Natural Calamities and Household Finance: Evidence from Kerala Floods*

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Abstract

We study the impact of a natural calamity on household budget and balance sheet items. A major Indian state (Kerala) experienced an exogenous environmental shock to economic activity due to heavy rainfall and the resulting floods during the months of June-August 2018. The bordering states i.e. Karnataka and Tamil Nadu did not experience such a shock during the same period. In this paper we use the distribution of rainfall and relief measures in Kerala to causally estimate the impact of floods on household finances. We show that relative to the households in the bordering states, income for households in Kerala decreased by 16 percent (cumulative) between June and August-2018 but was quick to rebound. Household expenditure on the other hand decreased by 7 percent (cumulative) during the same period but the decline persisted for a longer period. We also find that the key mechanism for the recovery of household finance post the floods was through borrowings from different sources, especially from banks.

JEL Codes: Q54, R22, D11

Keywords: natural calamity, household finance, spatial analysis

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1 Introduction

The economic losses due to natural disasters between 1998 and 2017 are valued at US$ 2908 billion of which 77 percent are due to climate-related disasters (UNISDR [2018]). According to the publicly available Emergency Events Database (EM-DAT), maintained by the Center for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvian, Belgium, a disaster is a situation or event that overwhelms local capacity, necessitating national or international assistance.[1] EM-DAT emphasizes that disaster is an unforeseen, and often sudden, event causing great damage, destruction and human suffering that are frequently caused by nature but can have human origins too. EM-DAT broadly classifies disaster into two categories - natural and technological. Natural disasters are geophysical events such as earthquakes and volcanic activities; meteorological events such as extreme temperature, fog and storms; hydro-logical events such as floods, landslides and wave actions; meteorological, biological and extraterrestrial events such as droughts, wildfires, epidemics, insect infestation, asteroid impact, etc. Technological disasters, on the other hand, include industrial accidents such as gas, poison and radiation leaks, oil spills, explosions and fires; transport accidents and other miscellaneous accidents. Barro [2009] shows that rare disasters such as the two world wars, the great depression, etc., have much larger welfare costs (20 percent of GDP) than normal business cycle volatility (1.5 percent of GDP).

The UNISDR [2018] report estimates the highest losses for the USA ($ 944.8 billion) followed by China ($492.2 billion) and Japan ($376.3 billion) due to natural disasters. India is a distant fourth in the ranking with losses reported at $79.5 billion. In relative terms however, the amount of economic losses is huge given that India is a low-middle income country. While for USA and Japan, the major causes of the economic losses are earthquake, storms and tsunami, for India, the major cause is floods. Interestingly, floods contribute 43.4 percent to the total number of disasters that occurred globally between 1998 and 2017.

[1] EM-DAT is most widely used databases in economic research related to natural disasters. See https://www.emdat.be. Also see Cavallo and Noy [2011] for a brief discussion on EM-DAT and other related data sources.

An event is included in EM-DAT as a disaster if it meets at least one out of four criteria - 10 or more people dead; 100 or more people affected; a declaration of state of emergency and; a call for international assistance. EM-DAT contains data on occurrence and effects of more than 21000 disasters around the world from 1900 to present. However, since inclusion criteria are extremely broad, most natural disasters included in EM-DAT would not classify as rare disasters in the sense of Barro [2009]. Nonetheless Cavallo and Noy [2011] shows that incidence of natural disasters has been growing between 1970s to 2000s across various regions of the world.[2] For example, in the Asia-Pacific region, one of the most vulnerable region when it comes to natural disasters, Cavallo and Noy [2011] find incidence of natural disasters has grown from an average of 11 events per country in 1970s to more than 28 events in 2000s. Truly large or catastrophic disasters, however are rare events. For example, for the Asia-Pacific region, Cavallo and Noy [2011] find on an average only 0.5 large disasters per country in 2000s which is a slight decline from the corresponding figure of 0.7 in 1970s.[3] Even though most natural disasters may not classify as catastrophic or rate disasters as considered by Barro, most have large economic consequences by directly affecting population and resources as well as indirectly affecting production and other economic decision making units in the affected regions.

In this paper we causally estimate the effect of a natural disaster on household income, expenditure and balance sheet items. First, we provide household-level estimates of the impact of the disaster on flow variables like income and expenditure and their sub-components. Although there are a number of studies that look at the aggregate impact of natural disasters, especially for the advanced countries, evidence regarding the impact natural disasters on household income and expenditure is seriously lacking for developing countries. Second, we look at some stock variables such as borrowings to identify the mechanism though which households recover their losses. Since the markets for insurance against natural calamities

[2]Cavallo and Noy [2011]point out that part of it may be due to improved recording of such events

[3]Cavallo and Noy [2011]define a large disaster as a disaster in which number of people dead as a share of population is greater than the world pooled mean of the entire sample.

are not well developed in developing countries, we provide evidence of the structural changes that may happen in household balance sheets in the medium term after the calamity occurs.

The setting of this study is the southern Indian state of Kerala that experienced severe rainfall between June and August 2018 that resulted in severe flooding in August-2018. We use a novel household level survey data that covers the same set of households before and after the floods occurred. The survey covers nationally representative sample of households, but we restrict our analyses to the households residing in Kerala and the bordering states of Karnataka and Tamil Nadu. We then use a difference in difference estimation strategy to estimate the causal impact of the floods on households finances for the households in Kerala relative to the households in Karnataka and Tamil Nadu. Our identification strategy hinges on two things. First, no natural calamity occurred during the months of June and August-2018 in Karnataka and Tamil Nadu. Second, in the months prior to the floods, the household budget items in the three states satisfy the parallel trends assumption which we show in our results.

Our results indicate that a natural disaster like floods negatively affect income and expenditure of households. Although income and wages recover fairly quickly after the floods, expenditure was slow to recover. We find that the impact of the floods on household finances may not be correlated with excessive rainfall alone. The impact of the floods are different for households due to overall infrastructure and geographical terrain. We also find that the main mechanism through which households recovered their consumption is through borrowings. The rest of the paper is organized as follows. Section 2 presents the related literature and the contribution of this paper to the literature. Section 3 presents some details about the floods in Kerala. Section 4 discusses the data and summary statistics. Section 5 presents the empirical strategy and Section 6 reports the results. Section 7 concludes.

2 Related Literature

Large natural or catastrophic disasters, particularly when they occur in developing countries, (disasters such as the December 2004 Tsunami in the Indian ocean, October 2005 earthquake in Pakistan; January 2010 Haiti earthquake; May 2008 landfall of cyclone Nargis in Myanmar; 2015 Nepal earthquake; Bhola and 1991 cyclones in Bangladesh and so on) can be expected to carry much larger welfare costs than that of rare disasters estimated by Barro [2009].[4] Issue 53 of Cred Crunch, a newsletter brought out by CRED which maintains EM-DAT, the 2018 Kerala flood - flash floods caused by abnormally high rainfalls between 1st June 2018 and 19 August 2018 and water discharge - were the worst in the state since 1924. Between 7th August - 20th August 2018, a total of 504 people died and 23 million people were directly affected by these flash floods. According to the same issue of CRED Crunch, the 2018 Kerala flood was the third costliest flood in India since 1900 with economic losses amounting up to US$2.85 billion and damage of 110,000 houses, 60000 hectares of agricultural culture destroyed (damage to fisheries), animals killed and more than 130 bridges and 83,000 km of roads damaged.[5] The Indian government classified it as a level 3 or "calamity of severe nature". Even though the 2018 Kerala flood does not fit into Barro's category of rare disasters or that of truly catastrophic events, it is one of the more destructive natural disasters to have struck the Indian subcontinent in the last decade. Our paper contributes to the economic literature on natural disasters and their consequences by studying causal effects of the 2018 Kerala floods on household income and consumption and their sub categories. What follows is a brief review of this literature.

The economic literature on natural disasters and their consequences can be categorized into two broad groups depending on whether one focuses on direct or indirect damages.[6] Direct damages include mortality and morbidity caused by a natural disaster as well as damage to fixed assets and capital including inventories, raw materials and extractable nat-

[4] Cavallo and Noy [2011]

[5] https://www.emdat.be/publications?field publication type tid=66

[6] Cavallo and Noy [2011]. This typology was introduced by ECLAC [2003], Pelling et al. [2002]

ural resources. Indirect damage, on the other hand, refer disruptions or prevention of any economic activity due to the disaster and in the period after the disaster. Indirect damage can be accounted at the aggregate level by looking at relevant macro variables such as GDP, investment, consumption expenditure, budget deficit, BOP, etc. At the household level, indirect damages include loss of income and consumption following a natural disaster. Direct damage to infrastructure and other resources can be a major cause of indirect damage of a natural disaster. Studies that focus on direct damage of natural disasters try to identify determinants of their initial direct costs using models of the following form:[7]

$$DIS_{it} = \alpha + \beta X_{it} + \epsilon_{it}$$

where DIS_{it} is a measure of direct damage of a disaster(s) in country i and time t. DIS includes measures of initial damage such as fatality and morbidity counts or capital losses. X_{it} is a vector controls which typically includes a measures of disaster magnitude and variables for vulnerability to disasters of a country. Finally, ϵ_{it} is an i.i.d. error term. Instead of panel regressions such as the above specification, many studies use only variables that are averaged over a given time period.

A key concern in this class of literature is how direct damage of natural disaster varies with economic development. Kahn [2005] finds that even though rich countries face similar incidence of natural disasters, their death toll is much lower compared to poor countries. Cavallo and Noy [2011] argue that this might be because rich countries spend more on prevention efforts and enforcement of mitigation rules. Jaramillo [2009], Keen et al. [2003] argue that policy measures regarding land-use planning, building codes and engineering interventions are rarer in less developed countries. Kellenberg and Mobarak [2008], on the other hand, suggest a non-linear relationship between economic development and initial direct cost of natural disasters. The basic point being, with rise in income, initially risk might increase

[7] Cavallo and Noy [2011]

as a result of people shifting to more vulnerable locations such as coastlines or flood planes. Other papers emphasize on the impact of political and institutional factors on direct damage of natural disasters and in general find better institutions such as stable democratic regimes or secure property rights reduce initial disaster costs. Notable papers include Kahn [2005], Raschky and Weck-Hannemann [2007], StrÃ¶mberg [2007], Toya and Skidmore [2007]. Anbarci et al. [2005]. These papers find that inequality is an important determinant with more unequal societies lacking in collective actions required to implement in preventing and mitigating measures. Besley and Burgess [2002], Eisensee and StrÃ¶mberg [2007] highlight the role of media on flood impact in India and impacts of natural disasters in US respectively. Both these papers conclude that government response to natural disasters are sensitive to media coverage. In contrast to the above paper, Ferreira et al. [2013] challenge the notion of a decreasing monotonic relationship between development and number of fatalities during natural disasters. Using a data set of 2,171 large floods in 92 countries between 1985 and 2008, Ferreira et al. [2013] find no support for results indicating that higher income and better governance reduce fatalities during flood events when unobserved country heterogeneity and within-country correlation of standard errors are taken into account.

Our objective in this paper is to study causal effects of the 2018 Kerala floods on household budget and other balance sheet items such as assets and borrowings. Therefore it is more related to the literature on indirect damage of natural disasters. As discussed before, indirect damages are consequences on the economy following natural disasters such a loss of production, consumption, investment, employment, etc. and the impact on economic growth and other socio-economic effects. Unsurprisingly, the literature on indirect damages of natural disasters is more varied than that on direct damages. We can further categorize this literature into subgroups distinguishing papers depending on their focus - macroeconomic (both short run and long run), developments or household finance.

Papers that study macroeconomic impact of natural disasters examine short run and long run effects on economic growth. Seminal contribution in this literature is due to Albala-

Bertrand [1993], who developed an analytical model of disaster occurrence and reaction and collected data on 28 events across 26 countries between 1960 and 1979. Albala-Bertrand [1993] finds positive impact of natural disasters on GDP, capital formation, agricultural and construction output, fiscal and trade deficits and reserves but no effect on inflation and exchange rates. Further development in this strand of literature was made by using of robust cross-country specifications to draw inferences. Most papers using cross-country panel data estimate equations of the following form:[8]

$$Y_{it} = \alpha + \beta X_{it} + \gamma DIS_{it} + \epsilon_{it}$$

where Y stands for impact variable of interest such as GDP per capita, X is vector of controls that may effect Y including lags of Y , DIS is measure of direct impact of disaster such as fatality or morbidity count or capital loss. DIS can also be a discrete variable indicating variations in intensity of natural disaster or may even be a binary variable indicating just the occurrence of a disaster. i stands for country and t stands for time. ϵ_{it} is the error term.

