

Consumption Response to a Natural Disaster: Evidence of Price and Income Shocks from Chennai Flood

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Abstract

We utilize monthly individual-level financial data and item-level supermarket sales data to study how consumption responds to one of the costliest natural disasters in India. We find that consumption dropped by 11% during the disaster, 65% of which was recovered after the disaster. On average, consumption per capita dropped by \$312 per year, which costs about 5% of the GDP. We also show that natural disasters depressed consumption through income shocks instead of price shocks. Consumers smooth consumption using credit card, banks loans and wealth in coping with the shocks.

Key words: natural disaster, income shocks, price shocks, online shopping, household finance

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1. Introduction

Natural disasters like floods, droughts and wildfires are becoming more frequent and intense globally (Guha-Sapir, Hargitt, and Hoyois 2004). They damage ecological systems, reduce economic outputs, and cause death and disease, which are extremely costly for the well-being of the society and individuals. Academics and policy makers have evaluated the economic consequences of natural disasters (Cavallo et al. 2013; Gröger and Zylberberg 2016; Noy 2009). However, to the best of our knowledge, no study has systemically explored the impacts of natural disasters on consumption using transaction data. Household consumption represents around 60% of GDP (OECD 2020) and bears the brunt of natural-disaster shocks. Low-to-middle income countries with poor infrastructure and weak safety nets are especially vulnerable to natural disasters (World Bank 2020). Understanding the consumption response to natural disasters is important for increasing the resilience of the economy to extreme weather events.

Natural disasters could affect consumption through price and income channels. They disrupt value chains by damaging physical assets, such as road and stores, which constrain the supply and therefore raise the price of goods and services. With all the others being the same, such a price shock is expected to discourage consumption, especially on items with high price elasticity of demand. Natural disasters also depress economic activities as factories were forced to halt production due to reasons such as physical damages of productive capital, including equipment, and the infeasibility of working from home, which lowers household income. All else equal, such a negative income shock is expected to reduce consumption, especially for those with budget constraints. The concurrence of price and income shocks associated with natural disasters provide a nice setting for us to investigate the interplay between income and

price shocks in terms of their impacts on consumption. These insights on the underlying mechanisms of natural disasters further enable us to explore disaster-coping strategies.

Using monthly administrative data for around 100,000 individuals from 2015M1 to 2016M12, this paper evaluates the consumption response to the 2015 Chennai flood in India and explores the economic mechanisms as well as disaster-coping strategies. Floods are the most frequent disasters in India, which is one of the top countries most affected by natural disasters according to Centre for Research on the Epidemiology of Disasters. The Chennai flood that occurred in November and December of 2015 is one of the most severe floods in the history of both Chennai and India (Reuters 2015). It is also one of the most damaging disasters all over the world in 2015, costing over US\$14 billion and causing more than 500 deaths and numerous homeless (Business Standard 2015; Deccan Chronicle 2015). The 2015 Chennai flood provides an exogenous shock that allows us to evaluate its impacts on consumption using a difference-in-differences (DID) approach.

We compare individuals living in Chennai (the treatment group), the metropolitan city that is affected by the Chennai flood, with major cities from other states not affected by any natural disaster (the control group), and evaluate the consumption difference between the treatment and control group during and after the Chennai flood, relative to that before the flood. Our DID analysis shows that total spending declined by 11% during the Chennai flood, 65% of which was recovered after the flood. The post-flood consumption remained 4% below the pre-flood level. A similar pattern is observed for spending via cash, credit or debit card. The baseline result is robust when we transform the dollar amount of spending into its logarithmic form, exclude the demonetization episode from the sample, treat zero observations as missing, use matched samples derived from propensity score matching (PSM), apply alternative benchmark period, or focus on individuals in the treatment group only. It suggests that the impacts of the

flood on consumption is not transitory and that focusing only on the aftermath of the flood underestimates its overall impacts.

After documenting the baseline pattern of consumption response to a natural disaster, we proceed to explore the underlying economic mechanisms. The flood that disrupted the supply chain is expected to reduce supply of goods and services and therefore increase price. We first check whether the Chennai flood generated price shocks using transaction-level data from supermarket sales, which record the price, quantity and revenue for more than 15,000 goods sold in 28 stores located in and outside Chennai. Applying a similar DID approach, we find that price rose during the flood, which provides evidence of price shocks. Such a rise in price was however associated with higher sales quantity and revenue as individuals hoard essential goods to deal with the uncertainty in goods supply during the flood. However, after the flood, we find that supermarket stores in Chennai lowered price, which increased their sales quantity but did not affect the sales revenue. Comparing goods whose price increased with the others, we find that higher price indeed reduced sales quantity and revenue. This implies that supermarket stores in Chennai would have to lower the price in order to increase sales revenue. Given that other goods and services not sold in supermarkets are typically more discretionary and exhibit higher price elasticity of demand, business owners that seek to increase sales revenue are more likely to cut than increase the price, which mitigates the possibility that the flood reduced consumption through increasing price of goods and services.

The flood also likely created income shocks. It damaged productive capital such as factories and equipment, which is expected to undermine economic activities and reduce income. We check whether such income shocks exist by exploring how economic activities respond to the Chennai flood using night light data. Low night light intensity reflects early closure of shops or factories due to depression in business, which leads to low labour income especially for those earning daily- or hourly-rated wages. We find that economic activities exhibit similar

patterns with consumption, which dropped significantly during the flood and recovered partially afterwards, providing evidence of negative income shocks. We proceed to establish the relation between income shock and consumption response to the flood. Note that salarymen receive regular salaries despite extreme weather events, while those that derive income from daily operations such as street vendors suffer an income loss during and after the flood due to contracted economic activities. If the negative income shocks are driving the consumption response to the flood, consumption should decline less for the group of salarymen who have stable income. Consistent with this hypothesis, we find that salarymen reduced consumption less than the rest both during and after the flood. It implies that the falling consumption after the flood was mainly from individuals hit by negative income shocks. While incoming remittance can potentially offset the negative income shock for rural households (Gröger and Zylberberg 2016), we find no such evidence in the context of the Chennai flood, possibly because households in metropolitan cities such as Chennai are unlikely to rely on remittance for their daily living.

We further support the income channels documented above by demonstrating heterogeneous consumption responses to the Chennai flood that vary with their exposures to the income shocks. Online and onsite transactions are subject to similar price shocks that arise from the disruption of supply chains. However, they may face different income shocks if one allocates budget between the two categories in dealing with the natural disaster. During the flood, individuals may substitute onsite spending with online spending to avoid the hassle of travelling and therefore allocate more budget for online shopping. When damaged infrastructures are fixed and transportation facilities are recovered after the flood, while some may stick to online spending, others may switch back to onsite spending. Utilizing detailed card transaction-level data, we explore the heterogeneous response of online and onsite consumption during and after the flood. It turns out that onsite consumption dropped much

more substantially than online consumption during the flood, but recovered faster after the flood. This provides evidence that individuals switch between online consumption and onsite consumption during and after the flood. We further show that this result is driven by the extensive margin (the frequencies of transactions) rather than the intensive margin (the amount per transaction).

Moreover, the impacts of income shocks on consumption response to the flood vary with different spending categories. When faced with a budget constraint, individuals would prioritize consumption on necessities i.e. food over discretionary goods i.e. jewellery, which leads to a lower sensitivity of the former to the flood. Consumption on more visible goods are likely to be more sensitive to budget constraints according to Heffetz (2011). Durables such as furniture, floor and roofs that are damaged during the flood would need to be replaced to restore normalcy after the flood, which is expected to reduce the sensitivity of durable goods consumption to income shocks. Consistent with these hypotheses, we find that the negative consumption response to the Chennai flood is less pronounced on essential, visible and durable goods.

After documenting evidence supporting the income channel, we further explore how one can cope with the negative income shocks generated by the flood. Using credit cards, taking additional loans, or cashing out existing wealth help reduce the liquidity constraint and enable one to smooth consumption when there is a negative income shock. Our analysis reveals that individuals who increase their credit limits, take more bank loans or have more wealth were able to smooth consumption during or after the flood. Further analysis reveals that the wealth needs to be in the form of liquid assets, such as saving bonds, to play the role of consumption smoothing. Assets in the form of term deposit, stocks, mutual fund and gold may be too illiquid or too costly to provide timely liquidity for consumption during the flood.

This paper contributes to the literature in threefold. It is the first to explore economic impacts of natural disasters on consumption using administrative panel data. Moreover, it documents and distinguishes the price and income shocks underlying the impacts of a natural disaster on consumption, which cannot be done by survey data. Finally, it adds new evidence on onsite and online consumption and the substitution between the two during and after a natural disaster.

This paper fits into three strands of literature. First, it is closely related to the literature on natural disasters and households consumption. Anttila-Hughes & Hsiang (2013), Noy et al. (2019) and Arouri et al. (2015) document a negative impact of natural disasters on household expenditure in the context of Philippines, Thailand and Vietnam, respectively. Sawada & Shimizutani (2008) demonstrate that households, especially those experiencing major damage to their home, changed their consumption behaviour after the Great Hanshin earthquake in 1995. Gröger & Zylberberg (2016) show that consumption by rural households in Vietnam drop after the flood but the result is not statistically significant, as remittance sent by family members migrated elsewhere mitigate the income shock. Consumption is, however, not the major outcome of interest in these studies that universally use survey data. We differ from these studies by using administrative panel data at a monthly frequency, which allows us to uncover not only the consumption response after the natural disaster, but also that during the natural disaster. We show that consumption drops the most during the natural disasters, recovers partially after the natural disaster but remains below the pre-disaster level. The detailed transaction-level data also enable us to document rich patterns of consumption responses to a natural disaster, which differ between i.e. online and onsite transactions, durable and nondurable goods, essential and discretionary consumption.

Second, this paper fits into the growing literature on natural disasters and economic outcomes. Noy (2009), Jakobsen (2012), Hornbeck (2012), Cunado & Ferreira (2014), Hsiang & Jina (2014), Arouri, Nguyen, & Youssef (2015), Markhvida, Walsh, Hallegatte, & Baker (2020)

and Groen, Kutzbach, & Polivka (2020) study how natural disasters affect economic growth, income, welfare, and employment. Complementary to these macro-level evidence, Groen et al. (2020) document short-term income losses and long-term gains on wage growth in areas affected by Hurricanes Katrina and Rita. Gallagher & Hartley (2017) show that household debt declined after a natural disaster as flood insurance were used to repay debt, mainly mortgages. The resilience to natural disaster is lower in emerging economies with weak safety nets and low insurance coverage (Zimmerman and Carter 2003). Cole et al. (2013) argue that even if similar insurance contracts were to be offered in emerging markets, households' take-up rate would be very low due to the lack of trust and liquidity constraints. While formal insurance products do not seem to work, Gröger & Zylberberg (2016) find that remittance mitigates the negative income shock caused by natural disasters. We add to this strand of literature by documenting the causal impacts of natural disasters on consumption using administrative data and distinguishing the income and price shocks underlying such impacts.

Third, this paper is related to the literature on household consumption. Souleles (1999, 2002), Shapiro & Slemrod (2003), Agarwal et al. (2007), Agarwal & Qian (2014), Jappelli & Pistaferri (2014), Gelman et al. (2014), Christelis et al. (2019) Agarwal et al. (2020) have well documented how consumption responds to various policy shocks in the forms of tax rebates and stimulus payments. While existing literature on household finance focus on policy shocks, we explore the roles of natural disaster shocks. Similar to these policy shocks, we find that disaster shocks affect consumption through introducing income shocks. In addition, we show that, as supply chains are disrupted during the disaster and take some time to recover after the disaster, natural disaster shocks could change consumption through price shocks. We further add to this strand of literature by differentiating the roles of income and price shocks on consumption.

2. Background, Data and Methodology

2.1 Background of the 2015 Chennai Flood

Floods are the most frequent disasters in India. Unlike developed economies such as Japan and the US, the coverage of housing and catastrophic disaster-related insurance in India is extremely low, which makes them particularly vulnerable to natural disasters. Hence, it has become increasingly important to study how to increase the country's resilience to the frequent disasters. During the northeast monsoon season, southern India, especially the Tamil Nadu state of which Chennai is the capital, suffers from heavy floods every year. The Chennai flood, also referred as 2015 South India floods, that occurred in November and December of 2015 was unprecedented. The catastrophic rainfall in Chennai reached 490 mm or 19 inches over 24 hours, the highest in more than a century (Reuters 2015). It was also one of the most damaging disasters all over the world in 2015, costing over US\$14 billion and causing more than 500 deaths and numerous to be homeless (Business Standard 2015; Deccan Chronicle 2015). The Chennai flood had substantially disrupted business, logistics, transportation, and production. For example, Hindu, one of India's oldest newspaper that published daily since 1878, had to stop printing for the first time in its history due to the flood; and automakers such as Ford and Nissan had to temporarily halt production due to damaged equipment.

