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Natural Disasters and Economic Dynamics

Evidence from the Kerala Floods

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Abstract

Exceptionally high rainfall in the Indian state of Kerala caused major flooding in 2018. This paper estimates the short-run causal impact of the disaster on the economy, using a difference-in-difference approach. Monthly nighttime light intensity, a proxy for aggregate economic activity, suggests that activity declined for three months during the disaster but boomed subsequently. Automated teller machine transactions, a proxy for consumer demand, declined and credit disbursal increased, with households borrowing more for housing and less for consumption. In line with other results, both household income and expenditure declined during the floods. Despite a strong wage recovery after the floods, spending remained lower relative to the unaffected districts. The paper argues that increased labor demand due to reconstruction efforts increased wages after the floods and provides corroborating evidence: (i) rural labor markets tightened, (ii) poorer households benefited more, and (iii) wages increased most where government relief was strongest. The findings confirm the presence of interesting economic dynamics during and right after natural disasters that remain in the shadow when analyzed with annual data.

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Natural Disasters and Economic Dynamics: Evidence from the Kerala Floods*

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1. Introduction

Natural disasters can cause large economic damage both by directly impacting the population and their resources, as well as by indirectly affecting production capacity and economic decisions. Economic losses due to natural disasters are estimated to have been close to US$ 3,000 billion between 1998 and 2017 (UNISDR 2018). Over three-quarters of the damage have been caused by climate-related disasters, with the United States suffering the most, followed by China, Japan, and India. In Japan and the United States, most of the damage has been caused by earthquakes and storms, while for China and India, the major cause has been floods. Globally, floods account for nearly half of all natural disasters.[1] In India, more than 300 floods have been recorded since 1950, killing at least 75,000 people and rendering more than 900 million individuals injured, homeless, or otherwise affected.

The number of extreme rainfall events resulting in landslides, flash floods and crop damage has been increasing in India over time (Goswami et al. 2006; Roxy et al. 2017). The incidence of natural disasters has been growing in other parts of the world too. In the Asia-Pacific region, for example, the number of natural disasters grew from an average of 11 per country during the 1970s to more than 28 in the 2000s (Cavallo and Noy 2011). With accelerating climate change, the increase in natural disasters and flooding is likely to speed up.

In this paper, we study the short-run impact of a major flood in India on the economy and economic agents using several monthly and quarterly outcome variables. Kerala, a state in Southern India, experienced severe rainfall, landslides, and floods between June and August 2018. These were the worst floods in the state since 1924 and the third worst in India since 1900. A total of 504 people died and 23 million people were directly affected.[2] Since

[1] The publicly available Emergency Events Database (EM-DAT), maintained by the Center for Research on the Epidemiology of Disasters, is the most widely used database in economic research related to natural disasters. EM-DAT defines a disaster as a situation or event that overwhelms local capacity, necessitating national or international assistance and is often unforeseen and sudden. See https:www.emdat.be and Cavallo and Noy (2011) for more information.

[2] https://www.emdat.be/cred-crunch-53-flash-floods-sharing-field-experience-kerala

no natural disasters occurred in the neighboring states of Karnataka and Tamil Nadu, we can causally estimate the impacts of the Kerala floods on economic activity and household income and expenditure using a difference-in-difference estimation strategy.

We find that monthly nighttime light intensity, a proxy for aggregate economic activity, declined for three months during the disaster but increased subsequently, suggesting an economic boom likely due to reconstruction efforts. Automated teller machine (ATM) transactions, which proxy consumer demand, declined for six months and credit disbursal increased, with households borrowing more for housing and less for consumption. Income and expenditure declined strongly during the floods, but while expenditure remained lower in the medium-term, wage income recovered quickly. In September, right after the disaster, wages in affected districts started exceeding wages in unaffected districts. We provide indirect evidence that the overshooting can be attributed to reconstruction efforts. First, data on India's largest public work program, the Mahatma Gandhi National Rural Employment Guarantee Act 2005 (MGNREGA), suggest that rural labor markets tightened. Second, poorer households benefited more from increasing wages. Third, wages increased most where government relief was strongest, providing corroborative evidence on the link between reconstruction and increased wages.

The next section provides background on the Kerala floods and section 3 discusses related literature. Section 4 describes the data and summary statistics. Section 5 presents the analysis of aggregate economic activity and credit. Section 6 analyzes household expenditure and income, and section 7 analyzes the impact on household balance sheets. Finally, section 8 concludes.

2. The Kerala Floods of 2018

Every year in June, the southwest monsoon enters India and Kerala is usually the first state to be hit. From June 1 to August 19, 2018, Kerala received 2,335 millimeters (mm) of rain, which was about 46 percent above normal. Higher than normal rainfall in June and July led to the first onset of floods toward the end of July. Rainfall further intensified in August, with Kerala receiving total rainfall of 755 mm between August 1 and 19, about 163 percent above normal. Nearly half of the rain occurred in just three days, August 15 to 17, about 700 percent above normal.[3] Due to the continuous rain from June onward, reservoirs were already filled to capacity at that time, so that gates of 35 dams on upstream rivers had to be opened. The heavy rainfall and the opening of the gates, as well as the geography of Kerala with a steep descent from the eastern hill districts atop the Western Ghats to low-lying coastal areas facing the Arabian Sea, caused disastrous flooding in 13 of the state's 14 districts. The extreme rainfall also caused severe landslides, particularly in the hill districts of Idukki and Wayanad. The Indian government categorized the disaster as a level 3 calamity or "calamity of severe nature." According to the government's post disaster needs assessment, seven districts - Alappuzha, Ernakulam, Idukki, Kottayam, Pathanamthitha, Thrissur and Wayanad - were flooded entirely (GOK-UNDP 2018).

Due to the geography of Kerala, the areas that received the heaviest rainfall did not suffer the most from flooding. Figure A.2 in the appendix shows few flooded areas in the eastern hill region, which received the heaviest rainfall in August. Most of the flooded areas were in the low-lying coastal areas around the backwaters. Flooding in these areas was aggravated by adverse tidal conditions and sustained strong onshore winds that elevated the sea level and hampered the outflow of flood water. As a result, many of the low-lying areas were flooded for more than two weeks.[4]

Floods are frequent in some parts of India. Some of the most affected regions include Central India, stretching from Gujrat and Maharashtra in the West to Odisha on the east coast, and eastern states such as Bihar, West Bengal, and Assam. In regions with frequent floods, households and firms internalize them in their decisions and consequently they do not offer themselves to clearly identify the impact of a flood. In line with this, Kocornick-Mina et al. (2020) find permanent relocation of economic activity in response to large floods only

[3]Figure A.1, in the appendix, plots the daily actual and normal rainfall in Kerala from June to December 2018 using data from the Indian Meteorological Department.

[4]See Raman (2020) on how geographical features of Kerala shaped the course of this disaster.

in recently populated urban areas, likely due to substantial learning effects. The incidence of extreme rainfall is much lower in southern states such as Karnataka, Kerala, and Tamil Nadu (Roxy et al. 2017). There is no recent precedence for rainfall as in 2018 in Kerala, and the only other recorded floods of comparable magnitudes are those during the monsoons in 1924 and 1961 (CWC 2018). This makes the 2018 Kerala floods truly exogenous and supports our identification strategy.

3. Related Literature

This section briefly discusses the literature on the impacts of natural disasters on aggregate economic activity and household finances.

3.1 Natural Disasters and Economic Activity

Most papers quantifying the impact of disasters on economic activity are cross-country studies that use data on the occurrence of or damage caused by natural disasters, from the Emergency Events Database (EM-DAT).[5] Skidmore and Toya (2002) find a statistically highly significant positive correlation between the incidence of climatic disasters and long-run growth of real gross domestic product (GDP) per capita. They speculate that disasters may spur investment in updating the capital stock and that adopting newer technology could promote long-run growth.[6] Jaramillo (2009), however, finds mixed evidence on the long-run growth impacts of different disasters depending on the type of disaster, the measure, and the category of the country in terms of disaster vulnerability. Parida, Saini, and Chowdhury (2020) show that floods decrease economic growth of Indian states in the long run. Cavallo et al. (2013) find that very large disasters, if followed by radical political upheavals, lead to a

[5]EM-DAT records the incidence of more than 24,000 disaster events across the globe from 1900 to the present and contains data on the number people affected, injured, and killed in these events as well as estimates of property damage and loss of livestock. A less frequently used but similar source is NatCatSERVICE.

[6]This so-called "creative destruction" effect of natural disasters has been probed further in the literature. For example Cuaresma, Hlouskova, and Oberstriner (2008) examine if trade facilitates such a process following natural disasters but find that only richer countries benefit from capital upgrading while disasters tend to reduce technology spillovers between industrialized and developing countries.

persistent decline in GDP per capita.[7] Noy and Nualsri (2007) argue that a negative shock to human capital (loss of human lives) due to natural disasters has a significant negative effect on the medium-run (five year average) growth rate of real per capita GDP, while a similar shock to physical capital has a positive but insignificant effect. Loayza et al. (2012) find that the intensity of floods (measured using the fraction of the population affected) has a significant positive impact on medium-run GDP growth. Fomby, Ikeda, and Loayza (2013) find that the cumulative effect of droughts on GDP per capita in developing countries is negative, while it is positive for floods. Both Loayza et al. (2012) and Fomby, Ikeda, and Loayza (2013) attribute the positive impact of floods to possible productivity-enhancing effects in terms of improved land fertility and irrigation.

In contrast to the mixed findings on the medium- to long-run impacts of natural disasters, there is a broad consensus that their short-run impacts are negative. For example, Raddatz (2007) finds that the incidence of climatic disasters (floods, droughts, extreme temperature, and windstorms) and humanitarian disasters (famines and epidemics) has large, negative, and statistically significant impacts on the real GDP of low-income countries in the short run (one year after the event). Similarly, Noy (2009) argues that a negative shock to the capital stock due to property damage caused by natural disasters negatively affects the growth of real GDP in the same year. Adverse impacts of natural disasters on output are also documented by Hochrainer (2009). Raddatz (2009) notes that most of the negative impact of climate disasters on economic growth is realized in the year of the disaster itself. Felbermayr et al. (2022) investigate how weather anomalies affect economic activity approximated by nighttime light emissions. They find significant effects on local growth and significant spatial spillovers, both driven by lower income regions. Studies differentiating the impact on growth in developing and advanced countries consistently show that developing countries are more sensitive and vulnerable to natural disasters (Noy 2009; Raddatz 2009; Loayza et al. 2012; Fomby, Ikeda, and Loayza 2013).

