Chennai 2015: A novel approach to measuring the impact of a natural disaster

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Abstract

We estimate the impact of one flood on economic outcomes of households located in the region (Chennai, India). We measure the impact of the flood on income and consumption of households, and explore heterogeneity in impact by prosperity and financial constraints. We exploit a novel panel dataset (the CMIE CPHS) which covers 170,000 households in India, three times a year.

We find that immediately after the floods, there was a sharp increase in consumption, which is reversed over a year. Expenditures are financed by not saving, or postponing asset purchases. The expenditure increase for the more vulnerable, or the financially constrained households, is smaller. This may be consistent with greater hardship for them.

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Contents

1 Introduction

In November and December 2015, the city of Chennai in the Southern Indian state of Tamil Nadu, got heavily flooded owing to unprecedented rainfall. With a population of a little more than 7.1 million people, Chennai is one of the major urban centers of South India, and one of the four important metropolitan cities in India. The flooding is estimated to have led to the loss of more than 500 lives, and damages of about US$3 billion, making it the world's eighth most expensive natural disaster in 2015. In this paper we evaluate the impact of this event for households in Chennai.

Natural disasters, such as the Chennai floods, are important shocks which can influence all parts of the income distribution. In the aftermath of such a natural disaster, the issues of consumption smoothing, liquidity constraints and financial resilience play out. Natural disasters are important in their own right, as we need to understand more about the turmoil faced by households in such states of nature. All governments engage in redistribution in the aftermath of a natural disaster. This motivates research on studying the impacts of natural disasters. Natural disasters are also an opportunity to obtain insights into the economics of household, through observation of households when confronted with such a large shock.

Many researchers have gone into the field *after* a natural disaster has taken place, and produced evidence about health, income, consumption, and financial conditions in the aftermath of the disaster. But such research does not offer insights into the causal impact of the event as adequate information gathering about baseline conditions, before the event, is lacking.

When panel data about households is present, we observe households before and after the natural disaster. This makes possible the analysis of the adverse impact upon affected households, while additionally observing controls. The constraint in such research has been the time elapsed between two consecutive observations of each household. As an example, even if a panel is measured once a year, there would be many months of elapsed time between the two measurement dates that bracket a disaster event.

In this paper, we exploit the new opportunities for measurement which flow from the CMIE Consumer Pyramids Household Survey ("CPHS"), which measures a panel of 170,000 households across India. Each household is met with three times a year. There is thus a period of four months, across which the household is measured twice, within which each natural disaster lies. We setup difference-in-difference estimation where households in Chennai are the "treatment" group and unaffected households in the rest of the state of Tamil Nadu are the "control" group. As households in Chennai are among the more affluent ones in Tamil Nadu, the raw dataset has poor match balance, and we address this problem by also performing matched DiD analysis.

We investigate three questions. First, we evaluate the impact of a flood on household income and consumption expenditure. It is possible that a disaster leads to declines in household income and expenditures owing to the destruction. However, it is also possible that households *increase* their spending to cope with the disaster, or replace capital stock. For example, some household activities, such as cooking, would shift from internal production to purchases from external providers, which would augment demand for certain goods and services. Households would start buying goods and services for reconstruction almost immediately after destruction has taken place. Large scale expenditures on relief and reconstruction by the Indian state would bolster the local economy.

We find that there was no statistically significant impact on household income during the flood months. Households in Chennai, however, saw a 32% increase in consumption expenditure relative to the non-affected districts. The largest percentage increases in expenditure were seen on health, and power and fuel.

Second, we evaluate the variation in the change in expenditure for different households. The adverse impact upon persons who live in structures with inferior structural strength is likely to be larger. We categorise households as more vulnerable, or more financially constrained, through various characteristics such as not having a concrete roof, or not having modern finance (such as life insurance, mutual funds, equity market participation), or not having durable goods (such as ACs, refrigerators etc). We find that the consumption expenditure of the these weaker households increases by a smaller amount than those not financially constrained. This might mean more hardship, and a higher inability to cope with catastrophic events.

Third, we evaluate the mechanism that households use to finance the higher consumption. Households could either draw down their savings, or increase their borrowings to finance expenditures. Our analysis suggests that relative to the control group, fewer households in Chennai saved, borrowed, or purchased assets, in the period after the floods. This suggests that reduced savings and reduced purchase of assets was the channel through which the consumption surge was financed. In our data, after about a year, the consumption surge ended, and was followed by a further decline in consumption. This may be consistent with households refocusing on repairing their balance sheet.

Natural disasters kill around 90,000 people and affect close to 160 million people worldwide. The frequency and intensity of disasters are expected to increase with global

Table 1 Dates of the floods

9-10 November 2015	First spells of rains in regions of Cuddalore
13 November 2015	Floods in Kanchipuram
13-17 November 2015	Floods in the low-lying areas of Chennai
1-2 December 2015	Heavy rains and floods in Chennai

warming. Greater understanding is required about how natural disasters impact economic outcomes, so that better public and private responses may be designed. The contribution of this paper lies in bringing new tools of measurement (panel data, three times a year) to bear on an important problem (natural disasters) and discover the phenomena that are at work. The novel estimation strategy shown here can now be applied for many natural disasters in India. Over time, a body of work can develop of this nature, through which more abstract insights can be obtained.

Section 3 presents a brief review of the literature. Sections 2 and 4 describe the floods in Chennai, and the data-set respectively. The empirical strategy is presented in Section 4.2, and the results in Section 5. Section 6 presents the robustness checks while Section 7 concludes.

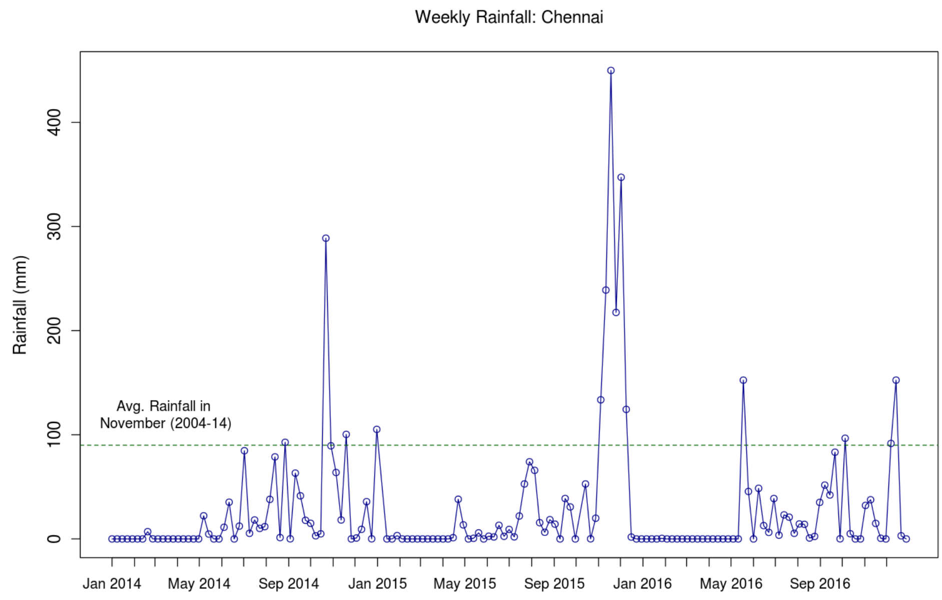
2 The Chennai floods of 2015

Chennai is the capital city of the southern state of Tamil Nadu. According to the 2011 census, it is the sixth-most populous city and fourth-most populous urban agglomeration in India. Two major rivers flow through Chennai, the Cooum River (or Koovam) through the centre and the Adyar River to the south. A third river, the Kortalaiyar, travels through the northern fringes of the city before draining into the Bay of Bengal.

