HOW DO SEVERE RAINFALL SHOCKS AFFECT RURAL INDEBTEDNESS IN INDIA? *

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Abstract

In an era of climate change, rainfall-dependent agricultural households are likely to be the most vulnerable economic class. Despite the significance of credit markets in Indian agriculture, few papers examine how credit access facilitates insurance and consumption smoothing during adverse weather events. Using pooled cross-sectional data, this paper shows that households respond to large-scale floods and droughts by reoptimizing their borrowing behaviour. This change is driven by new borrowing and not by the rollover of old debt. Households borrow to invest into the next crop cycle and dissave to smooth current consumption. While floods are weakly associated with credit constraints at the extensive margin, drought-affected districts observe similar constraints with higher intensity at the intensive margin. Further, I show that cooperative societies provide insurance when floods render informal insurance networks incapable of lending. Heterogeneity analysis suggests that large banks only serve borrowers at the higher end of the asset distribution and in more developed areas. Overall, these results underscore the importance of local credit access and capacity building in enhancing the resilience of rural economies to increasing climate variability.

JEL Classifications: D10, G21, G51, O13, Q12, Q54
Keywords: Household Debt, Climate Change, Crop Vulnerability, Rural Microfinance, Consumption Smoothing, India

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1 INTRODUCTION

Most Indians continue to be engaged in unirrigated agriculture. More than 70% of the population relies directly or indirectly on agricultural employment, and at least 50% of the cultivated area they work on is rain-fed (Carranza (2014); Nordman et al. (2020); Kumar et al. (2014)). There has also been very little growth in the irrigated area throughout the past decade (Mahajan (2017)). Therefore, it is reasonable to assume that Indian agriculture is particularly vulnerable to fluctuations in seasonal rainfall. According to the sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC 2022) [1], extreme weather events including heavy rainfall, heat waves, and dry spells are becoming more frequent and pervasive in south Asia. Amongst these countries, India is particularly vulnerable due to its large coastline and dependence on rainfed agriculture. A report by the World Bank [2] also notes that India's drought-prone area has increased by 57% since 1997, while instances of heavy rainfall have risen by nearly 85% since 2012 [3]. These adverse events directly cause unpredictable changes in crop production, which affect expected earnings at the end of the harvest period as well as the seasonal demand for casual agricultural labour [4]. In particular, landed farmers who face productivity shocks may not employ casual labor during the peak season. This effectively drives down agricultural wages. Other adverse effects of such shocks include an immediate decline in household consumption levels (Amare et al. (2018)), poor nutritional and educational outcomes for rural children exposed to droughts in early life (Shah and Steinberg (2017); Kumar et al. (2014); Mendiratta (2015)), rising gender wage gaps in rain-fed and rice growing regions (Mahajan (2017)), and increases in crime and conflict due to drought-driven consumption shocks (Iyer and Topalova (2014)).

Given imperfect factor markets in the rural parts of developing countries, a long line of literature exists on the assumption that production and consumption decisions are non-separable for agricultural households (Amare et al. (2018); Kebede (2022); Kazianga and Udry (2006)). One way to interpret this is that they don't have access to external smoothing mechanisms such as borrowing. In a *credit-constrained* rural

[1] See the report: https://shorturl.at/bE3EQ.

[2] WB blog: https://shorturl.at/5ayd5.

[3] If global warming continues at this rate, it is expected that 4.5 to 5 crore Indians will risk facing annual coastal floods and similar weather-related disasters by the turn of the century.

[4] See Jayachandran (2006); Mendiratta (2015); Kumar et al. (2014); Dasgupta and Karandikar (2021); Santangelo (2019); Nordman et al. (2020); Iyer and Topalova (2014); Kaur (2019). Also, see Dell et al. (2012) for a summary of the literature on climate shocks.

economy that suffers an agricultural productivity shock, people can either choose to dissave to smooth their consumption and/or supply labour towards more lucrative wage work [5]. Maitra and Tagat (2019) find that rural adults in India diversify into non-agricultural wage work contemporaneous to any shock, with differential effects by gender. Women are more likely to leave educational institutions and increase time spent on domestic duties–an example of dissaving, while men appear to leave casual wage work in public works and spend more time attending educational institutions. On a similar vein, Chuang (2019) shows an increase in both agricultural and non-agricultural wage work when farmers face a negative rainfall shock. Other mechanisms include withdrawing children from schools (Jacoby and Skoufias (1997)), selling productive assets (Rosenzweig and Wolpin (1993)), and marrying off daughters to households outside the proximity of the shock (Rosenzweig and Stark (1989)). This paper relaxes the ex-ante assumption that such households are credit-constrained in the face of income shocks. Credit markets are crucial to the functioning of local economies in rural India. In agrarian contexts, access to credit is critical for investment in productive inputs for the next crop cycle, for the adoption of new technologies such as high-yield crops, and to smooth consumption during the lean season when labour demand is uncertain (Ray (1998)). Credit markets have an even larger role to play when such economies suffer large covariate shocks.

Consider a farmer or a casual wage labourer in agriculture. Conditional on variable rainfall, they can either face a positive or a negative rainfall shock during the cultivation period. Evidence strongly suggests that positive rainfall shocks increase agricultural productivity, thereby reducing credit requirements (Shah and Steinberg (2017); Jayachandran (2006); Kaur (2019)), while negative rainfall shocks have the opposite effect. However, few works acknowledge that asymmetries in the impacts of positive and negative shocks can escalate at the tails of the rainfall distribution. Large floods have been shown to cause severe crop losses in the short as well as the long run, and drastically reduce income and consumption expenditure [6]. Chadha and Nandwani (2022) point out that studying the impact of such natural disasters is important in its own right, given the context of climate change. To that extent, I exploit exogenous variation in the Indian south-west monsoon [7] to analyze the mechanisms driving agri-

[5] They may also supply more labour hours towards agricultural work conditional on a low to moderate rainfall shock. However, as I will point out, this paper deals with extreme shocks.

[6] Lahiri and Biswas (2024) and Patnaik et al. (2019) summarize the literature on flood-related disasters. However, most of the papers are not in the context of rural India.

[7] The south-west monsoon accounts for more than 70% of India's annual rainfall, and is

cultural household liabilities through varying channels of credit. I estimate the direct and differential effects of large-scale district-level floods and droughts on household borrowing behaviour. In doing so, I add to a sparse body of literature that specifically analyzes credit as a smoothing mechanism in the face of severe rainfall shocks.

This paper uses household level data from the All-India Debt and Investment Survey 2019 (AIDIS 2019) to construct a pooled cross-section of rich liability data spanning 2018 and 2019. This allows me to generate variation in agrarian household indebtedness that is contemporaneous to the cultivation period of kharif crops and the south-west monsoon (the months of June to September). District-level data obtained from the Indian Meteorological Department (IMD) website are then used to assign quasi-random rainfall shocks to districts belonging to the 19 major kharif-intensive states. Based on the definition of said shocks, I assume that households are unable to take anticipatory short-term measures to mitigate adverse impacts. However, access to alternate smoothing mechanisms such as crop insurance and cross-district migration may bias the effects downwards. To that extent, I argue that such attenuation bias is unlikely in my context. First, Indian farmers are land-poor [8] and thus risk-averse to the adoption of formal insurance (Biswal and Bahinipati (2022)). Even for those who manage to purchase public insurance, untimely disbursement and corruption at the local level impedes any immediate benefits (Hazell (1992); Skees et al. (1999)). Second, evidence also suggests that rural men largely do not migrate across districts in search of higher wages. (Munshi and Rosenzweig (2016); Foster and Rosenzweig (2001)). A district can be considered as a distinct agricultural market in itself, causing any (within-district) wage differentials to smoothen over time.

The results show a large and statistically significant increase in indebtedness levels for households located in flood districts. Robust to a rich gamut of control variables and state and year fixed effects, this effect is analogous to an alarming **370%** increase in indebtedness levels relative to the average household which doesn't suffer any shock. On the other hand, the effect of droughts is significantly larger but not robust to the inclusion of control variables [9]. The result on floods is in soft contrast [10] to a large body of literature finding positive shocks to be beneficial in the agricultural context

critical for a successful harvest of Kharif crops. See https://shorturl.at/jW3Z9.

[8] Kaur (2019) points out that the median household farm size is 0.9 acres, in the category of what is termed as *marginal farmers*.

[9] The penultimate paragraph of section 4 discusses potential reasons.

[10] Most papers analyze moderate positive shocks. I show that the adverse effects dominate any such benefits when analyzing extreme shocks.

[11]. In this regard, the study that is closest to mine is Lahiri and Biswas (2024); they find that a flood in urban Tamil Nadu significantly increases the incidence of household indebtedness in the post-shock period.

Next, I investigate two channels that could be driving higher household indebtedness on average. These constitute *A*. a fall in the repayment of pre-existing loans at the start of the cultivation period, and *B*. a rise in new household borrowing during the cultivation period, both contemporaneous to a severe rainfall shock. I find that overall indebtedness is driven by new borrowing, and not by the roll-over of older debt. This finding is also contrary to the result that opposing rainfall shocks exhibit symmetric effects (Zimmermann (2020)); I provide evidence to show that the impacts of flood and drought are differential and asymmetric. At the extensive margin, drought-affected households are significantly more likely to become borrowers, with the effect being small and statistically insignificant for flood-affected households. Surprisingly, these trends reverse at the intensive margin. Those flood-affected households which would have borrowed (irrespective of a shock) increase their borrowing by 26.7%, while similar drought-affected households decrease their borrowing by 50.8%.

This result contributes to a small but growing body of literature highlighting the asymmetric impact of differential rainfall shocks on agricultural productivity. For example, Kulkarni (2024) emphasizes the non-linearity of these effects: an extreme shock on either end of the distribution can make rice yields more vulnerable. Using reduced form estimation, the paper further analyzes how such shocks force rural households to reoptimize their borrowing behaviour. Berg and Schrader (2012) point out that flood damage can potentially increase the barrier to entry into credit markets, and Patnaik et al. (2019) empirically confirm this in the context of Chennai. It is possible that some flood-affected households are able to take advantage of pre-existing credit channels, while new credit market entrants in the same district are considerably more credit-constrained. Drought affected-households, on the other hand, appear to be largely credit constrained at the intensive margin. This is potentially driven by the abrupt increase in the demand for credit by new entrants, which drives down the effective supply of loans available to pre-existing borrowers due to higher interest rates.