[7] They define large natural disasters using the distribution of number of people killed due to natural disaster from EM-DAT.

The use of disaster data from databases such as EM-DAT and NatCatSERVICE for estimating the macroeconomic consequences of natural disasters has been criticized for possible issues related to endogeneity and measurement.[8] An alternative is to use the physical strength of disaster events to measure their intensity. Albala-Bertrand (1993), in a seminal contribution, collected data on 28 events across 26 countries between 1960 and 1979 and argues that natural disasters have a positive effect on GDP. Strobl (2011) constructs a "Hurricane Disaster Index," by combining estimates of monetary losses, wind speed, as well as local exposure, and finds that hurricane strikes significantly reduced the annual economic growth of coastal counties in the United States between 1970 and 2005. Hsiang and Jina (2014) show that tropical cyclones cause permanently lower levels of GDP, using a data set containing information on the exposure of all countries to all known cyclones between 1950 and 2008. Felbermayr and Gröschl (2014) construct a data set of physical intensities of earthquakes, volcanic eruptions, storms, floods, droughts, and extreme temperature events from primary geophysical and meteorological information. They find that, on an average, natural disasters have had a substantial, negative impact on the growth of per capita GDP in the years subsequent to the disasters, but that there is a recovery later.[9]

Another approach consists of studying specific disasters in case studies. Disasters are treated as "natural experiments" for causal estimation of their impacts on different variables of interest. On the one hand, Coffman and Noy (2012) find that even 18 years after Hurricane Iniki hit Hawaii in 1992, Kauai's economy had not fully recovered. On the other hand, Heger and Neumayer (2019) find that the 2004 Indian Ocean tsunami depressed economic growth in the Indonesian province of Aceh only for one year after the disaster. They argue that growth was considerably boosted subsequently by reconstruction efforts.

We contribute to this literature by causally estimating the impact of the Kerala floods on district-level economic activity, proxied by monthly nighttime lights and ATM transactions.

[8] See, for example, Felbermayr and Gröschl (2014).

[9] Both Felbermayr and Gröschl (2014) and Hsiang and Jina (2014) reject the notion of growth-enhancing creative destruction of natural disasters.

In contrast to the rest of the literature, the high frequency of the data allows us to focus on the short-run dynamics during and right after the disaster. The results show that local-level aggregate activity declined for some months but then recovered quickly and even overshot within the first year.

3.2 Natural Disasters and Household Finances

Amid developing countries' high vulnerability to natural disasters, an important concern is their impact on rural households. Many papers focus on Southeast Asia and South Asia, two particularly vulnerable regions in terms of natural disasters.[10] Bui et al. (2014) and Arouri, Nguyen, and Youssef (2015), for example, find that natural disasters reduced household expenditure and income in Vietnam in the 2000s. Lohmann and Lechtenfeld (2015) show that droughts deteriorated health conditions and increased the share of health expenditure in rural Vietnam between 2007 and 2013. Karim (2018) finds that recurrent flood risks negatively affect the income and non-food expenditure of agricultural households. In line with these findings, Kurosaki (2015) shows that floods significantly reduce the consumption of rural households in Pakistan. In contrast, Bandyopadhyay and Skoufias (2015) find that proneness to floods does not affect the consumption of rural households in Bangladesh, but rainfall variability in non-flood-prone subdistricts has a negative effect. This strand of the literature highlights access to microcredit, internal remittances, education, social allowances, and land ownership as potential mitigating factors.[11]

Case studies of specific disasters contribute to a better understanding of their impact on household finances and consumption. Akter and Mallick (2013), for example, find that while poor households in Bangladesh suffered greater damage during Cyclone Aila than others due to low-quality housing and distant cyclone shelters, they experienced higher income

[10] They tend to use cross-sectional or longitudinal data from primary surveys or nationally representative household surveys such as the Vietnam Household Living Standards Survey, the Household Income and Expenditure Survey of Bangladesh, or the Indonesian Family Life Survey.

[11] See, for example, Arouri, Nguyen, and Youssef (2015), Karim (2018), and Kurosaki (2015).

growth and were more likely to find employment after the cyclone.[12] Mottaleb et al. (2013) compare paddy-farming households in moderately and severely devastated districts during Cyclone Aila in Bangladesh and find that the latter spent more on food and health but less on children's education after the cyclone. Kirchberger (2017) finds that the Yogyakarta earthquake in Indonesia increased the incomes of agricultural workers because their wages increased as labor moved from agriculture to the construction sector.

A number of important papers from the early 1990s show that rural farming households in developing countries mitigate idiosyncratic income shocks and smooth consumption using community-based credit arrangements and dis-saving/saving as coping mechanisms.[13] Sawada and Shimizutani (2008) find that only households with enough collateralizable assets could maintain their consumption by borrowing after the Kobe earthquake of 1995 in Japan, whereas others were subject to a binding borrowing constraint that adversely affected their consumption. Gallagher and Hartley (2017) show that Hurricane Katrina in the United States reduced household debt in most flooded blocks in New Orleans as homeowners used flood insurance claims to lower their mortgage debts. Patnaik, Sane, and Shah (2019) find that the 2015 Chennai flood in India increased household consumption in the months immediately after the event and argue that households financed it by reducing asset purchases and savings. Acconcia, Corsetti, and Simonelli (2020) also find evidence of a temporary increase in homeowners' consumption after three major earthquakes in Italy, which they attribute to increased liquidity positions of homeowners due to receipt of public funds for reconstruction. Yao, Xu, and Zhang (2019) argue that natural disasters may have different psychological effects on households depending on the severity of suffering; they show that the 2008 Wenchuan earthquake in China had differential impacts on time preference and consequently on household savings in moderately and severely affected counties.

[12] Akter and Mallick (2013) conducted a survey in 12 of the worst hit villages of coastal Bangladesh one year after the cyclone and construct pre- and post-cyclone scenarios.

[13] These include Paxson (1992), Townsend (1994), Udry (1994), and Udry (1995). Shocks include rainfall variability and farm damages caused by various factors, such as wind, animal invasion, weeds, and poor germination caused by flooding.

We contribute to this literature by tracking monthly changes in household expenditure and income following the Kerala floods. The results in section 6 show a persistent decline in household expenditure, particularly non-essential expenditure, despite a quick recovery and subsequent increase household income. The flood also affected the composition of household debt and savings. In section 7, we show that households were more likely to borrow for housing and medical purposes, and less likely to borrow for consumption.

4. Data, Samples, and Summary Statistics

Our analysis employs numerous district-level and household-level variables from various sources. This section describes the data, discusses the sample selection, and reports summary statistics.

4.1 Data

Nighttime Lights

Nighttime lights are a widely used proxy for aggregate economic activity.[14] Felbermayr et al. (2022) use nighttime lights to investigate the impact of weather anomalies on economic activity. In India, they have been used to analyze the spatial impact of demonetization (Chodorow-Reich et al. 2020), regional convergence (Chanda and Kabiraj 2020), and the heterogeneous impact of the COVID-19 pandemic (Beyer, Franco-Bedoya, and Galdo 2021, Beyer, Jain, and Sinha 2021). To translate changes in nighttime lights into changes in economic activity, we rely on the quarterly elasticity estimated by Beyer, Hu, and Yao (2022). Although nighttime lights data are very noisy over time, they are useful for difference-in-difference analyses since most of the noise is common across the treated and untreated units.

We extract district level nighttime light data from the Visible and Infrared Imaging Suite Day Night Band (VIIRS-DNB) Cloud Free Monthly Composites (version 1) provided by the Earth Observation Group at the Colorado School of Mines.[15] The monthly composite

[14] For a summary of the literature, see Donaldson and Storeygard (2016).

[15] We employ the VIIRS Cloud Mask (VCM) configuration starting from April 2012. For information on the different versions, visit https://eogdata.mines.edu/products/vnl/. Due to a wider radiometric detection

still includes ephemeral light, for example from fires and gas flaring, which we filter out. Following Beyer et al. (2018) and Beyer, Franco-Bedoya, and Galdo (2021), we identify different clusters by removing monthly outliers, averaging the brightness of cells over time, and clustering areas based on their light intensity.[16] We then define a background noise mask based on these clusters and only include lights outside the mask. In practice, this approach amounts to setting to zero cells that are distant from homogeneous bright cores.[17] The cleaned monthly data are aggregated to the district level and standardized by area.

ATM Transactions

We obtained monthly data on ATM transactions at the Postal Index Number (PIN code) level from the National Payments Corporation of India, which is an umbrella organization set up by the Reserve Bank of India for operating retail electronic payment and settlement systems.

Credit Disbursements and Deposits of Scheduled Commercial Banks

We use district-level credit and deposits data from the Reserve Bank of India, which are available at quarterly frequency. The scheduled commercial banks (SCBs) provide these data as part of the Basic Statistical Returns.

Household Income and Expenditure

We obtained data on household-level income, expenditure, and their subcategories from the Consumer Pyramids Household Surveys (CPHS) database maintained by the Centre for Monitoring Indian Economy. This database is based on a large-scale survey that includes around 160,000 households covering all Indian states and union territories. The Centre for Monitoring Indian Economy visits each household once every four months and records

range and onboard calibration correcting for saturation and blooming effects, the data are more comparable over time than previous nighttime light products.

[16]The advantage of using a background mask is shown clearly by Gibson and Boe-Gibson (2021b), who compare results using masked and unmasked VIIRS data, for both within and between estimators on a panel of about 3,000 U.S. counties.

[17]Our approach basically replicates the approach of Elvidge et al. (2017) for monthly data.

information for the three months preceding the date of the survey. Our unit of observation is the household and we obtained information on monthly income and expenditure over time for each household. The CPHS database also includes qualitative information on household borrowing, savings, and asset ownership. The CPHS provides these data at a wave frequency (four months); however, different households are surveyed in different months within a wave.

MGNREGA

We obtained monthly data on the numbers of households that worked and those that demanded work under the MGNREGA for all the districts in Kerala, Tamil Nadu and Karnataka from the MGNREGA Public Data Portal maintained by the Ministry of Rural Development. MGNREGA is a demand-driven wage employment program. It provides at least 100 days of guaranteed employment in a financial year to every household residing in a rural area and covers all adult members of rural households who volunteer to do unskilled manual work. A surplus of households that demand work over those who work under MGNREGA reflects excess labor supply in rural labor markets. Declining excess demand for MGNREGA employment from households indicates a tightening of labor market conditions. We later examine the impact of the Kerala floods on the difference between the number of households that worked and number of households that demanded work under MGNREGA.