In one of the earliest contribution to this literature, Raddatz [2007] used a panel-VAR variant of (2) to estimate effects of external shocks, including natural disasters, on short-run output dynamics of developing countries and concluded that natural disaster have small adverse impact on output volatility in less developed countries. Noy [2009] also uses a cross-country panel regression to describe macroeconomic consequences of natural disasters, however employs the Hausman-Taylor three-step estimation methodology to take into account of possible correlations between the error term and endogenous/predetermined variables. Noy [2009] finds that natural disasters not only have a statistically significant adverse impact on the economy, in fact the adverse impacts are larger in case of developing countries (or smaller economies) countries compared to developed countries (or bigger economies). Noy [2009] also finds that countries with a higher literacy rate, better institutions, higher per

[8] Cavallo and Noy [2011]

capita income, higher degree of openness to trade, higher levels of government spending, more foreign exchange reserves, and higher levels of domestic credit but less open capital accounts are more resilient to the initial disaster shock and prevent further spillovers. Raddatz [2009] extends the analysis of Raddatz [2007] to include both short-run and long-run impacts of natural disasters for countries in different income groups. Like Noy [2009], Raddatz [2009] also conclude that smaller and poorer countries are more vulnerable to climatic events in particular and most of the output costs of climatic events are borne in the disaster year itself. Adverse impact of natural disaster (although significant only for large shocks) on output is also documented by Hochrainer [2009] which uses ARIMA models to construct conterfactuals of evolution GDP if natural disaster would not have occurred. Loayza et al. [2012] using panel GMM estimation, find different impacts for different types of disasters as well as different impacts of the same disaster on different sectors. Interestingly, Loayza et al. [2012] conclude that small disasters might, on an average, positively impact the macroeconomy whereas large disasters invariably have severe and immediate negative macroeconomic consequences.

Many studies extend this literature by examining more detailed panel data sets (at the firm/county/region/state) instead of the cross-country levels. Notable contributions include Strobl [2011] who uses county level US data for hurricane impact; Noy and Vu [2010] use provincial disaster data from Vietnam; Rodriguez-Oreggia et al. [2013] use municipal data from Mexico and; Leiter et al. [2009] use European firm level data to examine impact of floods on firm-level capital stock, employment and productivity. Cavallo and Noy [2011] argue that consensus of this literature is that natural disasters, on an average, negatively impact short-run economic growth. Compared to the literature on short-run macroeconomic impacts of natural disasters, that on long-run impacts is sparse. According to Cavallo and Noy [2011], an important reason for this is difficulty in construction counterfactual of GDP growth path in the absence of natural disasters. Two main contributions here, Skidmore and Toya [2002] and Noy and Nualsri [2007], reach diametrically opposite conclusions with the former finding positive and the latter negative long-run impact of natural disasters on economic growth. Skidmore and Toya [2002] explain their finding of positive impact by arguing that natural disasters might speed-up Schumpeterian creative destruction process. However more recent papers such as Cuaresma et al. [2008], Hallegatte and Dumas [2009], Jaramillo [2009], Raddatz [2009] seem to lend more support to the finding of Noy and Nualsri [2007].[9]

Since a major consensus of the literature on macroeconomic impact of natural disasters is that developing countries are more adversely affected, at least in terms of short-run economic growth, than developed countries, it is not surprising that a major concern of economic research on natural disaster is the impact on development variables. These papers typically look for impact of natural disasters on variables other that the standard GDP per capita. For example, Mechler [2009] uses a cross-country panel regression exercise to estimate the impact of natural disasters on consumption. Similarly, Rodriguez-Oreggia et al. [2013] use their municipal level panel data set from Mexico to study effects of natural disaster on human development index (HDI) and poverty. The first paper finds a small decrease in consumption in low income countries due to natural disaster whereas the second paper finds significant increase in poverty and decline HDI in municipalities of Mexico affected by natural disasters. Evans et al. [2010] examine impact of storms on fertility using using storm advisory data and fertility data for the Atlantic and Gulf-coast counties of the USA and find strong (weak) storms have negative (positive) effect on fertility. Neumayer and Plumper [2007] find that natural disasters lowers life expectancy of women and girls much more that that of men.

In the literature focusing on development impact of natural disasters, it is quite common, and not unsurprisingly, to use household level micro data sets. For example, quite a few papers focusing on rural Vietnam study impacts of climate disasters such as flood, storms and droughts on household resilience, welfare and health outcomes. These include Arouri et al. [2015] which find that storm, floods and droughts have negative effects on household income

[9] We refrain from a more elaborate discussion of the literature on long-run impacts of natural disasters because our paper is concerned with only short-run effects of the 2018 Kerala floods.

and expenditure; Bui et al. [2014] which find natural disasters to worsen household income, expenditure, poverty and inequality and; Lohmann and Lechtenfeld [2015] which find health outcomes of households with reduced agricultural income and less access to coping measures are more adversely affected following droughts. Similar studies using household data for developing countries have been done by Bandyopadhyay and Skoufias [2015] and Karim [2018] for Bangladesh; De et al. [2015] for the Pacific Island of Samoa; Kurosaki [2015] for Pakistan; Skoufias et al. [2017], K and Patnaik [2010] and Balasubramanian [2015] for India with the last one being a farm-level study; Israel and Briones [2014] for Pasay City, Metro Manila, Philippines. These papers generally point out the adverse impact of natural disasters on various household or farm level variables. More importantly, this strand of literature has identified micro-credit access, internal remittances, social allowance, land ownership as some of the important mitigating factors that may allow households to withstand natural disasters and their aftermaths.

There is a well developed micro-development literature that studies household consumption behavior in the face of random income shocks due to factors such as rainfall variability, water-logging, insect attacks, etc., mainly using survey data. Seminal contributions to this literature include Paxson [1992], Townsend [1994],Udry [1995]. A major concern here is whether or not households are able to insure themselves against such random income shocks and are able smooth consumption. This literature has been extended to examine impact of natural disasters on household finance by Sawada and Shimizutani [2008]. Our paper is related to this literature, because we examine causal effects of the 2018 Kerala floods not only on household income but also on household consumption, borrowings and asset holding. We find that following the floods, not only income of households in Kerala declined sharply compared to that of Karnataka and Tamil Nadu but so did household consumption. Further we also find that while income of Kerala households relative to those of Karnataka and Tamil Nadu recovered quickly, consumption, particularly non-food consumption could recover only with lags of few months. The main difference between our paper and other papers discussed above is that our paper is a case study which looks at the economic impact of a specific natural disaster - the 2018 Kerala floods. Case studies play a significant role in economic research on natural disasters and there consequences. Their importance can be gauged by numerous papers that study economic impact of specific natural disasters such as Horwich [2000] and Sawada and Shimizutani [2008] on 1995 Kobe earthquake in Japan; Hallegatte [2008],Vigdor [2008],Gallagher and Hartley [2017] on 2010 Hurricane Katrina; Cavallo et al. [2010] on 2010 Haiti earthquake; Coffman and Noy [2012] on Hurricane Iniki that struck Kuwai island of Hawai in 1992; Halliday [2006],Vos et al. [1999] which study impact of El Nino weather pattern in Ecuador; Akter and Mallick [2013], Mottaleb et al. [2013] study impact of Cyclone Aila that hit coastal districts of Bangladesh in May 2009. Many of these papers are simply descriptive studies such as Horwich [2000],Vigdor [2008] while some, like Selcuk and E. [2001],Cavallo et al. [2010], were too soon after the incidence of specific disasters and are able to provide only initial estimates of short-term impact or causes of damage due to a particular disaster. [10]

However a recent trend has emerged in the economic literature on natural disasters and their aftermaths that encourages use of case studies. This trend treats specific natural disasters as 'natural experiments' while estimating their impacts on varied variables of interest. Sawada and Shimizutani [2008] show that, even in the same geographical region, households that suffered greater losses during the 1995 Kobe earthquake were more likely to decrease consumption that the households which suffered less. Sawada and Shimizutani [2008] further probe into household finance items to investigate coping mechanisms employed by victims of that earthquake. Coffman and Noy [2012] estimate the long-term impact of Hurricane Iniki which hit the Kuwai island of Hawaii using a synthetic control methodology. Treating the unaffected islands of Hawaii as controls, Coffman and Noy [2012] conclude that Kuwai's economy is yet to recover even after 18 years of the event. In our paper too, we follow the trend of treating natural disaster as natural experiment but we use the 'difference-in-difference

[10] Cavallo and Noy [2011]

(DiD) methodology to tease out causal effects of the 2018 Kerala floods on household income , consumption, borrowings and asset holdings. Therefore our paper is more closer to papers on Hurricane Katrina and Cyclone Aila by Gallagher and Hartley [2017], Akter and Mallick [2013] and Mottaleb et al. [2013] respectively. Gallagher and Hartley [2017] employ the DiD methodology to find causal effects of Hurricane Katrina on household finance of residents New Orleans and provides evidence of role that local and non-local mortgage lenders in the post-disaster recovery. Akter and Mallick [2013] designed a cross-sectional survey one after Cyclone Aila in 12 most badly hit villages of coastal areas of Bangladesh to construct pre- and post-Aila scenarios where per-scenarios were provided retrospectively by their respondents. They then use the DiD methodology to compare welfare outcomes across poor and non-poor households and pre and post cyclone. They conclude while Cyclone Alia had negative impact on income, employment, access to clean water and sanitation but poorer household exhibited better ability to withstand the shock. Mottaleb et al. [2013] also treat Cyclone Aila as a natural experiment and uses data from the Household Income and Expenditure Survey of Bangladesh government to conclude, using the DiD methodology, that the cyclone adversely affected rice farmer's spending on their children's education. While we also find that the 2018 floods adversely affected households of Kerala compared to those of Karnataka and Tamil Nadu but we follow Gallagher and Hartley [2017] by (1) not only estimating the aggregate post-flood impact but also month-wise disaggregate post-flood impacts and (2) by varying the intensity of treatment across districts of Kerala.

3 Kerala Floods

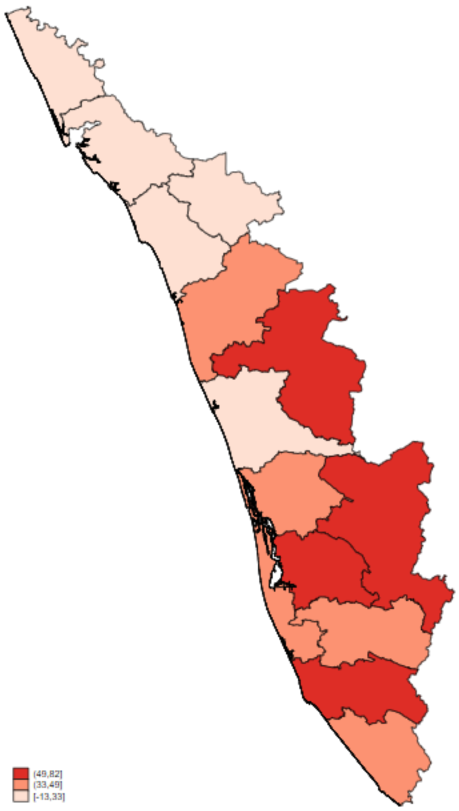
Every year in the month of June, the south-west monsoon enters the Indian land area and Kerala is the first state to be hit. The monsoon then traverses its path across the Indian land area over the next three months in varied intensity. In 2018, as per the Indian Meteorological Department (IMD), Kerala received about 2346.6 mm of rainfall during June 01, 2018 to

August 19, 2018 which was 42% above the normal. Between August 01, 2018 and August 19, 2018 total rainfall occurred in Kerala was about 758.6 mm which was 164% above normal. During this period, more than 50 percent of the rainfall occurred in just 3 days (Aug 15-17, 2018). Due to severe rainfall in these 3 days, 35 dams in the state saw above normal inflow of water in the reservoirs. Subsequently the gates of these 35 dams were opened discharging water to maintain the balance and to avoid a disaster. The heavy rainfall during a short span of time, the discharge of water from the dams and the geography of Kerala together caused severe flooding in almost all districts and landslides in the hilly districts. The Indian government categorized the disaster as a Level 3 calamity or “calamity of severe nature”. As per the report by Central Water Commission, the worst affected districts were Wayanad, Idukki , Ernakulam , Alleppey and Pathanamthitta.