In order to further disentangle the observed borrowing behaviour, I analyze the distribution of credit agencies supplying novel loans and the purpose for which the

[11]See Zimmermann (2020); Mahajan (2017); Iyer and Topalova (2014); Shah and Steinberg (2017); Maitra and Tagat (2019); Dasgupta and Karandikar (2021); Kaur (2019); Duflo and Pande (2007).

loans are taken. I find that the proportion of non-institutional loans [12] taken by households significantly reduces in flood-affected districts. The effect is predominantly driven by a substitution towards cooperative societies, and an equivalent substitution away from trust loans (loans from friends and relatives). This aligns with research showing that informal loans from friends and relatives form a critical component of rural consumption smoothing and insuring against expected income shocks (Ramsawak (2022); Banerjee et al. (2015); Islam and Nguyen (2018)). Such loans are attractive because of their collateral-free and/or interest-free nature (Munshi and Rosenzweig (2016)). However, local insurance networks are particularly susceptible to unexpected and large-scale covariate shocks. This is observed as a substitution away from trust loans, as mentioned before. In terms of the alternative, a substitution towards cooperative societies is reassuring; even though households are becoming more indebted, this does not necessarily translate into an excessive interest burden (high-interest loans from moneylenders/landlords). The evidence on the benefits of microcredit access in developing countries is expansive. For example, Islam and Maitra (2012) find that Bangladeshi households with access to microcredit do not need to sell livestock to get insured against health shocks. In the Indian context, cooperative societies play a key role in local institutional lending. Local knowledge minimizes the likelihood of adverse selection, and therefore, they directly compete with moneylenders on a risk-sharing basis (Ray (1998)). With respect to the effects of droughts, I find the coefficient on trust loans to be positive but imprecisely estimated. This suggests that, unlike a flood, a droughts doesn't necessarily impede local insurance networks.

This paper also contributes to a large body of literature on consumption smoothing. In contrast to the dominant paradigm that agricultural households borrow to smooth current consumption (Jayachandran (2006); Banerjee et al. (2015); Ray (1998)), I find that they borrow to invest into the next crop cycle instead. This investment is fuelled by a substitution away from consumption loans for both, flood, and drought-affected districts. What could this mean for marginal farmers? While microfinance is beneficial to an extent, my results indicate a disproportionate dependence on the succeeding harvest. This borrowing could be in ex-ante anticipation of future uncertainty and a consequence of risk aversion. Regardless, dissaving to smooth current consumption is likely to leave agricultural households worse off during the lean season.

Lastly, I show that the differential effects are heterogeneous. Patnaik et al. (2019)

[12] Loans from professional/agricultural moneylenders, friends and relatives (trust loans), and landlords.

posit that severe floods affect all parts of the income distribution, implying a relatively uniform effect throughout. Accordingly, I find that the effects of floods are not moderated to the same extent as the ones of droughts. This is also plausible because India has historically faced more droughts than floods (Mahajan (2017)). Despite having controlled for a variety of district level covariates, there may exist large variation in ex-ante drought preparedness across districts. Overall, a household with higher debt that is land-poor and lives in a less irrigated district is likely to bear the highest burden of credit constraints. Such households at the lower end of the wealth distribution are disproportionately catered to by cooperative societies, while the remaining households borrow from large institutional banks such as Scheduled Commercial Banks and Regional Rural Banks (particularly in more developed districts). Irrigation infrastructure significantly moderates this relationship, as empirically validated by Santangelo (2019) and Maitra and Tagat (2019). Drought-affected households in more irrigated districts observe less borrowing as they are insulated against a decline in crop productivity. According to the evidence, it is also possible that non-farm diversification cushions against the adverse effects of rainfall shocks. This can bias the coefficients downwards. However, I show that shock affected districts that are feasible for non-farm enterprises (as proxied by literacy rates) observe higher borrowing than their non-shock counterparts. If it is the case that the shock coefficients are biased, one would expect the interaction terms to be negative.

The remainder of this paper is structured as follows: Section 2 discusses the data, and summarizes key variables and relationships. Section 3 discusses causal identification and describes the empirical specifications used. Section 4 presents the main results along with a number of extensions discussing key channels. Section 5 presents and discusses four heterogeneity results, and section 6 concludes.

2 DATA AND DESCRIPTIVE STATISTICS

2.1 RAINFALL DATA

The Indian Meteorological Department (IMD) annually releases data on Indian rainfall in its flagship report titled *Rainfall Statistics of India* [13]. The data span all of India over the period of 1961-2025 and are prepared at numerous levels of temporal aggregation. To construct the shock variables, I make use of the fact that the report provides

[13]The data and all definitions used are available at https://shorturl.at/QQfVw and https://shorturl.at/fTAZs respectively.

rainfall deviations from normals that are aggregated on a seasonal basis. Deviations are defined as the % departure of actual observed rainfall from its long-run average *within* a particular district [14]. Figure 1 presents the histograms of the distribution of deviations from average long-run rainfall in the sample, by year. There is a lot of variation in the deviation scores across time, with 2019 exhibiting a more positively skewed distribution (higher flood occurrence) as compared to 2018. The distribution appears to slightly shift rightward and achieve higher peaks in 2019, indicating that drought occurence has fallen. On a similar vein, Chadha and Nandwani (2022) find that districts are far more likely to face positive shocks than negative ones in recent years.

Using 2018 and 2019 data on south-west monsoon deviations that average over June to September, I generate dummy variables according to the category of deviations termed as **Large Excess**: Rainfall deviations greater than or equal to 60% (of the within-district historical average) are labelled as *Flood* and deviations lesser than or equal to -60% are labelled as *Drought* respectively. Note that these cut-offs likely correspond to severe disasters as per the IMD definition. These definitions are similar to Chuang (2019) and Sekhri and Storeygard (2013), although they do not dichotimize the continuous deviations measure. Figure 2 illustrates the percentage of districts affected by floods and droughts across 2018-19. About 6% of districts are affected by severe floods while 1.3% of the districts suffer an analogous drought. While the number of affected districts is quite marginal, it is still a worthwhile endeavour to find out how rural households (differentially) cope with severe rainfall shocks. Also note that I am not comparing the extent of shocks across districts; some districts are more prone to extreme weather than others. Comparing within a district over time ensures that the weather shocks are district-specific.

Indian rainfall varies extensively over time and space. Over 75% of the annual rainfall is received in the four months of June to September (south-west monsoon). This period of rainfall is especially critical for a successful harvest of kharif (water-intensive) crops, the cultivation of which is typically done from June to July. Harvest dates vary across states, but can be expected to begin in November and conclude by early March the following year [15]. Within kharif crops, rice is the most commercial food grain domestically and internationally as India accounts for close to 26% of global

[14] Normals are based on rainfall records during the period 1961-2010 for the year 2019, and 1951-2000 for the year 2018 respectively. Also, a district is the smallest administrative unit for which data are available.

[15] See https://rb.gy/b7075s for state-specific data.

rice production [16]. Therefore, I limit the states in the sample to the 19 major rice-producing/kharif states [17].

2.2 AIDIS 2019 DATA AND OUTCOME VARIABLES

I source outcome variables related to rural households' financial liabilities from the NSS 77th round of the *All-India Debt and Investment Survey 2019 (AIDIS 2019)* [18]. Conducted decenially by the National Sample Survey Organisation (NSS), the survey provides a cross-sectional account of the financial status of the household sector in India; this includes micro-data on assets and liabilities, investment and capital expenditure, particulars of credit operations including credit agencies, purposes of borrowing, interest rates, as well as demographic characteristics for both urban and rural India. Collected through a multi-stage stratified random sampling process, the raw data encompasses 5,940 rural villages and 3,995 urban blocks, surveying 69,455 rural households and 47,006 urban households across two visits: Visit 1 (Jan-Aug 2019) and Visit 2 (Sep-Dec 2019) from the same set of sample households. This implies that each household was surveyed twice.

For the purpose of this paper, I consider a sample of rural households that are either self-employed in agriculture or perform casual agricultural labour. As discussed before, these households are the most likely to be affected by a weather-induced agricultural income shock. To generate my key outcome variable, I exploit the fact that within either visit the liability position of a household was ascertained with reference to a fixed date: 30th June 2018 for households surveyed in Visit 1 and 30th June 2019 for households surveyed in Visit 2. Taking the difference between household indebtedness as of the date of survey and as of the reference date (depending on the visit number) allows me to generate temporal variation in household indebtedness. To ensure that this variation lies contemporaneous to the South-West monsoon, I further restrict the sample to the months of Jan-Mar and Oct-Dec respectively. The result is a pooled cross-section of 25679 households surveyed across 2018 and 2019 [19]. The rationale is as follows: when

[16] See https://shorturl.at/9HEvf.

[17] I partially follow Mahajan (2017) in making this selection, the states are as follows: Punjab, Uttarakhand, Haryana, Rajasthan, Uttar Pradesh, Bihar, Assam, West Bengal, Jharkhand, Orissa, Chhattisgarh, Madhya Pradesh, Gujarat, Maharashtra, Andhra Pradesh, Karnataka, Kerala, Tamil Nadu, and Telangana.

[18] See the official report here: https://rb.gy/jio486.

[19] Note that the survey itself was only conducted in 2019; however, for visit 1 households, the endline data was used to back-calculate indebtedness as of 30th June 2018. Additionally, I am unable to create a panel for the households due to the sample restrictions imposed.

the sample is restricted to the first three months, households surveyed in visit 1 happen to provide endline data around the time of harvest (Jan-Mar 2019) and baseline data just as cultivation begins in June 2018. By definition, the cultivation period runs parallel to the 2018 South-West monsoon. Likewise, visit 2 households provide endline data during the (Oct-Dec 2019) harvest period with their baseline being 30th June 2019. Although there are bound to be inconsistencies, I argue that on average these data are able to capture variation in household indebtedness contemporaneous to severe rainfall shocks.

The first two panels of Table 1 summarize the key outcome variable and standard household characteristics at the baseline (that I merge with the master data using other Blocks from AIDIS 2019) [20]. Averaging across the sample, the difference in household level indebtedness between the date of survey (Oct to Mar 2018/19) and 30th June 2018/19 is quite unsubstantial, standing at Rs. 3135. Baseline household level indebtedness is Rs. 1,42,619 and likely captures the pre-cultivation expenditure on buying farm inputs.