The floods in Chennai took place after extreme rainfall. The first spell of rains took place on 8-9 November 2015. This was followed by a second spell of heavy rainfall between 15-17 November 2015. The final phase of rainfall took place in the beginning of December with devastating effects in parts of northern Tamil Nadu. Extreme rainfall led to the overflowing of rivers and lakes causing flood like situation in parts of coastal Andhra Pradesh, Tamil Nadu and Puducherry. Table 1 provides the exact time line of the rains and subsequent floods.

Chennai received a cumulative rainfall of 1044 mm during November 2015, an excess of 300% from the normal level. During the final spell of 1-2 December, Chennai received a record rainfall of 290 mm within 24 hours. It became the wettest December day in Chennai since 1901 (See Figure 1 for the weekly average rainfall in Chennai since January 2014.)

Figure 1 Weekly rainfall in Chennai



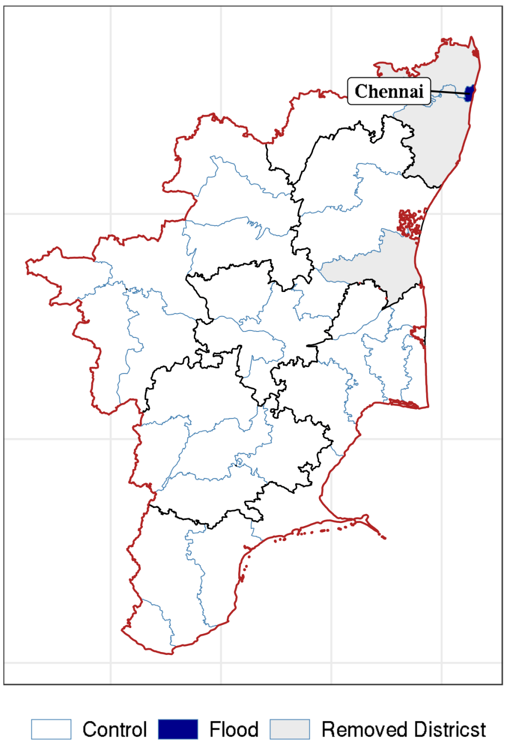
Heavy rainfall breached the carrying capacity of the Cooum, the Adyar and the Kosasthalayar, the three rivers that flow across Chennai and its suburbs, leading to inundation of low-lying areas. Reservoirs in the outskirts of Chennai, like the Chembarambakkam reservoir, also released water that flowed into these rivers.

Chennai was officially declared as a disaster area on the evening of 2 December. Although the floods were triggered by a natural phenomenon of heavy rainfall, man-made reasons also played an important part. Encroachment alongside rivers and lakes reduced their carrying capacity and made the nearby population susceptible to disasters. The reduced carrying capacity enhanced the flooding. The rains in the beginning of December inundated around 40% of Chennai with water depth as high as 11 feet in some areas. Apart from Chennai there were significant damages in other parts of the state.[1]

Panel (a) in Figure 2 shows the districts in Tamil Nadu (including Chennai) that were affected by the rains. Panel (b) shows the map of Chennai and the extent of flooding across Chennai. The floods caused extensive damages to human life and livelihood, private and public property in and around Chennai. Drinking water was often hard to find, and there were concerns of a health crisis owing to excessive flooding. The death toll was about 500, and about 1.8 million were displaced from their homes. 30% of households in Chennai were estimated to have faced losses between Rs.200,000 and Rs.2 million.

[1]These include the districts of Tiruvallur, Kancheepuram, Cuddalore, Villupuram, Nagapattinam, Tanjavur, Thiruvarur, Tirunelveli, Pondicherry.

Figure 2 Map of Tamil Nadu and Chennai during 2015 floods



(a) Districts in Tamil Nadu

(b) Chennai on 03.12.2015
Source: Maps of India

Table 2 Estimated economic loss

	Rs. billion
Real estate	300
SME (entire TN)	140
Insurance	480
Street vendors	2.25

Source: Narasimhan, Bhallamudi, Mondal, Ghosh and Mujumdar (2016)

While precise official estimates of the damage have been hard to find, Table 2 presents one estimate of the economic losses which ensued.

The State government sanctioned Rs 5 billion on 17 November from the State Disaster Relied Fund (SDRF) to carry initial relief work. Later a sum of Rs 10 billion was sanctioned for ex-gratia relief to affected households and Rs 3 billion for restoration of roads. If we juxtapose these expenditures, of Rs.15 billion, against a population of 7.1 million people, this works out to a per capita expenditure of Rs.2,112 per person. These are reasonably large values when compared with the magnitudes seen in this paper. More than 1.7 million people were rescued and moved to safer areas in Tamil Nadu. Around 72,000 people were moved to 432 camps outside Chennai.

3 The economic impact of natural disasters for households

The frequent recurrence of natural disasters has led to the emergence of a literature on evaluating the impact of these disasters on aggregate output as well as household welfare.

Research on aggregate output is mixed. Some studies show that there may be a positive correlation between disasters and economic growth (Albala-Bertrand, 1993). In fact, Skidmore and Toya, 2007 suggest that higher frequencies of climatic disasters may be correlated with higher rates of human capital accumulation, increases in total factor productivity, and economic growth. Research also suggests that reconstruction activity after mild disasters may overcome the initial negative effects (McDermott, Barry & Tol, 2014).

More recent research, however, suggests that overall effects may be negative (Cavallo & Noy, 2011; Klomp & Valckx, 2014; Noy, 2009). For example, Hsiang and Jina, 2014 study the universe of tropical cyclones and find that national incomes do not recover even 20 years after a disaster. The magnitude of the effect depend on the type of disaster, its intensity, and the economic characteristics of where it strikes. For example, Cavallo, Galiani, Noy and Pantano, 2013 suggests that only extremely large disasters have a negative effect on output in both the short and the long runs. Using data on floods in India, Panwar and Sen, 2019 also find that the effects vary depending on the the state-wise levels of human development and the flood intensity.