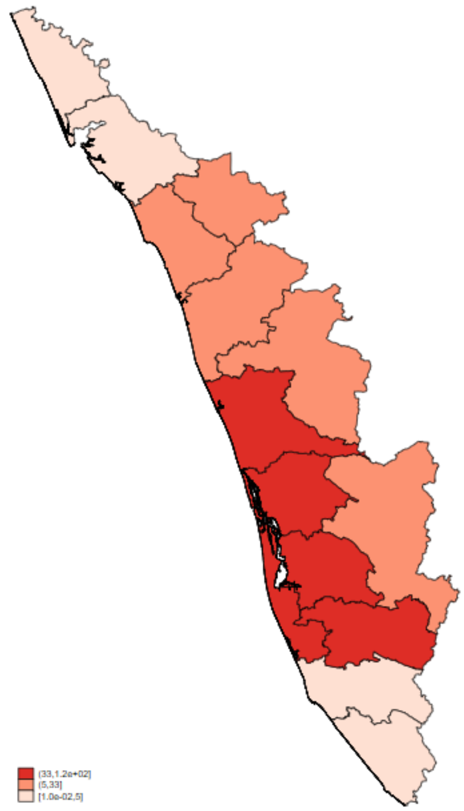
Figure 1 below shows the average deviation of rainfall between the June and August 2018 across the districts in Kerala. The districts are divided into three categories with the darker shades corresponding to the districts that received the heaviest rainfall above the normal. We see that except for the northern districts, all the districts received abnormally high rainfall during the period of June-August-2018. Interestingly however, the intensity of floods (as measured by the immediate assistance provided by the government) were not highly correlated with the intensity of the rainfall in the districts. This can been in the right panel of Figure 1. For example, Thrissur which is right next to the Palakkad district did not receive as much rainfall compared to the other districts, however the amount of assistance provided to Thrissur is quite high. Thus, it is clear that rainfall alone may not be the only cause of the floods. The discharge of water from the dams and the elevation of the land played a significant role in causing the floods. We thus, in this paper, try to separately identify the effect of rainfall and the floods on household finance. In figure 2, we show the rainfall deviations for the bordering states of Karnataka and Tamil Nadu. As can been from the categories, the deviations for many districts are negative and the magnitude of the positive deviations are far less when compared to the deviations in Kerala.

Figure 1: Flood Intensity

(a) Rainfall



(b) Assistance

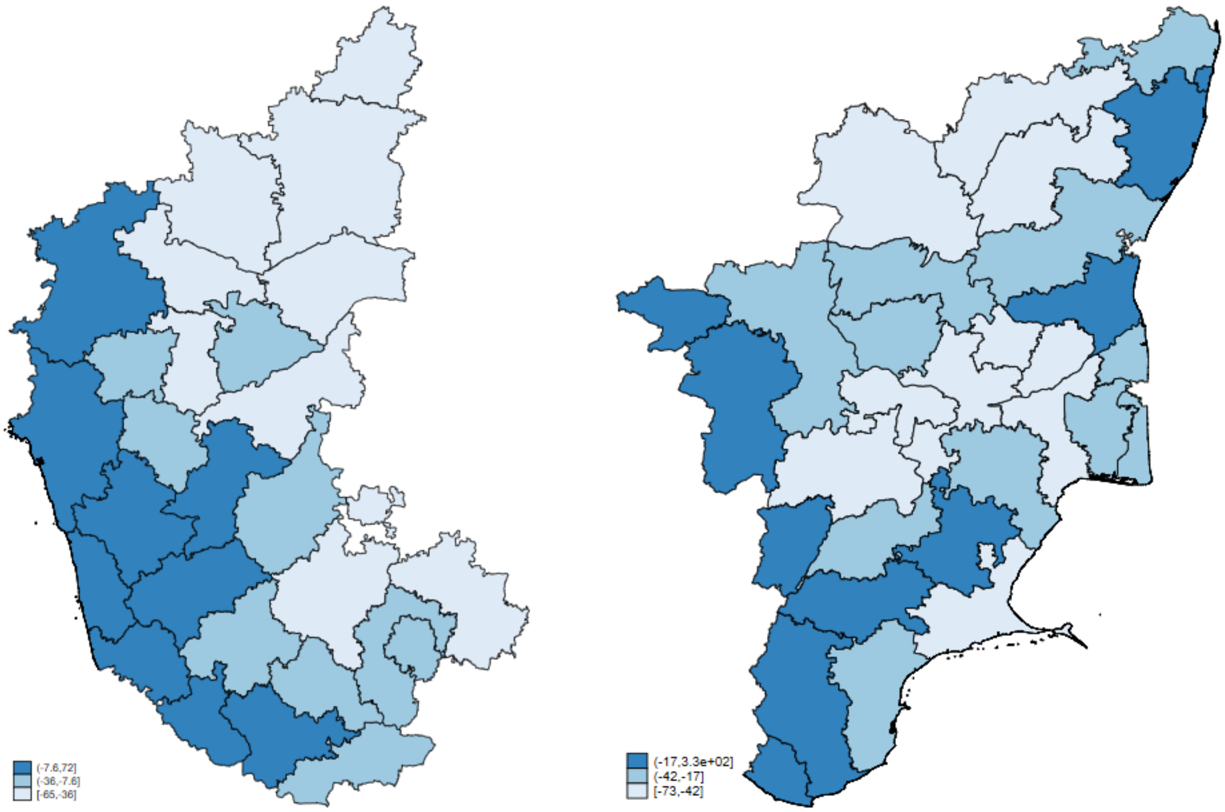


Notes: Rainfall refers to the average deviation from the normal (%). Source: IMD
Assistance refers to the immediate relief amount (in Rs. Crores) disbursed. Source: Chief Minister's Disaster Relief Fund, Kerala.
https://donation.cmdrf.kerala.gov.in/index.php/Settings/transparency#expenditure

Figure 2: Rainfall: Bordering States

(a) Karnataka

(b) Tamil Nadu



Notes: Rainfall refers to the average deviation from the normal (%).

4 Data and Summary Statistics

4.1 Data

The Consumer Pyramids (CP) database is a survey based data on households. The survey is conducted by the Centre for Monitoring the Indian Economy (CMIE). The database covers around 160,000 households during each wave of the survey. Each household in the database is surveyed every 4 months and a block of four months is called a wave. In each of the months in a particular wave, one-fourth of the sample is surveyed. During the survey, the households are asked to provide data for the preceding four months. The database is divided in to seven modules, each of which covers a different set of survey questions. Among these seven modules, four modules cover data on stock variables. These include questions regarding household characteristics, assets and liabilities, consumer sentiments and unemployment status. Data pertaining to these modules appear every four months in the data set. The dynamic variables pertaining to income, consumption, and their sub-components are covered in three different modules. Unlike the modules that cover static variables, data for these modules are available for every month.

The survey is primarily done at the household level that covers individual members as well. For example, demographic characteristics, unemployment status, and income composition are available for individual members of the households. However, expenditure details and asset and liabilities positions are available only at the household level. Since, in this paper, we are mainly looking at income and consumption, we restrict the unit of observation to the household. We use the demographic characteristics of the head of the household (HOH) whenever we need to dis-aggregate the data in those dimensions or use them as control variables. The final data set we use comprises of approximately 100,000 households over the period January-2015 to December-2018. To maintain consistency we have tried to work on a balanced sample. The dropping of observations while ensuring a balanced sample is mainly due the movement of families or change of family structure, and not due to any sample selection issues.

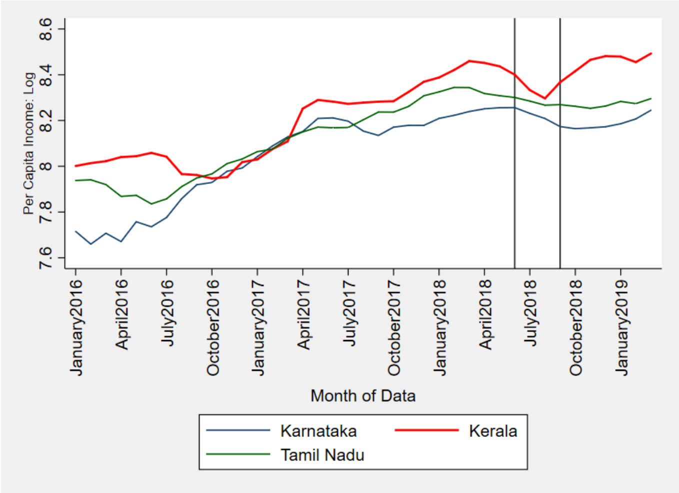
One important distinction of this data set when compared to other available household level databases is the panel structure. In this data set, information on household income and expenditure, asset holdings are available over a period of time. The panel structure of the data is essential for our analysis because we want to capture the change in household income and consumption pattern before and after the calamity which cannot be executed using a cross section data. Since the floods happened during a particular month, one needs information on both the pre and post policy periods on a homogeneous group of individual units.

4.2 Summary Statistics

In this section, we look at some aggregate trends for the components of income and expenditure for three states: Tamil Nadu, Karnataka and Kerala. Our identification strategy relies on a geographical difference in difference (DiD) method. Thus, we focus on the two bordering states of Kerala. Figures 1 and 2 show the trends for income and expenditure. The left panel in the figures plots the component in log terms while the right panel plots the year -on-year (YoY) growth rates that takes care of seasonality. The vertical bars denote the months of June and August-2018- the period of heavy rainfall in Kerala. We see that the levels of both income and expenditure are higher for Kerala (red line) compared to the two other states. We observe a sharp drop from the pre-existing trend for Kerala in the month of August-2018, while we do not observe any visible trend for the other two states (green and blue lines). The YoY growth rates for Kerala, unlike the levels, are not always above the growth rates for the neighboring states. In fact, during the pre-flood months, the growth rates were significantly higher for Kerala, but fell below both the neighboring states between June and August-2018. For wages, both levels and growth rates are higher for Kerala compared to the neighboring states. However, there is a sharp drop for Kerala in the month of Aug-2018 compared to the pre-existing trend. Food expenditure for Kerala, both in levels and growth rates seem to be higher than the neighboring states in most months before the floods. But during the floods, the growth rates fell significantly below the neighboring states. These aggregate trends give us an overall picture of the intensity of the floods in Kerala compared to the neighboring states.