Motivating my hypothesis, Table 2 shows that the key outcome variable (Row 1) burgeons to much larger differences when stratified by rainfall shock status. Compared to the control value of Rs. 1569, the difference is Rs. 17,544 and Rs. 36,602 in flood-affected and drought-affected districts respectively. Row (2-4) refer to additional outcome variables that are meant to uncover the channels driving the results in Row 1: overall indebtedness contemporaneous to a severe rainfall shock can constitute a rise in novel borrowing (post 30th June 2018/19), and/or a fall in the repayment of those historical loans the household is indebted on already (as of 30th June 2018/19). It is also possible that novel borrowing is driven not just by existing borrower households taking more loans (intensive margin) but also by more households entering the credit market itself (extensive margin) [21]. Accordingly, the outcome in Row 2 is a dummy variable that captures *any* novel borrowing, and Row 3 shows the absolute amount of novel borrowing (conditioned on taking a loan) stratified across shock status. I find that drought-affected households take more loans at the extensive margin, while households affected by either shock borrow more at the intensive margin (much higher for flood-affected households). Interestingly, Row 4 shows that the repayment of historical loans does not change much across shock status.

Table 3 summarizes novel household borrowing, stratified across credit agencies,

[20] Block 3, 4, and 5 respectively. I source the indebtedness data from Block 12.
[21] Section 4.1 elaborates on this further.

purpose of borrowing, and shock status. Each outcome variable refers to the loan amount taken from that particular credit agency/for that purpose [22] as a proportion of the total novel borrowing amount. In terms of institutional loans, I find a moderate substitution towards Scheduled Commercial Banks for households facing either shock, a large substitution towards cooperative societies for flood-affected households, and a similar movement towards Regional Rural Banks for drought-affected households. Non-institutional loans do not seem to differ much across shock status, except for a sharp drop in trust loans (friends and relatives) for flood-affected households.

Lastly, in terms of the purpose of borrowing, households borrow more for agricultural investment and less for consumption purposes across both shocks.

3 EMPIRICAL STRATEGY

Ramsawak (2022) and Chuang (2019) consider two ways by which climate (rainfall) shocks can affect household behaviour: **direct** and **adaptive**. The direct impacts are short-term in nature and often cause physical damage such as the loss of immovable assets, crop failure, and can be life-threatening if severe enough. On the other hand, adaptive mechanisms refer to the expectations rural households develop by virtue of their residence in climate-risky areas. They can potentially into account historical information when making ex-ante decisions aimed at mitigating the effects of such shocks. This is a threat to my identification. However, I argue that my definition of rainfall shocks (as representative of severe floods and droughts) nullifies this concern to a great extent. My estimation strategy hinges on the fact that severe rainfall shocks are *quasi-random* events with spatial and temporal variation. Large *within-district* deviations in rainfall from the historical mean are by definition unpredictable, even in riskier districts [23]. This procedure also plausibly allows for the exogenous assignment of shocks after controlling for fixed effects and household/district level characteristics as described below. Similar to Maitra and Tagat (2019), I assume that weather forecasts

[22] In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, cooperative society, Bank-linked Self Help group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing any non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. In order, the purpose categories are as follows: Agricultural loan (revenue and capital expenditure in farm business), Consumption loan (other household expenditure), House loan, Medical loan, Education loan, and Repayment of debt respectively.

[23] The historical mean involves data as recent as 2010: it captures any novel and contemporary climatic trends that households may have taken into account.

and/or previous information do not influence ex-ante financial behavior, thus allowing me to estimate the ex-post and short-term causal impact of severe weather shocks on household borrowing behaviour.

A formal model is described as follows:

$$Y_{hdv} = \beta_0 + \beta_1 \xi^{+}_{dv} + \beta_2 \xi^{-}_{dv} + \beta_3 H_{hd} + \beta_4 D_d + \beta_5 \alpha_s + \beta_6 \phi_v + \epsilon_{hdv} \tag{1}$$

where Y_{hdv} is the outcome variable for household h in district d surveyed in visit number v. ξ^{+}_{dv} and ξ^{-}_{dv} are treatment dummy variables as defined in section 2.1. Conditional on exogeneity, β_1 and β_2 capture the short-term causal effects of contemporaneous floods and droughts on borrowing behaviour. Note that the non-linear nature of eq(1) allows me to check for differential effects by type of shock. A similar definition is widely used in the literature. H_{hd} and D_d are vectors referring to baseline household and district level characteristics [24] respectively, as summarized in table 1. District level economic/infrastructure characteristics ensure that the treatment estimates are not confounded by access to non-farm wage income and other smoothing mechanisms such as access to irrigation, and transport infrastructure (Jayachandran (2006); Chuang (2019)). Additionally, following Duflo and Pande (2007), I control for geographical characteristics that predict the likelihood of dam construction across districts [25]. Other covariates are added to make the treatment effects more precise. I also include state fixed effects α_s and visit fixed effects ϕ_v to control for systematic time-invariant differences across states and any country wide shocks to the outcome variable that affect all districts simultaneously within a visit. Heteroscedasticity robust standard errors are clustered at the district level to allow for correlated errors within a district. Finally, ϵ_{hdv} denotes idiosyncratic errors specific to each household.

To capture heterogeneity effects of floods and droughts, I further estimate OLS regressions of the following type:

$$Y_{hdv} = \beta_0 + \beta_1 \xi^{+}_{dv} * X + \beta_2 \xi^{-}_{dv} * X + \beta_3 H_{hd} + \beta_4 D_d + \beta_5 \alpha_s + \beta_6 \phi_v + \epsilon_{hdv} \tag{2}$$

where the specification is identical to eq(1) but the treatment dummies are interacted with the heterogeneous variable of concern X [26]. They are as follows: baseline

[24] *The Spatial Database for South Asia* provides district level controls from the 2011 census of India. See the metadata here: `https://rb.gy/5cf0cj` as compiled by the World Bank. The lower half of table 1 summarizes and categorizes them accordingly.

[25] Maitra and Tagat (2019) find dams to have large insulating effects against rainfall shocks.

[26] X itself is added also to either H_{hd} or D_d depending on its level of aggregation.

household level indebtedness (as of 30th June 2018/19), land owned, and district level measures of area irrigated (as a % of total) and literacy rate.

Although I do not test it explicitly, I assume that the key pathway mediating this reduced form estimation is a change in agricultural productivity (Jayachandran (2006); Mendiratta (2015); Kumar et al. (2014); Santangelo (2019); Nordman et al. (2020); Iyer and Topalova (2014)). To that extent, I propose three ways in which severe rainfall shocks can affect households' financial liabilities: an expected fall in the agricultural sales of those who are self-employed in agriculture, a contemporaneous fall in the demand for casual agricultural labour (and thus wages), and lastly, the direct effects referred to at the beginning of this section. Regardless of which mechanism is at play, I hypothesize that β_1 and β_2 will be **positive**, provided that households face minimal credit constraints. This is a point of diversion from previous literature which consistently finds that positive shocks improve agricultural productivity. Additionally, I expect the differential impacts of floods and droughts to be **asymmetric** by nature. This is alluded to by Kulkarni (2024), which finds that extreme wet and dry events significantly increase the vulnerability of crop yields (further highlighting non-linear effects).

3.1 OTHER THREATS TO IDENTIFICATION

State fixed effects ensure that β_1 and β_2 are not biased by specific soil types, cropping patters, cultural norms, and institutions that differ across states (Carranza (2014)). However, they can be biased towards 0 [27] if there is an endogenous household-level response to mitigate the impact of these shocks other than through the channels considered. Inclusion of district-level characteristics mitigates this issue to a large extent, but not entirely. One possibility is that households temporarily migrate to a low-shock district and access a less constrained labour market to smooth their consumption. However, this is unlikely because cross-district mobility in rural India is very limited (Mahajan (2017); Foster and Rosenzweig (2001); Iyer and Topalova (2014)). Districts can be considered to be distinct agricultural markets on their own [28]. Another source of downward bias is access to public crop insurance. If well implemented, risk-averse

[27] Nonetheless, a bias towards 0 means that the treatment effects are underestimating the true impact; they provide a lower bound.

[28] Jayachandran (2006) finds that landless workers are more likely to out-migrate in response to a weather shock. As a robustness check, table A2 estimates triple interactions to see whether landless households reduce their borrowing in districts with high road or station density contemporaneous to a rainfall shock. The interaction terms are insignificant for the same.

rural households are likely to be under lower financial stress and less incentivized to borrow more and/or allow previous debt to roll over. Tiwari (2022) [29] points out that such insurance is usually not available in the Indian context. Even if we assume otherwise, small and marginal farmers in India do not adopt formal insurance. This is largely driven by their inability to finance the same, as well as their poor financial literacy (Biswal and Bahinipati (2022)). Close to 70% of this sample consists of marginal farmers, and therefore the prior argument is applicable here [30]. A third and more likely possibility is that households diversify into non-farm employment within the district itself, as discussed before. I test for this implicitly in table 11 of the heterogeneity section.

4 MAIN RESULTS

Table 4 presents the results of the main specification as portrayed by eq (1) and captures the causal relationship between differential rainfall shocks and the difference in household level indebtedness between the date of survey (Oct to Mar 2018/19) and 30th June 2018/19. To keep the presentation clean, I only report the exogenous variables of interest, i.e., *Flood* and *Drought* respectively. Column (1) begins with an uncontrolled OLS regression with each corresponding column capturing additional covariates: Column (2) adds state and visit fixed effects, column (3) adds household level covariates, and column (4) is inclusive of a rich set of district level controls. Finally, column (5) adds the baseline amount of household level indebtedness (as of 30th June 2018/19) as an additional, potentially endogenous, predictor [31]. The table also reports an F statistic testing the null hypothesis that the shock coefficients are equal.

Results indicate a large and statistically significant increase in indebtedness levels for households located in flood districts, and the coefficient remains largely robust to the inclusion of fixed effects and sets of household/district level controls. Furthermore, column (5) enables me to reject the possibility that endogenous baseline household indebtedness contaminates the causal pathway. The inclusion of this predictor substantially increases the precision of the treatment effects (p values for both coefficients

[29] Preprint available at https://rb.gy/1zey4r.

[30] A cultivator with a landholding of 2.5 acres (1 Ha) or less. I follow the definition provided in this official document on NAIS: https://rb.gy/oaor6y.

[31] I expect the shock variables to be orthogonal to baseline household indebtedness on identification grounds. However, the values in this particular specification affects the difference outcome by construction. Therefore, the coefficients in Column (5) should be cautiously interpreted.

fall by more than 10 percentage points). However, I continue with column (4) as my main specification and treat the prior as an upper bound on said effect. On average, a flood-affected household incurs a higher indebtedness of Rs. 15,405 over a non-shock household at the end of the survey period. Relative to the mean household indebtedness level of Rs. 3275 over the cultivation period, this represents a shocking 370% increase in the same. Depending on the kind of interest burden that the households in this sample face, this result is in contrast to a long array of literature [32] suggesting that positive shocks improve rural outcomes [33]. In comparison to a similar research design, albeit in the context of urban Tamil Nadu, Lahiri and Biswas (2024) find that a flood significantly increases the incidence of household indebtedness in the post-shock period.