The microeconomics literature generally finds that disasters lead to reductions in income and consumption expenditure. For example, Ninno, Dorosh and Smith, 2003 finds that households in Bangladesh exposed to the 1998 flood suffered severe crop losses (equal to 24% of the total value of anticipated production for the year), resulting in declines in non-food household expenditure. Kazianga and Udry, 2006 find crop incomes halved in Bukria Faso owing to excess rainfall and droughts, Baez, Lucchetti, Genoni and Salazar, 2016 report falls in consumption in Guatemala owing to storm "Agatha" in 2010.

The impact of disasters is heterogeneous, and depends on exposure to the disaster and socio-economic characteristics of households (del Ninno & Lundberg, 2005; Kurosaki, 2015; Masozera, Bailey & Kerchner, 2007). The impact of disasters are long-term, especially when it comes to health outcomes. For example, Alderman, Hoddinott and Kinsey, 2006 find that stunting in children because of droughts or floods is never reversed, having implications on school attainment and earnings in adulthood.

Recent work on the impact of natural disasters on households has started to examine the factors that improve the "resilience" of households to disasters. For example Smith and Frakenberger, 2018 find that besides disaster preparedness and mitigation, factors such as social capital, human capital, exposure to information, asset holdings, livelihood diversity, safety nets, access to markets and services, women's empowerment, governance, and psycho-social capabilities such as aspirations and confidence to adapt improve resilience.

All of this research has used household surveys to estimate the impact of disasters. Surveys are often carried out after the event, and have to rely on household recall to estimate the effects. Even if panel data exists, the survey may actually take place a year or two after the disaster, making it difficult to obtain precise estimates on household responses to the immediate impact of a natural disaster.

From this vantage point, we pursue three questions about the Chennai floods in this paper.

The first question is that of the impact upon income and consumption. India is a middle income country, Tamil Nadu has better state capacity when compared with median Indian conditions, and Chennai is one of the biggest cities of India. As a consequence, relief and reconstruction is likely to be relatively rapid and efficacious.

While many firms would be destroyed by the floods, we would expect a surge in economic activity owing to expenditures by the state, and expenditures by households who are engaged in reconstruction that is financed by drawing down financial assets. The overall impact upon income would reflect a combination of the negative impact (where some firms are disrupted) and the positive impact (of a surge of post-disaster expenses and thus economic activity).

In terms of consumption, we expect households to increase expenditures in response to disruption of their ordinary cooking arrangements, higher health expenditures and money spent on reconstruction. These increases would be financed through a mix of labour income, transfers from the state, and the financial system.

The second question that we pursue is that of the heterogeneity of impact. Less affluent households are likely to experience greater destruction of housing stock, larger adverse health impacts owing to flooding inside the house, and greater destruction of assets ranging from household appliances to tools of the trade. At the same time, their ability to increase consumption is likely to be limited through limited liquid assets and borrowing capacity.

The third question consists of the interplay between household consumption and finance. When there are ample liquid assets or there is an ability to borrow, we would expect a swift and large surge of expenditures for reconstruction, followed by a period of reduced consumption in order to rebuild the household balance sheet. When there are inadequate liquid assets and/or borrowing constraints, the reconstruction would be spread over a longer time period. The dynamics of consumption are thus shaped by finance. We aim to measure this response in time, and obtain insights into the inter-relationship with finance.

4 Estimation strategy

4.1 A novel panel dataset

The Consumer Pyramids Household Survey (CPHS) is a pan-India panel household survey of about 170,000 households carried out by the Centre for Monitoring Indian Economy, three times a year. In the Indian context, this is an unusual dataset in that it is panel data about households. In addition, this is an unusual panel dataset in conducting three waves per year.

The survey captures data on household demographics which includes member-wise characteristics, household amenities such as access to water and electricity, household income

Table 3 Number of households interviewed in Chennai

Month of visit	Sample size
Mar 2014	607
Jul 2014	586
Nov 2014	577
Mar 2015	555
Jul 2015	522
Nov 2015	500
Mar 2016	531
Jul 2016	515
Nov 2016	497
Mar 2017	470

and expenses and household assets and borrowing by households. For the purpose of sampling, CPHS creates one or more Homogeneous Regions (HR) for each state from a set of neighbouring districts that have a similar agro-climatic condition, urbanisation levels and female literacy. There are a total of 102 HRs in the CPHS database.

The data is captured through a visit to the household three times a year (known as a Wave or Round). In one wave, all households in India are met, and this takes place over four months. Wave 1 in each year takes place from 1 January to 30 April. Wave 2 takes place from May to August, and Wave 3 takes place from September to December.

In each visit the household is asked about income and expenditure for the previous four months. The information on assets, liabilities, and member characteristics is as of the month of the survey. If the household was visited in April 2015 in Wave 1, the income and expenditure details would be collected for the previous four months. However, member characteristics, assets and borrowing would be as of April 2015.

For the purpose of this paper, the measurement of households in Chennai is of great importance. Table 3 shows facts about the number of households which are observed in Chennai in the database. In the survey plan, all the households in Chennai were met with in the third month of the wave, i.e. in March, in July and in November of all the years. This implies that the questions on income and consumption pertaining to the months of November and December 2015 were asked in March 2016.

This data, therefore, allows us to estimate the impact on households immediately after the floods. In contrast, most conventional research on natural disasters (Arouri, Nguyen & Youssef, 2015; Baez et al., 2016; Dercon, Hoddinott & Woldehann, 2005; van den Berg, 2010) is only able to estimate the effects through survey data collected a year (or more) after the floods, and require recall of the preceding months to estimate short and medium term impacts.

4.2 Empirical specification

We use the time and spatial variation of the Chennai floods to carry out a difference-in-difference analysis. Our specification includes a panel data difference-in-differences regression model as follows

$$y_{it} = \beta_0 + \beta_1 \text{treat}_{it} + \beta_2 \text{post}_{it} + \beta_3 \text{treat*post}_{it} + \eta_i + \epsilon_{it}$$

Here, y_{it} refers to the the outcome variable of interest (such as per capita income, or per capita expenditure) for household i at time t. "Treat" takes the value 1 if the household is in Chennai, and 0 otherwise. "Post" captures if the observation is from the period during the floods. This includes the months November and December 2015. The pre-treatment months include September and October 2015. η_i refers to the household fixed effect.

$\hat{\beta}_3$ will be significant if there is a greater change in the relevant outcome variable in the treated households after the floods relative to the control households. Standard errors are robust to heteroskedasticity and are clustered at the household level.