Disruption of supply chains due to the Chennai flood is expected to cause an increase in the price of goods and services. Damaged productive capital such as factories and equipment should also reduce economic activities and therefore household income. Hence, both the rise in price and the decline in income are expected to depress consumption.

2.2 Data

Financial Transactions

Our main dataset is transaction-level financial data from ICICI Bank. It covers spending by cash, credit and debit card for about 180,000 consumers in six cities including Chennai (the treatment group), Bangalore, Delhi, Gurgaon, Kolkata and Mumbai. Out of the five cities in the control group, Delhi and Gurgaon were hit by North India cold wave in 2017M1, and Mumbai and Kolkata were respectively affected by Mumbai floods and West Bengal floods in 2017M8. We therefore limit the sample to 2016M12 before most cities in the control group were contaminated by other extreme weather events. We require consumers to have at least three-month transaction records between 2015M1-2015M5 to be included in the sample. After this step, the sample has a total number of 2,479,398 observations for around 100,000 customers over 24 months. We winsorize these financial variables by the top and bottom 0.5% to exclude potential outliers. However, our results are similar based on data without winsorization.

For card-related spending, we have access to merchant information and transaction venue (online or onsite) for each transaction. This allows us to dig into different consumption categories and explore their heterogeneous response to natural disasters. Other than the consumption data, we also know the profession of each customer (static), the credit limits for each credit card users at each point of time, the size and types of loans, remittance, and wealth for each customer. These additional data enable us to explore the roles of income shocks as well as consumption smoothing via credit card, bank loans, or wealth.

Supermarket sales

Although the financial data provide comprehensive coverage of spending on different types of goods, they do not have information on the price and quantity of goods consumed. Supermarket transaction data that record the sale price and quantity for each item well complement the financial data. This dataset enables us to identify price shocks, price elasticity of demand, and the impact of price shocks on consumption. If there are price shocks, prices of goods should increase in response to the natural disaster. If price shocks are driving the impact of the natural disaster on consumption, the sales quantity and therefore the sales revenue should change in response to the price shocks. Our data on supermarket sales are from 2015M4 to 2016M12. It covers a total of 15265 distinct goods items sold in 28 stores (13 in Chennai, the treatment group, and 15 outside Chennai, the control group).

Night lights

We use monthly average night light intensity in each city to measure real economic activity and evaluate their response to the occurrence and aftermath of the Chennai flood. When there is no business, shops or factories may be closed early after dark, which shows low night light intensity on satellite-collected image. Such night light data have been frequently used to measure high-frequency spatial economic activities following Henderson, Storeygard, & Weil (2012). To increase the comparability, we focus on capital cities of 28 states and 8 Union Territories in India. Comparing the night lights in Chennai with that in other capitals before and after the Chennai flood, we can directly estimate the impact of a natural disaster on economic activity.

2.3 Summary Statistics

We first check whether the parallel trends assumption is met in our context. Figure 1 demonstrates the time trends of average total spending for both the treatment and control group. It shows that before the Chennai flood during 2015M1 to 2015M10, the average spending for individuals in Chennai (the treatment group) commoved with that outside Chennai (the control group), with the former being consistently higher than the latter.² Such a pattern broke down as soon as the Chennai flood hit the city. The average spending for the treatment group dropped below that for the control group during the occurrence of the Chennai flood (2015M11-2015M12). After the Chennai flood (2016M1-2016M12), the average spending for the treatment group rose above that for the control group, but the gap between the two shrank compared to the pre-flood level. These observations provide preliminary evidence that consumption drops both during and after the flood.

[Insert Figure 1 here]

Table 1 presents the mean and standard deviation of the monthly spending, sale price and night light intensity for the treatment and control group before, during and after the Chennai flood. Comparing the total spending difference between the treatment and control group during the flood with that before the flood, we find the difference shrank by Indian Rupee (INR) 3850 or \$52 per month, which is statistically significant at less than 1% level. Similarly, the spending difference between the treatment and control group contracted by INR 1260 or \$17 per month after the flood compared to that in the pre-flood period. This suggests that consumption remains lower than the pre-flood level even after the end of the flood. However, consumption after the flood picked up by INR 2590 (3850-1260) relative to that during the flood. This provides

² On October 2015, the spending difference between the treatment and control group is narrowed a bit. This was mainly driven by the annual celebration of Diwali, the biggest festival in India that is often celebrated between mid-October and mid-November, in the control group. Diwali, the Indian festival of lights, is celebrated in all cities in our control group but not in Chennai, the treatment group. Although Diwali was on November 11, 2015, spending related to this festivals could start a month early, which leads to a rise in total spending in the control group and therefore a narrower gap in the spending difference between the treatment and control group.

preliminary evidence that consumption dropped during the occurrence of the Chennai flood and recovered partially afterwards. Appendix Table A1 provides similar summary statistics for cash, credit and debit card spending, which exhibits similar patterns.

Before the flood, the average sale price of supermarket items in the treatment group is INR 9 lower than that in the control group. Such a difference increased to INR 10 during the flood, and further to INR 18 after the flood. The price difference between the treatment and control group after the flood is statistically more negative than that before the flood, which provides preliminary evidence that price in Chennai dropped after the flood. The night light intensity in the treatment group declined during the flood and recovered partially after the flood. The average night light intensity in the treatment group is higher than that in the control group before and after the flood, but lower than the latter during the flood. The difference in night light intensity between the treatment and control group is however not statistically significant.

[Insert Table 1 here]

2.4 Methodology

We employ a DID approach to evaluate consumption response to the Chennai flood using individual-level financial data. The treatment group includes all individuals having bank accounts in Chennai, while the control group consists of individuals from other cities. The pre-treatment period is from 2015M4 to 2015M10, and the post-treatment period is decomposed into two subperiods: one during the flood (2015M11 to 2015M12) and one after the end of the flood (2016M1 to 2016M12). The baseline DID framework is

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it}. \quad (1)$$

The dependent variable Y_{it} is the thousand rupee amount of total spending by individual i in month t . The total spending can be decomposed into cash and card spending, the latter of which comprises credit and debit card spending. The treatment group dummy T_i equals to 1 for all individuals in Chennai, which was affected by the flood, and 0 otherwise. The pre-treatment dummy, S_{pre} , equals to 1 for the pre-flood period from 2015M4 to 2015M10. The flood dummy, S_{flood} , equals to 1 during the occurrence of the Chennai flood from 2015M11 to 2015M12. The after-flood dummy, S_{after} , equals to 1 after the end of the Chennai flood from 2016M1 to 2016M12. Individual and time fixed effects are absorbed respectively by a_i and m_t , and ε_{it} is the error term. Observations in the first three months of the sample from 2015M1 to 2015M3 (benchmark period) are absorbed to identify the benchmark consumption patterns before the flood.

The coefficient β_{flood} captures the consumption difference between the treatment and control group during the occurrence of the Chennai flood relative to that in the benchmark period. If the occurrence of the Chennai flood reduced consumption, β_{flood} should be negative and statistically significant. Similarly, the coefficient β_{after} should be negative and statistically significant if consumption fell below the benchmark level after the end of the Chennai flood. If the coefficient β_{after} is not statistically significant, it means that consumption restored to its pre-flood level. If both β_{flood} and β_{after} are both negative and statistically significant with the latter significantly less (more) negative than the former such that $\beta_{after} > \beta_{flood}$ ($\beta_{after} < \beta_{flood}$), it means consumption after the flood dropped less (more) than that during the flood when compared to the benchmark level. That is, consumption after the flood had partially recovered (fallen further) from its low level during the flood. If the coefficient of β_{pre} is statistically insignificant, it indicates that the consumption difference between the treatment

and control group in the pre-treatment period is similar to that in the benchmark period, which provides additional justification for the application of DID approach.

We also utilize the DID framework in Eq.(1) to evaluate the response of economic activities to the Chennai flood by referring the subscript i to city instead of individual so that $T_i = 1$ for the city Chennai and $T_i = 0$ for the rest.

To explore the heterogeneous consumption response to the Chennai flood, we expand Eq.(1) to include two triple interaction terms:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}T_i * S_{flood} * H_i + \gamma_{after}T_i * S_{after} * H_i + a_i + m_t + \varepsilon_{it} \quad (2)$$

where H_i is a dummy variable that equals to 1 for individuals in a specific category, i.e. those that increase their credit limits, and 0 otherwise. If individuals in the specific category respond to the flood differently with the rest, the coefficient γ_{flood} (γ_{after}) should be statistically significant.

To evaluate the dynamic response to different stages of the flood, instead of differencing the post-treatment period into two episodes (during and after the flood), we look into the consumption response within each time period in our sample. Following Agarwal, Liu, & Souleles, (2007), we estimate the following equation:

$$Y_{it} = \sum_{k=-7}^{k=14} \theta_k T_i \times S_k + a_i + m_t + \varepsilon_{it}, \quad (3)$$

where S_k is a dummy variable that equals to 1 for the time period that is k –month before (or after if k is positive) the first occurrence of Chennai flood on 2015M11, and 0 otherwise. The coefficient θ_k thus captures the consumption response to the flood at a given period of time.

The cumulative response N months after the initial occurrence of Chennai flood (2015M11) can then be calculated as $\sum_{k=-7}^N \theta_k$.

Finally, to understand how price level responds to the flood that affects both supply and demand of goods, we adjust Eq.(1) to fit into the context of item-level supermarket sales:

$$Y_{jkit} = \beta_{pre} T_i * S_{pre} + \beta_{flood} T_i * S_{flood} + \beta_{after} T_i * S_{after} + \delta_j + a_k + m_t + \varepsilon_{jkit} \quad (4)$$

where the dependent variable Y_{jkit} is the sale price of item j in store k located in city i at period t . The treatment dummy T_i equals to 1 for all stores in Chennai. Item, store and time fixed effects are absorbed by δ_j , a_k and m_t , respectively. All the other parameters and variables follow similar definition from Eq.(1). The coefficient β_{flood} (β_{after}) should be statistically significant if there were price shocks in the occurrence (aftermath) of the flood. We also replace the price with the sales quantity, and sales revenue (in thousand rupee) to understand how consumption respond to the price shocks, if any.

3. Empirical analysis

3.1 Baseline result

Table 2 reports the consumption response to Chennai flood. The coefficient of $T_i * S_{flood}$ in column 1 is negative and statistically significant, suggesting that total spending drops during the flood. In particular, compared to benchmark period, the total spending by each individual in Chennai declined by INR 3969 (\$54) per month during the flood. Such a decline is equivalent to 11% of the average monthly consumption in the pre-flood period. Similarly, the estimated

coefficient of $T_i * S_{after}$ in column 1 suggests that total spending after the flood dropped by INR 1376 (\$19) relative to that in the benchmark period, which is statistically significant at the 1% level. Such a contraction after the flood is equivalent to 4% of the average total spending before the flood. Although the total spending after the flood was still lower than the benchmark level, it was higher than that during the flood. The coefficient of $T_i * S_{after}$ is about one-third of that of $T_i * S_{flood}$ and the difference between the two coefficients is statistically significant at the 1% level (F statistics = 150). It means that total spending after the flood recovered by about 65% (calculated as $1 - 1.376/3.969$) from the sharp contraction during the flood. To summarize, total spending declined significantly during the Chennai flood, recovered after the flood but remained significantly below the pre-flood level.

[Insert Table 2 here]

Decomposing total spending into cash and card spending, we find similar patterns of consumption decline during the flood and partial recovery after the flood. The coefficient of $T_i * S_{flood}$ in column 2 is -2.586 and statistically significant at the 1% level. It means that during the flood, cash spending declined by INR 2586 per month or 21% of its pre-flood level. Similarly, we find that card spending declined by INR 1276 per month during the flood, which is equivalent to 14% of its pre-flood level. The difference in the coefficient of $T_i * S_{flood}$ between columns 1 and 2 is -1.31 and statistically significant at the 1% level, which suggests that cash spending declined more than card spending. A possible explanation is that the flood made it difficult to withdraw or pay cash, i.e. by blocking the traffic, but constrained credit cards that can be used for online transaction to a lesser extent. No similar evidence is found after the flood: the coefficient of $T_i * S_{after}$ is similar in columns 2 and 3. Compared to the

benchmark period, cash and card spending after the flood dropped by INR 682 and 600, respectively. This implies that cash spending recovered much faster after the flood than card spending. In particular, cash spending after the flood recovered 74% of its consumption drop during the flood (calculated as $1 - 0.682/2.586$), while card spending only recovered 53% ($1 - 0.600/1.276$). Further decomposing card spending into credit and debit card spending, we find similar patterns in columns 4 and 5 that consumption declined during the flood and recovered partially after the flood.

