0.033***	-0.054***	-0.023**	0.034	-0.014	0.330***	0.080***	0.597***
	(0.009)	(0.010)	(0.009)	(0.031)	(0.034)	(0.049)	(0.013)	(0.176)
Flood	-0.003	0.041**	0.008	-0.525***	-0.006	-0.134	0.038**	-0.252
	(0.013)	(0.017)	(0.010)	(0.050)	(0.011)	(0.087)	(0.019)	(0.197)
Post	-0.132***	-0.057***	0.032***	0.699***	0.086***	-0.347***	-0.134***	-1.097***
	(0.006)	(0.006)	(0.004)	(0.020)	(0.012)	(0.031)	(0.007)	(0.157)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,230	15,147	20,230	19,182	15,224	14,512	15,224	2,273

The above table presents the marginal effects of probit (columns 1,3,5 and 7) and OLS columns (2,4,6, and 8) regression for different types of assets. Columns 1-4 present the regression result for types of illiquid assets, and columns 5-8 present the results for types of financial assets. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

Table 7: Purpose of loan

	(1)	(2)	(3)	(4)	(5)
Dependent variables	Business expenditure	Households' expenditure	Education and health	Housing loan	Repayment of debt
*Flood*Post*	-0.028	0.068***	0.012	-0.027***	-0.027
	(0.018)	(0.021)	(0.023)	(0.006)	(0.023)
Flood	-0.106***	-0.083**	0.064	-0.046***	-0.096***
	(0.027)	(0.037)	(0.041)	(0.012)	(0.035)
Post	-0.074***	-0.223***	-0.064***	0.009	-0.059***
	(0.012)	(0.015)	(0.014)	(0.007)	(0.014)
Other control variables	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7,861	7,861	5,175	7,510	5,175

The above table presents the marginal effects from probit regression of indebtedness of the households after the flood experience for several purposes of the loan, e.g., business purpose (column 1), household expenditure purpose (Column 2), education and health (column 3), housing purpose (column 4) and repayment of debt (column 5). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Additional Analysis- Rate of interest and share of formal borrowing

	(1)	(2)
Dependent variables	Rate of interest	Share of formal borrowing
*Flood*Post*	1.680***	-0.004
	(0.635)	(0.014)
Flood	0.147	-0.069***
	(1.135)	(0.025)
Post	-10.509***	-0.093***
	(0.481)	(0.012)
Other control variables	Yes	Yes
District fixed effects	Yes	Yes
Observations	7,861	7,861

The above table presents the marginal effect from ordinary least square regression of the rate of interest and share of formal borrowing in the indebted subsample. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1: Rainfall in regions affected by Tamil Nadu flood 2015

	1.10.2015-9.12.2015		
Tamil Nadu districts	Actual rainfall (in mm)	Normal rainfall (in mm)	Percentage departure from normal
Kancheepuram	1808.6	577.5	213
Chennai	1612.1	708.6	128
Thiruvallur	1468.5	532.3	176
Cuddalore	1215.6	603.2	102
Nagapattinam	1339.0	786.5	70
Villupuram	920.2	436.8	111
Pondicherry districts			
Puducherry	1552.1	727.8	113
Karaikal	1291.8	855.1	51