A standard assumption for a DID model is that the differences between the treatment and comparison groups would have remained constant in the absence of the floods. This is best tested using the "parallel trends assumption". Figure 3 shows the trends in per capita expenditure in the treated and control groups over a period of time. We find that the per capita expenditure trend in both the treated and control regions was roughly parallel in the period before the Chennai floods. This gives us reason to move ahead with our DID specification.

Table 4 presents the summary statistics of the pre and post treatment period averages in the two groups on some variables of interest. We find that the treatment group i.e. Chennai district had higher per capita expenditure and income relative to the control group, and that this expenditure rose by a much greater amount in Chennai relative to the control group. There is a lack of match balance. We address this, later in the paper, through a matched DiD design.

We form a balanced panel of households where facts are observed in the four months of interest (September to December). This yields a dataset with 450 households in Chennai and 3278 households in the control districts.

Figure 3 Per capita expenditure: Treatment effects

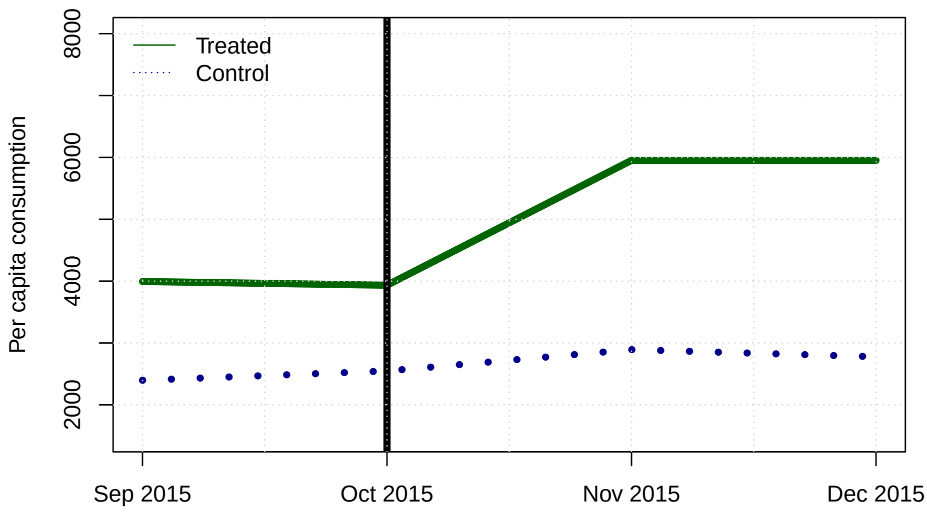


Table 4 Pre (Sep 2015 - Oct 2015) and post (Nov 2015 - Dec 2015) treatment: Summary statistics

This table presents the average per capita income and expenditure for the treated (Chennai) and control (rest of Tamil Nadu) groups in the months prior to the floods (Sep - Oct 2015) and the two months of the floods (Nov - Dec 2015).

	District affected?	
	No	Yes
Per capita expenditure		
Before	2473.88	3963.62
After	2832.72	5951.93
Per capita income		
Before	4020.08	6534.75
After	4253.57	7114.89
Number of individuals observed	15947	2062

5 Results

The analysis focuses on the short-run impact of the floods. The treatment period therefore are the flood months of November and December 2015. The control period are the months preceding the floods, that is, September and October 2015.

5.1 Summary statistics

We restrict our sample to households in Tamil Nadu as households within a state are likely to be culturally similar and face the same economic conditions within the state. Households in the district of Chennai are labeled as treated households (N=604), while those outside of Chennai are labeled as control households (N=5390). Households in the other flood affected districts were removed from our control sample. Our data spans from January 2015 to December 2016, a total of 24 months. This gives us 114,261 observations, with 46,343 in the pre-treatment period and 67,918 in the post treatment period.

The pre-treatment characteristics of the sample are described in Table 5. The average age and family size is not very different between the treated and control households. The per capita income and expenditure of households in the treated region (Chennai) are higher than that of the control region (TN). This is true of per capita food expenditure as well as expenditure on power and fuel, but not true of health expenditure. In other words, the vanilla DiD regression has poor match balance.

A larger proportion of households have investments in life insurance and mutual funds in the treated region. This is once again not surprising, as Chennai is a large metropolis which is likely to have the highest access to modern financial products. A lower proportion of households in Chennai have household debts than in the rest of TN. There is a larger proportion of Graduates in Chennai, and a very small proportion involved in agriculture.

5.2 Impact on per capita income and expenditure

Natural disasters have been shown to have a negative effect on income, especially if the disaster occurs in that time of the agricultural cycle when the adverse consequences can be larger. For example, Mottaleb, Mohanty, Hoang and M.Rejesus, 2013 study the impact of the May 2009 cyclone in Bangladesh and find an impact on income volatility of rice farmers. However, the impact may be different in an urban setting, where the reliance on weather and crops is lower. Similarly, Baez and Santos, 2008 find that the combined effect of both earthquakes in El Salvador is associated with a reduction in household income per capita of one third of the pre-shock average for households in the upper half

Table 5 Pre-treatment summary statistics of the sample (January - October 2015)

This table presents the household characteristics for the treated (Chennai) and control (rest of Tamil Nadu) groups in the months prior to the floods (Jan - Oct 2015).

	District affected?	
	No	Yes
Avg. monthly per capita inc (Rs.)	3790.77	6498.26
Avg. monthly per capita exp (Rs.)	2154.95	3575.89
Avg. monthly per capita exp: food (Rs.)	1041.90	1606.15
Avg. monthly per capita exp: health (Rs.)	49.33	39.44
Avg. monthly per capita exp: power/fuel (Rs.)	299.07	553.91
Share of food (%)	51.71	47.99
Share of health (%)	2.05	1.15
Share of power and fuel (%)	13.65	15.06
Age of Hoh	52.27	53.99
Household size	3.88	3.87
Have fixed deposits (%)	55.51	32.48
Have life insurance (%)	37.57	54.83
Have mutual funds (%)	0.11	0.16
Have gold (%)	99.53	100.00
Have outstanding debt (%)	9.36	5.72
Education of hoh (%)		
None	16.97	8.04
Less than 12	68.92	63.29
Class 12/Diploma	6.47	8.35
Graduate and above	7.64	20.32
Religion (%)		
Christian	3.28	6.43
Hindu	83.76	87.38
Muslim	3.32	3.81
Other	9.64	2.39
Caste (%)		
Upper	2.84	11.91
Intermediate	5.06	8.48
Obc	68.10	52.72
Reserved	24.00	26.89
Occupation (%)		
Agri	9.31	0.58
Business/self-emp.	18.39	24.32
Salary	40.26	42.36
Other	32.04	32.74
N	90,666	11,818

Table 6 Impact on log (per capita income and expenditure)

The table presents the results from the panel difference-in-difference regression of log (per capita income) and log (per capita expenditure). The DID is based on four moths of data, with two months prior to the floods, and two months post the floods.

	log (per capita inc)	log (per capita exp)
	(1)	(2)
TIME	0.049***	0.134***
	(0.007)	(0.004)
TIME:TREAT	−0.008	0.280***
	(0.020)	(0.010)
Observations	14,912	14,912
R^2	0.005	0.232
Baseline mean	4391	2717
Note:	Household FE	
Note:	Heteroscedasticity consistent SE	
Note:	*p<0.1; **p<0.05; ***p<0.01	

of the distribution. Similarly, on expenditure, in many papers, we see that flood affected households see a reduction in consumption expenditure.

