Who Lends When It Floods? Banks vs Non-Banks

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Abstract

We examine whether non-banks fill credit gaps following climate shocks. Using the August 2017 floods in two Indian states, Uttar Pradesh and Bihar, as a plausibly exogenous shock, we combine georeferenced flood-extent data with a novel, near-universe panel of Indian retail credit data. A difference-in-differences design, comparing non-banks and banks across flooded and unaffected zipcodes, reveals that non-banks expand lending by 5.75% in affected areas relative to banks, alongside broader borrower outreach. Product-level estimates show particularly strong responses in agricultural and consumption credit. While overall delinquency rates remain comparable to those of banks, we detect a rise in default rates for consumption loans. By linking flood exposure to high-frequency originations, this paper provides the first large-scale evidence of non-banks' countercyclical role in disaster recovery—delivering rapid, last-mile liquidity to vulnerable households and small firms, albeit with elevated risk in unsecured credit.

Keywords: Climate Change, Household Finance, Environmental Economics, Climate Shocks, Financial Intermediation

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1 Introduction

Climate change is intensifying, and with it, natural disasters are striking more often and with greater force. These extreme weather events trigger sharp, localized surges in demand for liquidity and reconstruction finance to smooth consumption, rebuild assets, and invest in adaptive capacity (Koetter et al., 2020; Abedifar et al., 2024; Allen et al., 2023; Blickle et al., 2021; Mahul & Signer, 2023). In advanced economies, insurance coverage and public financial assistance often mitigate the economic consequences of such shocks (Melecky & Raddatz, 2015). In contrast, many developing countries[1] lack comparable safety nets, making recovery highly dependent on access to credit from banks and other financial institutions. In the absence of strong institutional safety nets and given the centrality of private finance in recovery, the behavior of financial intermediaries—particularly their willingness and capacity to lend post-disaster—becomes a critical determinant of economic resilience.

Traditional banks often retrench lending post-disaster in the affected areas, consistent with heightened default risk and capital constraints. They cut originations, tighten lending toward safer borrowers, or reallocate credit away from the shock (Nguyen & Wilson, 2020; Choudhary & Jain, 2022; Brei et al., 2019; Rehbein & Ongena, 2022). In this context, non-banks or nonbank financial companies (NBFCs)[2] are well-positioned to provide last-mile credit in developing economies, providing timely liquidity to disaster-affected households and firms when bank lending is restricted. Despite extensive work on banks and household borrowing after disasters, evidence on how non-banks respond—relative to banks—remains scarce.

Using granular credit-bureau microdata matched to georeferenced flood-extent imagery, this paper quantifies the differential credit supply response of non-banks relative to traditional banks in disaster-affected areas. We show that, following a major flood event, non-banks expand loan volumes and borrower coverage more than banks in treated locations, consistent with their comparative advantage in last-mile origination and serving underbanked households. These findings highlight the importance of non-banks' networks in delivering rapid liquidity to vulnerable communities after natural disasters and, more broadly, in strengthening local resilience as climate risks intensify.

In studying lenders' responses to disasters, a first-order challenge is measuring expo-

[1]Developing countries bear a disproportionate share of climate-related losses (IPCC, 2023).

[2]NBFCs are companies that provide credit and other financial services; but do not take deposits.

sure at the right spatial scale. Much of the literature relies on datasets such as Emergency Events Database (EM–DAT). However, EM-DAT's state- or district-level tags are too coarse for zipcode–level credit outcomes and risk substantial misclassification and attenuation bias (Patel (2024)). We address this gap by georeferencing official flood-extent imagery to construct a zipcode -level treatment indicator, aligning the shock's spatial resolution with monthly originations and enabling sharper inference on lenders' post-flood behavior.

We use a novel, near-universe panel of retail credit originations from TransUnion CIBIL, India's oldest credit bureau—structured at the year–month $\times$ zip-code $\times$ lender type $\times$ product category level and containing consistent measures of both new originations and subsequent performance. This granularity, uncommon in prior work that relies on public aggregates, allows us to align the spatial and temporal scale of lending with flood exposure, compare banks with non-banks, and distinguish secured from unsecured products. As a result, we can trace the immediate and medium-run reallocation of risk and liquidity after floods and provide, to our knowledge, the first high-frequency, large-scale evidence on the countercyclical role of non-banks in flood-affected areas.

We particularly look at the disastrous floods in 2017 in India which affected the states of Uttar Pradesh (U.P.) and Bihar[3]. U.P and Bihar sit in the Ganga basin and experienced exceptionally severe flooding in August 2017. The flood led to a death toll of 617 people, with about 1.9 crore people directly affected by the floods. The total damages are reported to be 1.56 billion USD (adjusted to current prices, it is estimated to be approximately 2 billion USD). These two states are also among India's most populous— about 200 million in Uttar Pradesh and 104 million in Bihar as of the last Census[4]. These states remain predominantly rural, underscoring their vulnerability to riverine floods. Labour markets are heavily agrarian, implying that flood shocks directly hit vulnerable livelihoods. Against this backdrop, examining short-run credit needs and the responsiveness of lenders in the immediate aftermath of the 2017 floods is essential for understanding how households and small firms adapt in the flood-exposed regions.

We implement a difference-in-differences strategy comparing non-banks and traditional banks across flooded and non-flooded zipcodes before and after the 2017 flood event.

[3]Developing countries bear a disproportionate share of climate-related losses (IPCC, 2023), with India being one of the worst-affected countries, ranking in the top ten most affected nations by extreme weather related calamities (Adil et al., 2025). In India, floods are the most frequent natural disaster (see Figure 5). India also ranks as the second-most flood affected country in the world.

[4]U.P. population is equivalent to the combined population of Germany and France.

The results show that non-banks increase lending by 5.75% in flood-affected areas relative to banks. Non-banks also expand credit on the extensive margin, as they extend 6.07% new loans relative to banks after the natural disaster. To address concerns that the credit expansion may reflect a shift toward riskier borrowers and a buildup of non-performing assets, we examine portfolio quality and find no statistically significant change in overall delinquency rates for non-banks relative to banks in treated areas.

To unpack the aggregate lending patterns further, we move to a more disaggregated analysis and examine whether non-banks' lending expansion is concentrated in specific loan types—distinguishing between collateralized and uncollateralized products. Disaggregated results by loan type reveal substantial increases in both collateralized (15.8%) and uncollateralized (26.6%) lending. The expansion is particularly pronounced on the extensive margin, with the number of new uncollateralized loans rising by 28.6%, compared to a 13.1% increase in new collateralized loans. These findings suggest that non-banks play a countercyclical, last-mile role by expanding credit supply following climate shocks.

To further refine the analysis by product category, we find that non-banks expand lending disproportionately in agricultural and consumption loans. Within the collateralized segment, agricultural lending increases by 20.4%, while within the uncollateralized segment, consumption lending rises by 23.1%. These effects are primarily driven by expansion on the extensive margin: non-banks increase the number of new agricultural loans by 22.1% and new consumption loans by 25.1%. In contrast, traditional banks exhibit increased lending only in gold-backed loans, where households pledge gold as collateral.

To explore heterogeneity in borrower access, we also examine how non-banks respond across borrower types and informational margins. Our findings show that non-banks significantly increase lending to borrowers with whom they have no prior relationship, while also expanding the number of accounts among existing borrowers. Importantly, non-banks disproportionately extend credit to individuals historically excluded from the formal financial system—those with no credit history or with subprime credit scores. Compared to traditional banks, non-banks lend more to borrowers below the prime threshold. These results contribute to a growing literature on financial inclusion and credit access (e.g., Dell'Ariccia & Marquez (2006)), by showing that non-banks play a distinct role in reaching informationally opaque and marginal borrowers. The findings suggest that in the aftermath of climate shocks, non-banks not only serve as last-mile lenders but also help bridge persistent access gaps in underserved credit markets, albeit with implications for risk exposure in less-screened segments.