Figure 3: Aggregate trends: Total Income per capita

(a) Log



(b) YoY

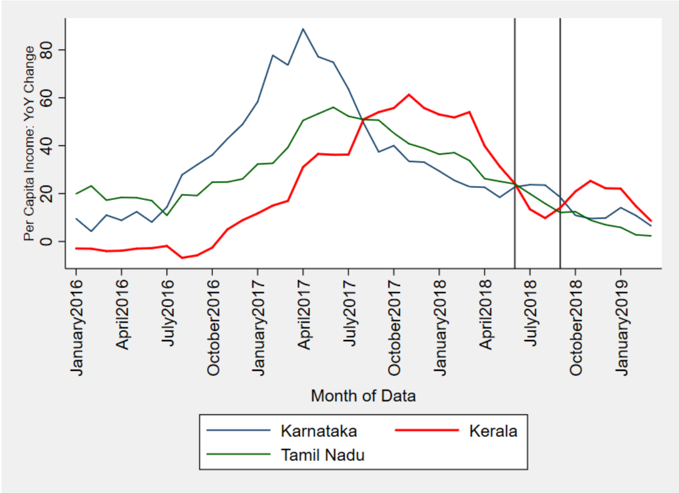
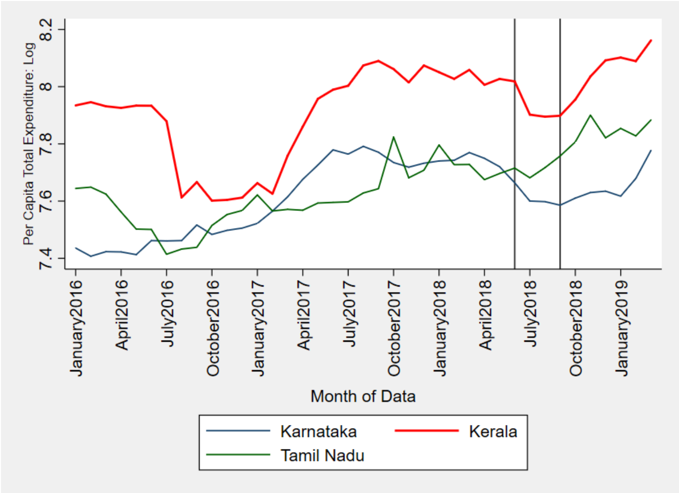


Figure 4: Aggregate trends: Total Expenditure per capita

(a) Log



(b) YoY

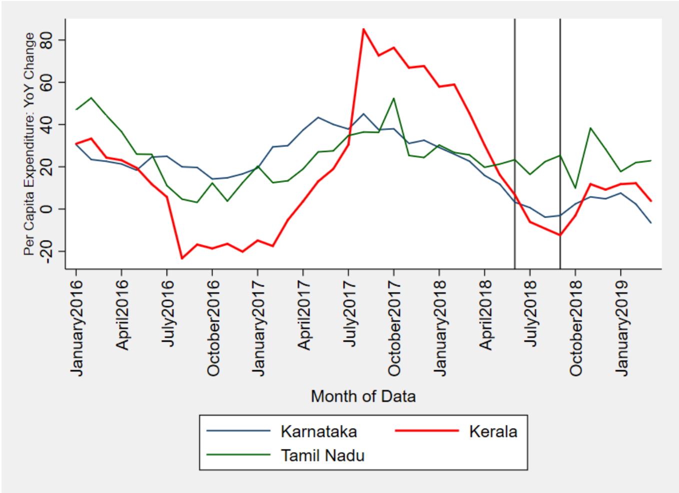


Figure 5: Aggregate trends: Wages

(a) Log

(b) YoY

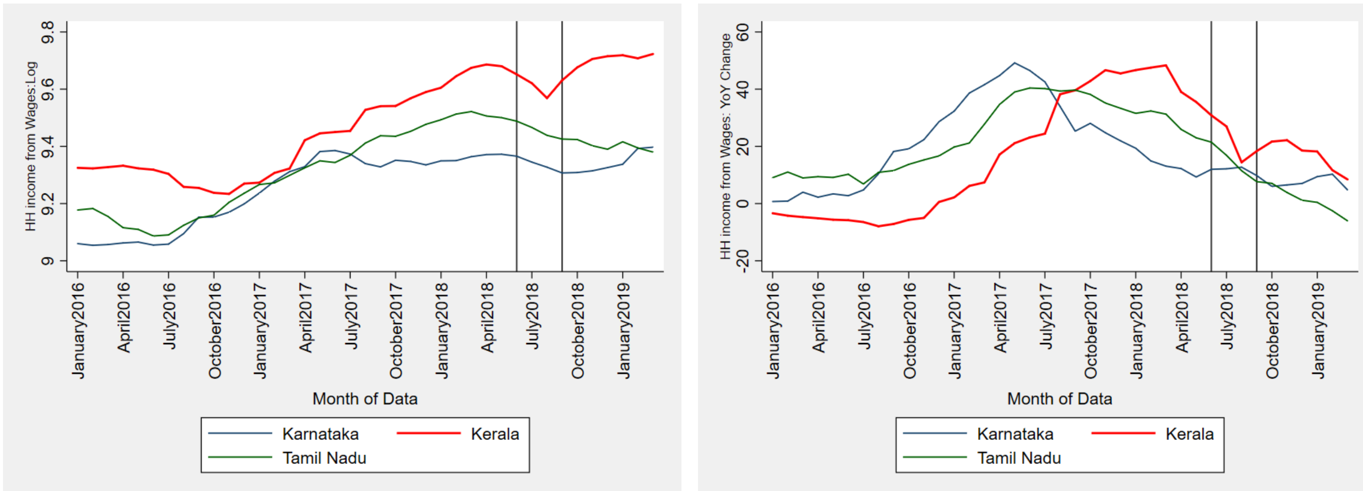
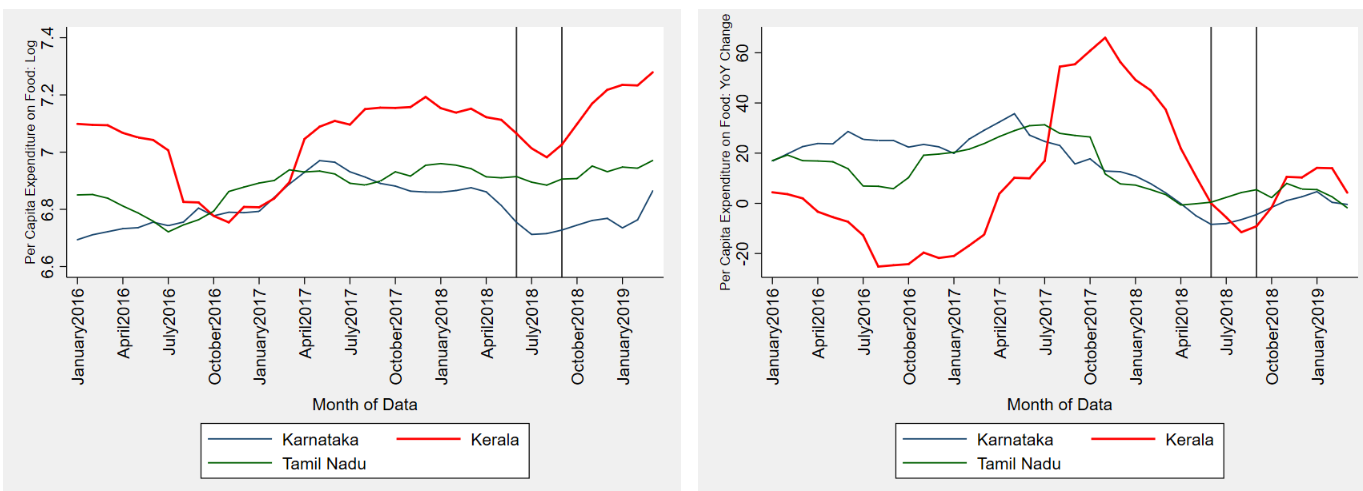


Figure 6: Aggregate trends: Expenditure on food per capita

(a) Log

(b) YoY



5 Empirical Strategy

The objective of our empirical exercise is to causally estimate the effect of the floods on household income, consumption and balance sheet items. We know that the floods occurred in Kerala while the neighboring states of Tamil Nadu and Karnataka were not affected. In order to cleanly identify the impact of floods on household finances, we employ a difference-in-difference in strategy based on the domicile of the households. Specifically, our treatment group includes households belonging to the state of Kerala and our control group includes all households residing in the states of Tamil Nadu and Karnataka. We restrict the time period of our sample between Dec-2014 and Dec-2018. In specification 1 below, the variable $Treatment$ takes the value 1 if a household resides in Kerala and 0 otherwise. $Post$ takes the value 1 for the months after Aug-2018, while $\gamma_t \, and \, \theta_i$ denote the time fixed effects (Month x Year) and household fixed effects respectively. The coefficient β captures the impact of floods for the households in Kerala relative to the households based in Tamil Nadu and Kerala. Since the $Post$ variable includes the months after the floods, the coefficient β would capture any recovery that may have taken place after the floods.

$$y_{it} = \beta * (Treatment * Post) + \gamma_t + \theta_i + \epsilon_{it}, \tag{1}$$

In order to identify the causal impact of the floods in the month of the flood, we modify the above specification to include the month-wise interaction with the the treatment group (specification 2). We use the following specification:

$$y_{it} = \sum_{t=-6}^{+4} \beta_t * (Treatment * Month_t) + \gamma_t + \theta_i + \epsilon_{it} \tag{2}$$

where the coefficients β_t give us the month-wise effect of floods 6 months before and 6 months after the floods happened in August-2018. The Treatment variable takes the value 1 if the household is located in Kerala. All specifications include household fixed effects. Standard errors are clustered at the household level.

Within Kerala, the intensity of the rains and floods varied across districts. We thus exploit the heterogeneity of the treatment intensity to estimate the relative impact of the floods. In order to do this, we divide the districts in Kerala into three quantiles based on the intensity of the rains and assistance provided. The quantiles are based on the distribution of cumulative rainfall between Jun and Aug-2018 across the districts. We can thus do an objective assessment of the intensity of the rains and the its impact on household finances. However, high rainfall in one district may not be correlated with the floods and the damage caused by the floods. This is because of the difference in the geographical terrain and the infrastructure across districts. The proximity of dams also play a role in causing floods. Thus, in order to identify the impact of the floods and the relative intensity, we divide the households based on the district-wise allocation of monetary assistance extended toward flood relief. We assume that the assistance provided in the districts wyold be correlated with the damage caused by the floods. We use the following specification to exploit the heterogeneity in the treatment groups based on the intensity of rains and floods.

$$y_{it} = \sum_{i=1}^{+3} \beta_i * (Q_i * Post) + \gamma_t + \theta_i + \epsilon_{it}, \tag{3}$$

$$y_{it} = \sum_{t=-6}^{t=+4} \sum_{i=1}^{3} \boldsymbol{\beta_{it}[Q_i * Month_t]} + \gamma_t + \theta_i + \epsilon_{it}, \tag{4}$$

where $\boldsymbol{Q_i}$ denotes the indicator variable indicating whether the district the household resided in at the time of floods was in quartile i based on the disaster level. We define the quartiles based on two metrics: cumulative rainfall between June-2018 and August-2018 and the assistance extended to the districts.

The above specifications tell us the relative impact of the floods on the components of household income and expenditure which are flow variables. We now look at an important component of household balance sheets: borrowings. Household may borrow from different sources and for different purposes to smooth out their consumption. We use the following linear probability model to estimate the effect of floods on borrowings of households:

$$(Pr\, b_{it} = 1|\boldsymbol{X}) = \beta * (Q_i * Post) + \gamma_t + \theta_i + \epsilon_{it} \tag{5}$$

where $\boldsymbol{Q_i}$ and *Post* variables have the same interpretation as above. The coefficient β now tells us the change in the probability of borrowing for households residing in Kerala post the floods relative to the households based in Tamil Nadu and Karnataka.

6 Results

In this section we present the results. We first present the baseline results pertaining to the specifications 1 and 2. We then dig deeper and present the results based on the treatment intensity measures namely rainfall and flood.

6.1 Baseline specification (Equation 1)

Table 1 below reports the difference in difference (DiD) coefficient (β) for the sub-categories of income from specification 1. As mentioned earlier, this specification includes the time period when the households experienced some recovery after the floods occurred. We see that income increased by 4.3 percent and wages by 7.1 percent post the floods relative to the control group. However, government transfers and pension payments decreased post the floods. Table 2 reports the DiD coefficient for the subcategories of expenditure. We see that although income and wages saw some recovery, expenditure did not recover fully after the floods. In fact, total expenditure decreased by 5.3 percent which was mainly contributed by decreases in spending on apparels and transport. The floods seem to have no significant effect on food expenditure.