Note that the coefficient of $T_i * S_{pre}$ is statistically insignificant in columns 1-5, which further justifies the parallel trends between treatment and control groups before the Chennai flood and supports our application of DID approach. It also rules out the possibility that the Chennai flood was anticipated before its occurrence. This allows us to ascribe the estimated change in consumption to the flood.

3.2 Economic Mechanism

So far, we have documented that consumption declined during the flood and recovered partially after the flood. In this section, we proceed to explore the economic mechanisms underlying such impacts of natural disasters on consumption. Natural disasters may disrupt the supply chains, which reduce supply and increase price of the goods and services (price shocks). They could also slow down economic activities, which undermine labour income (income shocks). We first present evidence of the supply-side price shocks and demand-side income shocks accompanied with the Chennai flood, and then evaluate their impacts on consumption.

3.2.1 Price shocks

The Chennai flood damaged production capital and forced factories and stores to halt operations, which reduced the supply of goods and services. It also paralyzed public transportation networks and submerged warehouses, which heavily disrupted supply chain logistics. Such negative supply shocks are expected to increase the price of goods and services. We use item-level supermarket sales data from a large Indian supermarket chain to test whether the flood generated price shocks. Estimating Eq.(4) based on the rupee amount of price, we report in column 1 of Table 3 that the average price increased during the flood and dropped after the flood. In particular, the price for each item sold in the supermarket stores in Chennai increased by INR 0.8 on average, or about 1% of its pre-flood price, which provides evidence of negative supply shocks. In contrast to the findings during the flood, the price dropped by INR 5.5 after the flood, which is equivalent to 6% of its pre-flood level. A possible explanation for the falling price after the flood is that supermarket stores strategically cut price in an attempt to increase sales when consumers faced more budget constraints after the flood. We provide further evidence on this point later.

[Insert Table 3 here]

Rising (falling) price is expected to decrease (increase) the sales quantity (demand by consumers) given the negative price elasticity of demands for most goods. However, the flood may also motivate consumers to hoard essential goods to cope with a potential goods shortage due to disrupted supply chains, which generates a positive demand shock. While the price elasticity should be in play both during and after the flood, the positive demand shock shall fade away after the flood when the supply chain logistics gradually return to normal. To understand how the changes in price during and after the flood affected the demand, we

estimate Eq.(4) based on the sales quantity and report the result in column 2 of Table 3. We find that average sales quantity per item increased by 2 units or 11% of its pre-treatment level in each month during the flood, and by 2.5 units or 13% of its pre-treatment level after the flood. After the flood, the sales quantity increased when the price dropped, which implies a negative price elasticity of demand among supermarket goods. Thus, if only price shocks were at work, the sales quantity for these supermarket goods during the flood should have dropped when prices increased. However, we find the opposite. This suggests that the positive demand shock driven by the anxiety to hoard essential goods dominated the positive price shocks during the flood.

The price shocks could directly affect sales revenue, or indirectly through the channel of sales quantity. To understand the overall relation between price shocks and sales revenue, we re-estimate Eq.(4) using sales revenue for each item as the dependent variable. The result in column 3 of Table 3 shows that the sales revenue per item increased significantly by INR 69 (\$0.93) or 7% of its pre-treatment level in each month during the flood but fell back to its pre-treatment level after the flood. This suggests that the impact of falling price after the flood on sales revenue was offset by that of rising sales quantity, which implies that the rise in sales revenue during the flood should be mainly due to the demand-side shock driven by the incentive to hoard essential goods, rather than price shocks.

To further test the roles of price shocks on sales quantity and revenue, we differentiate supermarket goods according to whether their price had increased above the pre-flood level. If price increment indeed reduced the demand, we should expect the sales quantity to drop more for those whose price had gone up during or after the flood. To test this hypothesis, we expand Eq.(4) to account for the interaction between H_i , a dummy that equals to 1 for items whose price increased above the pre-treatment level, and $T_i * S_{during}$ as well as $T_i * S_{after}$ and repeat the analysis for sales quantity and revenue respectively. The estimation results are reported in

columns 4 and 5 of Table 3. The coefficients of $H_i * T_i * S_{after}$ in columns 4 and 5 are both negative and statistically significant, which means that rising prices were associated with lower sales quantity and sales revenue after the flood. This explains why supermarkets in Chennai that seek to increase revenue cut price after the flood. Note that the coefficient of $T_i * S_{after}$ is positive and statistically significant in column 4, which means that demand for goods whose prices dropped or remained unchanged increased. It could be driven by consumers substituting goods whose prices increased for cheaper alternatives. The coefficients of $H_i * T_i * S_{during}$ are not statistically significant in either column 4 or 5, which corroborates with the previous finding that the impact of price increment on sales quantity and revenue during the flood was muted by the incentive to hoard essential goods. In the absence of the demand-side shocks, if price elasticity of demand were to be the same as that during the flood, the sales revenue would be falling instead of rising. Thus, rising price during the flood was not the reason why sales revenue improved.

To summarize, we document evidence that prices increased during the flood and declined after the flood. During the flood, the positive demand-side shocks driven by the incentive to hoard essential goods enabled supermarket stores in Chennai to raise prices without hurting the sales revenue. However after the flood, when demand-side shocks disappeared and income shocks kicked in, to deal with the falling demand, supermarket stores had to cut prices to maintain sales revenue. These results based on supermarket sales have important implications on the general consumption responses to price shocks. Supermarkets sell more essential goods in general. Thus, demand for supermarket goods are relatively inelastic to price as compared to other goods and services. When faced with the same price increment, demand for other goods and services are likely to drop more substantially than that for supermarket goods, which leads to a greater drop in sales revenue. Given that items not sold in supermarkets are mostly non-essential and are unlikely to be hoarded during the flood—that is, no demand-side shocks—

business owners who seek to increase their revenue would cut rather than increase their price. The same logic applies for after the flood. Therefore, even though rising price depresses consumption, most business owners are likely to reduce rather than increase price in order to boost sales revenue.

3.2.2 Income shocks

After documenting the price shocks and their impacts on consumption, we proceed to explore the roles of income shocks. The Chennai floods damaged productive capital such as factories and equipment and deterred business operations, which reduced income especially for those who cannot work from home. To check for the presence of income shocks, we estimate Eq.(1) based on city-level night light data. The result in column 1 of Table 4 shows that economic activity, as proxied for by nightlight light intensity in Chennai, declined significantly by 9 units or 33% of its pre-treatment level during the flood. After the flood, the night light intensity is still 0.7 units or 3% lower than its benchmark level. The response of economic activity to the Chennai flood is consistent with that of consumption: they both fell the most during the flood, recovered after the flood but still remained below their pre-flood level. These results provide evidence of negative income shocks during and after the flood.

[Insert Table 4 here]

To evaluate the impacts of income shocks on consumption, we compare two group of individuals with and without stable income. Although individual income level is not directly observable from our dataset, we can still uncover their effects from consumers' characteristics. Salarymen's income remain stable despite of natural disasters and are less likely to be affected by income shocks as compared to those whose incomes are subject to weather, like street

vendors. We hypothesize that salarymen who face less income shocks reduce their consumption less intensively in response to the flood than the rest.

To test this hypothesis, we create a dummy variable H_i that equals to 1 for individuals receiving regular salary and estimate Eq.(2). We show in column 2 of Table 4 that the coefficients of the two triple interaction terms, $T_i * S_{flood} * H_i$ and $T_i * S_{after} * H_i$, are both positive and statistically significant. This means that individuals receiving regular salaries consume more than the rest both during and after the flood, which supports our hypothesis. The different consumption patterns between salarymen and the rest provides evidence that income shocks contribute to the consumption contraction during and after the flood.

Summing up the coefficient of $T_i * S_{flood}$ and $T_i * S_{flood} * H_i$ yields -2.86, which is statistically significant at the 1% level. It means that salarymen's consumption still dropped during the flood. This is because, even without income shocks, positive price shocks during the flood may still deter consumption. Summing up the coefficient of $T_i * S_{after}$ and $T_i * S_{after} * H_i$ yields -0.3, which is economically small and statistically insignificant. It means that, after the flood, salarymen's consumption recovered fully to the pre-flood level. After the flood, when supply chains recovered, those unaffected by the negative income shocks were able to resume their regular consumption patterns. On the other hand, those subjected to negative income shocks reduced their consumption both during and after the flood as revealed by the negative and statistically significant coefficients of $T_i * S_{flood} * H_i$ and $T_i * S_{after} * H_i$ in column 2.

There is a small group of individuals (10245, about 10%) in our sample that receive or send out remittance. Gröger and Zylberberg (2016) document that incoming remittance provides a buffer against negative income shocks using rural household survey data from Vietnam. If similar mechanism is at work in the context of a metropolitan city like Chennai, we should

expect those receiving more remittance to be less affected by negative income shocks, and therefore cut consumption less substantially than the rest. Redefining the dummy variable H_i as 1 for individuals who received any kind of remittance since the occurrence of the flood and 0 otherwise, we re-estimate Eq.(2). The result in column 3 of Table 4 shows that the coefficients of the two triple interaction terms are not statistically significant, which provides no evidence that remittance offsets the negative income shocks. Redefining the dummy H_i as 1 for those that had sent (or either received or sent) remittance since the irruption of the Chennai flood, we re-estimate Eq.(2) and present the result in column 4 (column 5) of Table 4. Again, the coefficients of the two triple interaction terms are not statistically significant, which provides no evidence that outgoing or any form of remittance matter for the consumption response to the flood.

One may argue that those receiving remittance are typically poorer and more vulnerable to shocks, and as a result, the triple interaction term captures the difference between the poor and the rich rather than the roles of remittance. To address this concern, we focus on the small group of individuals with incoming remittance and compare those receiving above-median remittance with those receiving below-median remittance. The result in column 4 of Appendix Table A3 provides no evidence that more remittance was transformed into more consumption during or after the flood. We obtain similar results in columns 5 and 6 in Appendix Table A3 when looking at the outgoing and net remittance.³

Is it possible that remittance provides a buffer against income shocks but just fails to improve consumption? After all, Gröger and Zylberberg (2016) show that remittance mitigates income shocks but its impact on consumption is not statistically significant. To check for such a possibility, we estimate Eq.(1) using incoming, outgoing and net remittance as the dependent

³ Similar results are obtained when we calculate time-varying dummy variable based on different measures of remittance.

variable and present the results in columns 1-3 Appendix Table A3 respectively. There is no evidence that either incoming, outgoing or net remittance respond to the Chennai flood. It suggests that the remittance into and out of Chennai was not a means to coping with the income shocks caused by the flood. Our finding implies that the role of remittance for urban households in metropolitan cities like Chennai differs from that for rural households, possibly because the former group is less likely to rely on remittance for their daily living.

3.3 Heterogeneous consumption response

So far, we have documented that the Chennai flood generated price and income shocks and mainly reduced consumption through negative income shocks. The exposures to income shocks are likely to vary with different types of consumption, which leads to a heterogeneous consumption response to the flood. In this section, we utilize the detailed card transaction data to explore how the impacts of the Chennai flood on consumption vary with online and onsite transactions as well distinct consumption categories.

3.3.1 Online and onsite consumption

Both online and onsite consumption are subject to supply-side price shocks. However, they may face different constraints from income shocks as consumers can easily shift their budget between online shops and brick-and-mortar retailers. If more budget is allocated from onsite transactions to online shopping to cope with the risk and hassle of travelling during the flood, online consumption is expected to be less responsive to income shocks than onsite consumption.

After the flood, consumers may switch back to onsite shopping as stores and transport infrastructure resume service. If this is the case, onsite consumption should face less budget constraint and therefore recover faster than online consumption. We now turn to test these hypotheses.

Depending on whether the card payment is online or via a point of sale terminal (POS), we differentiate card transactions into online and onsite spending and evaluate their responses to the Chennai flood separately by estimating Eq.(1). Columns 1 and 2 of Table 5 show that both online and onsite card spending drop during and after the flood. Compared the coefficient of $T_i * S_{flood}$ in columns 1 and 2, we find that onsite consumption declined by INR 1346 (\$18) during the flood, which was more than three times as much as that for on online consumption (\$5). When we quantify the amount of these declines as a ratio corresponding to their pre-flood levels, we find that onsite consumption dropped by 10% during the flood, which is more than online consumption (6%). The finding that onsite consumption dropped more aggressively than online consumption during the flood supports our hypothesis that consumers switch to online shopping during the flood when it is risky and difficult to travel. We find the opposite after the flood: while online consumption drops further, onsite consumption recovers about 4/5 of its loss during the flood. In particular, the coefficient of $T_i * S_{after}$ in column 1 (-0.609) is more than twice of that in column 2 (-0.283), which suggests that online consumption drops more than onsite consumption after the flood. This provides evidence that consumers switch back to onsite consumption after the flood. Note, however, that the coefficient of $T_i * S_{pre}$ in column 1 is negative statistically significant at the 5% level, so we should be careful in interpreting the result for online consumption.