Flood Relief

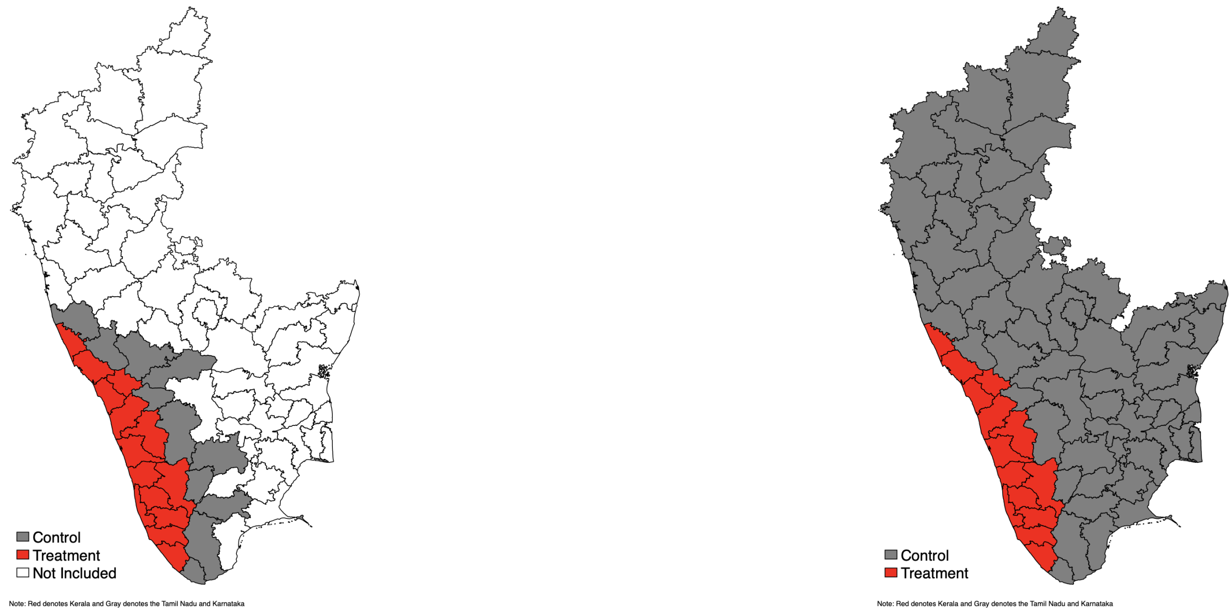
We collected district-wise flood relief data from a scanned copy of a report issued by the Disaster Management (A) Department of the Government of Kerala, obtained from the official web portal of the Government of Kerala.[18] It contains the allotment of state disaster response funds sanctioned for 18 items - including agricultural crop loss, ex gratia, food and clothing, and repair of damaged houses - to district collectors in all 14 districts of Kerala. We normalize the relief amounts using district-wise population data from the Census. Every district in Kerala received some amount of assistance and the amount varied from around 250

[18]The report is G.O. (Rt) No. 460/2018/DMD, issued by the Disaster Management (A) Department of the Government of Kerala, dated Thiruvanthapuram, August 27, 2018.

Figure 1: Sample Selection

(a) Baseline Sample

(b) Alternative Sample



INR (US$3.5) per person in Ernakulam and Thrissur to only around 15 INR (US$0.2) per person in Thiruvananthpuram and Kannur, with the average across districts being 100.24 INR (US$1.4).[19]

4.2 Sample Selection and Summary Statistics

Figure 1 shows the different samples we use for our analyses. For ATM transactions as well as household income and expenditure, we use all the observations in Kerala as our treatment group and all the observations from the bordering districts as our control group (figure 1, panel a). The border districts have more similar agro climatic conditions than the rest of the neighboring states. The nighttime light data as well as the credit and deposit data are only available at the district level. To ensure a sufficiently large number of observations, we consider all the districts in Karnataka and Tamil Nadu as the control group (figure 1, panel b). We also use this sample to perform robustness checks for our results on ATM transactions and household finances.

[19]For the amounts per district, see table A.1 in the appendix.

Table 1: Nightlights, ATM transactions, Credit and Deposits, and MGNREGA

	(1) Treatment	(2) Control
ATM transactions (INR, millions)	39.56	60.04
	(2.957)	(4.042)
N (pincodes)	1,400	693
Lights per square kilometer (nanowatts)	1.794	7.038
	(2.502)	(23.86)
N (districts)	14	62
Credit (INR, billions)	190.6	211.0
	(181.9)	(613.6)
Deposit (INR, billions)	307.0	243.0
	(219.5)	(731.5)
N (districts)	14	62
Total households worked under MGNREGA (1)	35,209.1	33,257.4
	(26,113.9)	(39,267.8)
Total households demanded work under MGNREGA (2)	38,929.7	36,330.4
	(26,826.1)	(39,926.6)
Difference (2) - (1)	3,720.6	3,073.1
	(3,477.9)	(2,921.7)
N (districts)	14	62

Note: Summary statistics are based on the period June 2017 to May 2018.
For credit and deposits, the sample period pertains to the relevant quarters.
Standard deviations are in parentheses. MGNREGA = Mahatma Gandhi National Rural Employment Guarantee Act 2005

Table 1 presents the summary statistics for nighttime lights, ATM transactions (in logs), as well as credit and deposits for all the pin codes/districts and all pin codes/districts in the treated and control groups. On average, control districts have a much higher nighttime light intensity than treated ones, consistent with higher per capita state domestic product in Karnataka and Tamil Nadu and more advanced industrialization, especially in Tamil Nadu. The control districts also have higher ATM transactions. The amount of outstanding credit is comparable between the two groups, and the treated districts have somewhat higher deposits. Table 1 also reports the average numbers of households that worked and demanded work under MGNREGA in the three states. In all of them, employment demanded exceeded actual employment from June 2017 to May 2018, indicating excess supply in the rural labor market.

Table 2: Household Income and Expenditure in INR

	Treatment	Control
Total income	5965.6	5140.5
	(524.9)	(383.8)
Wage income	4344.2	4549.9
	(386.6)	(363.6)
Total expenditure	4266.4	2833.0
	(136.7)	(183.9)
Food expenditure	1713.7	1404.0
	(65.18)	(46.69)
Nonessential expenditure	322.3	112.7
	(17.55)	(24.53)
Number of households	3403	3214

Note: Summary statistics are based on the period June 2017 to May 2018. Total income; wage income; and total, food and nonessential expenditures are expressed in terms of per household member.
Standard deviations are in parentheses.

Our baseline household sample comprises 6,617 households, of which 51.4 percent are in Kerala and the rest are in Tamil Nadu (34.8 percent) and Karnataka (13.7 percent). Table 2 reports the summary statistics for the key household level variables (in logs). Treated households (those in Kerala) earn and spend on average more than those in the control districts (those in Tamil Nadu and Karnataka).

5. Impact on Aggregate Economic Activity and Credit

This section examines the impact of the disaster on aggregate economic activity, consumer demand, and credit. We examine the impact on monthly nighttime light intensity, monthly ATM transactions, and outstanding quarterly credit by estimating the following equation:

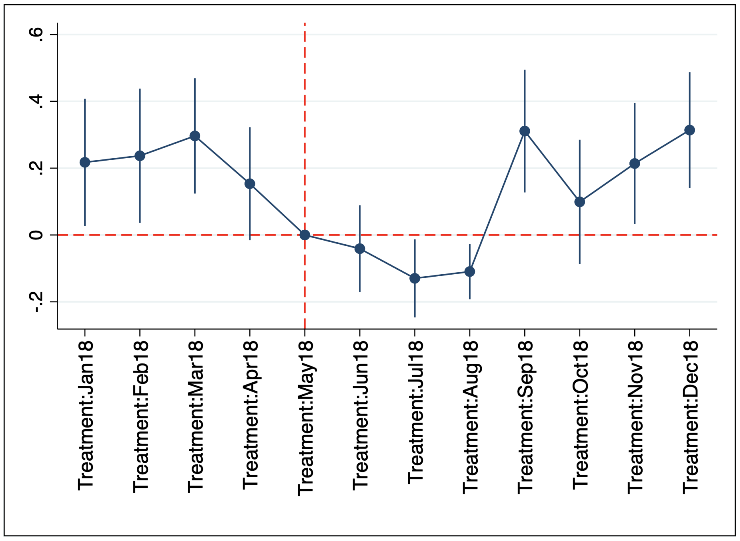
$$\ln y_{it} = \sum_t \beta_t (Kerala_i * Month_t) + \gamma_i + \delta_t + \epsilon_{it}. \quad (1)$$

The left-hand side represents the log of the dependent variables. The cross-section unit i refers to districts for nighttime light intensity and credit, and to pin codes for ATM transactions. Time period t refers to months for nighttime light intensity and ATM transactions, and to quarters for credit. We define May 2018 as the base month and the quarter containing May 2018 as the base quarter. The sample covers January to December 2018 for monthly data, and the fourth quarter (Q4) of calendar year (CY) 2017 to Q4 of CY 2018 for quarterly data. The right-hand side includes the interaction between the dummies of units located in Kerala and months before and after the floods. We include cross-section fixed effects (γ_i) that absorb any characteristics specific to a district or pin code that are constant over time, that is, not changing within a year. Among others, they account for differences related to infrastructure, financial outreach, and cash use intensity. We also include time fixed effects (δ_t) that absorb any aggregate macroeconomic shocks that may affect economic activity in both affected and unaffected districts.

5.1 Nighttime Lights

Figure 2 shows the effect of the disaster on nighttime lights intensity. Two caveats stand out immediately: first, nighttime lights are a very noisy measure of economic activity and the standard deviations of the month-treatment interaction terms are very large; second, the large positive and highly statistically significant coefficients for January, February, and March violate the parallel trend assumption. However, while the coefficient for April is still large, it is not statistically significant even at the 5 percent level. We hence assume that without the floods, parallel trends would have held starting in April onward. With the onset of the rains, light intensity in Kerala declined below that in the control group. In July and August, light intensity was 13 and 11 percent lower, respectively, with both coefficients statistically significant at the 0.1 percent level. From September onward, however, nighttime light intensity exceeded that of the control group. Between September and December, it was on average 23 percent higher. While highly uncertain, these results point to a substantial negative impact on economic activity during the disaster, but a very sudden and strong boom subsequently. The results are very much in line with what Heger, Julca, and Paddison

Figure 2: Monthly Effects on Nighttime Lights



Note: The vertical lines are 99% confidence intervals. Table A.2, in the appendix, provides the full set of results.