While the expansion of non-bank lending following natural disasters plays an important countercyclical role and improves financial access, it also raises concerns about underlying credit risk and its implications for financial stability. Increased lending can become problematic if financial institutions disproportionately extend credit to riskier borrowers, potentially leading to higher default rates. In our setting, although differential aggregate delinquency rates of non-banks remain statistically insignificant relative to traditional banks, this masks important heterogeneity across loan types. Specifically, the overall stability in delinquency rates reflects a relative decline in defaults within collateralized lending—most notably in agricultural (7.9%) and vehicle loans (8.8%)—which offsets rising delinquencies in uncollateralized segments. In uncollateralized lending, delinquency rates increase by 7.12%, with consumption loans accounting for a substantial 7.8% rise. This concentration of risk in unsecured, post-disaster consumption credit is especially important, as it signals a vulnerability that may not be captured in aggregate figures. These findings highlight the need for policy interventions that support consumption smoothing for affected households, thereby mitigating risk spillovers to the financial sector and preserving financial stability in the aftermath of climate shocks.

Related Literature. A growing body of evidence suggests that countries with more developed insurance markets experience smaller economic losses following natural disasters, as insurance mechanisms help absorb and redistribute risk (Melecky & Raddatz, 2015). In settings where such insurance coverage is limited or absent, affected households and firms must rely on banks as alternative sources of post-disaster financing. Accordingly, a large literature has examined the behavior of bank lending in the aftermath of natural disasters (Koetter et al., 2020; Abedifar et al., 2024; Choudhary & Jain, 2022; Brei et al., 2019; Rehbein & Ongena, 2022; Gallagher & Hartley, 2017; Cortés & Strahan, 2017; del Valle et al., 2024). These studies find that banks often retrench lending in disaster-affected areas, partly due to the deterioration of collateral values and heightened uncertainty around borrower repayment capacity (Nguyen & Wilson, 2020). Moreover, disaster-induced increases in funding costs may further tighten credit supply, disproportionately affecting borrowers with limited credit histories or weaker financial access (Choudhary & Jain, 2022; Brei et al., 2019). Prior research finds that geographically diversified banks manage climate-related risks by rebalancing their portfolios toward regions with lower exposure to such risks (Islam & Singh, 2025; Cortés & Strahan, 2017; Rehbein & Ongena, 2022).

In disaster-hit areas (notably flood-intensive hurricanes), lenders tilt originations toward loans eligible for securitization, shifting climate risk off the balance sheet (Ouazad & Kahn (2022)). Flood exposure also leads to the change in composition of credit (del Valle et al. (2024)). Moreover, the difference in bank capitalization conditions can propagate flood shocks to credit in non-flooded areas (Rehbein & Ongena (2022)).

Despite accounting for a substantial and growing share of global financial assets,[5] the role of non-bank financial institutions (NBFIs) or non-banks in post-disaster climate finance remains underexplored in the academic literature (Financial Stability Board, 2025). This paper contributes to filling this gap by shifting the analytical focus from banks to non-banks, documenting their differential lending behavior following a natural disaster. In doing so, it underscores the importance of non-banks in providing last-mile liquidity to vulnerable households—particularly in contexts where formal insurance mechanisms and traditional bank credit are limited or disrupted.

While natural disasters often increase the demand for credit, banks tend to allocate post-disaster lending primarily to those with whom they have prior relationships or are safe borrowers, leveraging established relationships to mitigate information asymmetries and default risk (Abedifar et al., 2024). In contrast to this relationship-based lending behavior, our findings show that non-banks expand credit supply to borrowers with whom they had no prior lending relationship—often including households previously excluded from the formal financial system.

Nonbanks respond differently to credit shocks than traditional banks because they operate under a distinct regulatory environment—particularly with respect to micro- and macroprudential requirements—and adopt alternative lending technologies (Darst et al., 2025). They also differ informationally from banks in how borrower screening and monitoring are organized (Chernenko et al., 2022). In environments with stringent prudential constraints and limited information on prospective borrowers, banks may be reluctant to extend credit to borrowers without prior relationships. Complementing these findings, we show that non-banks fill this gap by expanding supply to borrowers who are new to credit and lack prior relationships to formal lenders, underscoring their role in extending access when relationship-based bank lending is least responsive. This suggests that non-banks play a crucial role in broadening financial access in the wake of climate shocks,

[5] According to the Global Monitoring Report on Non-Banking Financial Intermediation, in 2024, the NBFI sector expanded by 9.4%—double the growth rate of the banking sector—and represented 51.0% of total global financial assets.

particularly by channeling liquidity to underserved households.

While some recent studies have examined non-bank lending in the context of natural disasters (e.g., Allen et al., 2023), they tend to focus on a single credit product, such as mortgages (Nguyen et al., 2022; Kousky et al., 2020) or credit card borrowing (Gallagher & Hartley, 2017). In contrast to these product-specific analyses, our study leverages granular product-level data that spans both secured and unsecured retail credit—including agriculture, business, vehicle, consumption, and microfinance loans. This broader coverage enables us to provide a more comprehensive picture of how liquidity provision scales across multiple credit markets outside the traditional mortgage segment following climate shocks.

This paper also contributes to the emerging literature on the impact of climate-related extreme weather events on the financial stability of banks (Noth & Schüwer, 2023). By comparing delinquency rates at the aggregate, across collateralized and uncollateralized segments, and across different loan products, it identifies a concentration of credit risk in unsecured consumption loans. These findings underscore the potential for climate-induced credit posing broader risks to macro-financial stability.

Methodologically, this paper contributes by introducing a novel approach to identifying disaster-affected areas. Existing studies often rely on the EM-DAT database to determine the temporal and spatial scope of flood exposure when assessing the economic impacts of natural disasters (e.g., Cavallo et al., 2013; Noy, 2009; Kahn, 2005; Skidmore & Toya, 2002; Raddatz, 2007). However, recent research has highlighted several limitations of EM-DAT, including inconsistent flood definitions, a bias toward detecting floods in richer or more densely populated areas, and a tendency to overstate flood coverage, all of which can introduce misclassification bias (Patel, 2024). To address these limitations, we leverage high-resolution inundation imagery from the National Database for Emergency Management and geo-reference flood-affected areas using pin-code-level shapefiles. This more granular and accurate identification strategy enhances the precision of our empirical analysis and offers a replicable framework for future research on the localized impacts of natural disasters.

In addition, this paper leverages a novel, proprietary, and near-universal panel dataset of retail credit originations from CIBIL, structured at the year–month × zip-code × lender type × product category level. This paper is among the first to leverage this dataset, which has been used in only a handful of prior studies (Mishra et al., 2022; Cramer et al., 2025).

The granularity of this data—uncommon in prior research that typically relies on aggregated public statistics—enables us to precisely align the spatial and temporal dimensions of lending activity with flood exposure. It also allows for a systematic comparison between banks and non-banks, and across secured and unsecured credit products.

The paper is organized as follows. Section 2 provides the background on floods in India. Section 3 details the data used in identifying the affected zip-codes and the granular credit bureau data. We elaborate on the empirical strategy in Section 4, and present our findings and results in Section 5. Section 6 concludes.

2 Background: Floods in India

Floods are among the most frequent natural disasters in India, significantly disrupting various aspects of socio-economic well-being. A substantial portion of the population is adversely affected by floods, which manifest their impacts through human mortality, migration, and extensive damage to agriculture and infrastructure, particularly during the summer monsoon season. According to India's National Remote Sensing Centre, India ranks as the second most flood-affected country in the world, following Bangladesh, and accounts for one-fifth of the global death toll due to floods. The National Flood Commission reports that approximately 4 crore hectares of land in India are susceptible to flooding, with an average of 1.86 crore hectares affected annually. The Brahmaputra and Ganga River basins in the Indo-Gangetic-Brahmaputra plains of North and Northeast India are the most flood-prone areas, containing 60 per cent of the nation's total river flow. Other flood-prone regions include the northwest area with west-flowing rivers like the Narmada and Tapti, as well as Central India and the Deccan region with major east-flowing rivers such as the Mahanadi, Krishna, and Cauvery.