[Insert Table 5 here]

We further explore whether the difference between online and onsite consumption in response to the Chennai flood was driven by the extensive or intensive margin. Columns 3 and 4 show that the number of online and onsite card transactions (extensive margin) exhibited similar patterns with that of total spending discussed above: the number of online transactions dropped less than that of onsite transactions during the flood, but reversed the trend after the flood. This provides further evidence that consumers switch between online and onsite shopping to cope with the flood.

Columns 5 and 6 provide no evidence that the average amount per online and onsite transaction (intensive margin) changed relative to the benchmark period during the flood. Thus, the drop of onsite and online spending as well as their difference during the flood were mainly driven by the fall in the number of transactions (extensive margin). A possible explanation is that the flood increased the difficulty and cost of onsite purchase and online delivery through i.e. blocking traffics, which reduces the frequency of transactions.

It is clear from columns 3 and 5 that the online spending patterns during and after the flood were mainly driven by the number of transactions (extensive margin). Turning to the extensive and intensive margin of onsite consumption after the flood, we find that the number of transactions increased but the average amount per transaction declined significantly (see columns 4 and 6). This implies that fallen onsite spending after the flood was mainly driven by the decline on the intensive margin. After the flood, the number of transactions increased possibly because consumers could purchase goods onsite relatively easily, and the average amount per transaction dropped likely due to fallen prices documented in Section 3.2.1.

3.3.2 Consumption categories

Based on the merchant information from the card transaction data, we classify consumption into different categories and estimate Eq.(1) by replacing the dependent variable with the total card spending in each category. The heterogenous consumption response across different categories is reported in Table 5 and described below.

[Insert Table 6 here]

Essential and discretionary goods

It is difficult to cancel, reduce or delay essential consumption, i.e. on food, even in the presence of a natural disaster. Given any credit and liquidity constraint caused by negative income shocks, priority would always be given to essential consumption relative to discretionary consumption. We therefore expect essential consumption to be less responsive to income shocks than discretionary consumption. Consistent with our hypothesis, the results in columns 1 and 2 of Table 5 show that while essential spending remained resilient, discretionary spending declines significantly both during and after the flood. We document similar findings when loosening the definition of essential consumption to include education, dining and repairing-related activities (see Appendix Table A4).⁴

Durable goods

Browning & Crossley (2009) show theoretically that when facing temporary income loss, cutting budget on durables yields a higher welfare than reducing nondurables. Indeed, they support their theoretical prediction by showing that cutting unemployment insurance benefits

⁴ The result that discretionary consumption responded more sensitively to the Chennai flood is unlikely to be driven by the price shocks. According to the result in section 3.2.1, business owners would suffer a loss if they increase prices for supermarket items which are mostly essential goods. The negative impact of rising price on discretionary consumption should be stronger given the high price elasticity of demand for essential goods. Those selling discretionary goods are thus more likely to reduce rather than increase prices so as to boost revenue. If prices for discretionary goods fell, consumption should rise, which contradicts with our finding.

reduce workers' consumption on clothes more than that on food. Thus, if consumers are rational, they should cut their expenditure on durable goods more than that on non-durable goods. However, in the context of a natural disaster, many durable goods like housing roofs and floors are damaged, and would need to be replaced or reconstructed in order to resume normal daily living. Such a special post-disaster occasion may increase the demand of durable goods rather than reduce it. Thus, income shocks accompanied with the Chennai flood could either reduce or increase consumption on durable goods. To test which force dominates, we explore how consumption on durables and nondurables respond to the Chennai flood. We first classify the consumption into service, durable and nondurable goods spending and estimate Eq.(1) for each category. Columns 3-5 of Table 5 show that consumption across the three categories drops significantly during the flood. After the flood, consumption on both nondurable and durable goods recovers almost fully to the pre-flood level but service-related consumption falls further. The quick recovery of durable goods consumption is not consistent with the prediction by Browning & Crossley (2009) as the importance and priority of durable goods consumption is much higher during post-disaster reconstruction than in normal times.

Visible consumption

Income elasticity is documented to be higher for more visible goods (Heffetz, 2011). We therefore expect consumption on visible goods and services, that is more exposed to negative income shocks, to be more responsive to the flood. We follow Heffetz (2011) to identify consumption categories that have a visibility index higher than 0.5 as visible consumption, which includes spending on clothes, jewellery, beauty, home, etc. All the rest are classified as nonvisible consumption. As shown in columns 6 and 7 of Table 5, visible consumption dropped significantly during and after the flood. However, we only find weak evidence that nonvisible consumption responded to the flood. This suggests that the baseline response to the Chennai flood is mainly driven by visible consumption. A similar result is found when we classify

visible and nonvisible consumption based on Charles et al. (2009) which adopt a narrower definition of visibility (see Appendix Table A4).

3.4 Coping with natural-disaster shocks

Natural disasters generate both price and income shocks. When coping with price shocks, individuals may substitute necessities with cheaper alternatives, which was documented in Section 3.2.1. In dealing with negative income shocks, one can smooth consumption through borrowing from credit cards, banks or utilizing their existing wealth. Given that income shocks were the major channel of how the Chennai flood affected consumption, we explore how individuals smooth consumption in the presence of income shocks.

[Insert Table 6 here]

3.4.1 Credit cards

Credit cards can be used to smooth consumption when there are income shocks (Agarwal et al. 2007; Scholnick 2013; Agarwal and Qian 2014; Olafsson and Pagel 2018). Increasing credit limits raises disposable income, which provides a buffer to negative income shocks and helps smooth consumption. To see whether the increase in credit limits helps to smooth consumption during and after the flood, we set the dummy variable H_i to 1 for individuals whose credit limits in the post-treatment period exceeded the highest level in the pre-treatment period. Column 1 of Table 6 shows that the coefficient of the triple interaction term $T_i * S_{after} * H_i$ is positive and statistically significant. This suggests that individuals whose credit limits have increased

consumed more than the rest after the flood, which provides evidence of consumption smoothing through credit cards. Summing up the coefficient of $T_i * S_{after}$ and $T_i * S_{after} * H_i$ yields 4.1, which is statistically significant at the 1% level. It means that individuals with higher credit limits increased their consumption after the flood, possibly due to the replacement of durable goods damaged by the flood such as housing floors and roofs. There is, however, no significant evidence that increasing credit card limits helps to smooth consumption during the flood, possibly because physical barriers such as the disruption of the transport system exert a much larger negative impact on consumption as compared to the income shocks. Decomposing the total spending into cash and card spending, we show in Appendix Table A4 that, the increase in credit limits increased credit card spending but did not affect other types of spending. This further supports our argument that the rising consumption is driven by increase in credit limits.

Indeed, many credit card holders do not fully utilize their credit limits. For those who did not increase their credit card limit, they may still smooth consumption by utilizing a higher percentage of their existing credit limits. Those with higher credit limits have more flexibility to buffer against negative income shocks and are likely to be less responsive to the flood. To test this hypothesis, we redefine the dummy variable H_i as 1 for individuals with higher-than-median credit limits as of 2015M10, the last month in the pre-treatment period. The determination of credit limits in 2015M10 is exogenous as it was not affected by the flood. The result in column 2 of Table 6 shows that high-credit-limit individuals reduce their consumption significantly less than the low-credit-limit group after the flood, which provides similar evidence of consumption smoothing via credit cards.

3.4.2 Bank loan

Individuals who are able to borrow more from banks gain additional liquidity, which may help them cope with the negative income shocks and therefore cut their consumption less intensively during and after the flood.⁵ To explore whether individuals smooth consumption through bank loans, we define the dummy variable H_i as 1 for individuals in Chennai that have taken any additional loans in the post-treatment period (2015M11-2016M12), and 0 otherwise. Re-estimating Eq.(3), we show in column 3 of Table 6 that the two triple interaction terms $T_i * S_{flood} * H_i$ and $T_i * S_{after} * H_i$ are both positive and statistically significant. This suggests that individuals who took additional loans consumed more than the rest during and after the flood, which provides evidence that bank loans helped to smooth consumption. To address the possibility that one may delay loan payments to gain additional liquidity, we redefine the dummy variable H_i as 1 for individuals that have any outstanding loans repeat the analysis. We find similar evidence in column 4 of Table 6 that bank loans smoothed consumption.

The size of bank loans may also matter in the extent of consumption smoothing. We therefore redefine the dummy variable H_i based on the size of new loans and outstanding loans, and repeat the analysis. The results in columns 1 and 2 of Appendix Table A6 provide similar evidence that individuals with higher new or outstanding loans consumed more during and after the flood. Different types of bank loans are also likely to have different impacts on consumption smoothing. Decomposing loans into different categories, we find in columns 3-6 of Appendix Table A6 that the documented increase in consumption driven by bank loans are mainly from other loans that include credit loans.

⁵ Scholnick (2013) show that individuals increased consumption after paying out auto loans. Islam and Maitra (2012) find that being able to access microcredit mitigates the impact of health shocks on consumption.

3.4.3 Wealth

Other than using credit cards and bank loans to smooth consumption in the presence of negative income shocks, individuals may also turn to their saving or investment accounts for additional liquidity. Wealth in the form of stock, pension and housing could increase household consumption (Agarwal et al. 2020; Agarwal and Qian 2017; Di Maggio, Kermani, and Majlesi 2020). To understand whether wealth smooths consumption in the presence of negative income shocks, we create a dummy variable H_i that equals to 1 for those having any type of asset-related accounts, and 0 otherwise. The results in column 5 of Table 6 show that those with wealth consumed more than the others during but not after the flood.

To what extent can wealth smooth consumption may depend on its liquidity. Relatively liquid assets such as saving bonds and term deposits can be easily cashed out at a low cost, while less liquid assets such as security, mutual funds, public provident funds and gold can be costly to cash out. To check whether liquidity differentiates the role of wealth in consumption smoothing, we create a dummy variable H_i that equals to 1 for those having liquid assets (saving bond and term deposits) and illiquid assets (security, mutual funds, public provident fund and gold), respectively, and estimate Eq.(3). The coefficient of $T_i * S_{flood} * H_i$ in column 5 of Table 6 is positive and statistically significant, which means that individuals with liquid wealth consumed more than the others during the flood. The coefficient of $T_i * S_{flood} * H_i$ in column 6 is positive but not statistically significant, which offers no evidence that individuals having illiquid wealth behave differently from others during the flood. These results provide evidence that individuals smooth consumption during the flood with liquid assets but not with illiquid alternatives, possibly because the latter is costly to cash out. The coefficients of $T_i * S_{after} * H_i$ are not

statistically significant in both columns 5 and 6, which means neither liquid nor illiquid wealth smooths consumption after the flood. One possible reason why liquid wealth helped to smooth consumption during the flood but not after the flood is that liquid wealth may have been exhausted during the two-month flood, leaving little to cope with the persistent income shocks after the flood.

The size of wealth may also matter for consumption smoothing. Repeating the analysis above by redefining the dummy variable H_i as 1 for those having above-median total, liquid and illiquid wealth respectively, we provide similar evidence in columns 1-3 of Appendix Table 7 that only liquid wealth smoothed consumption during the flood. Further decomposing the total wealth into assets stored in saving bond, term deposit, security, mutual fund, public provident fund, and gold, we find in Appendix Table A7 that consumption smoothing through wealth is mainly from saving bonds which have relatively high liquidity. There is no evidence that individuals with other investment positions smooth their consumption during or after the flood, possibly due to their relatively low liquidity.

4. Further analysis

4.1 Dynamic consumption response

To gain a better understanding of the time-variation in consumption patterns, Figure 2 illustrates the cumulative consumption response to the Chennai flood per individual based on Table 2. In the pre-treatment period, or 1- to 7-months before the Chennai flood hit on 2015M11, the cumulative consumption response is trivial and statistically insignificant. It thus

rules out the possibility that other forces beyond the flood are driving our baseline result and that individuals have foreseen the Chennai flood and acted pre-emptively. During the peak of the flood on 2015M11 and 2015M12, consumption declined sharply. After the end of the flood, the cumulative consumption response stabilized at around INR -10,000 (-\$136) for a few months before dropping further on 2016M8. The stabilization from 2016M1 to 2016M7 could be due to the one-off rising demand for durable goods driven by reconstructions. After finishing the reconstructions, consumption fell again as income shocks kicked in. Since 2016M8, continued to follow the falling trends. By the end of our sample period (2016M12), the cumulative consumption per individual in our sample had dropped by INR 26,000 (\$353) over 14 months, or around INR 23,000 (\$312) per year.