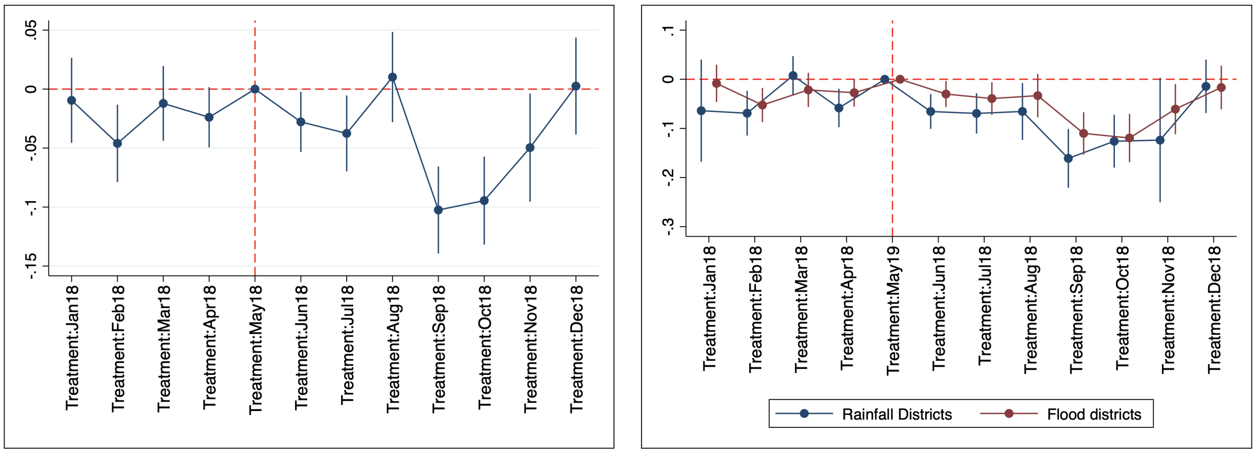
(2008) find for Aceh in Indonesia after the 2004 tsunami, which first depressed economic activity but caused a subsequent reconstruction boom.

Changes in nighttime light intensity cannot be directly converted into changes in GDP. Instead, this requires knowledge of the elasticity between the two variables. Although there are useful estimates from cross-country studies (Henderson, Storeygard, and Weil 2012; Hu and Yao 2021), any conversion needs to be interpreted with caution since the elasticity may be different across locations and under different circumstances (Asher et al. 2021; Gibson et al. 2021). We use the elasticity estimated by Beyer, Hu, and Yao (2022) as it seems to be most applicable to our analysis.[20] Using this elasticity suggests that the disaster lowered economic activity during the disaster by 7.7 percent (July and August), while during the post-disaster boom, economic activity was 14.8 percent higher than normal. Although these numbers are large, they are not unrealistic. During the disaster, the activity of many businesses was severely interrupted; after the disaster, reconstruction may have resulted in high economic

[20]This is mainly for two reasons: first, it is the only properly estimated elasticity with VIIRS data, and second, it is the only elasticity estimated with quarterly data. In addition, their sample includes India and they show that the elasticity for emerging markets and developing economies does not depend much on economic structure or income level.

Figure 3: Monthly Effects on ATM Transactions.

(a) ATM transactions (b) ATM: Flood versus rainfall



Note: The vertical lines are 99% confidence intervals. Table A.3 in the appendix, provides the full set of results on ATM transactions.

activity. Since the damages from the disaster exceeded the forgone economic activity by an order of magnitude, it is plausible that the negative contemporaneous impact was smaller than the subsequent boom.

5.2 ATM Transactions

The number or value of ATM transactions can be considered a proxy for consumer demand as people withdraw cash from ATMs to pay for their purchases. If ATM transactions decline, it very likely reflects a corresponding decline in purchases usually conducted in cash. Panel (a) in Figure 3 plots the coefficients on the interaction term from estimating equation (1) for ATM transactions (values).

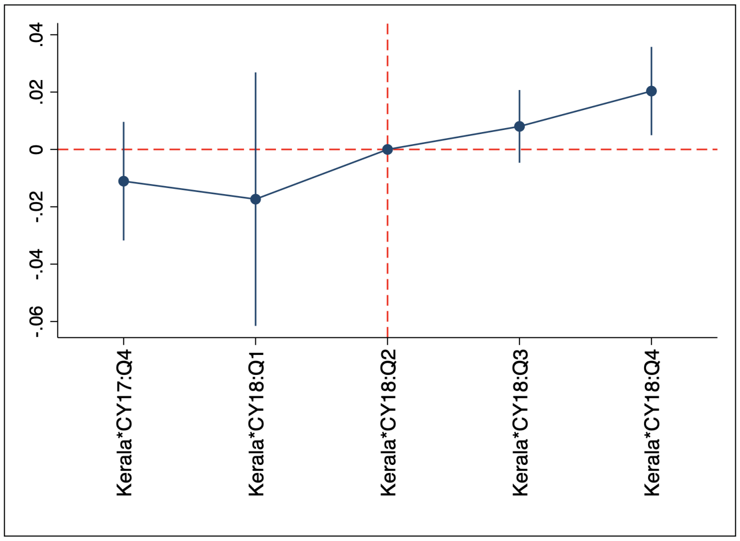
Prior to May, the coefficients were mostly insignificant, hence validating the parallel trends assumption. This implies that there were no systematic differences between the pin codes located in Kerala and the bordering districts of Karnataka and Tamil Nadu prior to May 2018. ATM transactions in Kerala fell in June and July by 2.8 and 3.8 percent, respectively. In both months, the differences are statistically significant at the 1 percent level. ATM transactions in Kerala fell sharply in September, when they were 10 percent lower than in unaffected areas. They stayed at that level in October and then started recovering. By December, they reached the same level as before, with no more difference compared with those in unaffected areas. The results for the number of transactions are very similar (see table A.3).

Panel (b) in figure 3 separates the districts impacted by strong rains from those impacted by floods. Among the affected districts, ATM transactions fell earlier and stronger in those experiencing strong rains, very much in line with the rains preceding the floods. ATM transactions in flooded districts declined strongly only in September and later behaved nearly identically to those in districts affected by the strong rains. However, none of the differences is statistically significant at conventional levels.

5.3 Credit Disbursement

Natural calamities like heavy rainfall and floods may affect credit demand. If disruptions due to such events result in revenue losses for firms, they may need more working capital. During or after a severe natural disaster, firms may also require fixed capital for replacing machinery and repairing plants. Similarly, households may need to finance disaster-related expenditure by borrowing. Hence, we analyze credit disbursed by SCBs and expect that credit increased in affected districts.

Figure 4: Quarterly Effects on Scheduled Commercial Bank Credit



Note: The vertical lines are 99% confidence intervals. Table A.4, in the appendix, provides the full set of results.

Figure 4 plots the coefficients on the interaction terms from the estimation of equation 1 for SCB credit with CY 2018:Q2 as the base quarter. First, we find that there are no pre-trends. Second, we find that credit increased somewhat in CY 2018:Q3, with no significant effect during the flood quarter. However, in the following quarter, we observe a significant increase in SCB credit. Since credit disbursement by SCBs involves institutional procedures, there is usually a lag between loan application and loan disbursement. The increase in credit in the post-flood period is not commensurate with an increase in SCB deposits.[21] Thus, we can say that the increase in credit was due to the floods and not a response to higher liquidity.

6. Impact on Household Expenditure and Income

This section presents the impacts of the floods on household income and expenditure. We estimate the following specification:

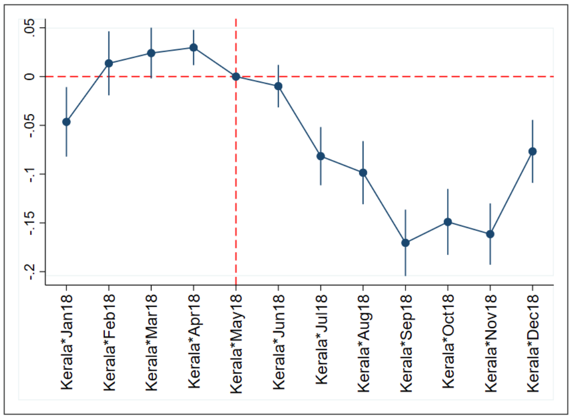
$$\ln y_{it} = \sum_t \beta_t (Kerala_i * Month_t) + \gamma_i + \delta_t + \epsilon_{it}, \tag{2}$$

where $\ln y_{it}$ represents the log of per capita expenditure or income (or their subcategories) for household i in month t. The right-hand side of equation (2) contains the interaction term between the disaster months and the dummy for households residing in Kerala. The sample period includes all months of 2018, and May 2018 is the base month. Household and month fixed effects are denoted by γ_i and δ_t, respectively. Household fixed effects control for household-level characteristics that are constant over time and may affect household income like caste, religion, gender, and occupation. The month fixed effects control for any aggregate shock that affects all households. To estimate the impact on household expenditure (and its subcategories), we also control for household income as it is an important driver of household expenditure. The results reported in this and the subsequent sections are from our baseline sample, which includes households located in all the districts in Kerala and the districts

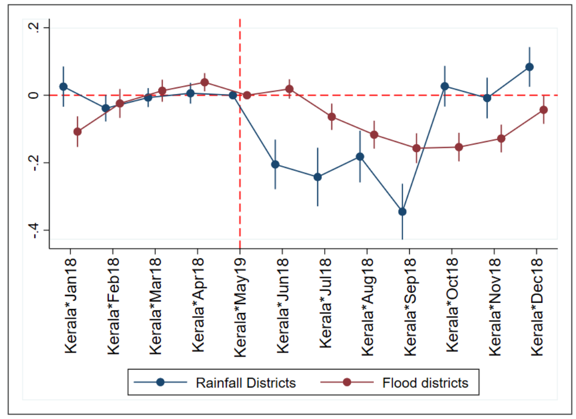
[21]Deposits did not increase in Kerala compared with the neighboring states. The results are available upon request.