Nearly 75 per cent of India's total rainfall is concentrated within the brief monsoon season spanning four months from June to September. During this period, rivers experience heavy discharge, leading to widespread flooding in densely populated states such as Uttar Pradesh, Bihar, West Bengal, and Assam. The Himalayan rivers, in particular, carry a significant amount of sediment, which contributes to the erosion of riverbanks. Combined with soil saturation and increased runoff, as well as deforestation activities, this leads to the loosening of large quantities of topsoil during rainfall. Consequently, downstream water levels rise sharply, resulting in extreme flooding events.

2017 Floods in UP and Bihar. The 2017 South Asian monsoon produced one of the largest flood disasters globally that year. EM–DAT's 2017 statistical review highlights the August flood across India, Nepal, and Bangladesh as a single event that affected 26.9 million people—the most affected by any disaster worldwide in 2017—and lists India among the countries with the highest number of recorded disaster events that year. Within India, contemporaneous situation reports document exceptional severity concentrated in the Ganga basin states. The floods in UP and Bihar in August 2017 were particularly deadly. According to EM-DAT, the flood led to a death toll of 617 people, with about 1.9 crore people directly affected by the floods. The total damages are reported to be 1.56 billion USD (adjusted to current price, it is estimated to be approximately 2 billion USD). These impacts arose from short-duration, high-intensity rainfall episodes and upstream inflows during the August pulse of the southwest monsoon—hydrometeorological drivers that are orthogonal to local credit-market conditions. Consistent with this, the India Meteorological Department characterizes 2017 as a year with near-normal all-India seasonal totals but sharp spatial and intra-seasonal variability, implying that extreme flooding can occur even where seasonal rainfall is not unusually high (India Meteorological Department, 2018).

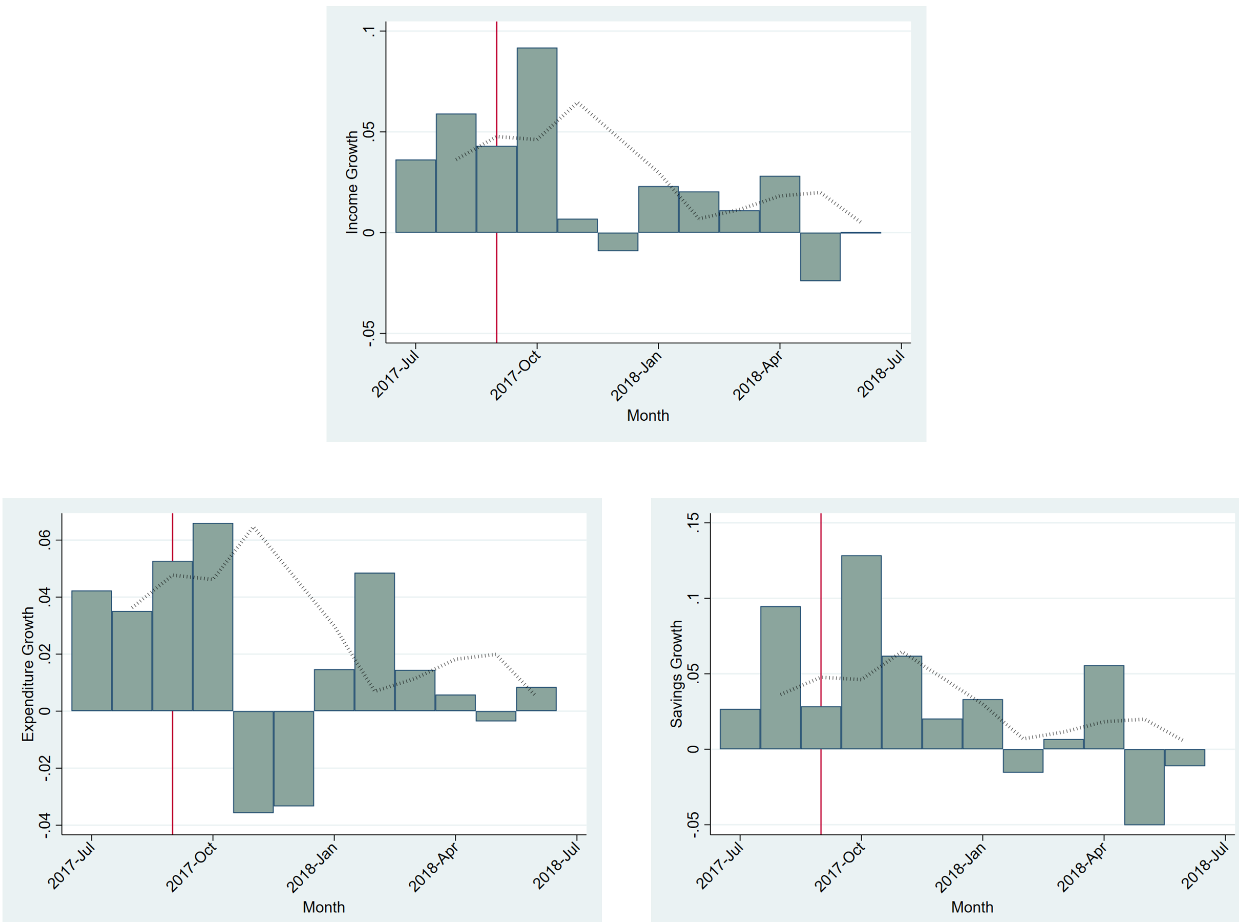
Income, Expenditure and Savings after Floods. Figure (1) shows that after the flood event, there is a short-term boost in income and expenditure in the affected districts in UP and Bihar, potentially due to reconstruction. However, as time passes, there is a decline in the income growth. The effect remains persistent as income, expenditure, and savings growth fall and fail to catch up even six months after the flood event. The figure indicates the credit demand to rebuild and adapt ,as economic growth falters in the month following the floods.

3 Data

3.1 Flood Exposure - Identifying Affected Zipcodes

A central challenge in this study is the precise identification of local areas exposed to flooding. Much of the existing literature relies on reporting-based datasets such as the Dartmouth Flood Observatory Archive and the EMDAT International Disaster Database. These datasets draw on government and media coverage to report flood incidents at the

Figure 1: Trend in Income (top), and Expenditure and Savings (bottom) growth after the August 2017 floods.

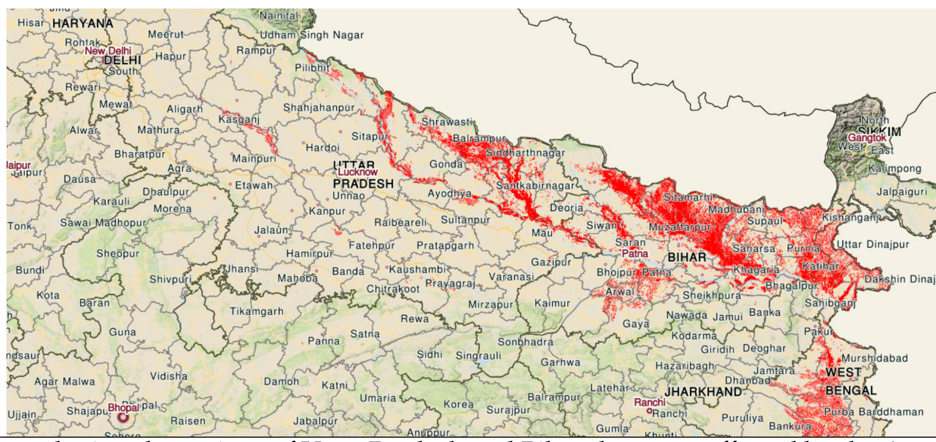


Notes: The figure plots the total income, expenditure, and savings year-on-year growth of households in districts which contain flood-affected zipcodes. Authors' calculation using CPHS[6].

district (ADM2) or state (ADM1) level. However, these face documented shortcomings: inconsistent definitions, a bias toward richer, urban, or developed areas, and omission of brief but economically significant floods (Patel (2024)). As a result of their dependence on ex post disaster recognition, they inherit inconsistent definitions of what constitutes a "flood" and tend to focus on highly visible disasters. Smaller or short-lived inundations—especially in poorer or more remote regions—are frequently unreported.