Table 1: Income

	(1) Income	(2) Wages	(3) Govt.Transfers	(4) Pensions
Post*Treatment	0.043***	0.071***	-0.221***	-0.119***
	(0.006)	(0.006)	(0.010)	(0.027)
Month FE	Yes	Yes	Yes	Yes
N	909465	835662	210023	88213

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds residing in Kerala
and the post-floods months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Expenditure

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	(7) Health
Post*Treatment	-0.053***	0.006	-0.104***	0.044**	-0.111***	-0.420***	-0.101***
	(0.005)	(0.005)	(0.014)	(0.015)	(0.010)	(0.012)	(0.011)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	909465	909465	615410	211297	440195	838351	833186

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds residing in Kerala
and the post-floods months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Monthly specification (Equation 2)

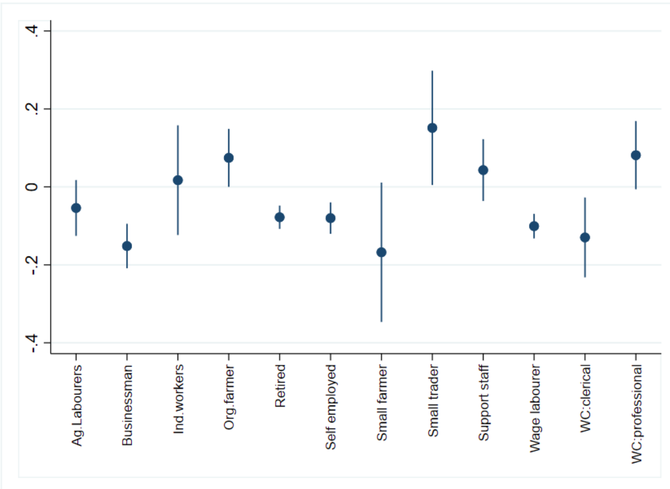
The tables above give us an idea of the recovery period post the floods for the households in Kerala. However, the specification cannot disentangle the pure effect of the floods particularly in the months of the Jun-Aug-2018. Thus in the following figures, we plot the monthly DiD coefficients for income and expenditure and their sub-categories. Figure 5 reports the monthly coefficients for income (left panel) and expenditure (right panel). We see that the months prior to Jun-2018 have no significant effect on both income and expenditure. Jun-2018 onward, when the heavy rains started, there is a significant negative effect on both income and expenditure with a sharp drop in Aug-2018 when the floods occurred.

Interestingly, post the the floods, we see a sharp rebound of income, however households were not able to recover their levels of consumption as the coefficients remained negative for the months of Sep, Oct and Nov-2018. Figure 6 plots the DiD coefficients for wages and food expenditure. We see that the recovery in income is mainly contributed by the recovery in wages. In fact, we don't see much effect of the floods on wages during the months of Jun-Aug-2018. Expenditure on food on the other hand declined more than 5 percent in Aug-2018 but was quick to rebound in the subsequent months.

In addition to showing the effect of floods during the months of June-Aug-2018, these results validates our parallel trends assumption. We see that for income and expenditure, the coefficients prior to June-2019 are not statistically significant and for most months the coefficients are close to zero. This means that prior to start of the monsoon and the heavy rainfall during June and Aug-2018, there was no statistical difference between the households in Kerala (treatment group) and the households in Tamil Nadu and Karnataka (control group). The components for both the groups were moving together prior to the June-2018 while the deviation from the trend occurred at the onset of the monsoon in June-2018. This is also corroborated by the aggregate trends that we have discussed in the previous section. The parallel trends assumption holds for wages and the expenditure on food as well. We do another set placebo analyses for the year 2017, the results of which are presented in the appendix.

Figure 7: Baseline specification (equation 1): Monthly effects

(a) Income



(b) Expenditure

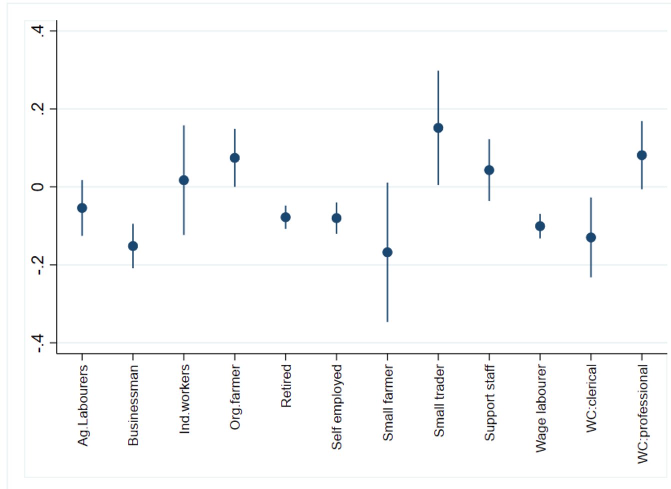
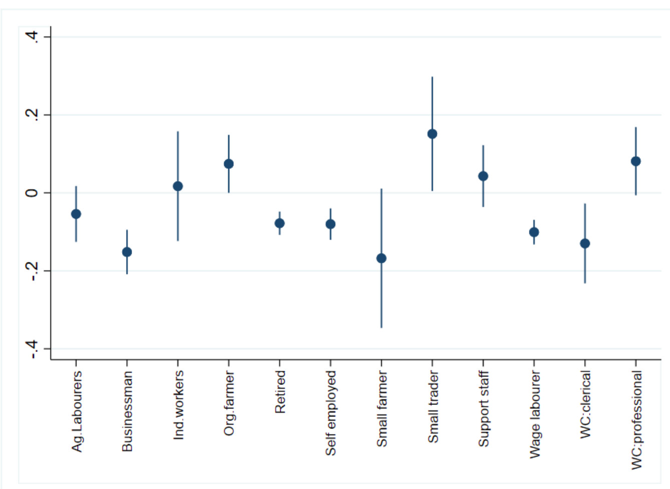
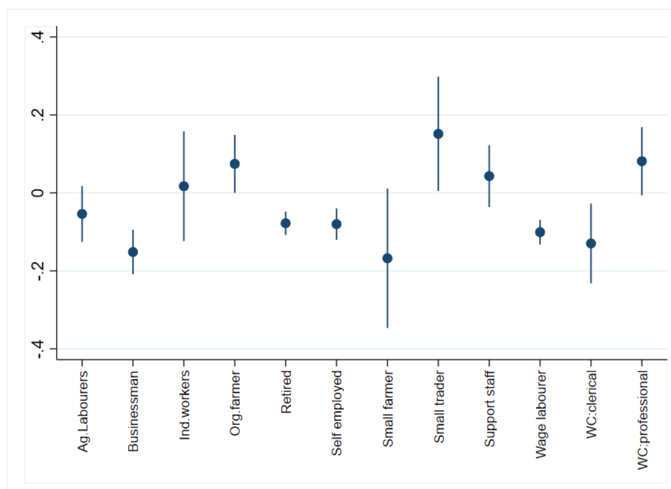


Figure 8: Baseline specification (equation 1): Monthly effects

(a) Wages



(b) Expenditure on Food

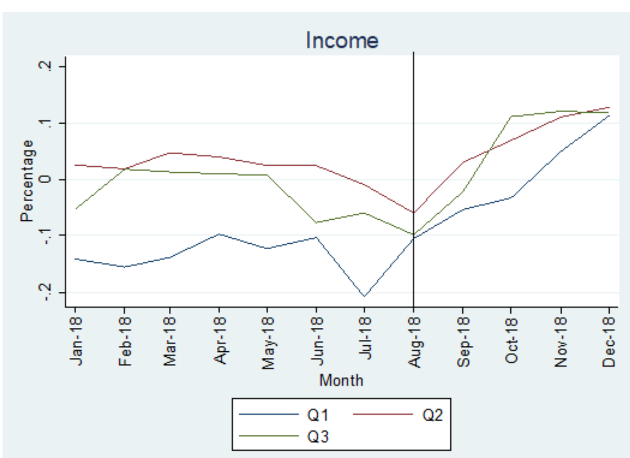


6.3 Rainfall Quartiles (Equation 4)

In this section, we report the DiD coefficients based on specification 4.[11] Specifically, we divide the districts based on rainfall intensity between Jun and Aug-2018. The first quartile includes the districts with low rainfall while the third quartile includes the districts with highest rainfall. The figures below plot the monthly DiD coefficients interacted with the quartile the households belong to. We have removed the confidence bands for better visualization. We see that for income and wages, there was a larger fall for the households belonging to the first quartile during the months of Jun-Aug-2018, while the households in the second quartile did not experience any significant fall. The households in the highest quartile experienced a fall in the months of Jun-Aug-2018 that lie between the first and second quartiles. We see a similar picture for expenditure as households in the first rainfall quartile faced a larger drop during Jun-Aug-2018 compared to the households in the first and second quartiles. These results show that districts with highest rainfall may not be the ones that experienced a greater damage due to the floods. This may happen due to the difference in geographical terrain and the proximity to dams.

Figure 9: Rainfall Quartiles: Monthly effects

(a) Income

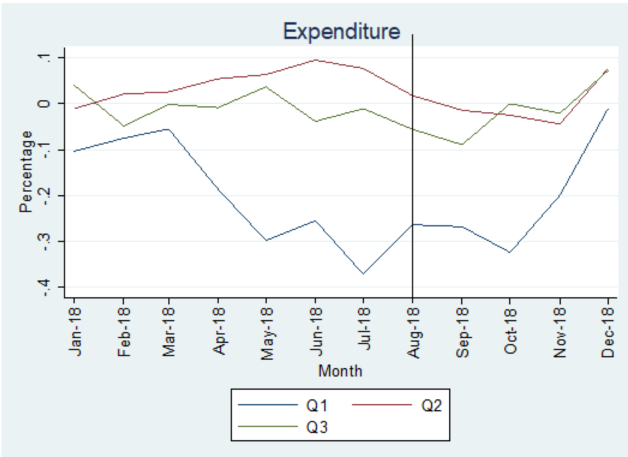


(b) Wages

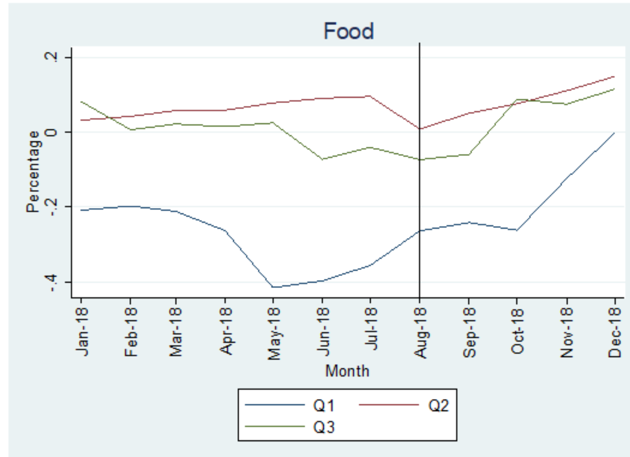
[11] Tables A.1-A.4 in the Appendix present the results based on specification 4.

Figure 10: Rainfall Quartiles: Monthly effects

(a) Expenditure



(b) Food



6.4 Assistance Quartiles (Equation 3)

In this section, we divide the districts in to three quartiles based on the amount of monetary assistance provided by the government after the floods. The amount of assistance will be a proxy for the intensity of the floods and the resulting damage. Figure 9-10 reports the DiD coefficients interacted with the quartile that the households belong to, for income and expenditure and their sub-components. From Figure 9, we see that households belonging to quartile 2 and 3 faced a significant fall in income and wages during the months of Jun-Aug-2018, while the households in quartile 1 did not face any significant fall income and wages during the same period. Figure 10 also shows a similar picture for expenditure. The households in quartile 2 and 3 faced a sharp drop during Jun-Aug-2019. For the households belonging to quartile 1, although the coefficients during the same period are positive, they experienced a drop from the pre-existing trend. These results show that the intensity of the floods and the relative damage have been quite different when compared to the rainfall intensity.