Alternatively, I find that while the effect of drought is considerably larger, it is not robust to the inclusion of fixed effects and further controls. This is likely because India has historically faced many more droughts than floods (Mahajan (2017)). Therefore, these noisy estimates potentially capture a large variation in ex-ante drought preparedness across districts, despite having controlled for a variety of district level covariates. The effect strongly varies, but it is insignificant on average. Additionally, while the large effect size is indirectly supported by literature [34], this sample may be underpowered to precisely detect it due to a much smaller number of drought-affected households (thereby increasing the standard error of the estimate). This can be attributed to a reduction in large-scale drought events after 2018, as discussed in section 2.1.

Comparing differential effects, the F statistic testing the equality of shock coefficients fails to reject the null when averaging over the full sample.

4.1 DRIVING CHANNELS

Conditional on falling agricultural productivity, there are two ways by which household indebtedness at the date of survey can be greater than its baseline value before the onset of the South-West monsoon. This section attempts to disaggregate the con-

[32] See footnote 11.

[33] Amongst children and women, one such channel is substituting away from investing time in education and towards agricultural employment. However, a caveat is that this effect is conditional on an expected increase in crop productivity due to positive rainfall shocks. This is likely not the case here because of the way the shocks are defined: the deviation is extreme to the point of potentially reducing the marginal returns to a positive shock.

[34] There is clear consensus that droughts represent a rural income shock through the channel of reduced crop productivity, which is likely to induce borrowing when averaged over all kinds of households.

tributing effects of each channel to overall indebtedness contemporaneous to a severe rainfall shock, i.e., a rise in novel borrowing (post 30th June 2018/19), and/or a fall in the repayment of older loans (as of 30th June 2018/19). Furthermore, this distinction gives rise to another dimension of inquiry. A household that was previously capable of out-of-pocket repayment may be induced to become a *borrower* in the wake of a flood or a drought. This constitutes novel borrowing at the extensive margin, while households that would have borrowed in spite of the shock may increase their borrowings at the intensive margin. The following subsections perform these estimation exercises, respectively [35].

4.1.1 EXTENSIVE MARGIN

In Table 5, I estimate the probability of a household borrowing at the extensive margin using a Linear Probability Model. The outcome is a dummy variable capturing *any* novel borrowing, and is the same across the columns. Column (1) and (2) both include state and visit fixed effects along with a complete set of household and district level covariates. In addition, column (2) includes potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a covariate.

As per the results, there is no evidence to suggest that households in flood-affected districts borrow at the extensive margin: the effect size is small and imprecisely estimated. On the other hand, column (1) indicates that a drought-affected household is 12% more likely to become a *borrower* and this effect is significant at the 5% level. The effect size remains qualitatively similar upon inclusion of baseline indebtedness.

I also reject the null that the shock coefficients are statistically the same at conventional levels of significance.

4.1.2 INTENSIVE MARGIN

Table 6 performs a similar estimation exercise, but separately after sub-sampling by households that take *any* new loan contemporaneous to a severe rainfall shock and households that do not. These correspond to the following outcome variables: for the prior, the absolute amount of novel borrowing, and for the latter, the absolute amount of older loans repaid. Clearly, this form of sub-sampling gives rise to endogeneity concerns, however, I do not attempt to compare across households exhibiting different ex-post behaviour. The idea is to make within-sample comparisons at the intensive

[35] See section 2.2 for more details.

margin such that unobservables are kept at a minimum with the inclusion of a rich set of covariates.

Columns (1)-(4) all include state and visit fixed effects along with a complete set of household and district level covariates. In addition, column (2) and column (4) include potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a covariate [36].

Results indicate that on average, overall household indebtedness in flood-affected districts is driven by novel borrowing at the intensive margin. Although slightly imprecise, column (3) finds that novel borrowing increases by Rs. 25,791. Surprisingly, the drought coefficient shows an unusually large and statistically significant decline in the opposite direction; households that borrow contemporaneous to a drought decrease their borrowing by Rs. 56,214 as compared to non-shock households that borrow during the same time. Both the results remain qualitatively similar in column (4) [37], and I strongly reject the null that the shock coefficients are statistically the same at the 1% level.

Columns (1)-(2) indicate that falling repayment is unlikely to drive overall household indebtedness in either shock-affected district. The coefficients, albeit negative, are much smaller and imprecisely estimated. Taken together with the extensive margin result, it is now clear that the impact of floods and drought on household indebtedness is asymmetric. This result is in contrast to Zimmermann (2020), which finds symmetric impacts of positive and negative shocks in the context of rural educational enrollment. Drought-affected households are more likely to borrow, but the incremental loans are much smaller in size as compared to non-shock households [38]. Conversely, flood-affected households borrow more entirely at the intensive margin.

4.2 SOURCES OF NOVEL BORROWING

Having established that overall household indebtedness is largely driven by novel borrowing contemporaneous to shocks, this section attempts to characterize the distribution of credit agencies that households borrow from. If flood-affected households are

[36] While the treatment effects are unbiased, the endogeneity concerns remain for interpreting other control variables. Accordingly, I refrain from interpreting any of those coefficients.

[37] Approximately 54% of the households in this sample have 0 baseline indebtedness. Therefore, it is clear that including the baseline value as a predictor is prudent in terms of explained variation.

[38] This variation likely contributes to the insignificance of the drought coefficient in the full sample regressions.

forced to take incremental loans from agricultural/professional moneylenders because of credit constraints, exorbitant interest rates are likely to drive indebtedness at the date of survey. Despite such rates, exploitative credit agencies continue to be attractive because of flexible collateral requirements and repayment clauses. Alternatively, it is also possible that households take a larger volume of loans from institutional sources of credit. However, I don't expect this to be the case. Rural land is a major asset that serves as institutional collateral and I establish before that a large proportion of this sample consists of marginal farmers. The process of taking a loan from large institutional sources is also long and burdensome. Therefore, it is reasonable to assume ex-ante that households are constrained in terms of collateral requirements.

Table 7 performs the aforementioned estimation exercise. Columns (1)-(7) refer to institutional sources of borrowing while columns (8)-(12) refer to non-institutional sources. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, cooperative society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing *any* non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. Columns (1)-(12) all include state and visit fixed effects along with a complete set of household, and district level covariates, and baseline household indebtedness (as of 30th June 2018/19) as a predictor.

To begin with, the proportion of non-institutional loans taken by households significantly reduces by 9 percentage points in flood-affected districts. This effect is primarily driven by two factors: a decrease in the proportion of trust loans from relatives and friends by 7 percentage points and an increase in the proportion of loans taken from cooperative societies by 7 percentage points. Given that these point estimates are almost identical but in opposite directions, they support the broad trend of substitution away from trust loans and towards loans from cooperative societies.

A plethora of previous literature has established the fact that informal social networks including friends/relatives and caste-based insurance networks play a critical role in supplying credit within Indian rural economies. Particularly during the lean season when there is a lack of demand for agricultural labour, there is evidence to show that households borrow for the purpose of consumption smoothing and insuring against expected income shocks (Ramsawak (2022); Jayachandran (2006); Ray (1998); Banerjee et al. (2015)). Harvest failure also induces immediate borrowing to smooth consumption against higher expected earnings in the future. In this context, informal insurance

is attractive because the loans are often collateral-free and/or interest-free depending on the lender-borrower relationship. Alternatively, lenders also share a lower risk burden in this arrangement because close social proximity enhances the effectiveness of endogenous enforcement (Munshi and Rosenzweig (2016)). Table 3 confirms this trend: I find that the largest fraction of novel borrowing (approximately 20%) in non-shock districts comes from Friends and Relatives, the same as Scheduled Commercial Banks and closely followed by Professional Moneylenders. However, by definition, these insurance networks can get overwhelmed when there is a correlated shock across the village or even beyond (Mahajan (2017); Ray (1998)) [39]. Given this context it makes sense that households substitute away from trust loans in flood-affected districts; they are constrained by the fact that the entire social network suffers the same shock which reduces their lending ability. This effect is likely to be more pronounced in districts highly dependent on agriculture and with fewer avenues for non-farm employment [40].

Coming to the next key result in flood-affected districts, a substitution towards cooperative societies is reassuring, but not too surprising. There is a common consensus about the fact that large financial institutions such as Scheduled Commercial Banks and even Regional Rural Banks are not informationally equipped to cater to rural credit requirements [41]. Solving this issue to an extent, cooperative societies are usually in direct contact with rural borrowers at the local level, minimizing information asymmetries and reducing their lending risk. This circles back to the idea of community-based networks (spots are largely reserved for members of the *in-group*), which often foster trust and subsequently drive norm-based endogenous enforceability of repayment [42]. Cooperative societies also lend the largest number of interest-free loans compared to other credit agencies.

All other flood coefficients appear to be very small, barring Scheduled Commercial Banks, and statistically insignificant. This suggests that the novel debt burden acquired by households is not necessarily exploitative. However, there is also no evidence to

[39] Although there are bound to be heterogeneities in the amount of rainfall across villages within a district, I assume that villages in the lower deciles of the rainfall distribution are not immune to the shocks. Maitra and Tagat (2019) argue that such aggregation is reasonable since most districts in India are small administrative units.

[40] Carrying forward this logic, the coefficient for trust loans is likely underestimating the negative effect found; this is because the category of friends and family provided in this data undercounts any within-caste transfers that are equally susceptible to a district-wide flood.

[41] See https://shorturl.at/8hUKS. Evidence also suggests that the Indian banking sector is ill-equipped to handle the financial risks attributed to climate change.

[42] Reassuringly, using older rounds of AIDIS data, Pradhan (2013) finds that cooperative societies have over time become an important credit agency serving the rural sector.

conclude that borrowing from moneylenders has reduced. Alternatively, in drought-affected districts, I find small substitutions away from Cooperative Banks and Financial Corporations. There also seems to be a large substitution of 8 percentage points towards Regional Rural Banks, although the coefficient is imprecisely estimated.

Taken together, these results provide some insight into the kind of asymmetric impacts faced by households that force them to reoptimize their borrowing behaviour. Floods are correlated shocks that, given enough intensity, do more *short term* damage than just reducing crop productivity [43]. Lahiri and Biswas (2024) hypothesize that floods can cause widespread damage to property and immovable assets, and this phenomenon is empirically tested by Patnaik et al. (2019) in the context of Chennai floods. They find that households are likely forced to borrow in the post-flood period. One piece of evidence corroborating my claim is that households do not borrow at the extensive margin in flood-affected districts. Flood damage can potentially increase the barrier to entry into credit markets, while households having pre-existing credit channels are not as constrained (Berg and Schrader (2012)). On the other hand, droughts are often considered to be slow-onset disasters with crop damage being the most significant impact. Although statistically insignificant, the drought coefficient for trust loans switches signs while retaining some magnitude. This means that the lending ability of rural insurance networks remains unhindered contemporaneous to a drought, but not to a flood. This particular empirical pattern is indirectly referenced in Ramsawak (2022); they find that households facing lower-than-average rainfall levels invest more in family/caste-based networks, with the opposite being true for their higher-than-average counterparts.