Table A2: Parallel trend results

Dependent variables	(1) Illiquid1	(2) Illiquid2	(3) Financial1	(4) Financial2	(5) Indebtedness	(6) EOI
*Flood*Year*	0.310	0.151	0.454***	0.063	-0.011	0.066
	(0.191)	(0.983)	(0.054)	(0.077)	(0.047)	(0.073)
Flood	0.016	1.136	-0.296***	0.008	-0.083	0.135
	(0.264)	(1.680)	(0.086)	(0.138)	(0.079)	(0.122)
Year	-0.994***	-4.229***	0.216***	-0.404***	0.255***	1.149***
	(0.119)	(0.585)	(0.032)	(0.044)	(0.029)	(0.043)
Total assets	0.827***	-2.032***	0.254***	0.407***	0.102***	0.304***
	(0.031)	(0.182)	(0.007)	(0.011)	(0.007)	(0.012)
Age	0.394***	-0.193	0.068	0.004	-0.074*	-0.031
	(0.109)	(0.892)	(0.042)	(0.063)	(0.040)	(0.068)
Dependent ratio	0.184***	-0.167	-0.049***	-0.095***	-0.073***	-0.099***
	(0.038)	(0.268)	(0.013)	(0.019)	(0.012)	(0.020)
Gender: Male	-0.550***	0.663	0.110***	0.157***	0.235***	0.125**
	(0.114)	(0.810)	(0.033)	(0.051)	(0.032)	(0.053)
Religion: Base: Hindu						
Muslims	0.149	-0.666	-0.095*	-0.146**	-0.166***	-0.057
	(0.141)	(1.164)	(0.050)	(0.066)	(0.047)	(0.073)
Others	-0.408***	-1.512*	0.070	0.073	0.025	-0.028
	(0.147)	(0.918)	(0.052)	(0.070)	(0.045)	(0.072)
Caste: Base: General						
SC-ST	0.365**	4.073***	-0.369***	-0.460***	0.106*	-0.518***
	(0.179)	(1.048)	(0.064)	(0.082)	(0.055)	(0.088)
Others	0.300*	2.030**	-0.263***	-0.360***	0.091*	-0.229***
	(0.157)	(0.859)	(0.059)	(0.071)	(0.050)	(0.080)
Education: Base: Illiterate						
Primary education	0.188*	-1.711**	0.253***	0.165***	0.082***	0.020
	(0.109)	(0.719)	(0.031)	(0.049)	(0.031)	(0.047)
Secondary education and above	-0.218**	-4.468***	0.505***	0.748***	0.044	0.306***
	(0.107)	(0.730)	(0.033)	(0.051)	(0.032)	(0.049)
Occupation: Self employed						
Salaried	0.124	0.398	0.160***	0.741***	0.013	-0.077*
	(0.107)	(0.553)	(0.030)	(0.044)	(0.027)	(0.041)
Casual labor	0.559***	2.055***	-0.040	-0.057	-0.010	-0.265***
	(0.125)	(0.691)	(0.034)	(0.048)	(0.032)	(0.047)
Others	-0.106	-3.850***	0.002	0.555***	-0.412***	-0.039
	(0.149)	(0.903)	(0.045)	(0.072)	(0.045)	(0.083)
Sector: Urban	-0.094	-0.346	0.263***	0.716***	-0.015	0.349***
	(0.091)	(0.542)	(0.027)	(0.040)	(0.025)	(0.040)
Constant	0.310	0.151	0.454***	0.063	-0.011	0.066
	(0.191)	(0.983)	(0.054)	(0.077)	(0.047)	(0.073)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,996	5,159	14,996	9,434	14,996	5,159

The above table represents the result of checking the parallel trend assumption. It provides the coefficient of probit (columns 1,3 and 5) and OLS (columns 2,4 and 6) regression of assets on the interactive term of flood dummy and ppre-floodyear dummy and other socio-demographic factors. The model measures the change in household investment behaviours from 2003 to 2013. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Robustness Checks-Highly affected area

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Illiquid1	Illiquid2	Financial1	Financial2	Indebtedness	EOI
*High*Post*	-0.016***	-0.087***	0.115***	0.313***	0.061***	0.375***
	(0.004)	(0.015)	(0.021)	(0.063)	(0.017)	(0.073)
High	0.008*	-0.082***	-0.040**	0.189*	0.012	0.181*
	(0.005)	(0.016)	(0.019)	(0.098)	(0.024)	(0.106)
Post	-0.023***	-0.022***	0.291***	-0.619***	0.083***	1.073***
	(0.004)	(0.007)	(0.007)	(0.036)	(0.010)	(0.042)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,431	17,768	18,431	13,426	18,431	6,818

The above table presents the marginal effects from probit (columns 1, 3, and 5) and OLS regression (columns 2, 4, and 6) of assets and debt of the households considering highly affected areas as the treated group for the flood dummy as the alternative interest variable. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness Check-Alternative control group

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Illiquid1	Illiquid2	Financial1	Financial2	Indebtedness	EOI
*Alternative flood dummy*Post*	-0.010***	-0.059***	0.079***	0.159***	0.050***	0.279***
	(0.003)	(0.011)	(0.018)	(0.052)	(0.014)	(0.058)
Alternative Flood dummy	0.042**	-0.050	0.027	-0.585**	-0.000	-0.565**
	(0.017)	(0.035)	(0.039)	(0.231)	(0.054)	(0.233)
Post	-0.024***	-0.038***	0.314***	-0.557***	0.112***	1.134***
	(0.003)	(0.006)	(0.006)	(0.031)	(0.009)	(0.035)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,072	25,188	26,072	18,838	26,072	9,857

The above table presents the marginal effects from probit (Columns 1,3 and 5) and OLS regression (Columns 2,4 and 6) of assets and debt of the households considering alternative flood dummy by taking the alternate control group and other socio-economic factors. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.