Figure 11: Assistance Quartiles: Monthly effects

(a) Income (b) Wages

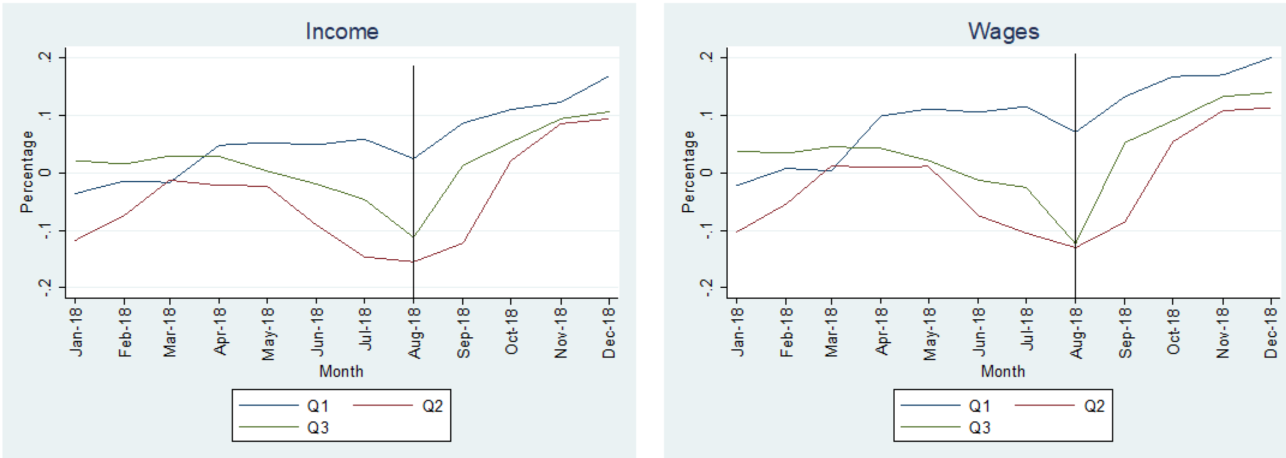
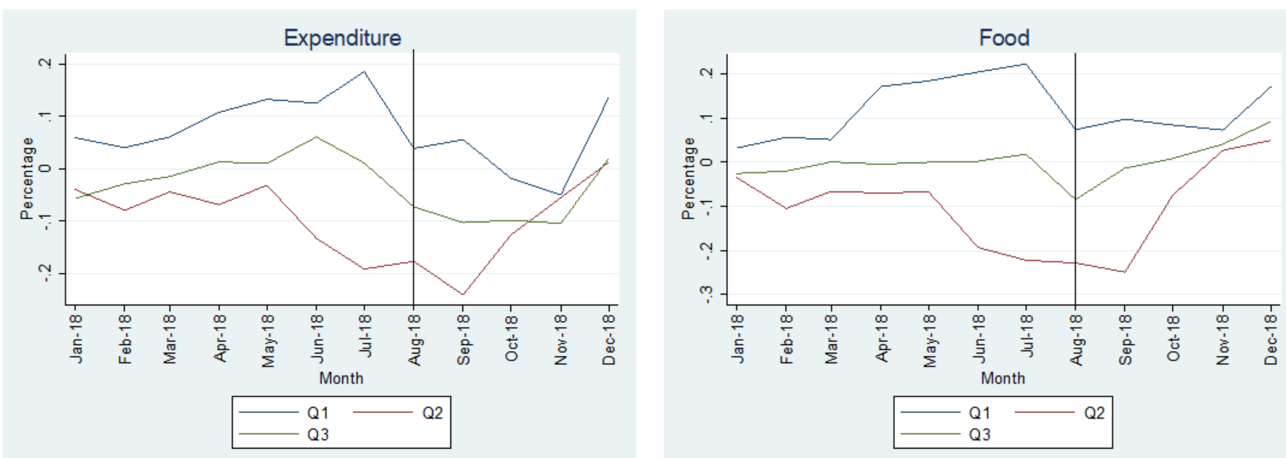


Figure 12: Assistance Quartiles: Monthly effects

(a) Expenditure (b) Food

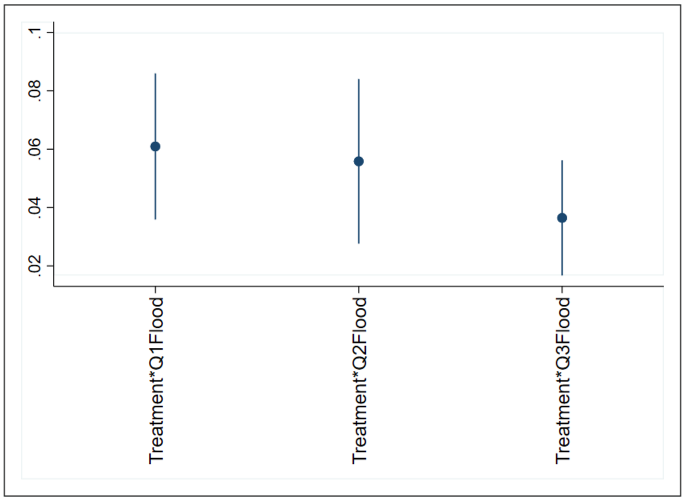


6.5 Borrowings

In this section we look at the effect of floods on borrowings which are an important component of household balance sheet. Households may resort to borrowings to smooth out their consumption. Thus, an increase in borrowings post the floods would give us an indication of households resorting to borrowing to smooth out their consumption. One complication arises from the data is that we do not observe the amount of borrowings for the households. We only know whether the households have resorted to any borrowing from different sources during the past 4 months from the date of the survey. We identify the waves (block of 4 months) the households were surveyed during and post the floods which we call the treatment period. While our definition of the treatment group remains the same. The figures below plot the DiD coefficients from a linear probability model interacted with the quartile the households belong to (equation 4). The coefficients may be interpreted as the change in the probability of borrowing for the treatment households post the floods relative to the control group. From Figure 11, we see that the probability of households borrowing from any source and particularly from banks increased significantly post the floods for all three quartiles. The increase is significantly higher for the households belonging to the first quartiles. This may hint at the fact that households belonging to the least affected districts (in terms of assistance provided) could cope up with the floods by resorting to borrowing. We see a higher recovery for these households as well. The probability of borrowings for consumption however decreased relative to the control group post the floods. This could be due to the immediate assistance provided by the government or the households were already in the recovery mode which lowered the probability of borrowing for consumption purposes. The probability of borrowing for housing on the other hand increased significantly for all the quartiles with the largest increase seen for the households in the second quartile. It could be the case that the government assistance were not enough for these households in which case, the households borrowed to repair their houses or build new houses.

Figure 13: Borrowings: Source

(a) From Any Source



(b) From Banks

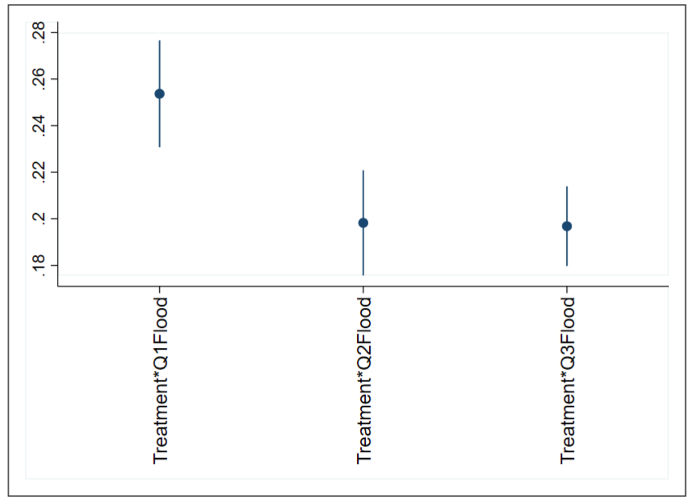
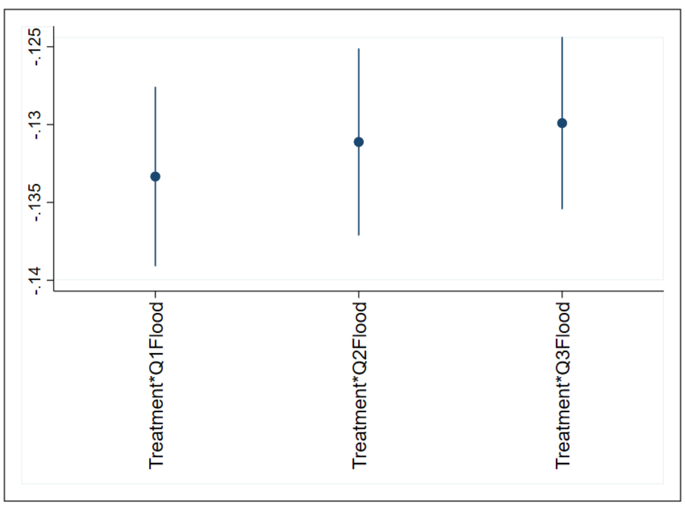
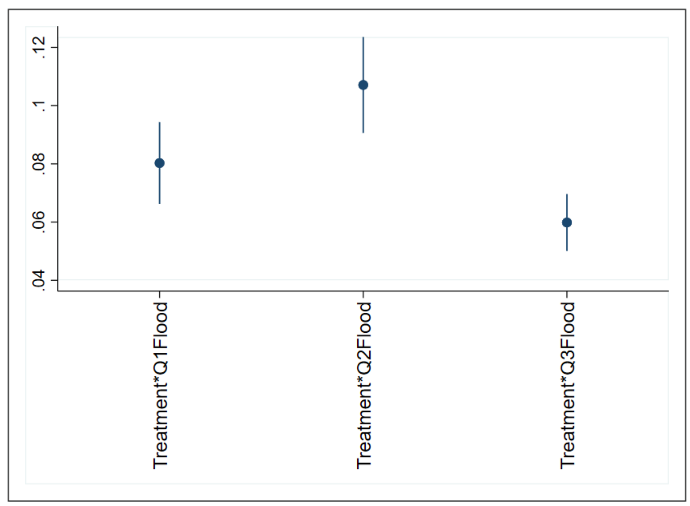


Figure 14: Borrowings: Purpose

(a) Consumption



(b) Housing



7 Conclusion

In this paper we causally estimate the effect of a natural disaster on household income, expenditure and balance sheet items. In August-2018, the southern Indian state of Kerala experienced severe while the neighboring states of Tamil Nadu and Karnataka were not affected. Our identification strategy relies on a geographical difference in difference (DiD) method. We find that relative to the households in the bordering states, income for households in Kerala decreased by 16 percent (cumulative) and June and August-2018 but was quick to rebound. Household expenditure on the other hand decreased by 7 percent (cumulative) during the same period but the decline persisted for a longer period. We also find that the key mechanism for recovery of household finance post the floods was through borrowings from different sources especially from banks.

References

Sonia Akter and Bishawjit Mallick. The poverty ,vulnerability, resilience nexus: Evidence from bangladesh. *Ecological Economics*, 96:114 – 124, 2013. ISSN 0921-8009. doi: https://doi.org/10.1016/j.ecolecon.2013.10.008. URL http://www.sciencedirect.com/science/article/pii/S0921800913003182.

J. M. Albala-Bertrand. *Political Economy of Large Natural Disasters*. Clarendon press, United Kingdom, 1993.

Nejat Anbarci, Monica Escaleras, and Charles A. Register. Earthquake fatalities: the interaction of nature and political economy. *Journal of Public Economics*, 89(9):1907 – 1933, 2005. ISSN 0047-2727. doi: https://doi.org/10.1016/j.jpubeco.2004.08.002. URL http://www.sciencedirect.com/science/article/pii/S0047272704001525.

Mohamed Arouri, Cuong Nguyen, and Adel Ben Youssef. Natural disasters, household welfare, and resilience: Evidence from rural vietnam. *World Development*, 70:59 – 77, 2015. ISSN 0305-750X. doi: https://doi.org/10.1016/j.worlddev.2014.12.017. URL http://www.sciencedirect.com/science/article/pii/S0305750X1400415X.

R. Balasubramanian. Climate Sensitivity of Groundwater Systems Critical for Agricultural Incomes in South India. Working papers 95, The South Asian Network for Development and Environmental Economics, 2015. URL https://ideas.repec.org/p/snd/wpaper/95.html.

Sushenjit Bandyopadhyay and Emmanuel Skoufias. Rainfall variability, occupational choice, and welfare in rural bangladesh. *Review of Economics of the Household*, 13(3):589–634, Sep 2015. ISSN 1573-7152. doi: 10.1007/s11150-013-9203-z. URL https://doi.org/10.1007/s11150-013-9203-z.

Robert J. Barro. Rare disasters, asset prices, and welfare costs. *American Economic Review*, 99(1):243–64, March 2009. doi: 10.1257/aer.99.1.243. URL http://www.aeaweb.org/articles?id=10.1257/aer.99.1.243.