We also present the cumulative response of cash and card spending, which exhibit similar patterns, in Appendix Figure 1. The differential consumption response between onsite and online transaction, essential and discretionary goods, durable and nondurable goods, visible and nonvisible goods are also illustrated in Appendix Figure 2 and 3.

4.2 Macroeconomic implications

To have a broad understanding on the macroeconomic implications of the consumption response, we delve into the macroeconomic statistics in Chennai provided in Berube et al. (2015). According to the report, the GDP per capita in terms of purchasing power parity for Chennai in 2014 is \$6,469. All else equal, the Chennai flood costed around 5% ($=\$312/\6469) of the city's GDP per capita. In other words, without the flood, the city's GDP per capita growth would have been 5% higher than what it was. Household consumption accounted for 58% of GDP in India as of 2014. Assuming the same ratio of household consumption to GDP in

Chennai, the household consumption per capita in Chennai should be \$3752 (= \$6,469*58%) before the occurrence of the Chennai flood. The Chennai flood thus wiped out 8% (=312/3752) of household consumption. That is, households in Chennai could have enjoyed 8% additional consumption without a flood.

4.2 Robustness Checks

We perform a battery of robustness checks and present the results in Appendix Table A8 and A9.

Demonetization

Our sample overlaps with the demonetization period starting from 2016M11, which affected every place in India. One may argue that the demonetization reduced consumption in Chennai more than that in other cities, which leads to our baseline result. To rule out such a possibility, we exclude the demonetization period (2016M11-2016M12) from our sample and repeat the analysis. The result in column 1 of Appendix Table A8 is consistent with our key finding that consumption dropped sharply during the flood, and partially recovered afterwards. It thus rules out the possibility that our result is driven by demonetization.

Alternative samples

Could our result be driven by rising consumption in the control group or zero observations in the sample? To address these concerns, we perform a simple analysis based on individuals in the treatment group only. We also repeat the DID analysis treating zero observations as missing. The results in columns 2 and 3 show that our baseline findings continue to hold. We also show in column 4 that the result remains robust when we use the original data without winsorization.

Matched sample

According to the summary statistics in Appendix Table A2, the treatment and control group may not be that comparable in terms of individuals' demographic characteristics and banking patterns, which prevents us from fully ascribing the documented consumption decline to the Chennai flood. We first use propensity score matching (PSM) and one-to-one matching to select a group of individuals from the treatment and control group that matched with each other in various demographic characteristics. In the matched sample, the difference between the treatment and control group along any of the listed dimensions is no longer statistically significant (Appendix Table A2). It suggests that the treatment and control group in the matched sample is comparable in most dimensions other than consumption. When estimating Eq.(1) based on the matched sample, column 5 of Appendix Table A8 shows that our baseline result remains robust.

Log transformation

While our analysis focuses on the rupee amount of consumption, we are also interested in the relative change in consumption. Using the log of the consumption amount as the dependent variable, we repeat the estimation of Eq.(3). The result in column 6 of Appendix Table A8 reveals similar patterns that consumption dropped respectively by 12% and 4% during and after the flood, compared to its pre-treatment level. This is consistent with the baseline result that consumption dropped during the flood and partially recovered after the flood.

Alternative benchmark periods

Finally, to show that our result is not sensitive to the choice of benchmark period, we replace it with (i) 2015M1-2015M2; (ii) 2015M1-2015M4; and (iii) 2015M1-2015M5. The results in

Appendix Table A7 show that, regardless of the choices of benchmark period, our finding that consumption drops during the flood and recovers partially after the flood remains robust.

6. Conclusion

We systematically explore the impacts of a natural disaster on consumption, the biggest component of GDP, in the context of the Chennai flood in India using detailed transaction-level data. We find that consumption dropped substantially during the natural disaster, recovered after the end of the disaster but remained below its pre-disaster level. Further analysis reveals that such negative impacts of a natural disaster on consumption are channelled through price shocks, and in particular, income shocks. We first document evidence of both price and income shocks during and after the flood, and then show how they affect consumption. We further uncover that the impacts of price and income shocks on consumption differ between online and onsite shopping as individuals switch between online and onsite shopping to deal with the hassles caused by the natural disaster. We also find that the impacts of price and income shocks are more pronounced for discretionary and visible goods, and for services which face different price elasticity and budget constraints. Delving further into the shock-coping mechanisms, we provide evidence that individuals smooth consumption by utilizing credit cards, borrowing from banks, and tapping on liquid assets to smooth their consumption either before or (and) after the flood.

Our findings have important policy implications especially for emerging markets that are vulnerable to natural disasters. First, governments that seek to mitigate the negative impacts of natural disasters on economic growth can try to mute price shocks, i.e. through strengthening the supply chain management. Second, policy makers that aim to recover the economy quickly

after a natural disaster can increase liquidity to target groups such as those having no stable income by granting loans or credit card limits.

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Figure 1. Parallel trends in consumption.

This figure plots the time series of average monthly total spending by the control and treatment group in solid and dashed lines, respectively. The interval between the two vertical lines highlight the occurrence of the Chennai flood from 2015M11 to 2015M12.

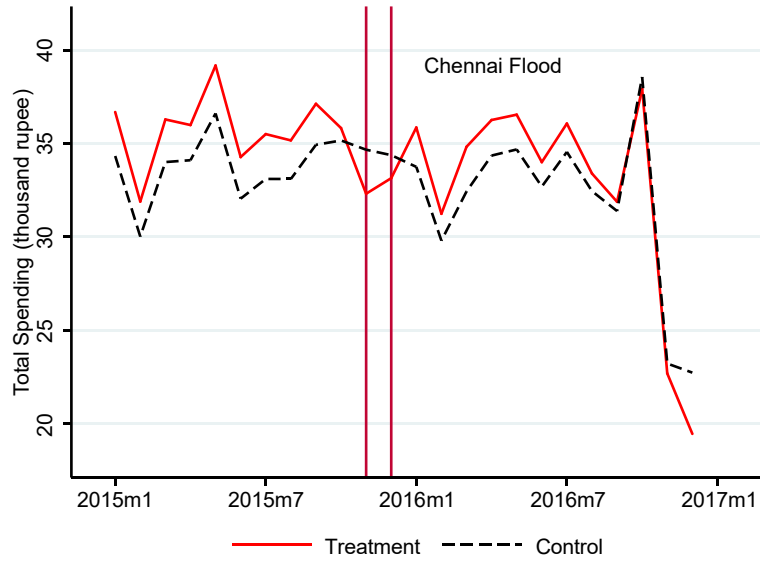


Figure 2. Cumulative consumption response to the Chennai flood.

The solid line plots the cumulative response of total spending (in thousand rupees) to the Chennai flood. The dashed lines present the 95% confidence intervals.

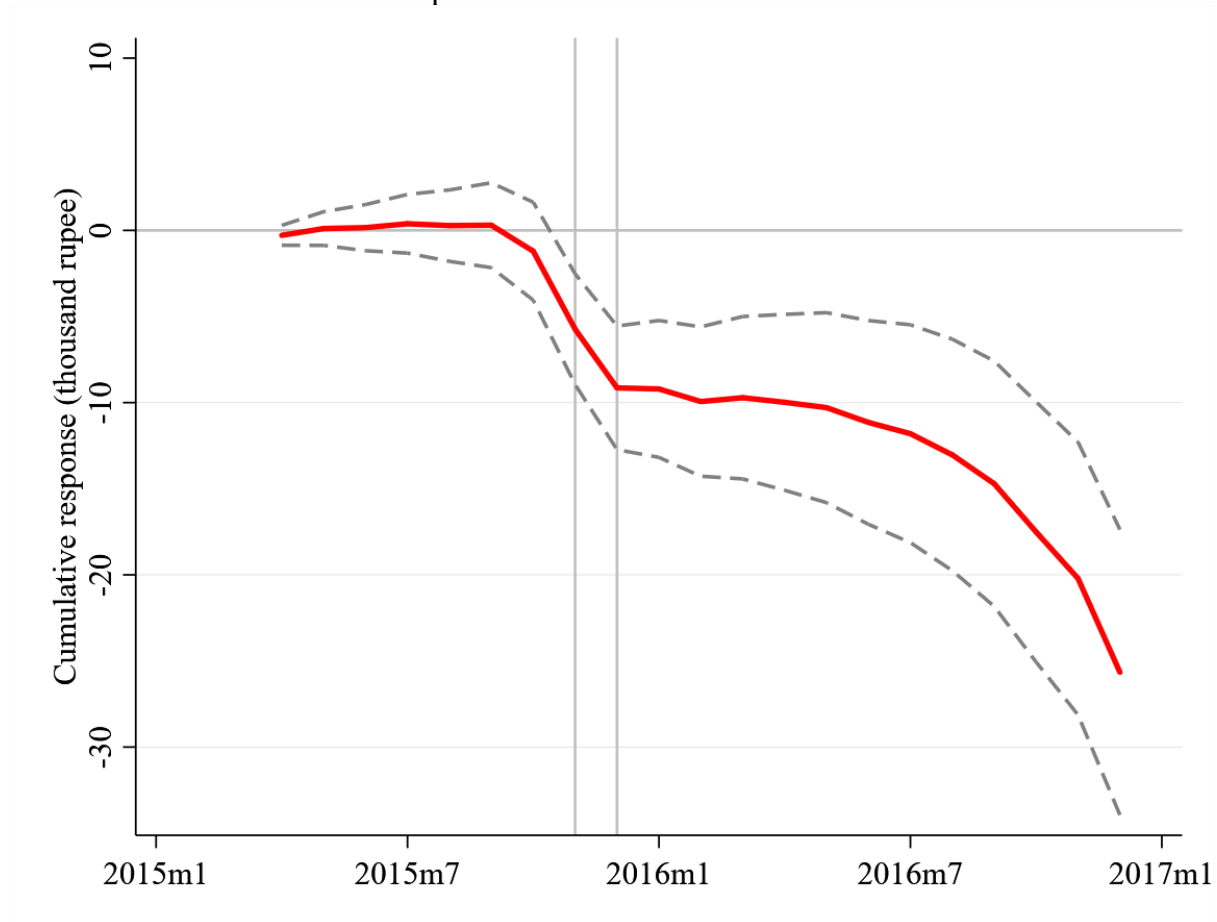


Table 1. Summary statistics

This table reports the mean and standard deviation of the total spending and supermarket item's sale price in thousand rupees, and the night light intensity for the treated (individuals in Chennai) and control group before, during and after the Chennai flood. The difference records the difference between the treatment and control group. The difference in difference (DID) compares the consumption gap between the treatment and control group before and after (during) the Chennai flood and reports the difference between the two and the associated p value.

	Treatment		Control		Difference	
	(1) Mean	(2) SD	(3) Mean	(4) SD	(1) - (3) Difference	p-value
Total Spending						
Before (2015M1-2015M10)	35.796	0.098	33.745	0.047	2.051	0.000
During (2015M11-2015M12)	32.730	0.219	34.526	0.104	-1.796	0.000
After (2016M1-2016M12)	32.514	0.089	31.720	0.043	0.794	0.000
DID (During - Before)					-3.846	0.000
DID (After - Before)					-1.257	0.000
Price						
Before (2015M1-2015M10)	100.40	0.19	109.31	0.36	-8.91	0.00
During (2015M11-2015M12)	102.60	0.37	112.71	0.66	-10.11	0.00
After (2016M1-2016M12)	97.31	0.14	114.77	0.26	-17.46	0.00
DID (During - Before)					-1.20	0.16
DID (After - Before)					-8.55	0.00
Night Light Intensity						
Before (2015M1-2015M10)	26.52	5.04	24.14	2.52	2.37	0.66
During (2015M11-2015M12)	19.16	11.27	29.80	5.64	-10.64	0.51
After (2016M1-2016M12)	25.99	4.39	24.20	2.19	1.79	0.71
DID (During - Before)					-13.02	0.35
DID (After - Before)					-0.58	0.94

Table 2. Consumption response to flood.

This table reports the average spending response to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

Y_{it} is the rupee amount (in thousand) of total spending, which is decomposed into cash and card spending, the latter of which. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 to 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by individuals. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
	Total Spending	Cash	Card	Card	
	= Cash + Card		= Credit + Debit	Credit	Debit
$T_i * S_{pre}$	-0.173 (0.207)	-0.049 (0.148)	-0.132 (0.112)	-0.061 (0.081)	-0.023 (0.063)
$T_i * S_{flood}$	-3.969*** (0.273)	-2.586*** (0.192)	-1.276*** (0.152)	-0.776*** (0.111)	-0.444*** (0.084)
$T_i * S_{after}$	-1.376*** (0.227)	-0.682*** (0.159)	-0.600*** (0.125)	-0.359*** (0.095)	-0.182*** (0.069)
Constant	33.199*** (0.033)	20.079*** (0.023)	12.713*** (0.018)	7.520*** (0.013)	4.876*** (0.010)
Observations	2,479,398	2,479,398	2,479,398	2,479,398	2,479,398
R-squared	0.489	0.464	0.492	0.565	0.427
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes

Table 3. Price shocks.