Figure 5: Monthly Effects on Household Expenditure

(a) Expenditure



(b) Expenditure: Flood versus rainfall



Note: Expenditure is expressed in per family member terms. The vertical lines are 99% confidence intervals. Table A.5, in the appendix, provides the full set of results on household expenditure.

in Karnataka and Tamil Nadu that border Kerala. We report the full set of results for household expenditure and income in tables A.5 and A.7, respectively, in the appendix.[22]

6.1 Expenditure

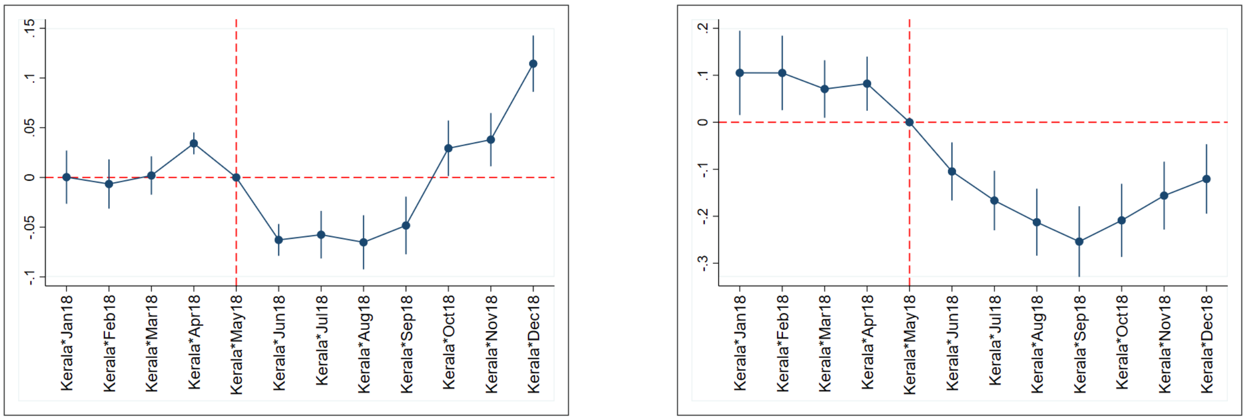
Panel (a) in figure 5 presents the monthly coefficient estimates of the interaction terms. Although total household expenditure is higher for households in Kerala in most months prior to May 2018, the differences are not large. Household total expenditure starts to decline sharply from July 2018, with the largest decline seen two months later in September. The monthly coefficients for expenditure remain negative through December 2018, although they decline in magnitude from October 2018 onward. Panel (b) in figure 5 shows a sharp contraction of expenditure for households residing in the districts with the heaviest rainfall from June to September 2018. Household expenditure also contracted in the districts with the worst floods during these four months, but the contraction was delayed and less severe, in line with the floods following the rain. By October, household expenditure in the districts

[22]As robustness checks, Tables A.6 and A.8, in the appendix, report results from our alternative sample, which includes households in all districts in Karnataka and Tamil Nadu. The impact of the disaster is somewhat smaller, but the results are qualitatively the same. In contrast to the baseline regression, now most coefficients prior to May are insignificant, somewhat mitigating the concern about the violation of the parallel trends assumption.

Figure 6: Monthly Effects on Household Food and Non-essential Expenditure

(a) Food expenditure

(b) Non-essential expenditure



Note: Food and non-essential expenditures are in per family member terms. The vertical lines are 99% confidence intervals. Table A.5, in the appendix, provides the full set of results.

with the heaviest rainfall recovered fully, while it remained lower in the districts with the worst flooding until December.

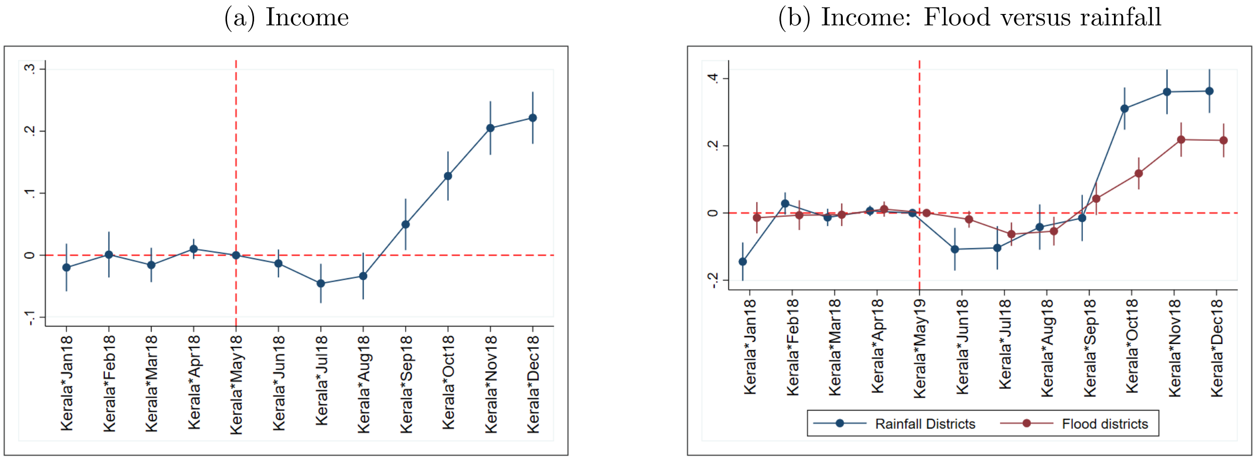
Panels (a) and (b) of Figure 6 present the monthly coefficients from separate regressions of food and non-essential expenditure. Expenditure on food declined sharply in June and continued to decline until September. However, unlike total expenditure, food expenditure increased in October and kept increasing until December 2018. Household expenditure on non-essentials declined sharply from June to September and was still low in December.[23] Thus, the decline in non-essential expenditure contributed a major portion of the decline in total expenditure. This is expected as households in times of financial stress are more likely to reduce their expenditure on non-essential items than on food. However, the violation of the parallel trends in this expenditure category does not allow us to make any strong claims.

6.2 Income

Panel (a) in figure 7 presents the monthly coefficients on the interaction terms. None of the coefficients prior to May 2018 is statistically significant, implying that the parallel trends

[23]Non-essential expenditure includes expenditure on appliances, restaurants, recreational activities, health, and beauty enhancement products and services.

Figure 7: Monthly Effects on Household Income



Note: Income is expressed in per family member terms. The vertical lines are 99% confidence intervals. Table A.7, in the appendix, provides the full set of results on household income.

assumption holds. Household total income started declining from June 2018 and declined further in July, when the difference becomes statistically significant at the 0.1 percent level. It remained lower in August 2018, but the coefficients turn positive and highly statistically significant after September and keep increasing until December, when the income of households in Kerala was 22 percent higher than that of households in the control group. Panel (b) of figure 7 shows that the incomes of households residing in both the districts with the heaviest rainfall and the districts with the worst floods declined in June and July 2018. For August 2018, the coefficients of the interaction terms remain negative. Household incomes recovered for both by September and then increased sharply in the next three months, with the increase being substantially larger for the districts with the heaviest rainfall compared with the districts with the worst floods.

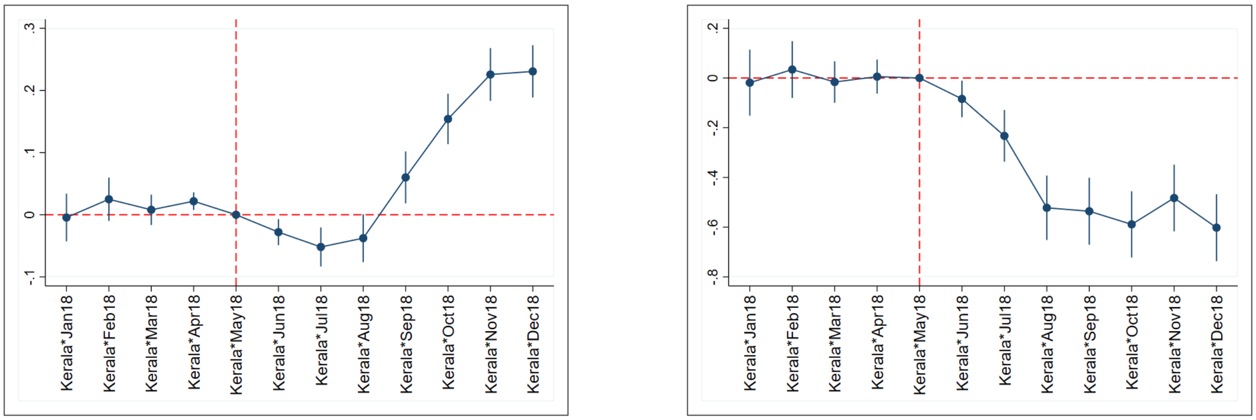
Figure 8 shows the results from estimating equation (2) separately for wage and non-wage incomes.[24] All the coefficients of the interaction terms in these two regressions are insignificant for all months prior to May 2018, except for a very small positive coefficient on wage income in April 2018. Panel (a) in figure 8 shows that wage incomes follow a

[24]Non-wage income is total income minus wage income of households. It includes income from business profits, dividends, interest, rent, and incomes from all other non-labor sources as well as government and private transfers.

Figure 8: Monthly Effects on Household Wage and Non-wage Incomes

(a) Wage Income

(b) Non-wage Income



Note: Wage and non-wage incomes are expressed in per family member terms. The vertical lines are 99 percent confidence intervals. Table A.7, in the appendix, provides the full set of results.

similar trajectory as total income.[25] However, the non-wage component of household income, declined strongly and was still far lower in December, as can be seen in panel (b) in figure 8. We report the full set of results in tables A.7 and A.8, in the appendix, for the baseline and alternative samples.

Kerala is the largest recipient of remittances among the Indian states (Jain, Gajbhiye, and Tiwari 2018). In our sample, about 18 percent of the households in Kerala receive private transfers, which include remittances. Remittances may act as a shock-absorbing cushion for these households. We hence re-estimated equation (2) for both household expenditure and income by restricting the treatment group, first, to households that receive remittances (private transfers) and, second, to those that do not. There was no statistically significant difference at conventional levels in the impact on expenditure or income between the two kinds of households. That said, households that receive remittances seem not to have experienced a decline in their income during the flood.

[25]As shown in Table 2, wage income accounts for about 72 percent and 90 percent of household income in Kerala and the control group, respectively.

6.3 Fast Wage Growth after the Floods

Section 6.2 showed that wages in Kerala increased relative to wages in unaffected bordering districts in Karnataka and Tamil Nadu in the post-flood months. In line with the results on aggregate economic activity, we hypothesize that a reconstruction boom increased wages. Kerala is heavily dependent on migrant labor from the rest of the country, particularly for menial jobs across sectors.[26] Hence, higher aggregate demand due to the reconstruction efforts may have increased wages.