Timothy Besley and Robin Burgess. The Political Economy of Government Responsiveness: Theory and Evidence from India*. *The Quarterly Journal of Economics*, 117(4):1415–1451, 11 2002. ISSN 0033-5533. doi: 10.1162/003355302320935061. URL https://doi.org/10.1162/003355302320935061.

Anh Tuan Bui, Mardi Dungey, Cuong Viet Nguyen, and Thu Phuong Pham. The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from vietnam. *Applied Economics*, 46(15):1751–1766, 2014. doi: 10.1080/00036846.2014.884706. URL https://doi.org/10.1080/00036846.2014.884706.

Eduardo Cavallo and Ilan Noy. Natural disasters and the economy - a survey. *International Review of Environmental and Resource Economics*, 5(1):63–102, 2011. ISSN 1931-1465. doi: 10.1561/101.00000039. URL http://dx.doi.org/10.1561/101.00000039.

Eduardo Cavallo, Andrew Powell, and Oscar Becerra. Estimating the Direct Economic Damages of the Earthquake in Haiti. *The Economic Journal*, 120(546):F298–F312, 07 2010. ISSN 0013-0133. doi: 10.1111/j.1468-0297.2010.02378.x. URL https://doi.org/10.1111/j.1468-0297.2010.02378.x.

Makena Coffman and Ilan Noy. Hurricane iniki: measuring the long-term economic impact of a natural disaster using synthetic control. *Environment and Development Economics*, 17(2):187, 2012. doi: 10.1017/S1355770X11000350.

C. J. Cuaresma, J. Hlouskova, and M. Oberstriner. Natural disasters as creative destruction? evidence from developing countries. *Economic Inquiry*, 46(2):214–226, 2008. doi: 10.1111/j.1465-7295.2007.00063.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1465-7295.2007.00063.x.

L. Le De, J. C. Gaillard, and W. Friesen. Poverty and disasters: Do remittances reproduce vulnerability? *The Journal of Development Studies*, 51(5):538–553, 2015. doi: 10.1080/00220388.2014.989995. URL https://doi.org/10.1080/00220388.2014.989995.

ECLAC. Handbook for estimating the socio-economic and environmental effects of disasters. Technical report, The Worl Bank, 2003. URL http://documents.worldbank.org/curated/en/649811468048531747/Main-report.

Thomas Eisensee and David StrÃ¶mberg. News droughts, news floods, and u. s. disaster relief. *The Quarterly Journal of Economics*, 122(2):693–728, 2007. ISSN 00335533, 15314650. URL http://www.jstor.org/stable/25098856.

R. W. Evans, Y. Hu, and Z. Zhao. The fertility effect of catastrophe: U.s. hurricane births. *Journal of Population Economics*, 23(1):1–36, 2010. URL https://doi.org/10.1111/j.1467-8306.2007.00563.x.

Susana Ferreira, Kirk Hamilton, and Jeffrey R. Vincent. Does development reduce fatalities from natural disasters? new evidence for floods. *Environment and Development Economics*, 18(6), 2013. doi: 10.1017/S1355770X13000387.

Justin Gallagher and Daniel Hartley. Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy*, 9(3):199–228, August 2017. doi: 10.1257/pol.20140273. URL http://www.aeaweb.org/articles?id=10.1257/pol.20140273.

StÃ©phane Hallegatte. An adaptive regional input-output model and its application to the assessment of the economic cost of katrina. *Risk Analysis*, 28(3):779–799, 2008. doi: 10.1111/j.1539-6924.2008.01046.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1539-6924.2008.01046.x.

StÃ©phane Hallegatte and Patrice Dumas. Can natural disasters have positive consequences? investigating the role of embodied technical change. *Ecological Economics*, 68

(3):777 – 786, 2009. ISSN 0921-8009. doi: https://doi.org/10.1016/j.ecolecon.2008.06.011. URL http://www.sciencedirect.com/science/article/pii/S0921800908002863.

T. Halliday. Migration, risk, and liquidity constraints in el salvador. *Economic Development and Cultural Change*, 54(4):893–925, 2006. ISSN 00130079, 15392988. URL http://www.jstor.org/stable/10.1086/503584.

S. Hochrainer. Assessing the macroeconomic impacts of natural disasters - are there any? Policy Research working paper WPS 4968, The World Bank, 2009. URL https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-4968.

G. Horwich. Economic lessons of the kobe earthquake. *Economic Development and Cultural Change*, 48(3):521–542, 2000. ISSN 00130079, 15392988. URL http://www.jstor.org/stable/10.1086/452609.

Danilo C. Israel and Roehlano M. Briones. Disasters, Poverty, and Coping Strategies: The Framework and Empirical Evidence from Micro/Household Data - Philippine Case. Discussion Papers DP 2014-06, Philippine Institute for Development Studies, 2014. URL https://ideas.repec.org/p/phd/dpaper/dp_2014-06.html.

C. R. H. Jaramillo. Do Natural Disasters Have Long-term Effects on Growth? Documentos CEDE 006647, Universidad de los Andes - CEDE, November 2009. URL https://ideas.repec.org/p/col/000089/006647.html.

Narayanan K and Unmesh Patnaik. Vulnerability and Coping to Disasters: A Study of Household Behaviour in Flood Prone Region of India. Working Papers id:2470, eSocialSciences, April 2010. URL https://ideas.repec.org/p/ess/wpaper/id2470.html.

Matthew E. Kahn. The death toll from natural disasters: The role of income, geography, and institutions. *The Review of Economics and Statistics*, 87(2):271–284, 2005. ISSN 00346535, 15309142. URL http://www.jstor.org/stable/40042902.

Azreen Karim. The household response to persistent natural disasters: Evidence from bangladesh. *World Development*, 103:40 – 59, 2018. ISSN 0305-750X. doi: https://doi.org/10.1016/j.worlddev.2017.10.026. URL http://www.sciencedirect.com/science/article/pii/S0305750X17303509.

M. Keen, M. Mani, and P. K. Freeman. Dealing with increased risk of natural disasters: Cgnges and options. IMF Working Paper 03/197, International Monetary Fund, 2003. URL https://www.imf.org/en/Publications/WP/Issues/2016/12/30/Dealing-with-Increased-Risk-of-Natural-Disasters-Challenges-and-Options-16830.

Derek K. Kellenberg and Ahmed Mushfiq Mobarak. Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics*, 63(3):788 – 802, 2008. ISSN 0094-1190. doi: https://doi.org/10.1016/j.jue.2007.05.003. URL http://www.sciencedirect.com/science/article/pii/S0094119007000770.

Takashi Kurosaki. Vulnerability of household consumption to floods and droughts in developing countries: evidence from pakistan. *Environment and Development Economics*, 20 (2), 2015. doi: 10.1017/S1355770X14000357.

Andrea Leiter, Harald Oberhofer, and Paul Raschky. Creative Disasters? Flooding Effects on Capital, Labour and Productivity Within European Firms. *Environmental & Resource Economics*, 43(3):333–350, July 2009. doi: 10.1007/s10640-009-9273-9. URL https://ideas.repec.org/a/kap/enreec/v43y2009i3p333-350.html.

Norman V. Loayza, Eduardo OlaberrÃa, Jamele Rigolini, and Luc Christiaensen. Natural disasters and growth: Going beyond the averages. *World Development*, 40(7):1317 – 1336, 2012. ISSN 0305-750X. doi: https://doi.org/10.1016/j.worlddev.2012.03.002. URL http://www.sciencedirect.com/science/article/pii/S0305750X12000393.

Steffen Lohmann and Tobias Lechtenfeld. The effect of drought on health outcomes and health expenditures in rural vietnam. *World Development*, 72:432 – 448, 2015. ISSN

0305-750X. doi: https://doi.org/10.1016/j.worlddev.2015.03.003. URL http://www.sciencedirect.com/science/article/pii/S0305750X15000625.

Reinhard Mechler. *Disasters And Economic Welfare: Can National Savings Help Explain Post-Disaster Changes In Consumption?* The World Bank, 2009. doi: 10.1596/1813-9450-4988. URL https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-4988.

K. A. Mottaleb, S. Mohanty, H. T. K. Hoang, and R. M. Rejesus. The effects of natural disasters on farm household income and expenditures: A study on rice farmers in bangladesh. *Agricultural Systems*, 121:43 – 52, 2013. ISSN 0308-521X. doi: https://doi.org/10.1016/j.agsy.2013.06.003. URL http://www.sciencedirect.com/science/article/pii/S0308521X13000735.

Eric Neumayer and Thomas Plumper. The gendered nature of natural disasters: The impact of catastrophic events on the gender gap in life expectancy 1981: 2002. *Annals of the Association of American Geographers*, 97(3), 2007. doi: 10.1111/j.1467-8306.2007.00563.x. URL https://doi.org/10.1111/j.1467-8306.2007.00563.x.

Ilan Noy. The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2):221 – 231, 2009. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2008.02.005. URL http://www.sciencedirect.com/science/article/pii/S030438780800031X.

Ilan Noy and Aekkanush Nualsri. What do Exogenous Shocks Tell Us about Growth Theories? Working Papers 200728, University of Hawaii at Manoa, Department of Economics, 2007. URL https://ideas.repec.org/p/hai/wpaper/200728.html.

Ilan Noy and Tam Bang Vu. The economics of natural disasters in a developing country: The case of vietnam. *Journal of Asian Economics*, 21(4):345 – 354, 2010. ISSN 1049-0078.

doi: https://doi.org/10.1016/j.asieco.2010.03.002. URL http://www.sciencedirect.com/science/article/pii/S1049007810000205.

Christina H. Paxson. Using weather variability to estimate the response of savings to transitory income in thailand. *The American Economic Review*, 82(1):15–33, 1992. ISSN 00028282. URL http://www.jstor.org/stable/2117600.

M. Pelling, A. Ozerdem, and S. Barakat. Macroeconomic impact of disasters. *Progress in Development Studies*, 2:283–305, 2002.

Claudio Raddatz. Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics*, 84(1):155 – 187, 2007. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2006.11.001. URL http://www.sciencedirect.com/science/article/pii/S0304387806001842.

Claudio Raddatz. The wrath of god : macroeconomic costs of natural disasters (english). Policy Research working paper WPS 5039, The World Bank, 2009. URL http://documents.worldbank.org/curated/en/955981468150888752/The-wrath-of-God-macroeconomic-costs-of-natural-disasters.

Paul A. Raschky and Hannelore Weck-Hannemann. Charity hazard-a real hazard to natural disaster insurance? *Environmental Hazards*, 7(4):321 – 329, 2007. ISSN 1747-7891. doi: https://doi.org/10.1016/j.envhaz.2007.09.002. URL http://www.sciencedirect.com/science/article/pii/S174778910700049X.

Eduardo Rodriguez-Oreggia, Alejandro De La Fuente, Rodolfo De La Torre, and Hector A. Moreno. Natural disasters, human development and poverty at the municipal level in mexico. *The Journal of Development Studies*, 49(3):442–455, 2013. doi: 10.1080/00220388.2012.700398. URL https://doi.org/10.1080/00220388.2012.700398.

Yasuyuki Sawada and Satoshi Shimizutani. How do people cope with natural disasters? evidence from the great hanshin-awaji (kobe) earthquake in 1995. *Journal of Money, Credit and Banking*, 40(2-3):463–488, 2008.

F. Selcuk and Yeldan E. On the macroeconomic impact of the august 1999 earthquake in turkey: a first assessment. *Applied Economics Letters*, 8(7), 2001. doi: 10.1080/13504850010007501. URL https://doi.org/10.1080/13504850010007501.

Mark Skidmore and Hideki Toya. Do natural disasters promote long-run growth? *Economic Inquiry*, 40(4):664–687, 2002. doi: 10.1093/ei/40.4.664. URL https://onlinelibrary.wiley.com/doi/abs/10.1093/ei/40.4.664.

Emmanuel Skoufias, Sushenjit Bandyopadhyay, and Sergio Olivieri. Occupational diversification as an adaptation to rainfall variability in rural india. *Agricultural Economics*, 48(1):77–89, 2017. doi: 10.1111/agec.12296. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/agec.12296.

David StrÃ¶mberg. Natural disasters, economic development, and humanitarian aid. *The Journal of Economic Perspectives*, 21(3):199–222, 2007. ISSN 08953309. URL http://www.jstor.org/stable/30033741.