This table reports the average response of sale price, quantity and value to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{jkit} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \delta_j + a_k + m_t + \varepsilon_{it}$$

where the dependent variable Y_{jkit} is the sale price, discount, sale quantity, and total sales (in thousand rupees) of item j in store k located in city i , in columns 1-4 respectively. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for stores in Chennai and 0 otherwise. Item, store and time fixed effects are included, and standard errors reported in the parenthesis are clustered by individuals. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

$H_i = 1$ for	(1)	(2)	(3)	Higher Price	
				(4)	(5)
	Price	Quantity	Value	Quantity	Value
$T_i * S_{pre}$	-0.286 (0.302)	0.535 (0.450)	-0.016 (0.024)	0.538 (0.450)	-0.016 (0.024)
$T_i * S_{flood}$	0.788** (0.394)	2.161*** (0.562)	0.069** (0.031)	1.440** (0.730)	0.080** (0.037)
$T_i * S_{after}$	-5.509*** (0.391)	2.512*** (0.555)	-0.018 (0.028)	3.431*** (0.662)	0.047 (0.033)
$T_i * S_{flood} * H_i$				1.117 (0.698)	-0.017 (0.032)
$T_i * S_{after} * H_i$				-2.106*** (0.754)	-0.149*** (0.039)
Constant	104.467*** (0.228)	24.194*** (0.324)	1.420*** (0.017)	24.184*** (0.324)	1.419*** (0.017)
Observations	1,184,839	1,184,839	1,184,839	1,184,839	1,184,839
R-squared	0.974	0.646	0.576	0.646	0.576
Item fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes

Table 4. Income shocks.

This table reports the response of economic activities and consumption to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}T_i * S_{flood} * H_i + \gamma_{after}T_i * S_{after} * H_i + a_i + m_t + \varepsilon_{it}$$

where Y_{it} is the nightlight data in city i in column 1 and the total spending (in thousand rupees) in columns 2-5. The dummy H_i equals to 1 for individuals that increase their credit limits, have higher-than-median credit limits, and have saving bonds in columns 2-5, respectively. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 to 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for city Chennai or individuals in Chennai, and 0 otherwise. Individual (or city) and time fixed effects are included, and standard errors reported in the parenthesis are clustered by individuals. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

Dependent variable	(1)	(2)	(3)	(4)	(5)
	Night Lights	Total Spending			
		Regular Salary	Incoming Remittance	Outgoing Remittance	All Remittance
$H_i = 1$ for					
$T_i * S_{pre}$	0.273 (0.562)	-0.172 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)
$T_i * S_{flood}$	-8.924*** (0.205)	-4.057*** (0.279)	-4.043*** (0.275)	-3.988*** (0.273)	-4.039*** (0.275)
$T_i * S_{after}$	-0.679*** (0.180)	-1.461*** (0.231)	-1.340*** (0.228)	-1.406*** (0.227)	-1.354*** (0.228)
$T_i * S_{flood} * H_i$		1.203* (0.686)	1.058 (0.957)	1.342 (2.224)	0.888 (0.920)
$T_i * S_{after} * H_i$		1.157** (0.556)	-0.503 (0.743)	2.015 (1.650)	-0.281 (0.707)
Constant	7.067*** (0.002)	33.199*** (0.033)	33.199*** (0.033)	33.199*** (0.033)	33.199*** (0.033)
Observations	864	2,479,398	2,479,398	2,479,398	2,479,398
R-squared	0.943	0.489	0.489	0.489	0.489
City/individual fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes

Table 5. Online versus onsite card spending

This table reports the average online and onsite card spending response to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

The dependent variable Y_{it} refers to the rupee amount of online and onsite card spending in thousands in columns 1 and 2, the number of online and onsite card transactions per month in columns 3 and 4, and the average amount per online and onsite transaction in columns 5 and 6. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during Chennai flood (2015M11 –2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 to 2016M12). Observations in the first three months (2015M1 to 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Amount of Transaction		Number of Transactions		Amount per Transaction	
	Online	Onsite	Online	Onsite	Online	Onsite
$T_i * S_{pre}$	-0.149** (0.072)	-0.115 (0.131)	-0.115*** (0.020)	0.003 (0.032)	0.009 (0.025)	0.010 (0.027)
$T_i * S_{flood}$	-0.394*** (0.098)	-1.346*** (0.176)	-0.249*** (0.028)	-0.496*** (0.042)	-0.013 (0.033)	-0.097*** (0.035)
$T_i * S_{after}$	-0.609*** (0.080)	-0.283** (0.142)	-0.333*** (0.029)	0.141*** (0.043)	-0.006 (0.025)	-0.049* (0.026)
Constant	5.520*** (0.012)	12.182*** (0.021)	2.584*** (0.004)	4.967*** (0.006)	1.340*** (0.004)	2.058*** (0.004)
Observations	1,664,854	1,664,854	1,664,854	1,664,854	1,664,854	1,664,854
R-squared	920,997	1,376,192	539,096	689,341	436,922	835,325
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Different consumption categories

This table reports the response of card spending in different categories of goods and services to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

The dependent variable Y_{it} refers to the card spending in the categories specified in the top row in thousand rupees. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Discretionary?		Goods Durability and Service			Visible?	
	Essential	Discretionary	Nondurable	Durable	Service	Visible	Nonvisible
$T_i * S_{pre}$	-0.079 (0.070)	-1.761 (1.157)	-0.072 (0.050)	0.019 (0.087)	-1.787 (1.154)	-0.040 (0.144)	-1.800 (1.149)
$T_i * S_{flood}$	-0.110 (0.114)	-3.786*** (1.370)	-0.254*** (0.077)	-0.801*** (0.135)	-2.841** (1.362)	-1.503*** (0.205)	-2.393* (1.352)
$T_i * S_{after}$	0.130 (0.090)	-3.344** (1.519)	0.090 (0.071)	-0.117 (0.095)	-3.188** (1.516)	-0.465*** (0.148)	-2.749* (1.512)
Constant	4.407*** (0.012)	23.370*** (0.222)	4.504*** (0.009)	6.655*** (0.014)	16.618*** (0.222)	10.537*** (0.022)	17.241*** (0.221)
Observations	1,340,695	1,340,695	1,340,695	1,340,695	1,340,695	1,340,695	1,340,695
R-squared	0.246	0.627	0.344	0.333	0.627	0.326	0.627

Table 7. Consumption smoothing

This table reports how individuals smooth consumption using credit card, bank loans and wealth during and after the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}D_i * T_i * S_{flood} + \gamma_{after}H_i * T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

Y_{it} is the amount of total spending (in thousand rupees) in all columns. In columns 1 to 5, the dummy variable H_i equals to 1 respectively if individual i increased his credit limit, has a credit limit that is higher than the sample median, acquires a new loan, has any outstanding loans, owns any form of wealth, owns liquid wealth such as saving bond or term deposit, and owns illiquid wealth such as stocks and mutual funds. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 to 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(5)	(6)
	Dependent variable = Total Spending						
	Increase Credit Limit	Higher Credit Limit	New Loan	Any Loan	Wealth	Liquid Wealth	Illiquid Wealth
$T_i * S_{pre}$	0.050 (0.278)	0.050 (0.278)	-0.172 (0.207)	-0.172 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.172 (0.207)
$T_i * S_{flood}$	-3.926*** (0.373)	-4.392*** (0.422)	-4.241*** (0.274)	-4.191*** (0.274)	-10.331*** (1.894)	-9.218*** (1.623)	-3.800*** (0.314)
$T_i * S_{after}$	-1.766*** (0.306)	-2.434*** (0.345)	-1.564*** (0.228)	-1.566*** (0.228)	-0.235 (1.473)	-0.121 (1.412)	-1.184*** (0.260)
$T_i * S_{flood} * H_i$	1.078 (1.157)	1.014* (0.530)	5.080*** (1.093)	4.480*** (1.099)	6.414*** (1.897)	5.304*** (1.625)	-0.426 (0.407)
$T_i * S_{after} * H_i$	5.822*** (0.980)	1.881*** (0.413)	3.497*** (0.780)	3.830*** (0.823)	-1.150 (1.475)	-1.268 (1.413)	-0.485 (0.315)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix

Figure A1. Cumulative consumption response to the Chennai flood by different payment methods.

This figure plots the cumulative response of card spending (top left), cash spending (top right), credit card spending (bottom left), and debit card spending (bottom right), to the Chennai flood. The solid line plots the cumulative response in thousand rupees, and the dashed lines present the 95% confidence intervals.

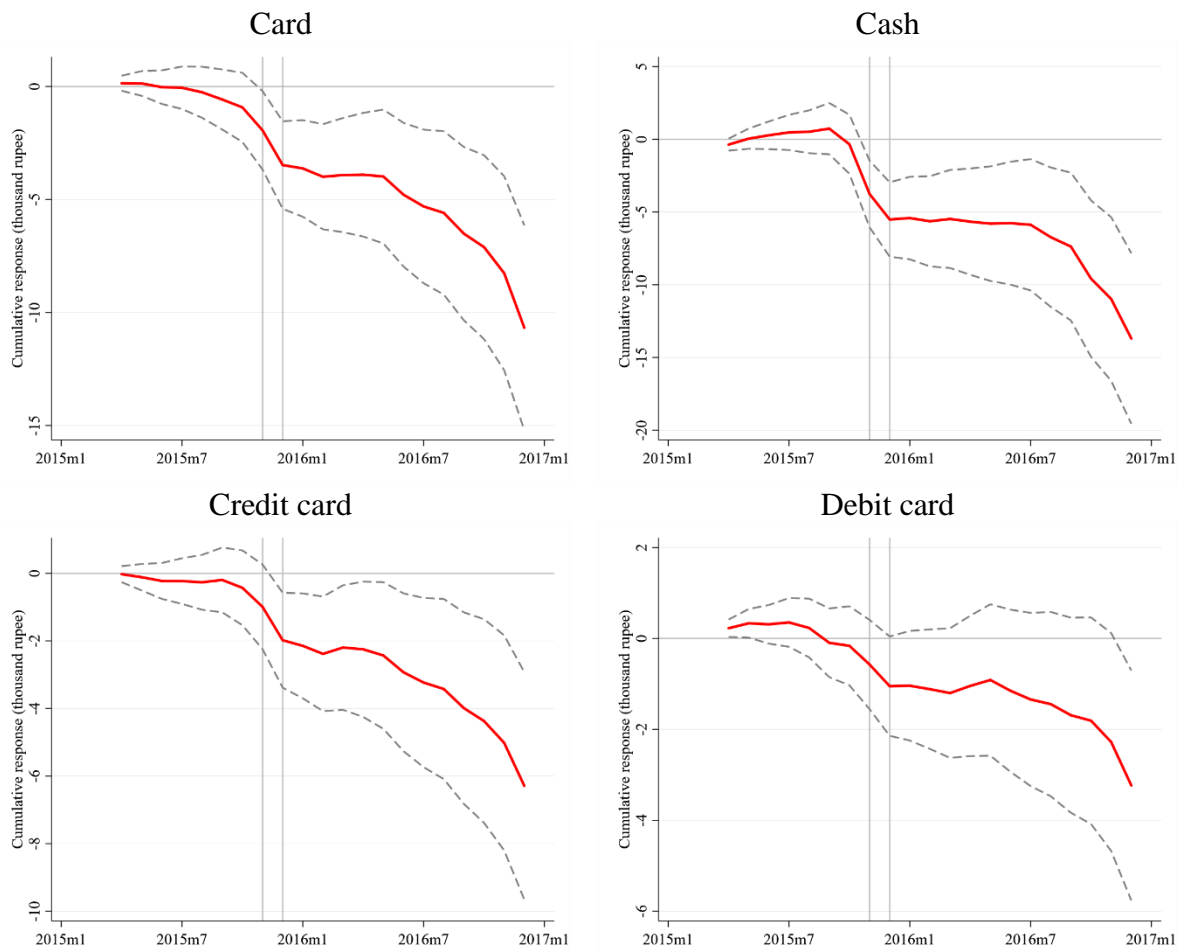


Figure A2. Online and onsite consumption responses to the Chennai flood.

This figure plots the cumulative response of online and onsite consumption to the Chennai flood on the left and right panels respectively. The cumulative response in terms of card spending, number of transactions, and average card spending per transaction, differentiated by online and onsite transactions, is presented on the top, middle and bottom panels, respectively. The solid line plots the cumulative response in thousand rupees, and the dashed lines present the 95% confidence intervals.