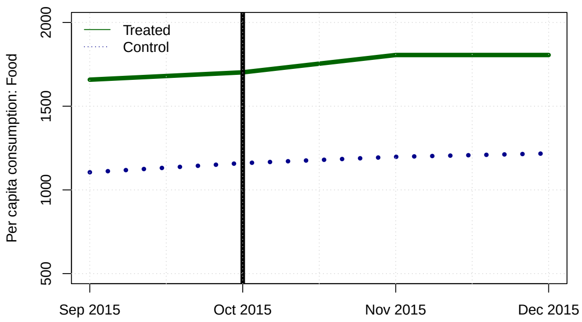
Table 6 presents the results of a fixed-effects regression on log (per capita income) in Column (1) and per capita expenditure in Column (2). The standard errors are het-roscedasticity consistent. The regressions on the 2 month period shows that there is a negative effect on per capita income between the treated and control groups after the disaster, even though it is not statistically significant.

There was a sharp increase in the per capita expenditure in the months immediately after the floods. The per capita expenditure of the treated group increased by 32% in the two months after the disaster. On a base of pre-treatment monthly consumption expenditure of Rs.2717, this is an increase of about Rs.870.

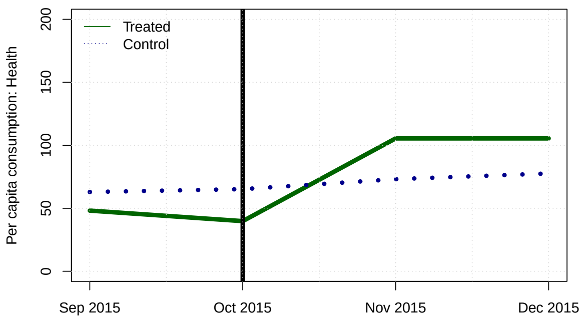
5.3 Impact on components of expenditure

We turn next to exploring the types of expenditures that increase as a result of the flood. We focus on food, health and power and fuel as these constitute almost 70% of the consumption basket of households. Figure 4 presents the per capita expenditure in the treated and control groups over time suggesting that there was a sharp rise in food and health expenditure after the floods. There was an increase in power and fuel expenditure, though this increase had been happening before the floods.

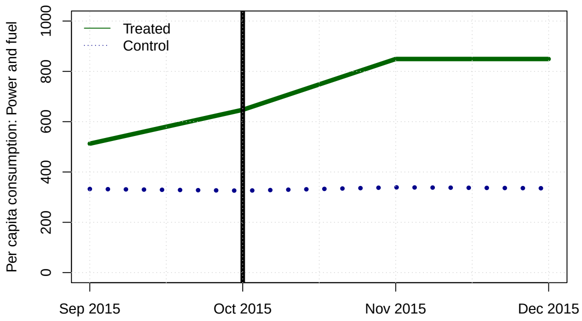
Figure 4 Per capita expenditure: Food, health and power and fuel



(a) Per capita expenditure: Food



(b) Per capita expenditure: Health



(c) Per capita expenditure: Power and fuel

Table 7 Expenditures on food, health, power

The table presents the results from the panel difference-in-difference regression of log (per capita expenditure on food, health and power/fuel).

	Food (1)	Health (2)	Power/fuel (3)
	log(Per capita expenditure)		
TIME	0.058***	0.049***	0.037*
	(0.002)	(0.014)	(0.020)
TIME:TREAT	0.030***	1.371***	0.520***
	(0.006)	(0.040)	(0.059)
Observations	14,912	14,912	14,912
R^2	0.073	0.113	0.009
Baseline mean	1216	63	369
Note:	Household FE		
Note:	Heteroscedasticity consistent SE		
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 8 Self-reported health: Treatment vs. control

This table presents the share of unhealthy people in Chennai and the control districts, before and after the flood.

Districts	Share Unhealthy (Per cent)
Control: Jan-Apr 2015	4.87
Control: Jan-Apr 2016	4.89
Chennai: Mar 2015	0.05
Chennai: Mar 2016	1.42

Table 7 describes the results of the panel regression on log of per capita expenditure on food, health and power/fuel. In the 2 months of the floods, we find that expenditure on each of these categories increased. The magnitude of the increase was 2.5% for food, 67% for power and fuel, and 200% for health. In absolute terms, the increase in food expenditure was small: on a pre-treatment base of Rs.1215, the change was only Rs.24. Similarly, while the percentage change in health expenditure is large, in rupee terms, it was an increase of about Rs.126. The magnitude of the change with expenditure on power and fuel was Rs.400, the largest of the three impacts when expressed in rupee terms.

We do not observe the state of health *during* the floods or immediately after the floods. We only observe self-reported health status on the date of the next survey wave, which is in March 2016. Table 8 examines this data. Here, the problem of match balance is substantial. In the pre-flood peroid, while 0.05% of the Chennai population reported they were unhealthy, the value for the control districts was 4.87%. This is consistent with the idea that Chennai is a much more prosperous place when compraed with the controls.

However, for the purpose of identifying the impact of the floods, we see that in March 2016 – a full three months after the flood – there was a large increase in the unhealthy fraction in Chennai, to 1.42%. Over this same period, nothing changed for the controls.

Our data thus shows two aspects of the impact on health: (a) *During* the period of the floods, there was a sharp increase in health expenditure and (b) *Three months after* the floods, there was an increased number of unhealthy persons in Chennai.

These results on health are consistent with other work about the impact of disasters on health and on health expenditures. For example, Ninno et al., 2003 study the impact of floods in Bangladesh, and find that individuals in all age groups experienced a deterioration in health status. Similarly Datar, Liu and Linnemayr, 2013 find that a disaster in the past month significantly increases the likelihood of diarrhea, fever, and ARI, by about two to three percentage points, in children in India.

5.4 Heterogeneous treatment effects on expenditure

The ability to cope with disasters depends on several factors - social capital, income, wealth, and financial constraints. For example, Dercon et al., 2005 find that poorer households report a much bigger impact of drought shocks experienced at least once in the last five years on current levels of consumption. Sawada and Shimizutani, 2008 show that the great earthquake in Japan, in 1995, had a larger effect on households that had a borrowing constraint prior to the earthquake than households who did not have a borrowing constraint.