4.3 PURPOSE OF NOVEL BORROWING

As discussed before, rural households largely borrow (or draw upon savings) for the purpose of consumption smoothing when there is a negative shock to crop productivity, and a subsequent drop in the demand for agricultural labour. However, the empirical evidence is mixed in the context of severe rainfall shocks. Beyer et al. (2022) find a decrease in consumption loans and an increased borrowing for housing and medical purposes after the 2018 Kerela floods. In contrast, Patnaik et al. (2019) show a sharp increase in consumption for households suffering floods in Chennai, driven by dissaving and reduced purchase of assets. Analyzing a more representative sample, Maitra and

[43] See section 3 for more details.

Tagat (2019) find no effect of contemporaneous rainfall shocks on household consumption; households appear to insure themselves by varying their labour allocations across various activities. I explicitly test this in table A1. Columns (1)-(6) refer to different purposes of novel borrowing. In order, the purpose variables are as follows: Agricultural loan (revenue and capital expenditure in farm business), Consumption loan (other household expenditure), House loan, Medical loan, Education loan, and Repayment of debt respectively. All columns include state and visit fixed effects along with a complete set of household, and district level covariates, and baseline household indebtedness (as of 30th June 2018/19) as a predictor. The results show a large and statistically significant substitution towards agricultural loans in flood-affected districts. The drought coefficient is very similar but marginally insignificant at conventional levels ($p = 0.103$). Furthermore, this agricultural investment appears to be fuelled by a significant decrease in the intake of consumption loans in both flood and drought-affected districts.

This makes sense because, in order to avoid a double burden, credit-driven rural consumption smoothing can only take place against higher expected earnings in the harvest season. Having observed a contemporaneous flood or drought, households appear to prefer credit for investment (for the next crop season) and likely dissave in order to meet current consumption needs.

5 HETEROGENEOUS EFFECTS

Main results are likely averaging over significant heterogeneities in novel borrowing [44]. If they exist, then the average treatment effects found in section 4 are potentially attenuated and provide lower bounds for the said effects. This section accounts for four such heterogeneities with respect to total novel borrowing and its disaggregation into various sources of credit. Based on previous results, it is reasonable to assume that more novel borrowing implies fewer credit constraints overall. All the tables use the specification described in eq (2), with the addition of total novel borrowing as an outcome variable in column (1). To define X in each specification, I generate a dummy variable based on the median value in the sample [45].

[44] I limit this analysis to novel borrowing as it is clear that borrowing is affected much more by rainfall shocks in comparison to repayment.

[45] Note that despite the addition of various controls, the moderator variables themselves may not be causally identified.

5.1 BASELINE INDEBTEDNESS

Having a higher baseline level of debt makes a household a risky borrower (Ray (1998); Lahiri and Biswas (2024)). To that extent, I expect to find that more indebted households become credit-constrained when they face a severe rainfall shock. Table 8 provides some evidence for this: the interaction terms are both negative, but imprecisely estimated. However, it is apparent that the effects of droughts are moderated by baseline debt to a larger extent. I find a large and significant substitution away from Regional Rural Banks for more indebted households. This is not surprising: economic theory suggests that large institutional lenders are risk-averse in the face of adverse selection, and therefore unlikely to fund such households. Some of this credit constraint is alleviated by cooperative societies, but they may also not have enough capacity or willingness to take on excessive risk burden.

5.2 LAND OWNED

Evidence suggests that land owned is a strong proxy for wealth in rural households and land-poor households are more vulnerable to agricultural income shocks (Chuang (2019); Nordman et al. (2020); Kumar et al. (2014); Amare et al. (2018)). Landed households are potentially able to offset adverse shocks as they have a greater ability to dissave and temporarily smoothen their consumption. Alternatively, as established before, land also serves as collateral against which they can borrow [46]. In this manner, land-poor households suffer a dual burden of an inability to dissave as much and also face credit constraints.

Table 9 gives some insight in this regard. Flood-affected but more landed households appear to borrow less, but the interaction term is statistically insignificant. Looking at credit sources, landed households significantly substitute away from trust loans and towards cooperative banks; this makes sense because wealthier households are in theory less reliant on social networks. Interestingly, land-poor households in drought-affected districts households are far more credit-constrained and the coefficient is significant at the 1% level. This is perhaps attributable to the fact that droughts are dry disasters: crop productivity monotonically decreases with a decrease in rainfall. On the other hand, the effect of wet disasters intimately depends on the extent of the rainfall deviation [47]. A more surprising finding is a large and significant substi-

[46] See https://shorturl.at/33Xqy.

[47] In almost all cases in the literature, this differential effect has been shown to exist.

tution towards professional moneylenders for drought-affected and landed households, in combination with falling trust loans. I speculate that while they can borrow from institutional sources, moneylenders are likely to offer them more flexible terms without a time-consuming and burdensome transaction process [48].

5.3 IRRIGATION

One can expect that land area irrigated in a district plays a key role in moderating the differential effects of rainfall shocks on agricultural income, particularly for droughts. Efficient usage of irrigation technology can insulate farms against rainfall shocks to a great extent, preserving crop productivity. On a similar vein, Santangelo (2019) finds that the effect of rainfall on agricultural productivity is strong only in districts having less than 20% of the cultivated area irrigated.

Indeed, Table 10 shows that area irrigated greatly moderates the effects of droughts on novel borrowing, particularly for institutional sources of credit. The sum of the drought coefficient and its interaction in column (1) is negative and statistically significant. This means that while households in drought-affected but irrigated districts borrow less than their non-shock counterparts, they are far less credit-constrained than households in less irrigated districts also suffering a drought. It is apparent that irrigation infrastructure potentially serves as an ex-ante mechanism against droughts (Maitra and Tagat (2019)). Additionally, the latter type of households are significantly less likely to borrow from large institutional credit agencies such as Scheduled Commercial Banks and Regional Rural Banks, cooperative societies being their largest source of novel borrowing. Additionally, despite much weaker moderation effects, I find that flood-affected households substitute away from Professional Moneylenders and Landlords [49].

5.4 NON-FARM EMPLOYMENT

Aside from migration and crop insurance, a third avenue likely to cause downward bias in the shock coefficients is non-farm diversification in employment. Mahajan (2017) posits that non-farm sector enterprises are more likely to operate in areas with greater

[48] The idea of risk sharing applies to both institutional and non-institutional lenders: landed households are less inherently risky and likely to borrow larger amounts for productive investment, at the cost of less exploitability; see Ray (1998).

[49] Irrigation infrastructure is likely correlated with other developmental indicators in a district. While irrigation doesn't directly insulate against floods, there can be indirect pathways at play.

development and a more literate population. Accordingly, education levels can potentially proxy for access to non-agricultural jobs and insulate against the adverse effects of falling agricultural income.

Table 11 tests for this. I find that, in contrast to the above hypothesis, households in flood-affected but literate districts possess a significantly higher novel borrowing. The trends are similar for drought-affected households, but the interaction term is not statistically significant. This provides some evidence for the fact that non-farm diversification may not be an endogenous reaction to rainfall shocks. In so far as literacy is a proxy for development, drought-affected households in more literate districts borrow significantly more from Scheduled Commercial Banks. Alternatively, the flood interaction terms show a substitution away from Cooperative Banks and towards Trust loans.

6 CONCLUSION

It is well-known that rural households in developing countries are vulnerable to large covariate shocks that affect agricultural productivity. Such households require immediate funds to smooth consumption, but the channels mediating this process are not as clear. In particular, the role of local credit remains under-explored in the literature. This paper analyzes the direct and short-term effects of severe rainfall shocks on household level indebtedness in rural India. Using pooled cross-sectional data for 2018 and 2019, I show that large-scale floods and droughts significantly increase ex-post borrowing, however, this effect is differential by the type of shock observed. Floods induce higher borrowing at the intensive margin, with no significant difference at the extensive margin. Alternatively, drought-affected households are more likely to become new borrowers, but the additional borrowing significantly reduces at the intensive margin. I also find that indebtedness is not driven by the roll-over of old debt.

To further disentangle these differential effects, I analyze a diverse set of credit agencies that fund the observed borrowing and the purpose for which the loans are taken. The results show a significant and robust substitution towards cooperative societies that is simultaneous to an equivalent substitution away from trust loans (friends and family loans) in flood-affected districts. Overall, the evidence strongly highlights the fact that nature of the rainfall shock is non-trivial in determining household borrowing behaviour. In terms of the purpose of borrowing, households borrow not to smooth current consumption, but rather to invest in agricultural inputs for the next

crop cycle. Conditional on inaccessibility to other forms of consumption smoothing, which I make a case for, this means that households temporarily dissave and invite an excessive risk burden upon themselves. Heterogeneous treatment effects show that the borrowing needs of indebted and land-poor households are majorly met by cooperative societies, while households on the opposite sides of the respective distributions borrow from large banks. Flood-affected households in developed districts are less likely to be credit-constrained, and the presence of irrigation infrastructure significantly moderates (insulates against adverse effects) the effects of droughts. I also show that my results are unlikely to be biased by alternate smoothing mechanisms such as cross-district migration, or access to crop insurance, and non-farm employment.

To conclude, I want to draw attention to two implications of the findings that are pertinent from a policy perspective. First, rural informal networks comprising friends, relatives, and members within the same caste contribute tremendously towards insuring poorer households against expected income shocks. Their lending ability is greatly diminished in the face of large and unpredictable covariate shocks, but this is more than made up for by cooperative societies at the local level. The key point to note is that both these institutions are driven by the mechanism of endogenous enforcement. Minimizing asymmetry between agents, borrowers and lenders in this case, increases trust levels and fosters greater risk sharing. Since large banks are often too risk-averse to cater to such households' credit needs (or, poor households select against their services due to bureaucratic barriers), an Ostrom-like strategy that builds the capacities of formal institutions at the local level is more efficient. Ray (1998) also notes that such a solution will generate natural competition against local moneylenders, forcing them to minimize exploitative credit arrangements. Second, evidence suggests that climate change is likely to induce a higher number of extreme weather events. This forces agricultural households to take on greater risk burdens that manifest as overdependence on upcoming, equally vulnerable, crop cycles for income. While the short-term solution still lies in expanding local consumption smoothing mechanisms, it is critical to consider that floods and droughts operate through noticeably different channels. Severe floods can impede mobility at the local level, creating novel credit constraints, and further deterring cross-district migration. In such a context, it is important to identify and support those households which specifically become credit-constrained at the extensive margin. Pre-existing borrower households should not be the beneficiaries. Alternatively, drought-affected districts observe a spike in entrant borrower households at the same margin. This can lead to a shortage in credit supply, or drive up the interest

rates to unreasonable levels. In this case, a potential welfare-maximizing strategy is to temporarily divert additional resources from unaffected districts to drought-affected ones. To summarize, strategic and short-term reallocation of institutional credit supply can play a significant role in alleviating climate change driven income shocks in rural India.