Eric Strobl. The economic growth impact of hurricanes: Evidence from u.s. coastal counties. *The Review of Economics and Statistics*, 93(2):575–589, 2011. doi: 10.1162/REST_a_00082. URL https://doi.org/10.1162/REST_a_00082.

Robert M. Townsend. Risk and insurance in village india. *Econometrica*, 62(3):539–591, 1994. ISSN 00129682, 14680262. URL http://www.jstor.org/stable/2951659.

Hideki Toya and Mark Skidmore. Economic development and the impacts of natural disasters. *Economics Letters*, 94(1):20 – 25, 2007. ISSN 0165-1765. doi: https://doi.org/10.1016/j.econlet.2006.06.020. URL http://www.sciencedirect.com/science/article/pii/S0165176506002175.

Christopher Udry. Risk and saving in northern nigeria. *The American Economic Review*, 85 (5):1287–1300, 1995. ISSN 00028282. URL http://www.jstor.org/stable/2950989.

UNISDR. Economic losses, poverty and disasters, 1998-2017. *Report*, 2018.

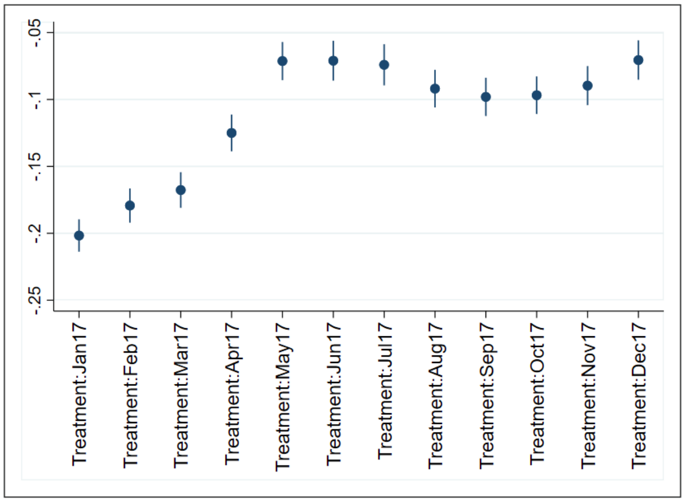
J. Vigdor. The economic aftermath of hurricane katrina. *The Journal of Economic Perspectives*, 22(4):135–154, 2008. ISSN 08953309. URL http://www.jstor.org/stable/27648281.

R.P. Vos, M. Velasco, and E. Labastida. Economic and social effects of "El Nino" in Ecuador, 1997-8. ISS Working Papers - General Series 19037, International Institute of Social Studies of Erasmus University Rotterdam (ISS), The Hague, 1999. URL https://ideas.repec.org/p/ems/euriss/19037.html.

Appendix

Figure A.1: Robustness: Placebos test 2017: Baseline specification: Monthly effects

(a) Income



(b) Expenditure

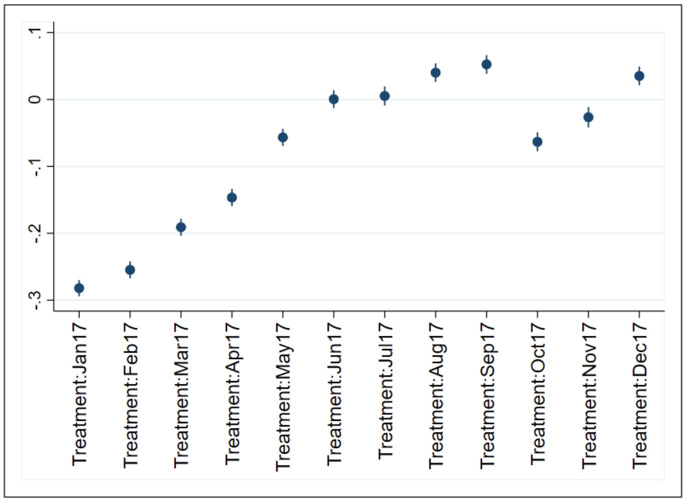
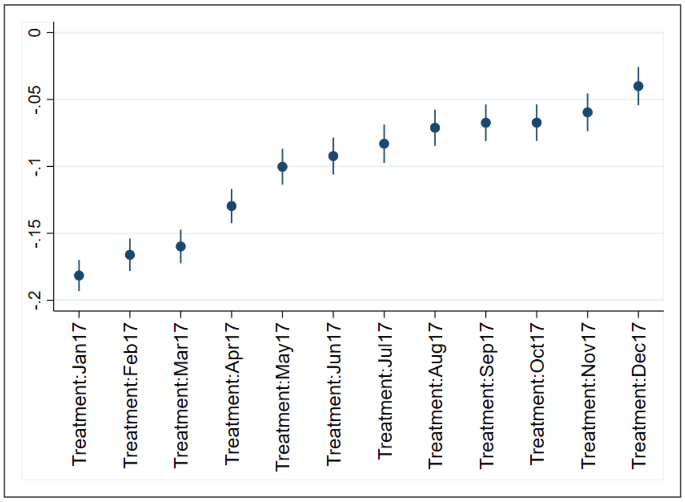


Figure A.2: Baseline specification (equation 1): Monthly effects

(a) Wages



(b) Expenditure on Food

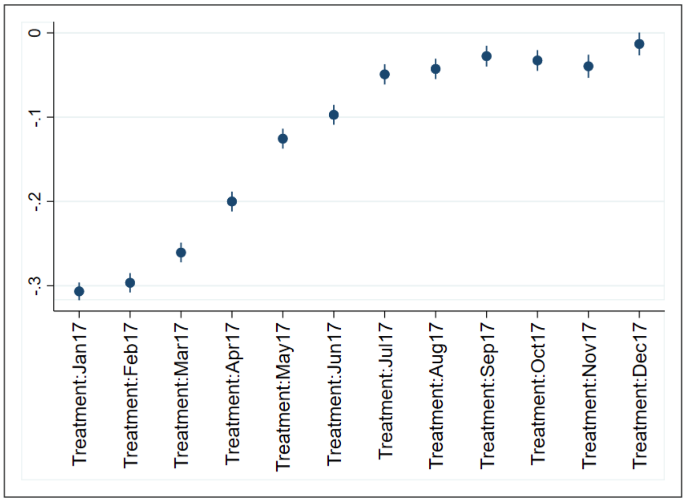


Table A.1: Rain Quartiles: Income

	(1) Income	(2) Wages	(3) Govt.Transfers	(4) Pensions	(5) x_12	(6) x_13	(7) x_15	(8) x_16
Rain:Post*Treatment*Q1								
Rain:Post*Treatment*Q2								
Rain:Post*Treatment*Q3								
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	70894	41869	25174	14559	167402	92917	60106	35773

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds residing in Kerala
and the post-floods months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Rain Quartiles: Expenditure

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	
Rain:Post*Treatment*Q1	-0.172***	-0.119***	-0.277***	-0.069*	-0.387***	-0.608***	-
	(0.010)	(0.009)	(0.024)	(0.029)	(0.016)	(0.019)	
Rain:Post*Treatment*Q2	-0.010	0.086***	-0.203***	0.110***	-0.017	-0.287***	-
	(0.008)	(0.007)	(0.024)	(0.021)	(0.014)	(0.019)	
Rain:Post*Treatment*Q3	-0.007	0.057***	-0.127***	0.077**	-0.057***	-0.413***	-
	(0.008)	(0.008)	(0.025)	(0.024)	(0.014)	(0.020)	
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	
N	909465	909465	615410	211297	440195	838351	

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds residing in Kerala
and the post-floods months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Flood Quartiles: Income

	(1) Income	(2) Wages	(3) Govt.Transfers	(4) Pensions
Assis:Post*Treatment*Q1	0.119***	0.158***	-0.228***	-0.026
	(0.009)	(0.010)	(0.021)	(0.054)
Assis:Post*Treatment*Q2	0.038***	0.062***	-0.184***	-0.198***
	(0.010)	(0.010)	(0.016)	(0.033)
Assis:Post*Treatment*Q3	0.068***	0.103***	-0.204***	-0.041
	(0.009)	(0.010)	(0.016)	(0.069)
Month FE	Yes	Yes	Yes	Yes
N	909465	835662	210023	88213

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds residing in Kerala
and the post-floods months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Flood Quartiles: Expenditure

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport
Assis:Post*Treatment*Q1	0.018*	0.088***	0.077***	0.156***	-0.038*	-0.220***
	(0.008)	(0.008)	(0.022)	(0.026)	(0.015)	(0.021)
Assis:Post*Treatment*Q2	-0.081***	-0.034***	-0.263***	0.023	-0.161***	-0.440***
	(0.009)	(0.008)	(0.024)	(0.024)	(0.014)	(0.016)
Assis:Post*Treatment*Q3	-0.069***	0.035***	-0.367***	-0.012	-0.140***	-0.518***
	(0.008)	(0.008)	(0.025)	(0.022)	(0.016)	(0.022)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	909465	909465	615410	211297	440195	838351

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds residing in Kerala
and the post-floods months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Definitions

1. Total income: This is the total income of a household during a month. It is the summation of total income of every earning member and the income of the household collectively, which cannot be attributed to any individual member. This includes income received from all sources such as rent, imputed income, private transfers, wages, overtime, bonus, etc.

2. Government Transfer: This is the total income received by the household from government transfers. Government transfer income includes Direct Benefit Transfer (DBT). It excludes pensions and salaries of government employees, payment under Mahatma Gandhi National Rural Employment Guarantee (MGNREGA) scheme.

3. Wages: This is the total income received by all the working members of the household in the form of wages during a month. This is the salary earned at the end of a month by the salaried people in India. If a businessman takes a salary from the business, it is included in wages. A salaried person may earn a salary from his employers and may also work as a home-based worker (for example, by giving tuitions). In such cases, the income earned from home-based work is also added into wages. All of these are added into a monthly salary appropriately during the capture of data.

4. Pensions: This is the total income received by all retired members of the household in the form of pension. Pension is applicable to persons who are more than 45 years of age.

5. Total expenditure: This is the sum total of household expenditure incurred on the purchase of consumption goods and services. A household incurs several kinds of expenses. This includes expenditure on food, intoxicants, restaurants & recreation, clothing & cosmetics, toiletries & home care products, bills, rent, EMIs & appliances, power, fuel, transport & communication, education, health and other miscellaneous items.

6. Expense on food: This is the sum total of household expenditure on food items, such as cereals & pulses, edible oils, spices, vegetables & fruits, meat, fish & eggs, milk & milk products, ready-to-eat food, spices, bread, biscuits, namkeens & salty snacks, noodles & pasta, flakes, muesli & oats, confectionery & ice-creams, health supplements, tea, coffee, sweeteners, and beverages, juices & bottled water. This includes expenditure on other food items such as ice, vinegar, food colours and food essence.

7. Expense on appliances: This includes household expenditure on kitchen appliances and household appliances. Kitchen appliances includes gadgets such as toasters, water filters, microwave oven, refrigerator, cooking range, stove, mixer/grinder, juicer, coffee machine, grill, induction, and any other appliances that are used in kitchens to improve the efficiency of cooking. This will also include expenses on a chimney or an exhaust system used in kitchens. Any expenditure that a household makes on any of these is included here. Expenditure on refrigerators is also captured here.

8. Expense on apparels: This is the sum total of the household expenditure on clothing (such as garments, jackets, woolens, etc), clothing accessories and footwear.

9. Expense on restaurants: This includes household expenditure on food and non-alcoholic beverages consumed in restaurants or snack joints or canteens or from the streets. This includes meals consumed in five star hotels or Bhel Puri from a street side vendor. This also includes milk products such as lassi, butter milk chaas, tea, coffee, cakes, desserts and non-alcoholic beverages that are consumed at home.

10. Expense on transport: This includes household expenditure on various modes of transport and other charges. This includes- Daily Bus/Train/Ferry Fare, Auto-rickshaw/Taxi Fare, Outstation Bus/Train Fare, Parking Fees, Toll Charges and Airfare.

11. Expense on health: This is the sum total of household expenditure on health. It includes expense on medicines, doctor 's fees, X-Ray tests, hospitalisation fees, premium for health insurance, etc.