One would expect that the impact of the floods in Chennai would be greater on households that were financially constrained. However, it is difficult to measure financial constraints *ex-ante*, as a household may not have borrowed because it does not need to, or because it is not able to. We therefore use proxies for financial constraints.

The first category is that of households that do not have a concrete roof. This is not just about poverty: The micro-finance industry considers this as a criterion for disbursing loans. Those with non-concrete roofs are less likely to be given loans, hence this dummy variable proxies for financing constraints.

The second category is where the households have no connection with modern finance: they do not have investments in provident funds, mutual funds, listed shares or insurance. This is likely to proxy for knowledge and awareness of finance, and relationships with employees of financial firms through which cross-selling of loans could take place.

Table 9 Heterogeneous treatment effects: Financially constrained households

This table presents the results of a difference-in-difference regression on per capita expenditure of groups that may be financially constrained. Column (1) includes those households who do not have a concrete roof, Column (2) includes those households that have not invested in modern finance (provident funds, mutual funds, listed shares or insurance), while Column (3) includes those households where less than 50% of members own a mobile phone. "z" indicates the interaction between the specific type of household and TIME and TREAT.

	No concrete roof	No modern finance	Less than 50% mem. have mobile
	(1)	(2)	(3)
		Overall	
TIME	0.134***	0.134***	0.134***
	(0.003)	(0.003)	(0.004)
z	−0.121***	−0.142***	−0.059**
	(0.024)	(0.019)	(0.024)
TIME:TREAT	0.302***	0.338***	0.291***
	(0.011)	(0.013)	(0.011)
Observations	14,912	14,912	14,912
R^2	0.234	0.236	0.233
Note:	Household FE		
Note:	Heteroscedasticity consistent SE		
Note:	*p<0.1; **p<0.05; ***p<0.01		

The third category consists of households where less than 50% of members own a mobile phone. This is likely to proxy for the modern digital pathways into lending.

Table 9 presents the results on per capita expenditure on different groups of people who may be differentially impacted by the flood. All of these categories are expected to be more vulnerable, and therefore, may have a differential response to floods.

The results indicate that the vulnerable financially constrained groups also saw an increase in per capita expenditure, however, the increase is *lower* than those of the less vulnerable groups. Hence, we would argue that a large consumption surge after the flood is welfare maximising, but these more vulnerable households were unable to finance that for want of liquid assets or borrowing.

Another way of measuring the heterogeneity of impact is through the behaviour of households as classified by asset ownership. Table 10 presents the results on impact on log per capita consumption by assets. Column (1) includes those who do not have either an AC or a cooler. Column (2) includes those who do not have a car or a two-wheeler. Column (3) includes those who do not have a fridge.

Here too we find that those without assets saw a smaller increase in lower per capita

Table 10 Heterogeneous treatment effects: By asset ownership

This table presents the results of a difference-in-difference regression on per capita expenditure of groups that have low asset ownership. Column (1) includes those households who do not have a cooler or air-conditioner, Column (2) includes those households that do not have a two-wheeler or a car, while Column (3) includes those households who do not own a refrigerator. "z" indicates the interaction between the specific type of household and TIME and TREAT.

	No AC	No vehicle	No fridge
	(1)	(2)	(3)
TIME	0.134***	0.134***	0.134***
	(0.003)	(0.003)	(0.003)
z	−0.139***	−0.190***	−0.145***
	(0.019)	(0.031)	(0.038)
TIME:TREAT	0.360***	0.299***	0.289***
	(0.015)	(0.011)	(0.010)
Observations	14,912	14,912	14,912
R^2	0.236	0.235	0.233
Note:	Individual and time FE		
Note:	Heteroscedasticity consistent SE; clustered at HH level		
Note:	*p<0.1; **p<0.05; ***p<0.01		

expenditures in the months of the floods than those with the assets. One way to interpret this is to assume that those without assets are not able to cope with the consequences of floods as much as those with the assets. The lower increase in consumption expenditure might mean more hardship, and a higher adverse impact of the disaster. This is consistent with many results in the literature which show that deprived populations generally carry the heaviest burdens in terms of lost income or consumption (Baez et al., 2016; del Ninno & Lundberg, 2005; Dercon et al., 2005; Masozera et al., 2007).

5.5 Impact on saving, asset purchase, borrowing

The results so far suggest that the floods had no short-term impact on household incomes, though it did lead to an increase in expenditure. This raises the question, how were these expenditures financed?

Table 11 explores the impact of the floods on saving, asset purchase and borrowing. The dummy variable for asset purchase is defined as "1" if the household has bought any of the following assets: house, refrigerator, air-conditioner, cooler, washing machine, television, computer, car, two wheeler, genset or inverter, tractor or cattle. We look at six months of data before and after the flood. Column (1) presents the results on a variable that indicates whether the household purchased an asset, column (2) indicates if it saved in any financial instrument, and column (3) presents results on a variable that indicates

Table 11 Saving, asset purchase, borrowing

This table presents the results of a difference-in-difference regression on probability of saving, of purchasing an asset and of having outstanding borrowings in the period after the Chennai floods relative to the period before the floods.

	Bought asset	Saved	Borrowed
TIME	0.060***	0.037***	0.176***
	(0.003)	(0.002)	(0.003)
TIME:TREAT	−0.044***	−0.030***	−0.163***
	(0.007)	(0.007)	(0.008)
Observations	32,772	32,772	32,440
R^2	0.017	0.008	0.108
Note:	Household FE		
Note:	Heteroscedasticity consistent SE		
Note:	*p<0.1; **p<0.05; ***p<0.01		

whether the household borrowed in the relevant time period.

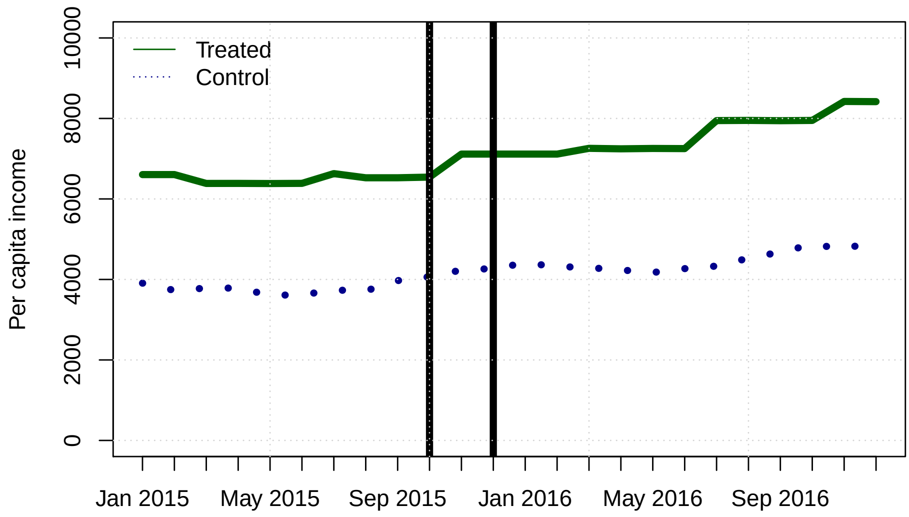
These results show that asset purchases were reduced and saving was reduced. This suggests that households probably finance the expenditure owing to the floods through a reduction in saving, or postponing asset purchases. These results are consistent with a fall in saving (income - expenditure) in the same time period. They are also consistent with the analysis of the number of units owned of durable goods by the household, compared with the controls.