Finally, reporting-based datasets record floods at relatively coarse administrative scales (often state or district level), which is valuable for national or state-level analysis, but too coarse for credit-market outcomes observed at the zip-code level. As a result, mapping district-level shocks to zip-codes introduces substantial spatial measurement error. Our approach innovates on this margin by constructing a high-resolution treatment indicator directly at the zip-code level.

Figure 2: Flood Extent Map from National Database for Emergency Management



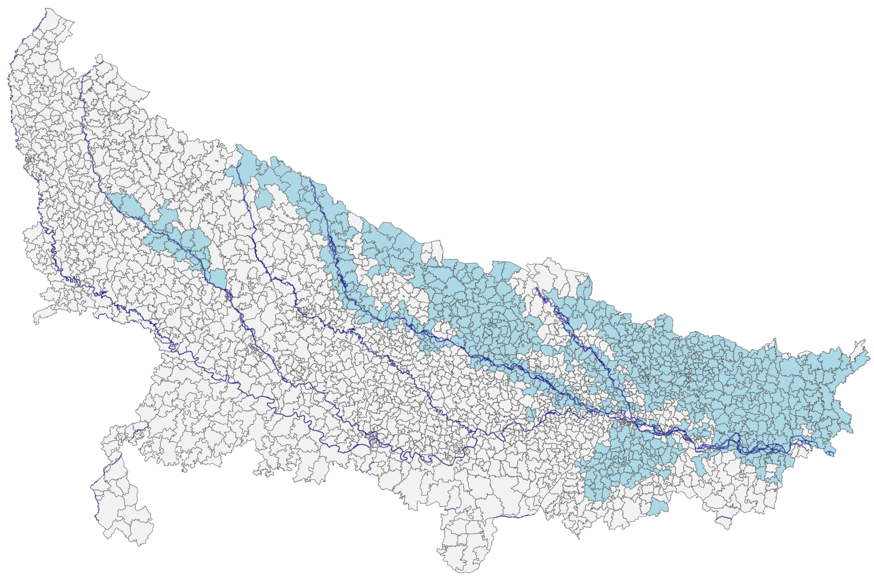
Notes: This map depicts the regions of Uttar Pradesh and Bihar that were affected by the August 2017 flood. This is reproduced from the National Database for Emergency Management's map viewer system

We extract authoritative flood-extent maps from India's National Database for Emergency Management (NDEM). Figure (2) shows the inundation levels and the flood affected areas reproduced by the NDEM[7]. Using QGIS, we geo-reference the NDEM flood imagery to a standard projected coordinate system by placing control points on stable landmarks (e.g., road intersections, river confluences) and minimizing reprojection error. We then overlay the georeferenced flood layer onto polygon shapefiles of Indian zip-code boundaries. A zip code is classified as "flood-affected" (treated) if its polygon intersects the flooded area

[7]The map viewer can be accessed here.

in the NDEM layer. This overlay-based assignment explicitly ties treatment to observed flood footprints, thereby sharply reducing the misclassification that arises when district-level exposure is imputed to all constituent zip codes.

Figure 3: Map of flood-affected zipcodes in U.P. and Bihar.



Notes: This map depicts the regions of Uttar Pradesh and Bihar that were affected by the August 2017 flood. Each polygon represents a zipcode. We obtain this map by geo-referencing NDEM flood imagery to shapefiles of Indian zipcode boundaries. Polygons shaded in blue are flood-affected. Lines in dark blue show major rivers.

In the main specification, treatment is a binary indicator equal to one for affected zip codes and zero otherwise[8]. In supplementary analyses, we show that results are robust to alternative exposure —e.g., requiring a minimum overlap share of the zip polygon with the flood footprint—further mitigating concerns that tangential boundary contacts drive the findings.

Unaffected zip codes located very close to flooded areas may differ systematically from more distant controls (e.g., in terrain, infrastructure, credit access), and they may also experience spillovers (transport disruptions, lender reallocation). To probe these issues, we implement a proximity-based robustness design. First, we compute great-circle distances between zip-code centroids using the haversine formula. We then identify a ring

[8]We additionally ensure that unaffected zip codes do not experience floods during or around August 2017.

of "nearby controls": zip codes that are classified as unaffected but whose centroids lie within 30 kilometers of the centroid of a treated zip code. Estimating the models on this restricted comparison set tightens geographic comparability while providing a conservative check against unobserved spatial heterogeneity. Results using this 30-km control ring—and alternative radii in sensitivity tests—remain consistent with the baseline.

While proximity-based controls improve comparability, they may amplify the aforementioned spillover concerns if lenders actively reallocate credit away from flooded locations to nearby zipcodes. To address this complementary concern, we implement a second robustness design using non-adjacent control locations—zip codes that are unaffected by flooding and lie outside a 30-kilometer radius. These locations are less likely to share branch networks and short-run balance-sheet reallocations with flooded areas, while still being exposed to the same aggregate macroeconomic and climatic conditions. Re-estimating our specifications on this sample yields qualitatively similar estimates of the differential post-flood expansion of non-bank lending relative to banks, indicating that our results are not driven by spatial spillovers from nearby control areas.

By moving from state/district aggregates (as in EM-DAT) to georeferenced, zip-level exposure constructed from NDEM flood footprints, this methodology materially advances identification of flood-exposed regions. It aligns the spatial resolution of the disaster shock with the spatial resolution of the credit data, reduces attenuation from treatment misclassification, and enables a finer characterization of heterogeneity in credit responses within flood-hit districts.

3.2 Data on Credit

We assemble a novel, near-universe panel of retail credit originations in India from TransUnion CIBIL, the country's oldest credit bureau. Under the Credit Information Companies (Regulation) Act, 2005 (CICRA), regulated lenders are required to report lending and repayment information to credit bureaus at a monthly frequency. In practice, virtually all formal lenders report to CIBIL, and submissions undergo routine integrity checks, yielding comprehensive and internally validated coverage of retail credit flows.

The dataset is organized at the year-month × postal code (zip-code) × lender type × product category level. We obtain all records for Uttar Pradesh and Bihar from September 2016 through June 2018, totaling approximately 3.1 million cell-month observations. Because the major flood event occurred in August 2017, the sample provides 11 months of pre-flood data (September 2016–July 2017), the event month (August 2017), and 10 months of post-flood data (September 2017–June 2018), enabling a high-frequency assessment of lending dynamics around the shock.

For each zipcode-month we observe (i) the number of new loans, (ii) the total rupee amount of new loans, (iii) lender-type (banks vs non-banks[9]), (iv) product-type, and (v) ex-post performance. A loan is classified as delinquent/defaulted if it reaches 90+ days past due (DPD) within 12 months of origination. We construct amount-based delinquency measures; the baseline delinquency rate is the share of origination amount that transitions to 90+ DPD within one year[10].

A key feature is lender-type coverage. The data distinguish traditional banks—public sector and private sector—from non-banks, allowing us to quantify substitution patterns across intermediaries during and after the flood. Product-level information further separates secured credit (e.g., agricultural, gold, and vehicle loans) from unsecured credit (e.g., business, consumption, and microfinance loans). This granularity permits an analysis of which lending technologies and collateral classes remain active—or retrench—under heightened default risk.

[9] We define traditional banks in the dataset as either public sector banks or private banks; and non-banks as non-bank financial companies (NBFCs), housing finance companies or fintechs

[10] We obtain delinquency rates for the entire period including delinquent amounts until July 2019, which are necessary for calculating delinquency rates for loans disbursed in July 2018, the final month of the study period.