Unfortunately, to the best of our knowledge, no data are available to test this hypothesis directly. Thus, we need to rely on indirect evidence. If our hypothesis is correct, we expect a tightening of labor market conditions in the post-flood period, that low-income earners benefited more, and that wages increased most where government relief efforts were strongest. In the following, we test these three implications one by one.[27]

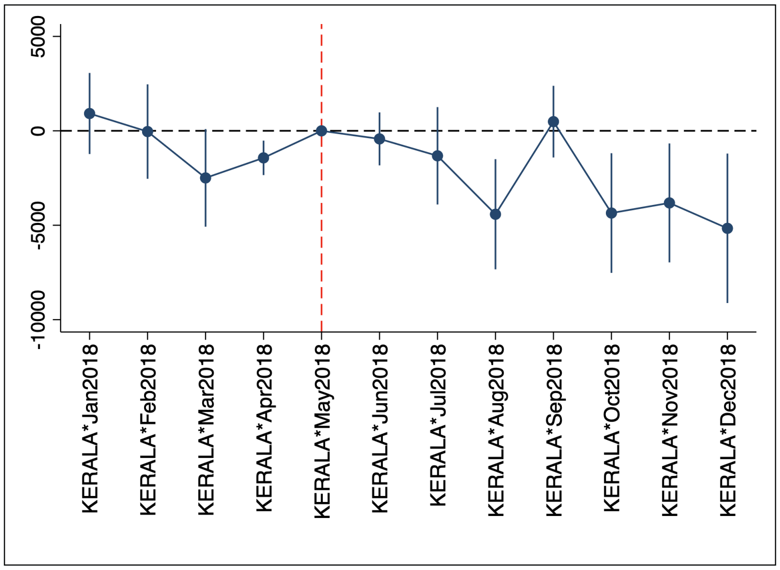
Tightening Labor Market Conditions

We use information on the number of households that actually provided employment under the MGNREGA scheme and the number of households that demanded employment by registering for the scheme. MGNREGA only covers rural employment under the government's employment guarantee scheme, but it still provides information on labor market conditions. The need to repair rural infrastructure after the disaster is likely to have increased MGNREGA employment. There is usually a positive difference between those registered and those actually working. If this difference widens, it suggests that there is an increasing excess supply of labor. If the difference decreases, it suggests a tightening of rural labor markets. We compute the difference for each month for each of the districts and run the same difference-in-difference specification as before with districts in Kerala as the treatment

[26] A study sponsored by the State Planning Board of the Government of Kerala estimates that migrant workers from other states in the country constituted 26.3 percent of the total workforce in Kerala in 2017-18. The largest migrant receiving sector was the construction sector. See Parida and Raman (2021) for more details.

[27] We also analyzed whether agricultural yields in Kerala differed from those in unaffected areas after the disaster, but do not find any evidence that they did.

Figure 9: Excess of Households Demanding Work under MGNREGA



Note: The vertical lines are 99 percent confidence intervals. Table A.10, in the appendix, provides the full set of results. MGNREGA = Mahatma Gandhi National Rural Employment Guarantee Act 2005.

group and districts in Tamil Nadu and Karnataka as the control group. In the aftermath of the floods, this difference declined significantly (see figure 9) in affected districts relative to the control group. This indicates a tightening of labor market conditions after the floods in the districts in Kerala, which may have contributed to the fast wage growth.

Heterogeneity in Wage Recovery

Akter and Mallick (2013) show that poorer households in Bangladesh were more likely than others to find new employment after Cyclone Aila and that their wages increased faster after the cyclone. Kirchberger (2017) shows that agricultural workers moved from agriculture to construction after the Yogyakarta earthquake in Indonesia, which increased their wages as well as those of workers remaining in agriculture. Hence, we estimate the impact on income separately for the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles of the income distribution. We employ the following specification:

$$q_\tau(\ln y_{it}|\gamma_i) = \sum_{t=-4}^{t=+7} \beta_{t\tau}(Kerala_i * Month_t) + \gamma_i + \delta_{t\tau} + \epsilon_{it\tau}, \quad (3)$$

where q_τ denotes quantile τ of the income distribution. Most of the terms in this equation are the same as before, including household and month fixed effects. Our coefficients of interest are the $\beta_{t\tau}$'s, which capture the difference between the variable of interest between households in Kerala and the control group in month t relative to the base month, May 2018, in quantile τ of the income distribution.

Table A.9 in the appendix shows that although the income of poorer households declined more during the floods, they benefited much more from the subsequent boom than richer households. This is very much in line with a construction boom and replicates the experience of Cyclone Aila and Aceh.

Government Relief

The Government of Kerala provided assistance towards immediate relief and rebuilding of damaged houses. It is likely that the reconstruction efforts were strongest in districts that received the most relief. In turn, households living in these districts may have seen faster wage growth. To test this hypothesis, we use the following specification:

$$\begin{aligned}(y_{idt} - y_{id,Aug18}) =& \beta_1 * \ln(Relief_d) + \beta_2 * (y_{id,Aug18} - y_{id,May18}) + \beta_3 * \triangle Credit_d \\ &+ \boldsymbol{\beta * Controls_i} + \epsilon_{it}, \end{aligned} \tag{4}$$

for all $t \in$ {Sep-18,Oct-18,Nov-18,Dec-18}. The left-hand side represents the change in income of household i located in district d between month t and August 2018. On the right-hand side, $\ln(Relief_d)$ is logarithm of $Relief_d$, which is state disaster response funds allotted to district d in per capita terms by the Government of Kerala on August 28, 2018. $Relief_d$ may not be an exhaustive measure of government relief but it captures the immediate government assistance to various districts. The coefficient β_1 will show if households in districts with larger per capita allocation of disaster relief funds (as on 28/08/2018) also experienced higher increases in income between August 2018 and month t. We include the change in credit between FY 2019: Q2 and FY 2019:Q3 in district d to control for possible effect of district-level credit expansion by SCBs. Since the initial impact may also impact the recovery, we also control for the average income change of household i between May 2018 and August 2018: $(y_{id,Aug18} - y_{id,May18})$. Finally, we also control for household characteristics (age, caste, religion, and profession).

Table 3 reports the results for income and expenditure recovery. We find that immediate government assistance, as captured by the variable $Relief_d$, seems to have contributed significantly toward income recovery in all the months from September to December 2018. Specifically, 1 percent higher per capita assistance is associated with roughly 4 percentage points additional income growth between August and December. This is again in line with the hypothesis, providing an additional indication that the fast wage growth was related to reconstruction after the disaster.

Table 3: Allocation of Disaster Response Funds and Household Income Growth

	(1) Sep-18	(2) Oct-18	(3) Nov-18	(4) Dec-18
Relief p.c(Log)	4.910***	0.348	3.535***	4.003***
	(0.783)	(0.945)	(1.049)	(1.100)
Income change (Aug-May)	-0.239***	-0.378***	-0.529***	-0.649***
	(0.030)	(0.030)	(0.029)	(0.029)
Controls	Yes	Yes	Yes	Yes
N	2112	2045	1993	1975

Note: Standard errors are clustered at the household level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7. Impact on Household Balance Sheet Items

Examining household balance sheet items, such as borrowing and saving, contributes to a better understanding of how households responded to the disaster. In this section, we use qualitative information on household borrowing and saving, from the CPHS, to estimate linear probability models of the following specification:

$$P(Z(k)_{it} = 1) = \beta_1(Kerala_i * Post) + \beta_2(Kerala_i * t) + \gamma_i + \delta_t + \epsilon_{it}, \quad (5)$$

where i denotes household and t denotes month ranging from January to December 2018. P indicates probability. $Z(k)_{it}$ are dummies, which take the value one if household i in month t has outstanding borrowing for purpose k, or outstanding saving in instrument k. $Post$ is a dummy that takes the value one for all the months post May 2018. We are interested in the coefficients of the interaction term between $Post$ and the dummies indicating whether household i resides in Kerala. Coefficient β_1 captures the relative difference in probability of $Z(k)_{it} = 1$ between households affected by the disaster and the control group.

The increase in wages after the disaster without an equivalent increase in expenditure suggests that households in Kerala increased savings. Nonetheless, a mixed picture emerges for outstanding savings of households in various instruments. Table 4 reports the estimates for five instruments: commercial bank deposits, Post Office accounts, business, gold and real estate.[28] The coefficient in column (2) is highly significant and positive suggesting that post-May 2018, households in Kerala were more likely to have invested in post office savings schemes.[29] At the same time, however, the highly significant but negative coefficients in columns (1) and (4) indicate that they were less likely to have investments in fixed or recurring deposits in commercial banks and gold. It is likely that some households had to dissolve existing savings to repair damaged property.

Table 5 reports the estimates of equation (5) for household outstanding borrowing for various purposes. The coefficient on borrowing for consumption in column (4) is negative and statistically significant at the 0.1 percent level. Thus, consistent with the decline in their consumption expenditure, households in Kerala were also less likely to have outstanding borrowing for consumption expenditure after May 2018.[30] However, columns (1) and (3)

[28]Commercial bank deposits include fixed or recurring deposits; Post Office transactions include savings schemes offered by the Department of Post of the Government of India, such as the Post Office savings accounts, Post Office time deposit accounts, and so forth; business refers to any investment in any private business; gold includes investment in gold funds or assets such as gold bars and jewelry; and real estate refers to investment in a house, plot of land, apartment, bungalow or farmhouse.

[29]Post Office savings schemes are popular and completely risk-free instruments for small savings. In general, they offer higher interest rates than similar schemes of banks.