A remarkable finding is the decline in the fraction of households who have outstanding borrowings after a disaster. At first blush, this seems surprising. One would expect that households would want to borrow more to cope with a disaster. There may be two reasons for this. First, it is possible that households prefer taking losses on the asset side of the balance sheet through losing home equity, or drawing down savings as was seen in the case of households affected by Hurricane Katrina in the US (Gallagher & Hartley, 2017). It is also possible that households wanted credit, but did not find it easy to obtain it as credit supply, especially to first time borrower households, is often more restricted after a disaster, as has been observed by (Berg & Schrader, 2012). We do not have the data to further explore these two potential pathways.

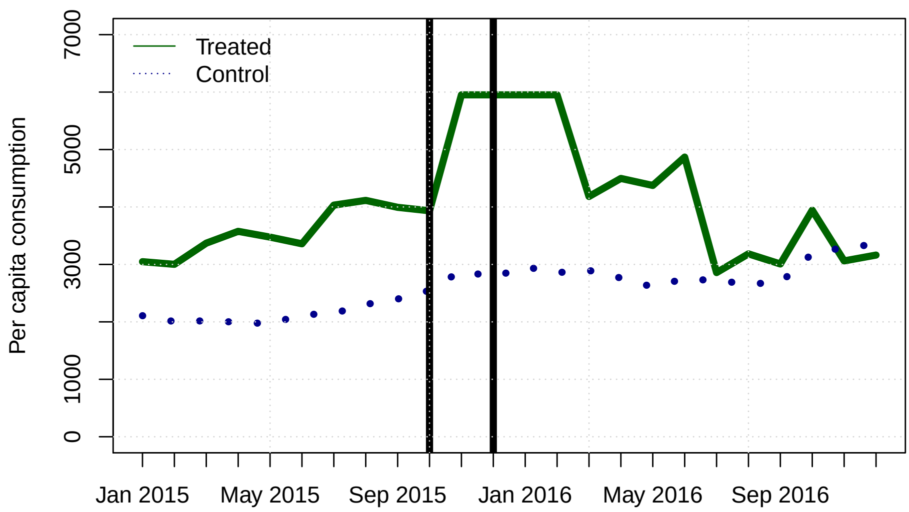
5.6 Longer term impact

We next turn our attention to the longer term impact of the floods on per capita household income and expenditure. Figure 5 presents the per capita income and expenditure in Chennai and the control group over the period of one year after the floods.

Figure 5 Per capita income and expenditure



(a) Per capita income



(b) Per capita expenditure

The data does not suggest a big change in the per capita income of the Chennai region. However, the per capita expenditure which increased during the two months of the floods, began to fall after February 2016. By the end of 2016, the per capita consumption of Chennai was at the same level as that of the control region, while at the start of the data these households were better off than the controls.

Table 12 presents the results of the panel DID regression on 6 months and 1 year of data. Columns (1-4) present the results on per capita income, while Columns (5-8) present the results on per capita expenditure. Over a period of 6 months, we see that per capita income decreased by about 8% while per capita expenditure increased by 10.7%. Over a period of a year, both per capita income and expenditure fell. Per capita income had fallen by 8% and 9% respectively. Our results of a decline in per capita expenditure over the period of a year are consistent with other research that has been able to evaluate the impact of disasters using surveys carried out in subsequent years (Arouri et al., 2015; Baez et al., 2016; Rodriguez-Oreggia, Fuente, Torre & Moreno, 2012).

This suggests that households respond to floods in several ways. First, immediately after the floods, households see a sharp increase in consumption expenditures perhaps as a result of having to cope with the immediate aftermath of the destruction caused by the event. However, over a six month and one year period, households see a sharp decline in expenditure, which is consistent with their objective of repairing their balance sheets.

6 Robustness checks

An important concern about this analysis is the differences between the treated and the control households. As we have observed earlier in this paper, while the conventional parallel trends assumption of the DiD regression is satisfied, there is a lack of match balance: it is apparent that the sample of households in Chennai is more affluent than the sample of households in the remainder of Tamil Nadu. This raises concerns about the extent to which the DiD regression is actually engaged in extrapolation in finding treatment effects between units of observation which are not comparable.

6.1 A matched DiD regression

In order to address this problem, we establish a matching methodology through which we filter down to a dataset that has match balance. This can involve dropping some households in Chennai if their matched controls in Tamil Nadu do not exist.

Such matching is often done using the Mahalanobis distance measure, which is just the

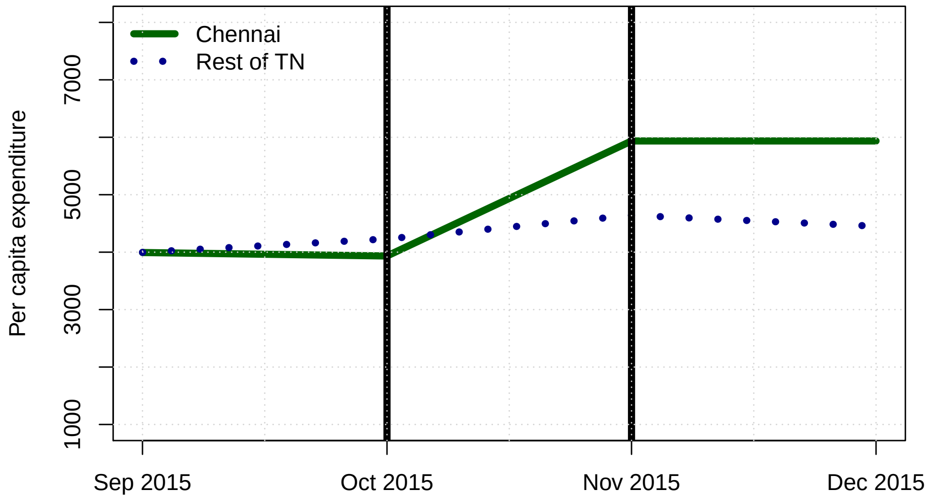
Table 12 Impact over 6 months and 1 year