Table 1: Summary Statistics: Credit Bureau Data

	Mean	Median	SD	Observations
Panel A: Loan amount (Million INR)				
Aggregate	1.23	0.28	42.43	3,179,420
Traditional (lender_id = 1)	1.32	0.30	50.74	2,205,261
NBFC (lender_id = 2)	1.02	0.22	6.91	974,159
Panel B: Number of accounts				
Aggregate	4.19	1.00	21.20	3,179,420
Traditional (lender_id = 1)	3.71	1.00	20.30	2,205,261
NBFC (lender_id = 2)	5.29	1.00	23.00	974,159
Panel C: Delinquency rate				
Aggregate	0.02	0.00	3.80	3,133,628
Traditional (lender_id = 1)	0.02	0.00	4.46	2,159,638
NBFC (lender_id = 2)	0.00	0.00	1.54	973,990

Notes: Numbers are rounded to two decimals. Loan amounts were reported in *billion* INR; we convert to *million* INR by multiplying by 10^3. The number of accounts was reported in *millions*; we convert to *counts* by multiplying by 10^6. Delinquency rate is the share of origination amount that becomes 90+ DPD within 12 months. Observation counts for Delinquency rates are lower due to missing values.

We also incorporate borrower credit score data and two borrower-lender relationship variables for heterogeneity analysis. Credit scores are encoded into five risk tiers and a sixth category for first-time borrowers with no credit score. The prior relationship indicator equals 1 if the lender had extended a loan to the same borrower within the past five years and captures informational familiarity or repeat borrowing. The inquiry indicator equals one if the lender made a credit inquiry to the credit union within 90 days prior to loan origination - which also servers as a proxy for familiarity of the borrower to the lender. Together, these variables allow us to test whether the differential post-flood response of non-banks relative to banks is stronger among existing borrowers or new borrowers.

Relative to publicly available aggregates, the novel dataset offers (i) near-census coverage across all formal lenders, (ii) monthly frequency at fine spatial resolution (zip code), and (iii) consistent measures of both originations and subsequent performance. These features make it possible to trace the immediate and medium-run response of credit outflows to flood exposure, to separate banks from non-banks, and to compare secured versus unsecured lending. As a result, the dataset enables a substantially more complete picture of how India's retail credit market reallocates risk and liquidity during climate-related disasters, and it provides the first systematic evidence—at scale and at high frequency—on the countercyclical role of non-banks in flood-affected zip-codes of Uttar Pradesh and

Bihar.

4 Empirical Strategy

4.1 Event Study

We first provide a dynamic analysis of the differential credit supply response of non-banks using an event-study design. We report the coefficient for the following specification:

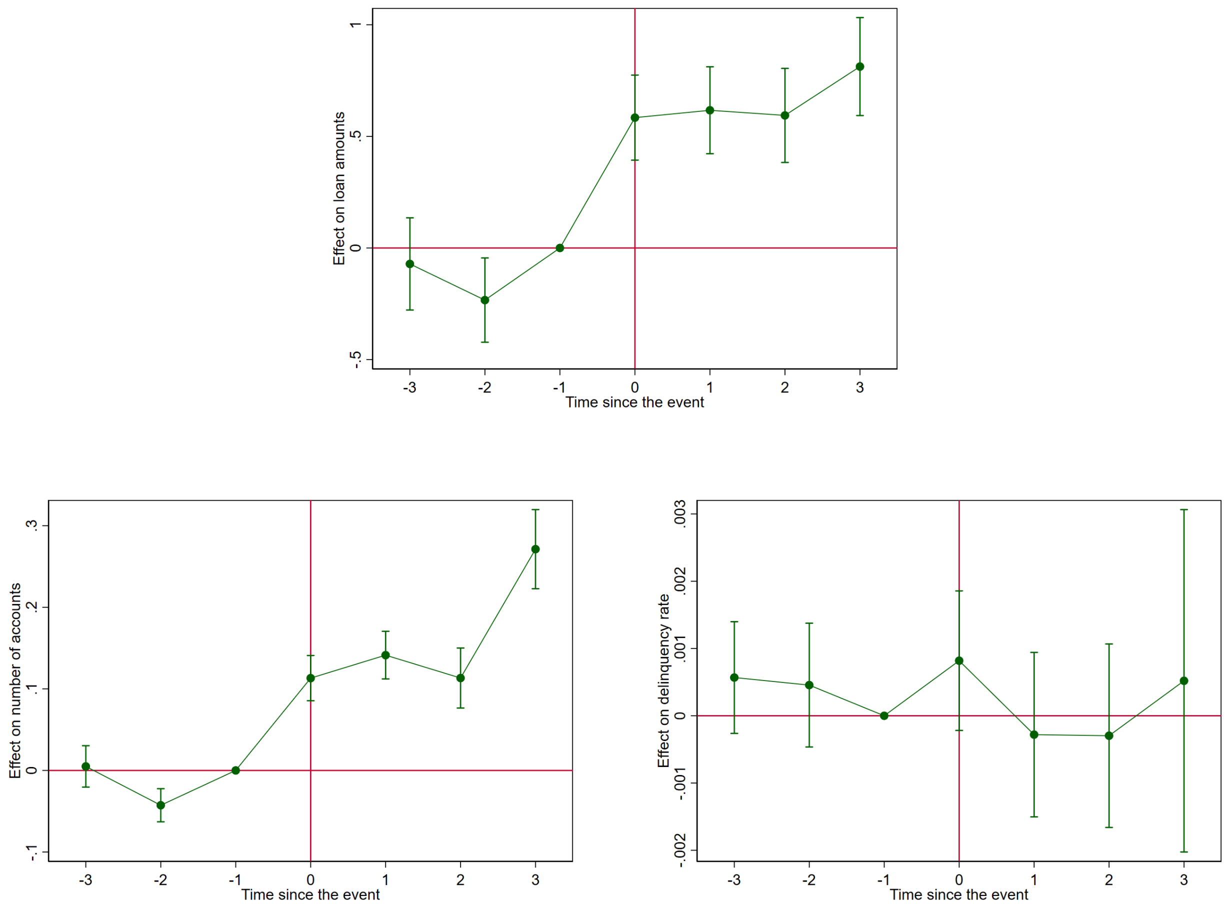
$$Y_{t,z,l,p} = \alpha + \sum_{k \neq -1} \beta_k D_{t,z} + \gamma_{t,z,p} + \eta_{t,l,p} + \delta_{z,l,p} + \epsilon_{t,z,l,p} \tag{1}$$

Here, $Y_{t,z,l,p}$ is the outcome of interest, the natural logarithm of the loan amount, the number of account, and the delinquency rate[11], measured at time t (quarter-year) at zip code (z) for a lender-type (l) and product-type (p). $D_{t,z}$ takes the value 1 for a flood-affected zipcode z at time period t. We take other granular fixed effects to address threats to identify β_k.

Figure (4) plots the dynamic response of differential lending by non-banks to banks. For the loan amount (or credit volume) and the number of new loans (top and left panel of 4), pre-trend coefficients are low or statistically zero, but post-flood coefficients are large and significant. This indicates the following the disaster shocks, non-banks differentially increase their lending to zipcodes affected by the shock. However, post-flood coefficients are consistently insignificant for delinquency rates (the right panel of Figure 4), implying that no such divergence takes place for delinquency rates across banks and non-banks. This reiterates the divergence in lending between banks and non-banks - the latter scale up lending after the flood shock for several time periods, but there is no differential effect on delinquency rates between banks and non-banks for loans extended at this time.

[11] Delinquency rate is the ratio of the delinquent amount at time $t + 12$ relative to the loan originated at time t.

Figure 4: Event study: effect on credit amount (top), number of accounts (left), and delinquency rate (right).



Notes: These graphs present the relative impact of the August 2017 flood on non-bank lending in flood-affected districts compared to traditional bank lending in an event-study specification (Equation 1). The dependent variables in the top, left, and right panels are loan amounts, number of loans, and delinquency rates. For all panels, X-axis represents time in quarters relative to the flood event.