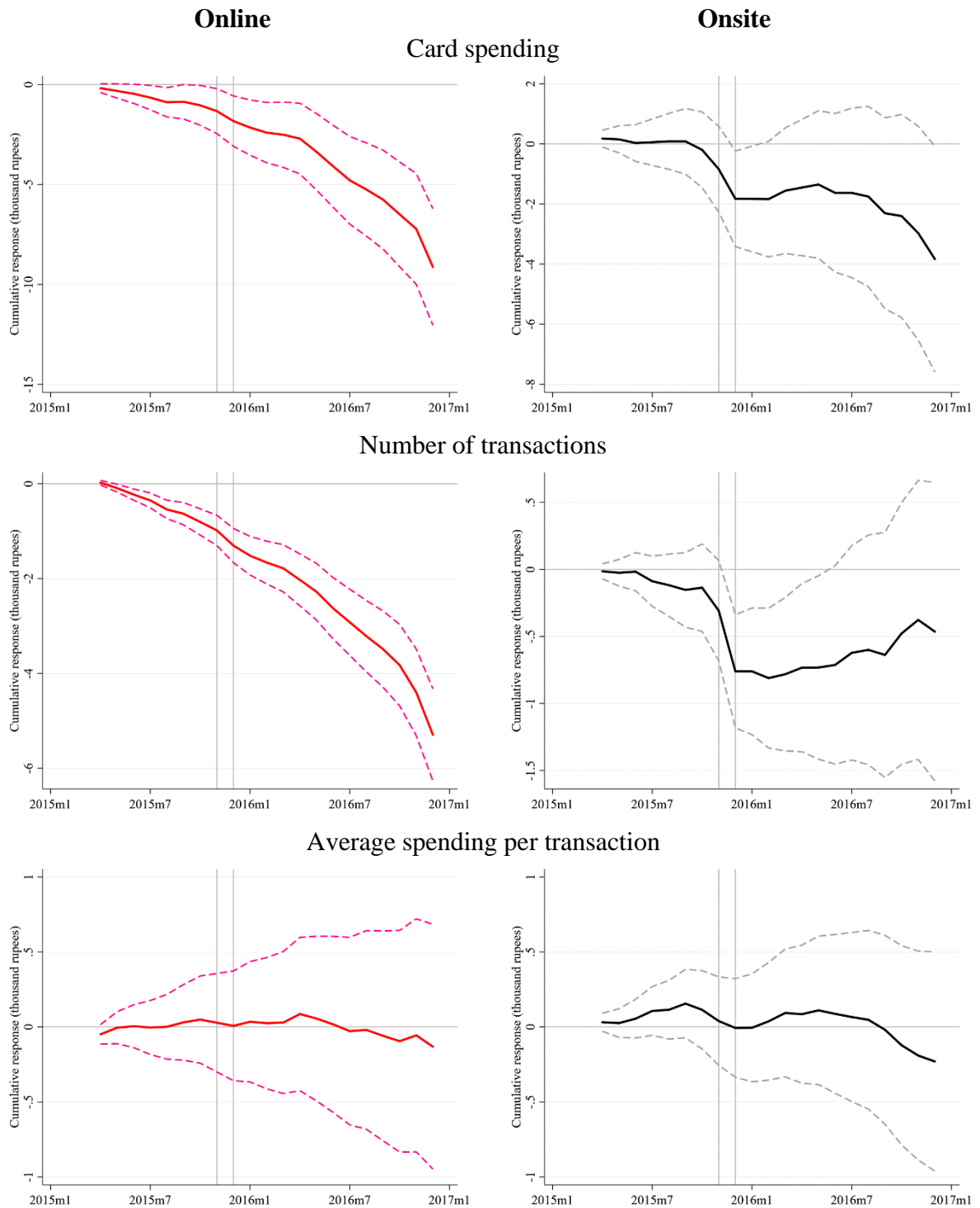


Figure A3. Heterogeneous consumption responses to the Chennai flood across different consumption categories.

This figure plots the cumulative response of essential and discretionary consumption to the Chennai flood on the left and right panels of the top row. Similar statistics for durable and nondurable goods, visible and nonvisible goods are presented in the middle and bottom rows. The solid line plots the cumulative response in thousand rupees, and the dashed lines present the 95% confidence intervals.

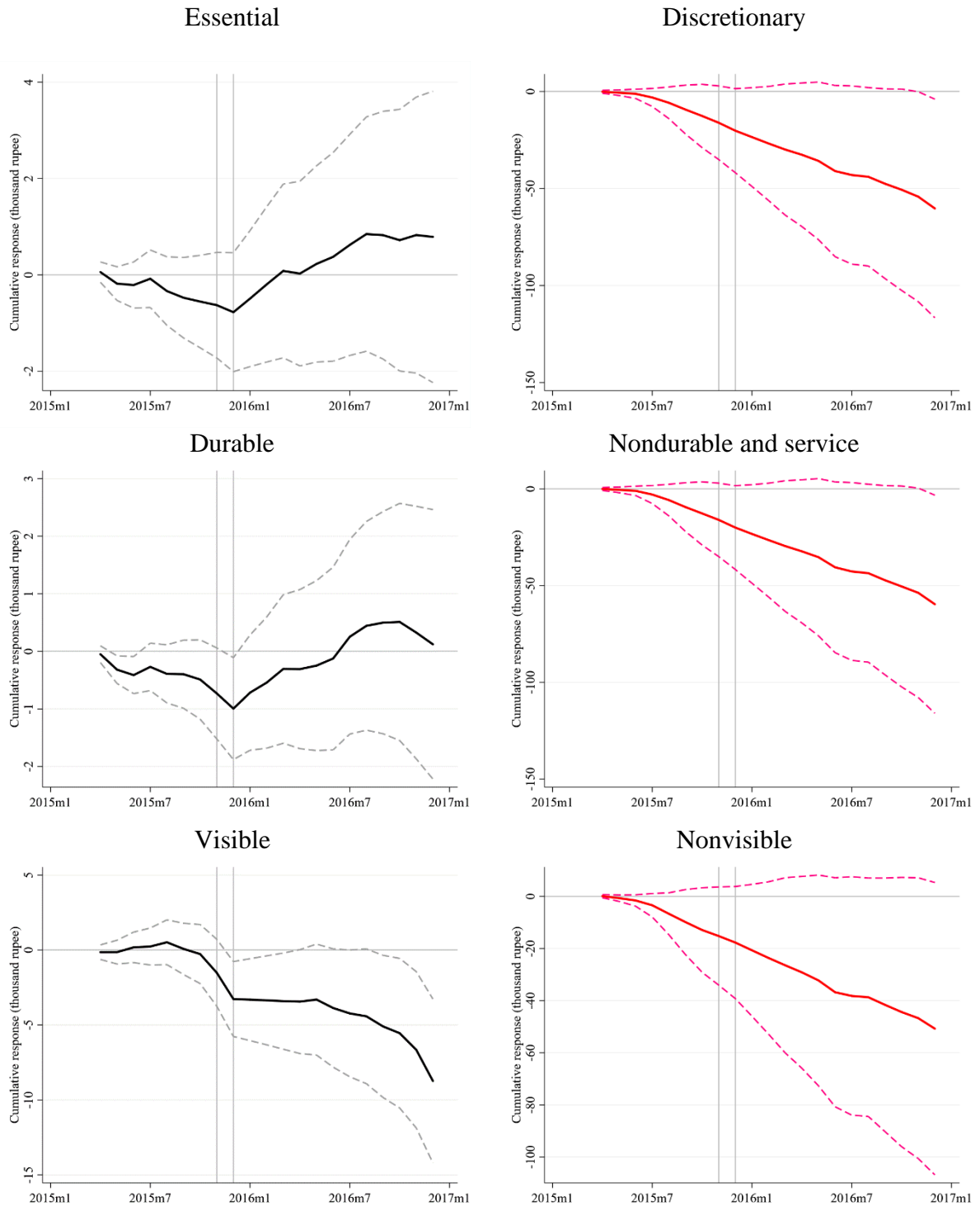


Table A1. Summary statistics

This table reports the mean and standard deviation of the cash and card (including credit and debit card) spending, online and onsite card spending, incoming, outgoing and net remittance for the treated and control group before, during and after the Chennai flood. All variables are in thousand rupees. The difference records the difference between the treatment and control group. The difference in difference (DID) compares the consumption gap between the treatment and control group before and after (during, or during and after) the Chennai flood and reports the difference between the two.

	Treatment		Control		Difference	
	(1) Mean	(2) SD	(3) Mean	(4) SD	(1) - (3) Difference	p-value
Cash						
Before (2015M1-2015M10)	23.056	0.066	21.517	0.032	1.539	0.000
During (2015M11-2015M12)	18.957	0.060	18.067	0.029	0.889	0.000
After (2016M1-2016M12)	23.056	0.066	21.517	0.032	1.539	0.000
DID (During - Before)					-2.550	0.000
DID (After - Before)					-0.649	0.000
Card = Credit + Debit						
Before (2015M1-2015M10)	12.267	0.059	11.851	0.028	0.417	0.000
During (2015M11-2015M12)	13.159	0.054	13.250	0.026	-0.091	0.139
After (2016M1-2016M12)	12.267	0.059	11.851	0.028	0.417	0.000
DID (During - Before)					-1.183	0.000
DID (After - Before)					-0.508	0.000
Credit						
Before (2015M1-2015M10)	7.283	0.047	7.070	0.022	0.213	0.000
During&After (2015M11-2016M12)	7.042	0.102	7.563	0.048	-0.521	0.000
During (2015M11-2015M12)	7.689	0.043	7.793	0.020	-0.104	0.034
After (2016M1-2016M12)	7.283	0.047	7.070	0.022	0.213	0.000
DID (During&After - Before)					-0.376	0.000
DID (During - Before)					-0.734	0.000
DID (After - Before)					-0.317	0.000
Debit						
Before (2015M1-2015M10)	4.742	0.030	4.501	0.014	0.242	0.000
During (2015M11-2015M12)	5.186	0.028	5.110	0.013	0.076	0.017
After (2016M1-2016M12)	4.742	0.030	4.501	0.014	0.242	0.000
DID (During - Before)					-0.427	0.000
DID (After - Before)					-0.166	0.000

Table A1. Summary statistics (continued)

	Treatment		Control		Difference	
	(1) Mean	(2) SD	(3) Mean	(4) SD	(1) - (3) Difference	p-value
<i>Online card spending</i>						
Before (2015M1-2015M10)	4.51	0.14	6.02	0.07	-1.50	0.00
During (2015M11-2015M12)	4.29	0.30	6.12	0.15	-1.83	0.00
After (2016M1-2016M12)	5.02	0.14	7.00	0.07	-1.98	0.00
DID (During - Before)					-0.33	0.37
DID (After - Before)					-0.48	0.03
<i>Onsite card spending</i>						
Before (2015M1-2015M10)	13.09	0.61	13.38	0.29	-0.29	0.66
During (2015M11-2015M12)	12.60	1.35	14.68	0.66	-2.08	0.19
After (2016M1-2016M12)	13.45	0.66	14.72	0.32	-1.28	0.12
DID (During - Before)					-1.79	0.28
DID (After - Before)					-0.99	0.37
<i>Incoming Remittance</i>						
Before (2015M1-2015M10)	0.22	0.04	0.42	0.02	-0.20	0.00
During (2015M11-2015M12)	0.24	0.09	0.32	0.06	-0.08	0.38
After (2016M1-2016M12)	0.20	0.07	0.41	0.04	-0.22	0.03
DID (During - Before)					0.11	0.34
DID (After - Before)					-0.02	0.85
<i>Outgoing Remittance</i>						
Before (2015M1-2015M10)	-0.16	0.03	-0.16	0.01	0.01	0.83
During (2015M11-2015M12)	-0.10	0.12	-0.14	0.03	0.04	0.45
After (2016M1-2016M12)	-0.16	0.02	-0.20	0.01	0.03	0.12
DID (During - Before)					0.03	0.80
DID (After - Before)					0.02	0.55
<i>Net Remittance</i>						
Before (2015M1-2015M10)	0.20	0.04	0.33	0.02	-0.14	0.00
During (2015M11-2015M12)	0.23	0.09	0.27	0.05	-0.04	0.63
After (2016M1-2016M12)	0.16	0.06	0.29	0.03	-0.13	0.12
DID (During - Before)					0.10	0.39
DID (After - Before)					0.00	0.97

Table A2. Demographic and bank account characteristics before and after matching. Panels A and B report the summary statistics for the original and matched sample respectively. Age is in year as of 2015M10. Female is a dummy that equals to 1 for females and 0 otherwise. Married is a dummy that equals to 1 if the consumer is married and 0 otherwise. Salary is a dummy that equals to 1 for consumers that receive regular salary payment. Mutual fund, equity, and gold are all dummy variables if the consumer has the corresponding asset account with the bank and 0 otherwise.