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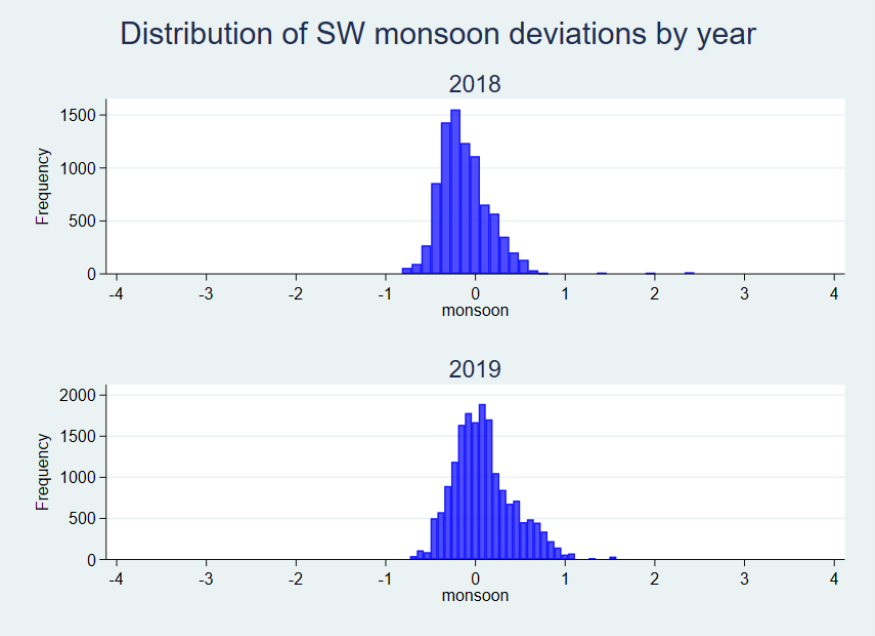
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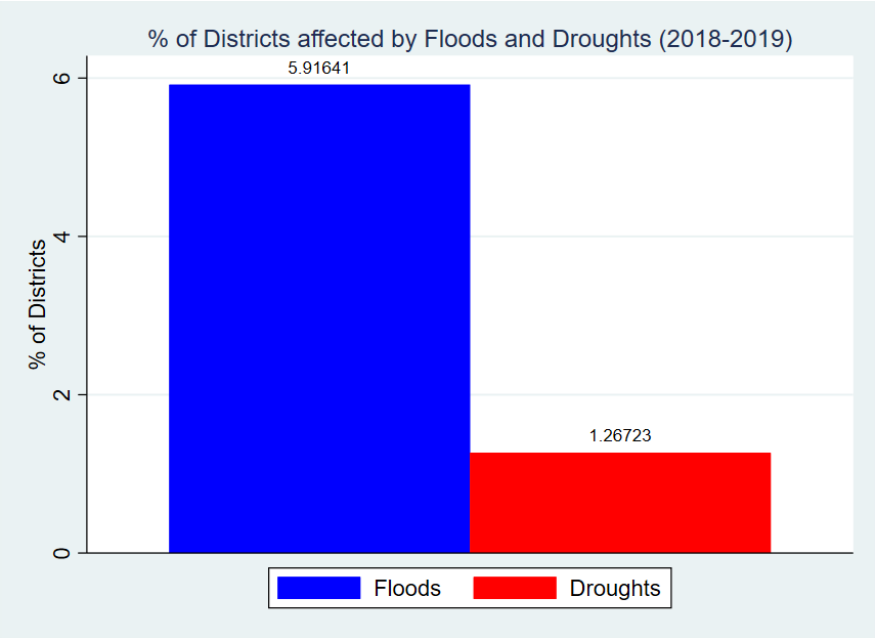
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Figure 1: Distribution of rainfall deviations across 2018 and 2019



Notes: This figure shows the histograms of the deviations of South-West rainfall from its historical average in 2018 (1951-2000) and 2019 (1961-2010) respectively. *Source*: *All-India Debt and Investment Survey 2019*

Figure 2: Percentage of flood and drought affected districts across across 2018 and 2019 (combined)



Notes: This figure shows the percentage of flood and drought affected districts across 2018 and 2019 (combined).
Source: *All-India Debt and Investment Survey 2019*

Table 1: Summary Statistics

	N	Mean	SD
Key Outcome and Treatment Variables			
Difference in HH indebtedness (Rs.)	25679	3135.30	150143
Flood = 1 if district suffers a flood	25679	0.07	
Drought = 1 if district suffers a drought	25679	0.01	
Household Characteristics			
Baseline HH indebtedness (Rs.) as of 30 June 2018/19	25679	142619.45	316217
Land owned (in acres)	25679	2.67	4
Age of the HH head (in yrs)	25679	50.40	13
Years of education completed by the HH head	25679	6.61	6
Proportion of female members	25679	0.48	0
Proportion of members of working age	25679	0.74	0
HH Size	25679	4.74	2
Gender of the HH head (Male = 1)	25679	0.92	
Religion: Hindu	25679	0.89	
Muslim	25679	0.07	
Others	25679	0.05	
Caste: SC-ST	25679	0.29	
OBC	25679	0.45	
Others	25679	0.25	
Economic Characteristics (District-level)			
Nightlight intensity (per sq km)	25679	8.24	6
Share of employment in agriculture	25679	66.06	15
Crop yield for all crops (in tonnes per hectare)	25679	4.37	5
Demographic Characteristics (District-level)			
Ratio of the number of females to the number of males	25679	94.88	5
Literacy Rate (7+ yrs)	25679	67.61	9
ST population as a share of the total population	25679	11.14	18
SC population as a share of the total population	25679	18.64	9
Access to Infrastructure (District-level)			
HH access to banking services as a share of the total	25679	54.83	16
Land area irrigated at least once per year as a share of the total area	25679	29.81	25
Ratio of the length of roads to the size of the area	25679	232.47	212
Ratio of the number of railway/metro stations to the size of the area	25679	1.23	1
Geographical Characteristics (District-level)			
Average elevation of the area	25679	266.70	263
standard deviation of the elevation of the area	25679	73.41	109

Notes: This table reports the summary statistics of 25679 agricultural households included in my sample. The key outcome variable (Row 1) is the difference in household indebtedness between date of survey (Oct to Mar 2018/19) and 30th June 2018/19. The treatment variables (Row 2 and 3) are dummies that equal 1 when a district is a flood or a drought affected district. The entries in Column (1) show the sample size, those in Column (2) report the mean of the characteristic, and Column (3) populates the standard deviation for reported means. Note that I omit the standard deviation values for dummy variables. Source: *All India Debt and Investment Survey 2019*

Table 2: Summary Statistics, Outcome variables and baseline indebtedness across rainfall shocks

	Flood	Drought	No Shock
Outcome Variables			
Difference in HH indebtedness	17544.44	36602.03	1569.23
	(146803.84)	(315606.55)	(147231.79)
New Loan (Ext)	0.25	0.31	0.24
	(0.43)	(0.46)	(0.42)
New Loan (Int)	141146.77	129018.52	99127.76
	(253770.67)	(151841.19)	(315841.90)
Loan Repaid	17042.52	24103.08	20041.77
	(54790.41)	(64686.54)	(91494.65)
Baseline HH indebtedness	166279.80	151724.00	140594.28
	(309887.11)	(236917.76)	(317478.67)

Notes: This table reports all the means of the concerned outcome variables stratified by rainfall shock status. The key outcome variable is the difference in household indebtedness between date of survey (Oct to Mar 2018/19) and 30th June 2018/19 (Row 1). The outcome in (Row 2)is a dummy variable that captures any novel borrowing (post 30th June 2018/19), and (Row 3) shows the absolute amount of novel borrowing (post 30th June 2018/19). (Row) 4 shows the absolute amount of loan repaid (post 30th June 2018/19). The numbers in parenthesis refer to the standard deviation. Source: *All India Debt and Investment Survey 2019*

Table 3: Summary Statistics, Proportions of novel borrowing (outcomes) across credit agencies, purpose and rainfall shocks

	Flood	Drought	No Shock
Institutional Loans			
SCB	0.26	0.31	0.20
	(0.43)	(0.45)	(0.39)
RRB	0.04	0.19	0.05
	(0.20)	(0.39)	(0.20)
Coop Soc	0.20	0.09	0.08
	(0.39)	(0.28)	(0.26)
Coop Bank	0.04	0.00	0.03
	(0.20)	(0.00)	(0.17)
SHG	0.03	0.00	0.10
	(0.17)	(0.00)	(0.30)
Fin Corp	0.02	0.00	0.02
	(0.15)	(0.00)	(0.12)
NBFC	0.03	0.02	0.03
	(0.17)	(0.16)	(0.17)
Dummy for any type of Non - Institutional Loan			
Dummy	0.35	0.37	0.48
	(0.47)	(0.47)	(0.49)
Non - Institutional Loans			
Trust Loans	0.08	0.22	0.20
	(0.27)	(0.41)	(0.39)
Pro Lender	0.18	0.13	0.16
	(0.38)	(0.33)	(0.36)
Agri Lender	0.04	0.02	0.05
	(0.20)	(0.13)	(0.22)
Landlord	0.01	0.00	0.01
	(0.09)	(0.00)	(0.10)
Purpose of Loan			
Agri	0.60	0.67	0.43
	(0.48)	(0.47)	(0.48)
Consumption	0.21	0.14	0.30
	(0.40)	(0.34)	(0.45)
House	0.04	0.03	0.06
	(0.19)	(0.17)	(0.24)
Medical	0.05	0.09	0.08
	(0.21)	(0.28)	(0.26)
Education	0.00	0.01	0.01
	(0.00)	(0.11)	(0.10)
Repayment	0.02	0.00	0.02
	(0.12)	(0.00)	(0.14)