4.2 Differences-in-Differences

Our main results employ a differences-in-differences (DiD) estimation strategy to estimate the differential lending response of non-banks, relative to traditional banks, after the flood exposure.

$$Y_{t,z,l,p} = \beta_0 + \beta_1 * Shock_{zt} + \beta_2 * Shock_{zt} * \mathbb{I}\{l = non - bank\} + \gamma_{t,z,p} + \delta_{z,l,p} + \eta_{t,l,p} + \epsilon_{t,z,l,p} \tag{2}$$

Here, $Y_{t,z,l,p}$ is the outcome of interest measured at time t (month-year) at zip code (z) for a lender-type (l) and product-type (p). $Shock_{zt}$ is an indicator variable that takes the value 1 for the treated/affected zipcode after the flood event. $\mathbb{I}\{l = \text{non-bank}\}$ takes the value one if the lender is a non-bank or an NBFC. Our coefficient of interest is β_2, which captures the differential impact of lending by NBFCs to flood-effected zipcodes relative to traditional banks.

To ensure that β_2 captures a causal differential effect, our identification strategy relies on the parallel trends assumption: absent the flood shock, lending by non-banks and banks within the same product and market would have followed similar trends over time. This assumption is supported by the pre-trend analysis in Figure 4, which shows no significant difference in the lending behavior of banks relative to non-banks prior to the flood event. In addition, we further address potential threats to identification by including a rich set of fixed effects that flexibly control for unobserved heterogeneity across time, geography, lender type, and product category.

We include other granular fixed effects to address potential threats to the identification of β_2. First, NBFCs might react more strongly because they could potentially specialize in products which see a huge demand in credit after the floods. For example, if NBFCs specialize in consumption loans and there is an increase in consumption credit after floods, our results will be biased. To address this, we include time x zipcode x product ($\gamma_{t,z,p}$) fixed effects. This ensures that we compare the differential lending response of NBFCs relative to traditional banks at the same time, within the same zipcode and for the same product.

Second, we also include zipcode x lender x product ($\delta_{z,l,p}$) fixed effects. This accounts for any lender-product specialization in a particular zipcode. We also control for time x lender x product ($\eta_{t,l,p}$) fixed effects, which accounts for any potential time-varyting shocks at the lender-product level. Standard errors are clustered at the zip code level to allow for arbitrary correlation in the error term across time within geographic markets.

5 Results

Main results. Table (2) reports estimates of Equation (2), comparing NBFCs to traditional banks in flood-affected zip codes. The coefficient of interest is the interaction β_2 (Shock $\times$ NBFC), interpreted as the differential post-flood change for NBFCs relative to banks. Across main specifications (cols. (1)–(3)), the point estimates on loan amounts are positive and statistically significant. The most saturated specification in col. (3)—with time$\times$zip$\times$product, time$\times$lender$\times$product, and zip$\times$lender$\times$product fixed effects—yields an effect of 0.058, implying an increase of about 5.75% in non-bank lending relative to banks after the flood. The magnitude is also positive and statistically significant in cols. (1) and (2), which adds time$\times$zip fixed effects to lender fixed effects. Notably, moving from col. (1) to col. (3) raises R^2 from 0.136 to 0.416 while leaving the non-bank effect positive, indicating that the result is not driven by omitted time-varying composition at the lender–product–zipcode level.

Extensive Margin. Turning to the extensive margin, Table (3) shows that the number of new loans originated by non-banks in treated zip codes increases by approximately 6.07% relative to banks in the post-flood period. This result suggests that non-banks expand their reach by issuing new credit to a broader set of households in flood-affected areas. The increase in the number of new loans—rather than higher loan volumes from existing borrowers—indicates that non-banks are more likely to serve previously unbanked or underbanked households in the aftermath of the shock. This pattern is consistent with a role for non-banks as marginal lenders that are more flexible or less risk-averse than traditional banks in extending credit under adverse conditions. In doing so, non-banks help relax liquidity constraints faced by vulnerable households and contribute to short-term recovery in disaster-affected areas. These findings highlight the importance of non-banks in promoting financial inclusion when traditional credit supply may be disrupted or constrained.

Default Rates. A common concern with countercyclical lending by non-banks is the po-

Table 2: Baseline Results: banks vs. non-banks

	(1)	(2)	(3)
		Loan amounts	
Shock X NBFC	0.0277**	0.127***	0.0575***
	(0.014)	(0.008)	(0.010)
Observations	3133555	3131640	3078807
R-squared	0.136	0.378	0.416
Date-Zip FE	Yes	Yes	No
Date-Zip-Product FE	No	No	Yes
Date-Lender-Product FE	No	No	Yes
Zip-Lender-Product FE	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The dependent variable is logarithm of loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Extensive margin: banks vs. non-banks

	(1)	(2)	(3)
		No. of accounts	
Shock X NBFC	0.0780***	0.0784***	0.0607***
	(0.007)	(0.007)	(0.007)
Observations	3179417	3179349	3124203
R-squared	0.127	0.137	0.299
Zip-Lender FE	Yes	Yes	No
Date-Zip FE	No	Yes	No
Date-Zip-Product FE	No	No	Yes
Date-Lender-Product FE	No	No	Yes
Zip-Lender-Product FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The dependent variable in Columns 1 through 3 is the logarithm of number of new loans. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

tential for increased exposure to riskier borrowers, which could lead to higher default rates. To examine this, Table (4) analyzes the impact of flood exposure on loan delinquency. We find that delinquency rates for non-banks in treated zip codes are slightly lower than those for banks, although the difference is statistically insignificant. This suggests that the expansion in non-bank lending following the flood is not associated with a deterioration in overall portfolio quality, at least in the short run and in the aggregate. In other words, non-banks are able to increase credit supply—both on the intensive and extensive margins—without incurring significantly higher aggregate credit risk relative to banks. This result mitigates concerns about adverse selection and underscores the capacity of non-banks to manage risk effectively while playing a stabilizing role in credit markets during times of local economic distress.

Table 4: Baseline Results: banks vs. non-banks - Delinquency results

	(1)	(2)	(3)
		Delinquency rate	
Shock X NBFC	0.000270	0.000366	-0.000133
	(0.000)	(0.000)	(0.000)
Observations	1755049	1754277	1708349
R-squared	0.0163	0.0479	0.123
Lender-Product FE	No	Yes	No
Date-Zip FE	Yes	Yes	No
Date-Zip-Product FE	No	No	Yes
Date-Lender-Product FE	No	No	Yes
Zip-Lender-Product FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Lending to Collateralized Products. Column (3) in Table (5) shows that non-banks significantly increase lending in collateralized products by 15.8%. This expansion is also reflected on the extensive margin, with the number of new loans rising by approximately 13.1%. These results indicate that non-banks are not only scaling up lending volumes but are also broadening access to secured credit, which may provide a safeguard against repayment risk. Importantly, Table (6) shows that delinquency rates for these collateralized loans are significantly lower for non-banks compared to traditional banks in the same markets. This suggests that the expansion in collateral-backed lending by non-banks is not accompanied by a deterioration in credit quality. Instead, non-banks appear to be leveraging collateralization to expand credit access while maintaining a sound risk profile, highlighting their role in providing stable, asset-backed credit in the wake of natural disasters.