Panel A: Original Sample						
	Treatment		Control		Difference	
	(1) Mean	(2) SD	(3) Mean	(4) SD	(1) - (3) Difference	p-value
Age	46.410	13.022	45.817	13.542	0.593	0.000
Female	0.175	0.380	0.199	0.399	-0.024	0.000
Married	0.573	0.495	0.585	0.493	-0.012	0.002
Salary	0.549	0.498	0.566	0.496	-0.017	0.000
Mutual Fund	0.387	0.487	0.432	0.495	-0.046	0.000
Demat	0.505	0.500	0.596	0.491	-0.091	0.000
Gold	0.224	0.417	0.096	0.295	0.127	0.000
Observations	19097		84221			

Panel B: Matched sample						
	Treatment		Control		Difference	
	(1) Mean	(2) SD	(3) Mean	(4) SD	(1) - (3) Difference	p-value
Age	46.159	12.494	46.139	12.395	0.020	0.893
Female	0.178	0.383	0.176	0.381	0.002	0.630
Married	0.583	0.493	0.573	0.495	0.010	0.103
Salary	0.530	0.499	0.538	0.499	-0.008	0.161
Mutual Fund	0.450	0.498	0.449	0.497	0.000	0.943
Demat	0.565	0.496	0.571	0.495	-0.006	0.303
Gold	0.258	0.438	0.253	0.435	0.005	0.335
Observations	14225		14225			

Table A3. Remittance and income shocks.

This table reports the response of remittance to the Chennai flood and how they affect the consumption response. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}H_i * T_i * S_{flood} + \gamma_{after}H_i * T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

Y_{it} is the amount of incoming, outgoing and net remittance (in thousand rupees) in columns 1-3, and the amount of total spending (in thousand rupees) in columns 4-6. All interaction terms including H_i are ignored in the estimation of the remittance's response to the flood in columns 1-3. The dummy variable H_i equals to 1 if individual i whose incoming (outgoing, or net) remittance is above the median value among those who have ever received or sent out remittance. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by individuals. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Incoming Remittance	Outgoing Remittance	Net Remittance	Total Spending		
				Incoming Remittance	Outgoing Remittance	Net Remittance
$H_i = 1$ for						
$T_i * S_{pre}$	-0.013 (0.045)	-0.050 (0.071)	-0.004 (0.040)	0.186 (0.867)	2.429 (1.885)	0.169 (0.823)
$T_i * S_{flood}$	0.010 (0.052)	-0.052 (0.083)	0.029 (0.047)	-3.829*** (1.387)	2.164 (3.401)	-3.296** (1.363)
$T_i * S_{after}$	0.015 (0.037)	-0.097 (0.091)	0.023 (0.034)	-0.919 (1.187)	-0.144 (2.582)	-0.883 (1.140)
$T_i * S_{flood} * H_i$				2.190 (1.871)	-5.958 (4.417)	0.768 (1.796)
$T_i * S_{after} * H_i$				-1.347 (1.451)	5.132 (3.272)	-1.026 (1.378)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table A4. Alternative definition of consumption categories

This table reports the response of card spending in different categories of goods and services to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

The dependent variable Y_{it} refers to the card spending in the categories specified in the top row in thousand rupees. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)
	Discretionary?		Visible?	
	Essential	Discretionary	Visible	Nonvisible
$T_i * S_{pre}$	-0.127 (0.080)	-1.713 (1.156)	0.253** (0.106)	-2.093* (1.154)
$T_i * S_{flood}$	-0.360*** (0.126)	-3.536*** (1.368)	-0.432*** (0.150)	-3.464** (1.363)
$T_i * S_{after}$	0.060 (0.104)	-3.274** (1.517)	-0.119 (0.101)	-3.095** (1.520)
Individual fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes

Table A5. Consumption smoothing via credit card.

This table reports how credit limits reshape the average spending response to the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}H_i * T_i * S_{flood} + \gamma_{after}H_i * T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

Y_{it} is the amount of cash and card spending (in thousand rupees) in columns 1 and 2, and credit and debit card spending in columns 3 and 4. The dummy variable H_i equals to 1 if individual i has ever increased his credit limits since the Chennai flood in panel A and for individuals whose credit limit is above the sample's median value in panel B. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by individuals. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

Panel A: Increasing credit limit

	(1) Cash	(2) Card	(3) Credit	(4) Debit
$T_i * S_{pre}$	0.093 (0.192)	-0.073 (0.161)	-0.064 (0.127)	0.012 (0.079)
$T_i * S_{flood}$	-2.249*** (0.251)	-1.588*** (0.225)	-1.206*** (0.180)	-0.350*** (0.107)
$T_i * S_{after}$	-0.639*** (0.206)	-1.038*** (0.182)	-0.756*** (0.149)	-0.202** (0.087)
$T_i * S_{flood} * H_i$	0.210 (0.866)	1.053* (0.555)	1.129*** (0.257)	-0.048 (0.420)
$T_i * S_{after} * H_i$	-0.041 (0.708)	5.954*** (0.588)	5.880*** (0.527)	-0.123 (0.320)

Panel B: Higher existing credit limit

	Cash	Card	Credit	Debit
$T_i * S_{pre}$	0.093 (0.192)	-0.074 (0.161)	-0.064 (0.127)	0.012 (0.079)
$T_i * S_{flood}$	-2.883*** (0.312)	-1.295*** (0.221)	-1.004*** (0.147)	-0.243* (0.139)
$T_i * S_{after}$	-1.052*** (0.255)	-1.214*** (0.177)	-1.009*** (0.131)	-0.120 (0.104)
$T_i * S_{flood} * H_i$	1.253*** (0.360)	-0.464 (0.321)	-0.280 (0.254)	-0.213 (0.159)
$T_i * S_{after} * H_i$	0.799*** (0.279)	0.937*** (0.242)	1.079*** (0.202)	-0.172 (0.116)
Individual fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes

Table A6. Smoothing consumption via bank loans.

This table reports how individuals smooth consumption using bank loans during and after the Chennai flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}D_i * T_i * S_{flood} + \gamma_{after}H_i * T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

Y_{it} is the amount of total spending (in thousand rupees) in all columns. The dummy variable H_i equals to 1 if individual i 's new loan, total loan, auto loan, mortgage loan and other loan since the occurrence of the flood was above the sample median in columns 1 to 5 respectively, and 0 otherwise. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 –2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable = Total Spending				
	New Loan	Total Loan	Auto Loan	Mortgage Loan	Other Loan
$T_i * S_{pre}$	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)
$T_i * S_{flood}$	-4.054*** (0.273)	-4.073*** (0.273)	-3.970*** (0.273)	-3.995*** (0.272)	-4.053*** (0.273)
$T_i * S_{after}$	-1.455*** (0.227)	-1.477*** (0.227)	-1.384*** (0.226)	-1.421*** (0.226)	-1.424*** (0.227)
$T_i * S_{flood} * H_i$	3.363** (1.653)	4.276** (1.744)	0.308 (3.136)	3.903 (3.747)	6.171*** (2.104)
$T_i * S_{after} * H_i$	3.103** (1.225)	4.154*** (1.290)	1.368 (2.879)	6.815** (2.849)	3.492** (1.533)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes

Table A7. Consumption smoothing via different assets.

This table reports how individuals smooth consumption using different forms of wealth during and after the flood. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + \gamma_{flood}D_i * T_i * S_{flood} + \gamma_{after}H_i * T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

Y_{it} is the amount of total spending (in thousand rupees). The dummy variable H_i equals to 1 if individual i 's wealth specified in the top row is above the sample median, and 0 otherwise. Liquid wealth includes saving bond and term deposit, while illiquid includes the wealth in columns 6-9. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Wealth	Liquid Wealth	Illiquid Wealth	Saving Bond	Term Deposit	Security	Mutual fund	Public Provident Fund	Gold
$T_i * S_{pre}$	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)	-0.173 (0.207)
$T_i * S_{flood}$	-4.883*** (0.312)	-5.305*** (0.309)	-3.997*** (0.286)	-5.195*** (0.308)	-4.027*** (0.283)	-4.104*** (0.283)	-4.062*** (0.275)	-3.967*** (0.273)	-3.923*** (0.273)
$T_i * S_{after}$	-1.116*** (0.264)	-1.265*** (0.263)	-1.272*** (0.238)	-1.093*** (0.260)	-1.473*** (0.236)	-1.389*** (0.236)	-1.406*** (0.228)	-1.364*** (0.227)	-1.315*** (0.227)
$T_i * S_{flood} * H_i$	1.843*** (0.397)	2.701*** (0.397)	0.143 (0.523)	2.482*** (0.397)	0.410 (0.578)	0.900 (0.580)	2.756** (1.216)	-0.168 (2.088)	-2.791 (1.972)
$T_i * S_{after} * H_i$	-0.525* (0.311)	-0.224 (0.312)	-0.525 (0.394)	-0.572* (0.312)	0.683 (0.429)	0.088 (0.427)	0.870 (0.918)	-1.173 (1.263)	-3.739** (1.514)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A8. Robustness checks.

This table reports the response of total spending to the Chennai flood using alternative samples and methodologies. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it},$$

where Y_{it} is the amount of total spending (in thousand rupees) in all columns except in column 6 where the dependent variable is $\log(Y_{it})$. The dummy variable S_{pre} equals to 1 for pre-flood period (2015M4 – 2015M10), S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). Observations in the first three months (2015M1 – 2015M3) are absorbed to identify the spending patterns. The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Columns 1-6 report estimation results that (i) exclude the demonetization period (2016M11 – 2016M12) from the sample; (ii) include the treatment group only while ignoring all observations in the control group; (iii) replace zero observations with missing value; (iv) use original data without winsorization; (v) base on matched samples where every individual in the treatment group is matched with one individual in the control group using propensity score matching; and (vi) use the logarithmic transformation of the total spending, $\log(\text{Total Spending})$, as the dependent variable. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

	(1) Exclude Demonetization	(2) Treat only	(3) Replace Zero with Missing	(4) Without Winsorization	(5) Matched Sample	(6) logarithmic transformation
$T_i * S_{pre}$	-0.173 (0.207)	1.197*** (0.190)	-0.167 (0.215)	-1.023 (0.682)	-0.415 (0.311)	-0.005 (0.006)
$T_i * S_{flood}$	-3.969*** (0.273)	-2.230*** (0.248)	-4.010*** (0.290)	-5.099*** (0.802)	-4.513*** (0.413)	-0.120*** (0.009)
$T_i * S_{after}$	-0.836*** (0.233)	-2.442*** (0.207)	-1.390*** (0.234)	-2.460*** (0.878)	-1.755*** (0.340)	-0.043*** (0.007)
Constant	34.092*** (0.032)	34.957*** (0.161)	37.857*** (0.033)	35.094*** (0.127)	35.712*** (0.132)	2.988*** (0.001)
Observations	2,272,753	458,333	2,172,629	2,479,398	682,619	2,172,629
R-squared	0.500	0.431	0.481	0.620	0.470	0.477
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table A9. Alternative benchmark periods.

This table reports the average spending response to the Chennai flood using alternative benchmark periods. The sample period is from 2015M1 to 2016M12. The estimation model is:

$$Y_{it} = \beta_{pre}T_i * S_{pre} + \beta_{flood}T_i * S_{flood} + \beta_{after}T_i * S_{after} + a_i + m_t + \varepsilon_{it}$$

where Y_{it} is the amount of total spending (in thousand rupees). The benchmark period is specified in the first row. The dummy variable S_{pre} equals to 1 for the pre-flood period that excludes the benchmark period. S_{flood} equals to 1 during the Chennai flood (2015M11 – 2015M12), and S_{after} equals to 1 after the Chennai flood (2016M1 – 2016M12). The treatment dummy T_i equals to 1 for individuals in Chennai and 0 otherwise. Individual and time fixed effects are included, and standard errors reported in the parenthesis are clustered by consumers. *, ** and *** denote significant at 10%, 5% and 1% level respectively.

Benchmark Period	(1) 2015M1-M2	(2) 2015M1-M4	(3) 2015M1-M5
$T_i * S_{pre}$	-0.079 (0.223)	-0.082 (0.199)	-0.284 (0.196)
$T_i * S_{flood}$	-3.911*** (0.290)	-3.897*** (0.260)	-3.990*** (0.251)
$T_i * S_{after}$	-1.318*** (0.246)	-1.304*** (0.212)	-1.397*** (0.203)
Constant	33.188*** (0.037)	33.186*** (0.029)	33.203*** (0.026)
Observations	2,479,398	2,479,398	2,479,398
R-squared	0.489	0.489	0.489