Notes: This table reports the mean of novel household borrowing (post 30th June 2018/19), stratified across credit agencies, purpose of borrowing, and shock status. Each outcome variable refers to the loan amount taken from that particular credit agency/for that purpose. The numbers in parenthesis refer to the standard deviation. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, Cooperative Society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing any non-institutional loan taken, Trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. In order, the purpose categories are as follows: Agricultural loan (revenue and capital expenditure in farm business), Consumption loan (other household expenditure), House loan, Medical loan, Education loan, and Repayment of debt respectively as a proportion of the total novel borrowing amount.Source: *All India Debt and Investment Survey 2019*

Table 4: Household level regressions for the differential effects of Floods and Droughts on household indebtedness

	Difference in HH Indebtedness				
	(1)	(2)	(3)	(4)	(5)
Flood	15867.88***	13366.91*	14710.11**	15404.87**	16335.73**
	(5739.71)	(7537.28)	(6957.91)	(6960.63)	(6529.02)
Drought	34925.48*	33217.85*	29505.46	28868.87	22082.86
	(20634.82)	(19288.47)	(20065.08)	(20211.19)	(19797.40)
Observations	25679	25679	25678	25678	25678
Mean of Dep Var	3272.48	3272.48	3275.33	3275.33	3275.33
R^2	0.00	0.01	0.01	0.02	0.06
F-Test ($\beta_F = \beta_D$)	0.79	0.90	0.49	0.40	0.08
(p-value)	0.37	0.34	0.49	0.53	0.78
State and Visit FE	N	Y	Y	Y	Y
HH controls	N	N	Y	Y	Y
District controls	N	N	N	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on the difference in household indebtedness between date of survey (Oct to Mar 2018/19) and 30th June 2018/19. The outcome variable remains the same throughout. The F statistic tests for equality of the shock coefficients. Column (1) is an uncontrolled regression while column (2)-(5) include State and Survey Visit Fixed Effects. Column (3) adds household level controls like gender, age, and education level of the household head (as measured by years of education completed), religion and social group, land possessed, proportion of working age members and proportion of female members. Column (4) adds a rich gamut of district level controls including nightlight intensity, share of employment in agriculture, crop yield for all crops, sex ratio, literacy rate, SC-ST population share, access to banking services, road and station density, proportion of land irrigated, elevation, and surface roughness. Column (5) is inclusive of potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 5: Differential effects of Floods and Droughts on novel borrowing at the extensive margin

	New Loan	
	(1) Baseline Debt: N	(2) Baseline Debt: Y
Flood	0.01	0.01
	(0.03)	(0.02)
Drought	0.12**	0.11**
	(0.05)	(0.05)
Observations	25678	25678
Mean of Dep Var	0.24	0.24
R^2	0.04	0.05
F-Test ($\beta_F = \beta_D$)	3.46	2.92
(p-value)	0.06	0.09
State and Visit FE	Y	Y
HH controls	Y	Y
District controls	Y	Y

Notes: This table reports the OLS coefficients from a linear probability model that estimates the chances of a household borrowing at the extensive margin, contemporaneous to a flood or a drought. The outcome variable is a dummy variable capturing *any* novel borrowing (post 30th June 2018/19), and is the same across both the columns. The F statistic tests for equality of the shock coefficients. Column (1) and (2) both include State and Survey Visit Fixed Effects along with a complete set of household and district level covariates (see Table 4). In addition, column (2) includes potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 6: Differential effects of Floods and Droughts on novel borrowing and historic repayment at the intensive margin

	Loan Repaid		New Loan	
	(1) Baseline Debt: N	(2) Baseline Debt: Y	(3) Baseline Debt: N	(4) Baseline Debt: Y
Flood	-1641.50	-3117.54	25790.99	27907.08*
	(1996.08)	(2012.02)	(16297.44)	(16576.28)
Drought	-8861.98	-2040.69	-56213.55**	-53139.32**
	(7767.10)	(6765.56)	(25263.60)	(25980.12)
Observations	22265	22265	4910	4910
Mean of Dep Var	20222.22	20222.22	104677.89	104677.89
R^2	0.05	0.19	0.20	0.21
F-Test ($\beta_F = \beta_D$)	0.82	0.02	9.63	9.07
(p-value)	0.37	0.88	0.00	0.00
State and Visit FE	Y	Y	Y	Y
HH controls	Y	Y	Y	Y
District controls	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the differential effects of contemporaneous floods and drought on historic repayment and novel borrowing respectively. The different sample size in column (3)-(4) reflects the fact that they are households with *any* new borrowing. Accordingly, the outcome variable is absolute novel borrowing (post 30th June 2018/19). For columns (1)-(2), the outcome variable is absolute repayment (for pre 30th June 2018/19 loans). The F statistic tests for equality of the shock coefficients. Columns (1)-(4) all include State and Survey Visit Fixed Effects along with a complete set of household and district level covariates (see Table 4). In addition, columns (2) and (4) include potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 7: Differential effects of Floods and Droughts on novel borrowing from various credit agencies

	Institutional							Non - Institutional				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SCB	RRB	Coop Soc	Coop Bank	SHG	Fin Corp	NBFC	NI	Trust	Pro Lender	Agri Lender	Landlord
Flood	0.04	-0.02	0.07**	-0.00	-0.01	-0.01	0.01	-0.09**	-0.07***	-0.00	0.01	0.00
	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.04)	(0.02)	(0.01)
Drought	-0.06	0.08	0.04	-0.02*	-0.01	-0.02**	0.01	-0.02	0.04	0.00	-0.02	-0.01*
	(0.06)	(0.06)	(0.07)	(0.01)	(0.01)	(0.01)	(0.03)	(0.07)	(0.06)	(0.04)	(0.02)	(0.00)
Observations	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910
Mean of Dep Var	0.21	0.05	0.08	0.03	0.09	0.02	0.03	0.47	0.19	0.16	0.05	0.01
R^2	0.12	0.06	0.09	0.07	0.10	0.03	0.04	0.09	0.08	0.10	0.07	0.01
F-Test ($\beta_F = \beta_D$)	2.27	2.63	0.16	1.28	0.01	0.67	0.06	0.90	3.07	0.02	1.46	2.98
(p-value)	0.13	0.11	0.69	0.26	0.93	0.41	0.80	0.34	0.08	0.90	0.23	0.08
State and Visit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on novel borrowing from various credit agencies. The outcome variables refer to the loan amount taken in each category as a proportion of total novel borrowing (post 30th June 2018/19). Columns (1)-(7) refer to institutional sources of borrowing while columns (8)-(12) refer to non-institutional sources. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, Cooperative Society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing *any* non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. The F statistic tests for equality of the shock coefficients. Columns (1)-(12) all include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 8: Differential effects of Floods and Droughts on novel borrowing from various credit agencies, Interaction

		Institutional							Non - Institutional				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	New Loan	SCB	RRB	Coop Soc	Coop Bank	SHG	Fin Corp	NBFC	NI	Trust	Pro Lender	Agri Lender	Landlord
Flood	31081.64	0.06	-0.01	0.07*	-0.00	-0.02	-0.00	0.00	-0.11*	-0.09**	0.00	0.00	0.00
	(21046.95)	(0.05)	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.06)	(0.03)	(0.05)	(0.02)	(0.01)
Flood*Indebted	-7593.56	-0.05	-0.01	-0.00	0.00	0.02	-0.02	0.02	0.06	0.03	-0.01	0.03	0.00
	(26184.71)	(0.06)	(0.02)	(0.05)	(0.02)	(0.02)	(0.01)	(0.02)	(0.07)	(0.03)	(0.05)	(0.03)	(0.01)
Drought	-38789.39	-0.10	0.22***	0.01	-0.01	-0.01	-0.02	0.00	-0.07	0.03	-0.04	0.00	-0.01
	(34545.51)	(0.09)	(0.06)	(0.07)	(0.01)	(0.01)	(0.02)	(0.02)	(0.11)	(0.10)	(0.03)	(0.02)	(0.01)
Drought*Indebted	-33115.00	0.09	-0.33***	0.07**	-0.01	-0.01	0.01	0.01	0.13	0.03	0.11	-0.04**	0.00
	(39697.53)	(0.11)	(0.07)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.15)	(0.13)	(0.08)	(0.02)	(0.01)
Observations	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910
Mean of Dep Var	104677.89	0.21	0.05	0.08	0.03	0.09	0.02	0.03	0.47	0.19	0.16	0.05	0.01
R^2	0.21	0.13	0.07	0.09	0.07	0.10	0.03	0.04	0.09	0.08	0.10	0.07	0.01
F-Test ($\beta_F = \beta_D$)	3.99	2.95	13.47	0.63	0.44	0.45	1.27	0.02	0.14	1.15	0.88	0.00	1.58
(p-value)	0.05	0.09	0.00	0.43	0.51	0.50	0.26	0.88	0.71	0.28	0.35	0.96	0.21
State and Visit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on novel borrowing from various credit agencies. All columns estimate the shock variables and their interaction with a dummy variable indicating that a household is in the top 50% of baseline indebtedness (as of 30th June 2018/19). The outcome variables refer to the loan amount taken in each category as a proportion of total novel borrowing (post 30th June 2018/19). Column 1 refers to absolute novel borrowing (post 30th June 2018/19). Columns (2)-(8) refer to institutional sources of borrowing while columns (3)-(12) refer to non-institutional sources. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, Cooperative Society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing *any* non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. The F statistic tests for equality of the shock coefficients. Columns (1)-(12) all include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 9: Differential effects of Floods and Droughts on novel borrowing from various credit agencies, Interaction