The table presents the results from the panel difference-in-difference regression of log (per capita income) and log (per capita expenditure). The DID is based on six moths and 1 year of data.

	log(PCI)				log(PCE)			
	6m	6m	1y	1y	6m	6m	1y	1y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TIME	0.113***	0.113***	0.170***	0.170***	0.237***	0.237***	0.272***	0.272***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
TIME:TREAT	−0.081***		−0.091***		0.102***		−0.137***	
	(0.015)		(0.013)		(0.009)		(0.009)	
mnov15		−0.072***		−0.134***		0.235***		0.255***
		(0.026)		(0.031)		(0.016)		(0.021)
mdec15		−0.072***		−0.134***		0.235***		0.255***
		(0.026)		(0.031)		(0.016)		(0.021)
mjan16		−0.072***		−0.134***		0.235***		0.255***
		(0.026)		(0.031)		(0.016)		(0.021)
mfeb16		−0.072***		−0.134***		0.235***		0.255***
		(0.026)		(0.031)		(0.016)		(0.021)
mmar16		−0.090***		−0.152***		−0.203***		−0.189***
		(0.026)		(0.031)		(0.016)		(0.021)
mapr16		−0.111***		−0.178***		−0.126***		−0.117***
		(0.026)		(0.031)		(0.016)		(0.021)
mmay16				−0.159***				−0.170***
				(0.031)				(0.021)
mjun16				−0.178***				−0.058***
				(0.031)				(0.021)
mjul16				−0.039				−0.499***
				(0.031)				(0.021)
maug16				−0.037				−0.404***
				(0.031)				(0.021)
msep16				−0.040				−0.458***
				(0.031)				(0.021)
moct16				−0.039				−0.232***
				(0.031)				(0.021)
mnov16				0.046				−0.416***
				(0.031)				(0.021)
mdec16				0.043				−0.397***
				(0.031)				(0.021)
Observations	32,772	32,772	46,104	46,104	32,772	32,772	46,104	46,104
R^2	0.015	0.015	0.025	0.028	0.178	0.204	0.118	0.169

Note: Household FE
Note: Heteroscedasticity consistent SE
Note: *p<0.1; **p<0.05; ***p<0.01

Figure 6 Per capita expenditure: Treatment effects on matched data



Euclidean distance in one dimension. such that there remains no statistically significant difference between the pre-treatment per capita expenditure between the treated and control households. We undertake such a matching exercise using pre-treatment monthly per capita expenditure. As was presented in Table 4, the pre treatment monthly per capita expenditure in Chennai was Rs.3576 while that in the rest of the state was Rs.2155. The difference between the two groups is statistically significant at the 1% level, and shows that there is a lack of match balance. This raises concerns about a conventional DiD regression.

After we have undertaken data pre-processing using matching, match balance is achieved. In the matched sample, the pre treatment monthly per capita expenditure in Chennai was Rs.3558 while that in the rest of the state was Rs.3548, and this difference is statistically not significant. We now proceed to analyse this matched dataset.

Figure 6 presents the treatment effects on this matched data. We find that our primary result remains and that the households in Chennai saw a marked increase in expenditure after the floods relative to the control households. In the vanilla DiD analysis, there was a parallel trend. In this graph, in addition, the treated and the control have highly similar values, pre-treatment.

Table 13 presents the results for the matched DiD regression. Our basic results do not change. There was an increase in overall per capita expenditure in Chennai after the

Table 13 Matched DiD regression on expenditures

This table presents the results of the difference-in-difference regression on log (per capita expenditure) for the matched data-set of households in Chennai with households in other parts of Tamil Nadu.

	Overall (1)	Food (2)	Health (3)	Power/fuel (4)
TIME	0.099***	0.041***	0.042	−0.015
	(0.010)	(0.005)	(0.051)	(0.043)
TIME:TREAT	0.314***	0.046***	1.378***	0.571***
	(0.014)	(0.007)	(0.070)	(0.060)
Observations	3,392	3,392	3,392	3,392
R^2	0.449	0.133	0.258	0.068
Note:	Household FE			
Note:	Heteroscedasticity consistent SE			
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 14 Placebo: 2014

This table presents the results of the difference-in-difference regression on log (per capita expenditure) for the data-set in 2014, one year prior to the floods.

	Overall (1)	Food (2)	Health (3)	Power/fuel (4)
TIME1	−0.011***	−0.014***	0.003	0.015
	(0.003)	(0.002)	(0.011)	(0.017)
TIME1:TREAT	−0.006	−0.005	0.032	0.230***
	(0.008)	(0.006)	(0.032)	(0.047)
Observations	17,256	17,256	17,256	17,256
R^2	0.002	0.004	0.0001	0.002
Note:	Household FE			
Note:	Heteroscedasticity consistent SE			
Note:	*p<0.1; **p<0.05; ***p<0.01			

floods - including that of food, health and power and fuel expenditure.

6.2 Placebo analysis

We now proceed with the standard placebo analysis of the internal validity of the identification strategy, namely that the outcomes for treated and control households would not have the different pathways in the absence of the flood. We focus on the same four months of data (September - December) but of the previous year (2014). We then estimate placebo treatment effects of a "fake" shock on per capita consumption.

The results are presented in Table 14. The double-difference estimators for overall per capita consumption, and per capita food, and health consumption are statistically insignificant. The results thus suggest that there is no evidence of diverging trajectories preceding the shock between the treatment and control groups.

7 Conclusion

Natural disasters are an important part of the stochastic environment for households and for policy makers. There is a need to know more about the time series and cross-sectional variation of the impact of a natural disaster.

In this paper, we propose a new strategy for measurement of the impact of a natural disaster for the affected population, which exploits recent developments in measurement: a large scale panel dataset which sees 170,000 households in India, three times a year. Each natural disaster then makes possible the construction of a sample of affected households which are matched against a sample of control households from unaffected areas. This statistical strategy has made possible a new precision in understanding the impact of the Chennai floods of 2015 upon the households of Chennai, rich and poor.

Our evidence suggests that for the more affluent households, consumption surges for the first few months, and after that, consumption drops as households turn to rebuilding their balance sheets. The less affluent households are able to surge consumption less, which would suggest the lack of liquid assets coupled with the lack of borrowing opportunities.

This new approach to measurement opens many new possibilities for research. An array of projects can now build such evidence, across multiple natural disasters. Depending on differences in the nature of the shock, the pre-existing financial resilience of affected households, and the efficacy of reconstruction of public infrastructure, we will see heterogeneity of impacts across multiple different disasters. Such a body of literature, of an examination of one natural disaster at a time, can then set the stage for drawing more general lessons about household finance, resilience and reconstruction.

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