[30]Consistent with declining consumption expenditure, households were less likely to have acquired durable assets such as a house, refrigerator, television, personal computer, car, two-wheeler or cattle during this

Table 4: Probability That Households Have Savings

	(1) FD	(2) POS	(3) Business	(4) Gold	(5) Real Estate
Kerala*Post	-0.160***	0.208***	-0.003	-0.019***	0.009
	(0.017)	(0.017)	(0.003)	(0.005)	(0.006)
HH FE	Yes	Yes	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes	Yes	Yes
Kerala*Timetrend	Yes	Yes	Yes	Yes	Yes
N	26264	26255	26265	26267	26267
Households	7967	7964	7967	7968	7968

Note: Standard errors are clustered at the Household level.
Kerala*Post denotes the interaction dummy for households residing in Kerala during the months post May 2018. FE = fixed effects; HH = households; FD = commercial bank deposits; POS = Post Office accounts.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Probability That Households Had Outstanding Borrowing for Six Purposes

	(1) Housing	(2) Education	(3) Medical	(4) Consumption	(5) CD	(6) Business
Kerala*Post	0.030***	0.003	0.016*	-0.081***	-0.009	0.001
	(0.008)	(0.006)	(0.007)	(0.020)	(0.012)	(0.006)
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kerala*Timetrend	Yes	Yes	Yes	Yes	Yes	Yes
N	26,267	26,267	26,267	26,267	26,267	26,267
Households	7,968	7,968	7,968	7,968	7,968	7,968

Note: Standard errors are clustered at the household level.
Kerala*Post denotes the interaction dummy for household residing in Kerala for the months post May 2018. HH = households; FE = fixed effects; CD = commercial bank loans.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in table 5 show that they were more likely to have outstanding borrowing for housing and medical purposes. In particular, the coefficient of housing in column (1) is highly statistically significant. Outstanding borrowing for housing includes both construction of new residential property and renovation. The increase in this probability likely reflects the need to rebuild or repair damage to residential properties due to the disaster as well as inadequate or delayed receipt of relief funding.

period. The coefficient of the interaction term from estimates of equation (5) for households acquiring these assets in the past 120 days is highly significant and negative. Results are available upon request.

8. Conclusion

In this paper, we causally estimated the impact of a major natural disaster in India - the Kerala floods of 2018 - on district-level economic activity, household income and expenditure, as well as household balance sheets. Extreme rainfall between June and August 2018 caused landslides and floods, in particular, disastrous flash floods during the middle of August, and affected the entire state of Kerala. We used a difference-in-difference estimation strategy exploiting the fact that Kerala's neighboring states, Karnataka and Tamil Nadu, were not affected by this disaster.

We showed that nighttime light intensity in the affected area declined for three months during the disaster but boomed subsequently. Analysis using an elasticity between nighttime light intensity and economic activity from Beyer, Hu, and Yao (2022) suggests that economic activity decreased by 7.7 percent during the disaster, but increased by 14.8 percent during the post-disaster boom. However, the actual elasticity between nighttime lights and economic activity in Kerala may be quite different, and the elasticity could have potentially changed during the flood. The GDP conversions are hence very uncertain and need to be interpreted with caution. ATM transactions in affected areas declined from June to October 2018 relative to those in unaffected areas, suggesting lower consumer demand. These findings support the consensus in the literature that natural disasters have adverse macroeconomic effects in the short run. Further, we provided evidence that credit disbursed by SCBs increased in districts affected by the disaster between September and December, with households borrowing more for housing and less for consumption.

At the household level, we found that both income and expenditure in Kerala declined from June to August relative to households in the bordering districts. Household income recovered by September and then kept increasing during the remaining sample period. However, expenditure continued to remain lower for the entire period, driven by lower spending on non-essentials. The negative impact of this disaster was initially more severe in the districts with the heaviest rainfall (Idukki, Kottayam and Kollam), but had more long-lasting effects in the districts with the worst floods (Alappuzha, Kottayam, Ernakulam and Thrissur).

We argue that increased labor demand due to reconstruction efforts could have increased wage income after the floods and provide corroborating evidence: (i) rural labor markets tightened, (ii) poorer households benefited more, and (iii) wages increased most where government relief was strongest. Immediate relief provided by the Government of Kerala after the disaster was a major factor in the recovery of household income. Specifically, we found that a 1 percent higher assistance per capita contributed roughly 4 percentage points higher household income between August and December.

Based on annual data, Raddatz (2009) concludes that most of the impacts of natural disasters materialize within the first year. Our analysis based on monthly and quarterly data shows that the negative impact can be even shorter and that there are interesting economic dynamics during and right after a disaster within the first year.

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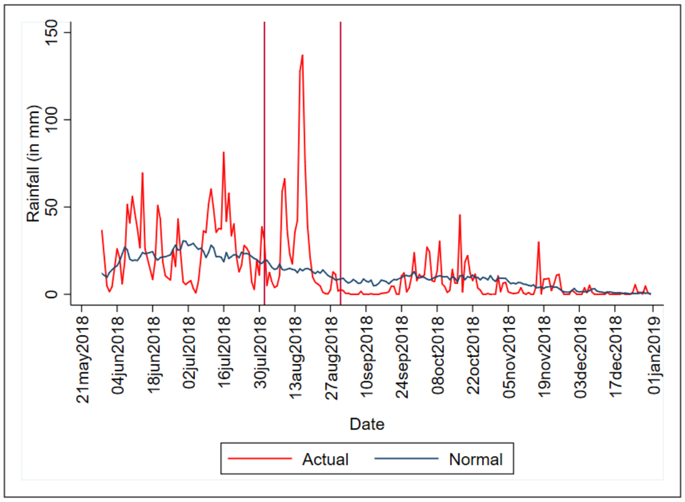
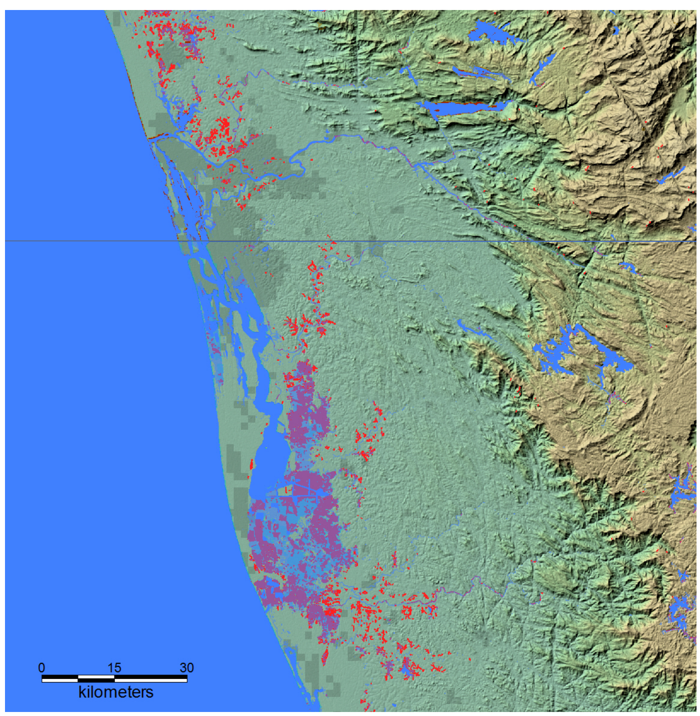
Appendix

Figure A.1: Daily Actual and Normal Rainfall in Kerala: June - December 2018



Source: Indian Meteorological Department.

Figure A.2: Maximum Observed Flooding in Kerala, Starting August 7, 2018



Source: Dartmouth Flood Observatory.

Table A.1: District Allotment of State Disaster Response Funds

District	Amount (INR)	Per capita amount (INR)	Per capita amount (US$)#
Thiruvananthpuram	52,164,239	15.8	0.22
Kollam	54,432,204	20.65	0.29
Phathanamthitta	184,725,581	154.27	2.17
Alappuzha	482,822,071	226.91	3.20
Kottayam	269,366,909	136.42	1.92
Idukki	92,216,210*	83.15	1.17
Ernakulam	798,106,293	243.15	3.43
Thrissur	793,632,903	254.27	3.59
Palakkad	95,387,707*	33.95	0.48
Malappuram	168,283,978	40.92	0.58
Kozhikod	161,366,953	52.29	0.74
Wayanad	81,638,813	99.87	1.41
Kannur	38,113,296	15.11	0.21
Kasargode	34,842,650	26.65	0.38

Note: *Figures for Idukki and Palakkad are imputed values. Funds allocated to these two districts under the item "repair to damaged houses" are not readable in the scanned copy of the government order because of poor quality of scan. However, the total amount sanctioned under this item is available, which we use to the find total amount sanctioned to these two districts under this item and then divide the amount between these two districts assuming that Idukki received 1.5 times of the amount that Palakkad received. #At 1 US$ = 70.81 INR, the historical US$-INR exchange rate on August 31,2018.

Table A.2: Effect on Nighttime Lights

	Lights per square kilometer
Kerala*Jan18	0.217*
	(0.095)
Kerala*Feb18	0.237*
	(0.101)
Kerala*Mar18	0.296**
	(0.087)
Kerala*Apr18	0.153
	(0.085)
Kerala*Jun18	-0.041
	(0.065)
Kerala*Jul18	-0.130*
	(0.059)
Kerala*Aug18	-0.110*
	(0.042)
Kerala*Sep18	0.311**
	(0.092)
Kerala*Oct18	0.099
	(0.093)
Kerala*Nov18	0.214*
	(0.091)
Kerala*Dec18	0.314***
	(0.087)
District FE	Yes
Month*Year FE	Yes
N	912
Clusters	76

Note: Standard errors are clustered at the district level.
Kerala*Month denotes the interaction dummy for districts in Kerala
Kerala*May18 is the base month which is omitted from the regression.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Effect on ATM Transactions

	(1) ATM Transactions (count)	(2) ATM Transactions (amount)
Keral*Jan18	-0.005	-0.010
	(0.015)	(0.018)
Kerala*Feb18	-0.026	-0.046**
	(0.014)	(0.017)
Kerala*Mar18	-0.011	-0.012
	(0.013)	(0.016)
Kerala*Apr18	-0.012	-0.024
	(0.011)	(0.013)
Kerala*Jun18	-0.014	-0.028*
	(0.010)	(0.013)
Kerala*Jul18	-0.029*	-0.038*
	(0.013)	(0.016)
Kerala*Aug18	-0.011	0.010
	(0.017)	(0.020)
Kerala*Sep18	-0.065***	-0.102***
	(0.016)	(0.019)
Kerala*Oct18	-0.083***	-0.095***
	(0.018)	(0.019)
Kerala*Nov18	-0.026	-0.050*
	(0.020)	(0.023)
Kerala*Dec18	0.031	0.003
	(0.018)	(0.021)
Month FE	Yes	Yes
Pincode FE	Yes	Yes
N	23,199	23,193
Pincodes	1,951	1,951

Note: Standard errors are clustered at the pin code level.
Post*Treatment denotes the interaction dummy for pin codes in Kerala and the post-floods months. ATM = automated teller machine.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Effect on Credit and Deposits of SCBs

	(1) Credit	(2) Deposits
Kerala*CY17:Q4	-0.011	-0.013**
	(0.008)	(0.004)
Kerala*CY18:Q1	-0.017	0.001
	(0.017)	(0.037)
Kerala*CY18:Q3	0.008	0.006
	(0.005)	(0.004)
Kerala*CY18:Q4	0.020***	0.009*
	(0.006)	(0.004)
District FE	Yes	Yes
Qtr X Year FE	Yes	Yes
N	380	380
Districts	76	76