		Institutional							Non - Institutional				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	New Loan	SCB	RRB	Coop Soc	Coop Bank	SHG	Fin Corp	NBFC	NI	Trust	Pro Lender	Agri Lender	Landlord
Flood	40737.64	0.02	-0.03**	0.03	-0.03*	-0.03	-0.00	0.03	-0.02	-0.03	0.02	0.02	-0.01*
	(26700.35)	(0.04)	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.02)	(0.06)	(0.04)	(0.05)	(0.03)	(0.00)
Flood*Landed	-19321.16	0.03	0.02	0.06	0.04*	0.03	-0.01	-0.03	-0.10*	-0.07**	-0.03	-0.01	0.01*
	(36465.06)	(0.06)	(0.02)	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)	(0.06)	(0.04)	(0.06)	(0.03)	(0.01)
Drought	-77587.10***	-0.12	0.05	0.04	-0.01	-0.03	-0.03**	-0.03**	0.12	0.26**	-0.07***	-0.03**	-0.01
	(29345.79)	(0.10)	(0.07)	(0.06)	(0.01)	(0.02)	(0.01)	(0.01)	(0.13)	(0.13)	(0.03)	(0.01)	(0.01)
Drought*Landed	39266.23	0.08	0.05	0.01	-0.02*	0.03*	0.02**	0.05	-0.20	-0.34**	0.12**	0.02	-0.00
	(42453.54)	(0.12)	(0.12)	(0.06)	(0.01)	(0.02)	(0.01)	(0.03)	(0.14)	(0.14)	(0.05)	(0.03)	(0.00)
Observations	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910
Mean of Dep Var	104677.89	0.21	0.05	0.08	0.03	0.09	0.02	0.03	0.47	0.19	0.16	0.05	0.01
R^2	0.21	0.13	0.06	0.10	0.07	0.10	0.03	0.04	0.09	0.08	0.10	0.07	0.01
F-Test ($\beta_F = \beta_D$)	9.05	1.97	1.19	0.01	1.22	0.01	2.67	5.82	0.96	4.47	3.01	2.73	0.01
(p-value)	0.00	0.16	0.28	0.92	0.27	0.94	0.10	0.02	0.33	0.04	0.08	0.10	0.94
State and Visit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on novel borrowing from various credit agencies. All columns estimate the shock variables and their interaction with a dummy variable indicating that a household is in the top 50% of land owned. The outcome variables refer to the loan amount taken in each category as a proportion of total novel borrowing (post 30th June 2018/19). Column 1 refers to absolute novel borrowing (post 30th June 2018/19). Columns (2)-(8) refer to institutional sources of borrowing while columns (3)-(12) refer to non-institutional sources. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, Cooperative Society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing *any* non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. The F statistic tests for equality of the shock coefficients. Columns (1)-(12) all include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 10: Differential effects of Floods and Droughts on novel borrowing from various credit agencies, Interaction

		Institutional							Non - Institutional				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	New Loan	SCB	RRB	Coop Soc	Coop Bank	SHG	Fin Corp	NBFC	NI	Trust	Pro Lender	Agri Lender	Landlord
Flood	30661.77*	0.04	-0.01	0.06	0.01	-0.00	-0.01	0.01	-0.08	-0.09***	0.02	0.02	0.01
	(17378.27)	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)	(0.05)	(0.03)	(0.04)	(0.02)	(0.01)
Flood*Irrigated	-11540.81	0.00	-0.04	0.07	-0.03	-0.04	0.01	0.03	-0.02	0.09*	-0.11*	-0.04	-0.03***
	(31521.00)	(0.07)	(0.03)	(0.07)	(0.02)	(0.03)	(0.02)	(0.03)	(0.07)	(0.05)	(0.06)	(0.03)	(0.01)
Drought	-115104.07***	-0.24***	-0.06***	0.30***	-0.03*	-0.02	-0.01	0.09	-0.02	0.01	0.05	-0.03	-0.01
	(39338.90)	(0.06)	(0.02)	(0.09)	(0.01)	(0.02)	(0.01)	(0.10)	(0.05)	(0.06)	(0.05)	(0.02)	(0.01)
Drought*Irrigated	83762.29*	0.22**	0.20***	-0.34***	0.01	0.01	-0.02	-0.11	0.01	0.04	-0.07	0.02	0.00
	(43699.80)	(0.09)	(0.07)	(0.09)	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)	(0.07)	(0.03)	(0.01)
Observations	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910
Mean of Dep Var	104677.89	0.21	0.05	0.08	0.03	0.09	0.02	0.03	0.47	0.19	0.16	0.05	0.01
R^2	0.21	0.13	0.06	0.10	0.07	0.10	0.03	0.04	0.09	0.08	0.10	0.07	0.02
F-Test ($\beta_F = \beta_D$)	17.98	22.30	5.70	7.04	1.69	0.60	0.09	0.59	0.86	2.73	0.35	4.86	5.08
(p-value)	0.00	0.00	0.02	0.01	0.19	0.44	0.76	0.44	0.35	0.10	0.56	0.03	0.02
State and Visit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on novel borrowing from various credit agencies. All columns estimate the shock variables and their interaction with a dummy variable indicating that a district is in the top 50% of crop area irrigated (as of 2011). The outcome variables refer to the loan amount taken in each category as a proportion of total novel borrowing (post 30th June 2018/19). Column 1 refers to absolute novel borrowing (post 30th June 2018/19). Columns (2)-(8) refer to institutional sources of borrowing while columns (3)-(12) refer to non-institutional sources. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, Cooperative Society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing *any* non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. The F statistic tests for equality of the shock coefficients. Columns (1)-(12) all include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table 11: Differential effects of Floods and Droughts on novel borrowing from various credit agencies, Interaction

		Institutional							Non - Institutional				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	New Loan	SCB	RRB	Coop Soc	Coop Bank	SHG	Fin Corp	NBFC	NI	Trust	Pro Lender	Agri Lender	Landlord
Flood	-5087.90	0.02	-0.01	0.05	0.03	-0.00	-0.02	0.02	-0.07	-0.11***	0.01	0.01	0.01
	(21832.10)	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.02)	(0.06)	(0.03)	(0.05)	(0.02)	(0.01)
Flood*Literate	76535.92**	0.05	-0.00	0.05	-0.07**	-0.01	0.02	-0.01	-0.05	0.08*	-0.04	-0.00	-0.02**
	(31174.11)	(0.06)	(0.03)	(0.06)	(0.03)	(0.03)	(0.02)	(0.02)	(0.08)	(0.05)	(0.06)	(0.03)	(0.01)
Drought	-72164.89**	-0.17***	0.08	0.06	-0.01	-0.02	-0.01	0.02	0.05	0.06	0.03	-0.01	-0.01
	(30021.46)	(0.06)	(0.08)	(0.09)	(0.01)	(0.01)	(0.01)	(0.03)	(0.08)	(0.08)	(0.05)	(0.02)	(0.01)
Drought*Literate	32277.36	0.29***	-0.00	-0.08	-0.02	0.02	-0.02	-0.04	-0.15	-0.05	-0.04	-0.03	-0.00
	(57204.23)	(0.09)	(0.09)	(0.09)	(0.02)	(0.03)	(0.02)	(0.04)	(0.10)	(0.10)	(0.09)	(0.04)	(0.01)
Observations	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910	4910
Mean of Dep Var	104677.89	0.21	0.05	0.08	0.03	0.09	0.02	0.03	0.47	0.19	0.16	0.05	0.01
R^2	0.21	0.13	0.06	0.09	0.07	0.10	0.03	0.04	0.09	0.08	0.10	0.07	0.01
F-Test ($\beta_F = \beta_D$)	5.25	7.03	1.22	0.02	2.42	0.45	0.05	0.05	1.37	4.16	0.05	0.61	6.31
(p-value)	0.02	0.01	0.27	0.88	0.12	0.50	0.82	0.83	0.24	0.04	0.83	0.44	0.01
State and Visit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on novel borrowing from various credit agencies. All columns estimate the shock variables and their interaction with a dummy variable indicating that a district is in the top 50% literacy rates (as of 2011). The outcome variables refer to the loan amount taken in each category as a proportion of total novel borrowing (post 30th June 2018/19). Column 1 refers to absolute novel borrowing (post 30th June 2018/19). Columns (2)-(8) refer to institutional sources of borrowing while columns (3)-(12) refer to non-institutional sources. In order, the credit agencies are as follows: Scheduled Commercial Bank, Regional Rural Bank, Cooperative Society, Bank-linked Self Helf group, Financial Corporation, Non Banking Financial Company, NI refers to a dummy capturing *any* non-institutional loan taken, trust loans refer to loans from friends and relatives, professional moneylender, agricultural moneylender, and landlord respectively. The F statistic tests for equality of the shock coefficients. Columns (1)-(12) all include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table A1: Differential effects of Floods and Droughts on the purpose of novel borrowing

	(1) Agri	(2) Cons	(3) House	(4) Med	(5) Edn	(6) Repay
Flood	0.11***	-0.06*	-0.01	-0.01	-0.01***	0.00
	(0.04)	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)
Drought	0.10	-0.10**	-0.02	0.03	0.01	-0.01
	(0.06)	(0.05)	(0.02)	(0.03)	(0.01)	(0.01)
Observations	4910	4910	4910	4910	4910	4910
Mean of Dep Var	0.01	0.01	0.01	0.01	0.01	0.01
R^2	0.16	0.09	0.02	0.05	0.01	0.04
F-Test ($\beta_F = \beta_D$)	0.00	0.59	0.03	1.52	2.12	1.21
(p-value)	0.96	0.44	0.85	0.22	0.15	0.27
State and Visit FE	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y
District controls	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on the purpose of novel borrowing. The outcome variables refer to the loan amount taken in each category as a proportion of total novel borrowing (post 30th June 2018/19). In order, the purpose categories are as follows: Agricultural loan (revenue and capital expenditure in farm business), Consumption loan (other household expenditure), House loan, Medical loan, Education loan, and Repayment of debt respectively. The F statistic tests for equality of the shock coefficients. Columns (1)-(6) all include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*

Table A2: Differential effects of Floods and Droughts on migration, Robustness

	Migration	
	(1) Road Density	(2) Station Density
Flood	64505.64	60394.30
	(71373.32)	(38523.15)
Flood*Landed*Road	66849.62	
	(82231.75)	
Drought	-73871.18**	-87381.12*
	(31474.28)	(50758.82)
Drought*Landed*Road	-72159.90	
	(63998.24)	
Flood*Landed*Station		67996.28
		(58417.86)
Drought*Landed*Station		-42285.81
		(74412.82)
Observations	4910	4910
Mean of Dep Var	104677.89	104677.89
R^2	0.22	0.22
F-Test ($\beta_F = \beta_D$)	3.36	5.82
(p-value)	0.07	0.02
State and Visit FE	Y	Y
HH controls	Y	Y
District controls	Y	Y

Notes: This table reports the results from OLS regressions to estimate the effect of a district-level flood and drought on migration metrics that are as follows: Column (1) refers to the ratio of the length of roads to the size of the area, and Column (2) refers to the ratio of the number of railway/metro stations to the size of the area. Both columns estimate the shock variables and their interaction with dummy variables indicating that a district is in the top 50% road density (as of 2011) or top 50% station density (as of 2011). The triple interaction is generated by adding a dummy indicating that a household is in the top 50% of land owned. The F statistic tests for equality of the shock coefficients. Both columns include State and Survey Visit Fixed Effects along with a complete set of household, and district level covariates (see Table 4), and potentially endogenous baseline household indebtedness (as of 30th June 2018/19) as a predictor. Robust clustered standard errors (clustered at the district level) are in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%. Source: *All India Debt and Investment Survey 2019*