Table 5: Baseline Results: banks vs. non-banks - Collateralized Lending

	(1)	(2)	(3)	(4)
	Loan amounts			No. of accounts
Shock X NBFC	0.781***	0.781***	0.158***	0.131***
	(0.026)	(0.026)	(0.022)	(0.018)
Observations	287106	287106	287096	287096
R-squared	0.467	0.467	0.498	0.578
Lender FE	No	Yes	No	No
Date-Zip FE	Yes	Yes	Yes	Yes
Date-Lender FE	No	No	Yes	Yes
Zip-Lender FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of new loans. The primary independent variable is an interaction term between the Shock and NBFC variables. The $Shock_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Banks vs. non-banks - Delinquency in Collateralized Lending

	(1)	(2)	(3)
	Delinquency rate		
Shock X NBFC	-0.0387***	-0.0387***	-0.0874***
	(0.006)	(0.006)	(0.009)
Observations	268540	268540	268516
R-squared	0.353	0.353	0.385
Lender FE	No	Yes	No
Date-Zip FE	Yes	Yes	Yes
Date-Lender FE	No	No	Yes
Zip-Lender FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Lending to Uncollateralized Products. In our most saturated specification, we find a substantial increase in uncollateralized lending by non-banks following flood exposure, relative to traditional banks. Column (3) of Table (7) shows that non-banks expand lending in uncollateralized credit products by 26.6%, and Column (4) shows a 28.6% rise in the number of new uncollateralized loans. These findings suggest that non-banks aggressively expand credit supply in markets typically underserved by collateral-backed products—potentially targeting more liquidity-constrained or higher-risk borrowers.

However, this expansion is accompanied by a notable increase in credit risk. Column (3) of Table (8) shows that delinquency rates on uncollateralized loans by non-banks rise by 7.12% relative to banks, and this effect is statistically significant. This elevated default risk raises concerns about the long-run sustainability of non-bank lending in riskier credit segments. While non-banks may serve an important role in alleviating short-term credit constraints post-disaster, the sharp rise in delinquencies in unsecured products highlights potential vulnerabilities.

If such risk-taking behavior is financed through opaque funding channels or involves maturity mismatches—common in segments of the non-bank sector—it could generate spillovers to broader financial markets, particularly if default rates continue to rise or economic conditions deteriorate. These findings underscore the importance of monitoring the credit quality of non-bank portfolios, especially in unsecured segments, to mitigate the buildup of systemic risk in the aftermath of localized shocks.

Table 7: Banks vs. non-banks - Uncollateralized Lending

	(1) Loan amounts	(2) Loan amounts	(3) Loan amounts	(4) No. of accounts
Shock X NBFC	0.0751***	0.0838***	0.266***	0.286***
	(0.027)	(0.027)	(0.034)	(0.023)
Observations	354063	350719	350719	350719
R-squared	0.459	0.550	0.551	0.607
Date-PIN FE	No	Yes	Yes	Yes
Date-Lender FE	No	No	Yes	Yes
PIN-Lender FE	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for uncollateralized lending. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of new loans. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Banks vs. non-banks - Delinquency in Uncollateralized Lending

	(1)	(2)	(3)
	Delinquency rate		
Shock X NBFC	0.0998***	0.0998***	0.0712***
	(0.008)	(0.008)	(0.009)
Observations	325478	325478	325445
R-squared	0.387	0.387	0.439
Lender FE	No	Yes	No
Date-Zip FE	Yes	Yes	Yes
Date-Lender FE	No	No	Yes
Zip-Lender FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for uncollateralized lending. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Lending by Product Type. Table (9) provides further disaggregation of lending patterns by product category. Within the collateralized loan segment[12], non-banks increase lending to agricultural loans by 20.4% relative to traditional banks. This is particularly important given the demographic and economic composition of the affected regions, where a substantial share of households rely on agriculture as their primary livelihood. In the context of increasing climate-related shocks, agricultural households are among the most vulnerable to income volatility and asset loss. By expanding access to credit in the aftermath of flooding, non-banks play a critical role in enhancing the resilience of rural agricultural households, enabling them to smooth consumption, restore productive capacity, and mitigate the long-term economic fallout of climate events. Traditional banks increase lending under the collateralized segment if housholds are willing to pledge gold as collateral. This is evident from the 44.7% differential in gold loans given by banks relative to non-banks.

In the uncollateralized segment, we observe that non-banks increase consumption loans by 23.1% relative to traditional banks. This likely reflects heightened demand for liquid-

[12]Collateralized products are agricultural, gold and vehicle loans, and uncollateralized products are business, consumption and microfinance loans.

ity among households facing flood-related expenditures such as repairs, replacement of goods, or short-term consumption needs. The willingness of non-banks to meet this demand—even in the absence of collateral—further underscores their countercyclical role. However, as noted earlier, the expansion in unsecured lending also necessitates close monitoring of credit risk, particularly given the observed rise in delinquencies in this segment.

Table 9: Banks vs. non-banks - Lending by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	0.204***	-0.447**	0.0382*	0.0807	0.231***	0.104
	(0.025)	(0.183)	(0.023)	(0.111)	(0.028)	(0.162)
Observations	174255	27099	196624	46283	349014	6428
R-squared	0.497	0.827	0.708	0.594	0.568	0.709
Time-Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The dependent variable is the logarithm of loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Extensive Margin by Product Type. Table (10) reveals that the expansion in lending by non-banks is also evident along the extensive margin—that is, through the origination of new loans. Specifically, non-banks increase the number of new agricultural loans by 22.1% and consumption loans by 25.1% relative to traditional banks in the months following the flood. These results suggest that non-banks are not merely increasing loan sizes or intensifying relationships with existing borrowers but are actively expanding credit access to new clients across key product categories.

Table 10: Banks vs. non-banks - Extensive Margin by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	0.221***	-0.475***	0.0707***	0.0995	0.251***	0.00447
	(0.024)	(0.136)	(0.018)	(0.078)	(0.021)	(0.123)
Observations	174669	27176	196841	48209	350719	7165
R-squared	0.502	0.816	0.785	0.641	0.591	0.660
Time-Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The dependent variable is the logarithm of the number of new loans. The primary independent variable is an interaction term between the Shock and NBFC variables. The $Shock_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The $NBFC_l$ variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Delinquency rate by Product Type. Table (11) presents heterogeneity in default outcomes across loan categories. We find no significant increase in delinquency rates in gold, business, or microfinance loans in treated zip codes following the flood. Moreover, for agricultural loans, delinquency rates in non-bank portfolios are statistically lower than those of traditional banks, suggesting strong repayment performance even amid adverse conditions. However, within the uncollateralized segment, the increase in overall non-bank delinquency is primarily driven by consumption loans, where default rates rise significantly relative to banks.

This pattern underscores a key vulnerability: while non-banks expand access to credit in underserved areas during climate shocks, the segment most exposed to repayment risk is consumption lending—often unsecured and issued to liquidity-constrained households lacking stable post-disaster income. These findings suggest that consumption credit, while vital for short-term relief, may not be sustainable without complementary income support mechanisms.

From a policy perspective, this highlights the need for state intervention to mitigate credit risk indirectly by supporting household consumption smoothing during climate-related shocks. Programs such as MNREGA (Mahatma Gandhi National Rural Employment Guarantee Act) could be strategically expanded or activated in flood-affected regions to provide temporary income support, reducing reliance on high-cost unsecured borrowing for basic needs. By addressing the root cause of repayment risk—temporary income disruptions—such interventions can limit the accumulation of non-performing assets (NPAs) in the non-bank sector. This, in turn, helps preserve financial stability, especially as non-banks become more prominent providers of last-resort credit during local economic distress.

These results point to the need for coordinated policy responses that integrate credit supply expansion by non-banks with targeted public safety nets, particularly in the face of increasing climate volatility and its asymmetric effects on vulnerable households.

Table 11: Banks vs. NBFCs - Delinquency Rates by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	-0.079***	0.079	-0.088***	0.033	0.078***	0.036
	(0.013)	(0.094)	(0.009)	(0.035)	(0.009)	(0.077)
Observations	130694	17186	168236	27796	324291	2174
R-squared	0.403	0.503	0.458	0.502	0.307	0.573
Time-Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The dependent variable is the ratio of delinquent loan amounts to the total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $Shock_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Delinquency rates for business loans are winsorized at the 1% level. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Heterogeneity in Effects across Borrowers. In the presence of climate shocks, banks may become more cautious in extending credit, particularly when borrower-specific information is limited (Dell'Ariccia & Marquez (2006)). To assess whether information asymmetry contributes to the observed differences in lending behavior, we examine whether non-banks increase credit to borrowers with whom they lack a prior lending relationship[13]. Results in Table (12) indicate that non-banks extend more credit to such borrowers. Furthermore, we observe an effect on the extensive margin: non-banks increase lending both to borrowers with and without pre-existing relationships, filling the credit gap after a climate shock. There is no subsequent differential increase in the delinquency rates for both kinds of borrowers.