Note: Standard errors are clustered at the district level
The sample period is CY2017:Q4 to CY2018:Q4
All the coefficients are relative to Kerala*CY18:Q2.
CY = calendar year; SCBs = scheduled commercial banks.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Effect on Household Total, Food and Non-essential Expenditures

	(1) Total	(2) Food	(3) Non-essential
Kerala*Jan18	-0.046***	0.000	0.105**
	(0.014)	(0.010)	(0.035)
Kerala*Feb18	0.014	-0.007	0.105***
	(0.013)	(0.010)	(0.031)
Kerala*Mar18	0.024*	0.002	0.071**
	(0.010)	(0.007)	(0.024)
Kerala*Apr18	0.030***	0.034***	0.082***
	(0.007)	(0.004)	(0.022)
Kerala*Jun18	-0.010	-0.063***	-0.105***
	(0.008)	(0.006)	(0.024)
Kerala*Jul18	-0.082***	-0.058***	-0.167***
	(0.012)	(0.009)	(0.025)
Kerala*Aug18	-0.099***	-0.065***	-0.213***
	(0.013)	(0.011)	(0.028)
Kerala*Sep18	-0.170***	-0.048***	-0.254***
	(0.013)	(0.011)	(0.029)
Kerala*Oct18	-0.149***	0.029**	-0.209***
	(0.013)	(0.011)	(0.030)
Kerala*Nov18	-0.161***	0.038***	-0.156***
	(0.012)	(0.010)	(0.028)
Kerala*Dec18	-0.077***	0.114***	-0.121***
	(0.013)	(0.011)	(0.029)
HH FE	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes
N	73417	73417	60905
Clusters	7055	7055	6908

Note: Standard errors are clustered at the household level.
Kerala*Month denotes the interaction dummy for household residing in Kerala;
Kerala*May18 is the base month, which is omitted from the regression.
FE = fixed effects; HH = households.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Effect on Household Total, Food and Non-essential Expenditures (Control Group Includes All Districts in Karnataka and Tamil Nadu)

	(1) Total	(2) Food	(3) Non-essential
Kerala*Jan18	-0.037***	0.016*	0.036
	(0.009)	(0.008)	(0.023)
Kerala*Feb18	-0.021*	0.007	0.023
	(0.009)	(0.007)	(0.021)
Kerala*Mar18	-0.013	-0.001	0.035
	(0.007)	(0.005)	(0.018)
Kerala*Apr18	-0.018**	-0.003	0.053**
	(0.006)	(0.004)	(0.018)
Kerala*Jun18	0.008	-0.028***	-0.061**
	(0.007)	(0.006)	(0.020)
Kerala*Jul18	-0.055***	-0.044***	-0.115***
	(0.009)	(0.008)	(0.021)
Kerala*Aug18	-0.062***	-0.078***	-0.167***
	(0.009)	(0.009)	(0.021)
Kerala*Sep18	-0.101***	-0.063***	-0.183***
	(0.010)	(0.009)	(0.024)
Kerala*Oct18	-0.091***	-0.007	-0.257***
	(0.010)	(0.008)	(0.022)
Kerala*Nov18	-0.093***	0.032***	-0.221***
	(0.009)	(0.007)	(0.022)
Kerala*Dec18	-0.000	0.085***	-0.151***
	(0.009)	(0.007)	(0.022)
HH FE	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes
N	228642	228624	159220
Clusters	21410	21410	20039

Note: Standard errors are clustered at the household level.
Kerala*Month denotes the interaction dummy for households residing in Kerala; Kerala*May18 is the base month, which is omitted from the regression.
FE = fixed effects; HH = households.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Effect on Household Total, Wage and Nonwage Incomes

	(1)	(2)	(3)
	Total	Wage	Non-wage
Kerala*Jan18	-0.020	-0.004	-0.019
	(0.015)	(0.015)	(0.052)
Kerala*Feb18	0.001	0.025	0.034
	(0.014)	(0.014)	(0.044)
Kerala*Mar18	-0.016	0.008	-0.016
	(0.011)	(0.009)	(0.032)
Kerala*Apr18	0.010	0.022^{***}	0.005
	(0.006)	(0.005)	(0.027)
Kerala*Jun18	-0.013	-0.028^{***}	-0.084^{**}
	(0.009)	(0.008)	(0.029)
Kerala*Jul18	-0.046^{***}	-0.052^{***}	-0.233^{***}
	(0.012)	(0.012)	(0.040)
Kerala*Aug18	-0.034^{*}	-0.038^{*}	-0.522^{***}
	(0.015)	(0.015)	(0.050)
Kerala*Sep18	0.050^{**}	0.060^{***}	-0.536^{***}
	(0.016)	(0.016)	(0.052)
Kerala*Oct18	0.128^{***}	0.154^{***}	-0.589^{***}
	(0.015)	(0.016)	(0.052)
Kerala*Nov18	0.205^{***}	0.226^{***}	-0.483^{***}
	(0.017)	(0.016)	(0.052)
Kerala*Dec18	0.222^{***}	0.231^{***}	-0.602^{***}
	(0.016)	(0.016)	(0.052)
HH FE	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes
N	73417	60341	36990

Note: Standard errors are clustered at the household level.
Kerala*Month denotes the interaction dummy for households residing in Kerala; Kerala*May18 is the base month, which is omitted from the regression.
FE = fixed effects; HH = households.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: Effect on Household Total, Wage and Nonwage Income (Control Group Includes All Districts in Karnataka and Tamil Nadu)

	(1)	(2)	(3)
	Income	Wage income	Non-wage income
Kerala*Jan18	-0.046***	-0.054***	0.143***
	(0.010)	(0.010)	(0.037)
Kerala*Feb18	-0.015	-0.013	0.086**
	(0.009)	(0.008)	(0.032)
Kerala*Mar18	0.002	0.006	0.077**
	(0.007)	(0.006)	(0.024)
Kerala*Apr18	0.010*	0.014**	0.027
	(0.005)	(0.005)	(0.022)
Kerala*Jun18	-0.035***	-0.048***	-0.094***
	(0.006)	(0.007)	(0.021)
Kerala*Jul18	-0.072***	-0.077***	-0.184***
	(0.008)	(0.009)	(0.028)
Kerala*Aug18	-0.089***	-0.099***	-0.283***
	(0.010)	(0.010)	(0.035)
Kerala*Sep18	-0.012	-0.012	-0.311***
	(0.010)	(0.011)	(0.036)
Kerala*Oct18	0.049***	0.065***	-0.237***
	(0.010)	(0.011)	(0.034)
Kerala*Nov18	0.113***	0.123***	-0.207***
	(0.010)	(0.011)	(0.035)
Kerala*Dec18	0.124***	0.135***	-0.136***
	(0.010)	(0.011)	(0.035)
HH FE	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes
N	228642	196102	136406
Clusters	21410	19742	18949

Note: Standard errors are clustered at the household level.
Kerala*Month denotes the interaction dummy for households residing in Kerala; Kerala*May18 is the base month, which is omitted from the regression.
FE = fixed effects; HH = households.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Quantile Regression Results for Household Total Income

	(1) 10th	(2) 25th	(3) 50th	(4) 75th	(5) 90th
Kerala*Jan18	-0.061	-0.053*	-0.037	-0.023	-0.016
	(0.133)	(0.024)	(0.274)	(0.505)	(0.628)
Kerala*Feb18	0.001	-0.003	-0.012	-0.019	-0.022
	(0.127)	(0.023)	(0.264)	(0.485)	(0.604)
Kerala*Mar18	-0.019	-0.018	-0.015	-0.012	-0.011
	(0.124)	(0.022)	(0.257)	(0.473)	(0.588)
Kerala*Apr18	-0.012	-0.007	0.000	0.007	0.011
	(0.119)	(0.021)	(0.246)	(0.453)	(0.563)
Kerala*Jun18	-0.032	-0.025	-0.013	-0.003	0.003
	(0.121)	(0.022)	(0.250)	(0.459)	(0.571)
Kerala*Jul18	-0.079	-0.069**	-0.050	-0.033	-0.024
	(0.121)	(0.022)	(0.251)	(0.461)	(0.574)
Kerala*Aug18	-0.116	-0.093***	-0.050	-0.012	0.009
	(0.121)	(0.022)	(0.250)	(0.460)	(0.573)
Kerala*Sep18	0.013	0.022	0.040	0.056	0.064
	(0.121)	(0.022)	(0.250)	(0.460)	(0.572)
Kerala*Oct18	0.130	0.135***	0.145	0.154	0.158
	(0.123)	(0.022)	(0.254)	(0.467)	(0.581)
Kerala*Nov18	0.204	0.197***	0.185	0.174	0.168
	(0.128)	(0.023)	(0.265)	(0.488)	(0.606)
Kerala*Dec18	0.290*	0.261***	0.206	0.159	0.133
	(0.137)	(0.025)	(0.284)	(0.523)	(0.651)
HH FE	Yes	Yes	Yes	Yes	Yes
Month*Year FE	Yes	Yes	Yes	Yes	Yes
N	73417	73417	73417	73417	73417

Note: Standard errors are in parenthesis.
Kerala*Month denotes the interaction dummy for households residing in Kerala;
Kerala*May18 is the base month, which is omitted from the regression.
FE = fixed effects; HH = households.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: Effect on Excess of Number of Households Demanding Work under MGNREGA

	(1)
	Employment (Demand-Actual)
Kerala*Jan2018	916.752
	(812.011)
Kerala*Feb2018	-39.987
	(945.937)
Kerala*Mar2018	-2493.899*
	(977.569)
Kerala*Apr2018	-1432.235***
	(345.016)
Kerala*Jun2018	-427.013
	(530.676)
Kerala*Jul2018	-1323.109
	(975.138)
Kerala*Aug2018	-4418.020***
	(1103.145)
Kerala*Sep2018	485.656
	(717.762)
Kerala*Oct2018	-4353.874***
	(1198.193)
Kerala*Nov2018	-3817.473**
	(1191.026)
Kerala*Dec2018	-5162.735***
	(1496.597)
District FE	Yes
Month*Year FE	Yes
N	900
Clusters	75

Note: Standard errors are clustered at the district level.
Kerala*Month denotes the interaction dummy for districts in Kerala;
Kerala*May18 is the base month, which is omitted from the regression.
FE = fixed effects; MGNREGA = Mahatma Gandhi National Rural Employment Guarantee Act 2005.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$