[13] *Prior Relationship* is 1 when the lender has made a loan to a borrower within the last 5 years.

To further investigate the role of information asymmetry, we exploit lender-reported data on whether an inquiry was made about the borrower prior to loan origination. Specifically, lenders indicate whether they requested information from TransUnion within the 90 days preceding the loan.[14] Table 13 shows that non-banks increase lending on both the intensive and extensive margins, irrespective of whether an inquiry was made.

Table 12: Effect heterogeneity - prior relationship with borrower

Dependent variable	*Prior Relationship*	
	0	1
Loan amounts	0.0684***	0.0181
	(0.011)	(0.020)
New loans	0.0649***	0.0651***
	(0.008)	(0.012)
Delinquency rate	0.000275	-0.00121
	(0.000)	(0.001)
Observations	1905704	1089310
R-squared	0.453	0.462
Date-Zip-Product FE	Yes	Yes
Date-Lender-Product FE	Yes	Yes
Zip-Lender-Product FE	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across lender-borrower pairs where the lender did (1) or did not (0) previously lend to the borrower, using estimates derived from Equation (2) where the prior relationship dummy is interacted with the β_2 term. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[14] *Inquiry* equals 1 if the lender made an inquiry to TransUnion about the borrower in the 90 days prior to loan origination.

Table 13: Effect heterogeneity - credit score inquiry

Dependent variable	*Inquiry*	
	0	1
Loan amounts	0.0424**	0.0838***
	(0.017)	(0.013)
New loans	0.0539***	0.0768***
	(0.010)	(0.009)
Delinquency rate	0.000735	-0.00107**
	(0.001)	(0.000)
Observations	1517859	1484607
R-squared	0.469	0.469
Date-Zip-Product FE	Yes	Yes
Date-Lender-Product FE	Yes	Yes
Zip-Lender-Product FE	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across lender-borrower pairs where the lender did (1) or did not inquire (0) about the borrower from the credit union, using split sample estimates derived from Equation (2). Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Heterogeneity by Score Band. What are the conditions under which lending behavior differs between banks and non-banks? Low deposit insurance coverage and stringent capital requirements can constrain banks from extending credit to new or riskier borrowers, thereby creating an opportunity for non-banks to expand their market share (Darst et al. (2020)). To test whether non-banks disproportionately lend to such borrowers, we examine lending patterns by credit score segment[15]. Table (14) shows that non-banks lend significantly more to borrowers with no credit history or to those classified as subprime, near prime, and prime. While this may suggest riskier lending behavior, we do not observe a corresponding increase in delinquency rates of such borrowers. This indicates that non-banks are not merely engaging in excessive risk-taking but are instead filling a gap by extending credit to borrowers typically excluded from the formal credit system. In the context of climate shocks, such lending behavior plays a critical role in providing vulnerable households with access to liquidity when it is most needed.

[15]Borrowers are classified by TransUnion CIBIL into six score bands based on credit history and repayment behavior: (1) No Credit Score, (2) Subprime, (3) Near Prime, (4) Prime, (5) Prime Plus, and (6) Super Prime.

Table 14: Effect heterogeneity - by CIBIL score

Dependent variable	*CIBIL score band*					
	No score	Subprime	Near prime	Prime	Prime plus	Super prime
Loan amounts	0.119***	0.0713**	0.0894***	0.0473**	0.0165	0.0288
	(0.016)	(0.035)	(0.022)	(0.021)	(0.034)	(0.091)
New loans	0.128***	0.074***	0.068***	0.064***	0.03	0.04
	(0.011)	(0.019)	(0.013)	(0.013)	(0.018)	(0.034)
Delinquency rate	0.001	-0.0007	-0.002*	-0.001*	0.0001	0.004
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	850054	331003	521225	653939	267784	70451
R-squared	0.502	0.555	0.557	0.536	0.552	0.616
Date-Zip-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender-Product FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across CIBIL score bands using sample split estimates derived from Equation (2). Each row corresponds to a measure of loan performance. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

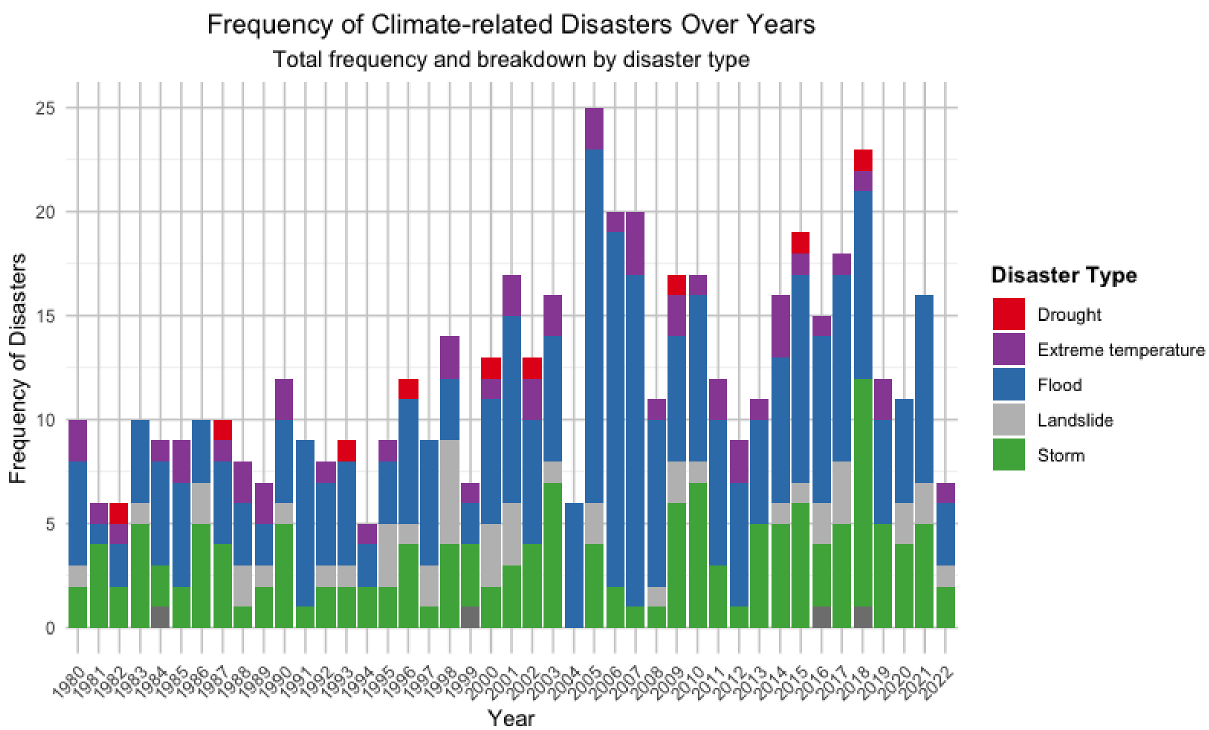
6 Conclusion

This paper examines how private credit supply responds to climate shocks, focusing on the role of non-bank lenders. Leveraging the August 2017 floods in Uttar Pradesh and Bihar as a plausibly exogenous shock, we combine georeferenced flood extent data with a near-universe panel of retail credit originations from TransUnion CIBIL. Using a difference-in-differences strategy that compares non-banks to banks across affected and unaffected zip codes, we find that non-banks expand lending by 5.75% in flooded areas relative to banks, with notable increases in both collateralized (15.8%) and uncollateralized (26.6%) credit—particularly in agricultural (20.4%) and consumption (23.1%) loans. While overall portfolio quality remains stable, we detect elevated delinquency rates in the uncollateralized segment, suggesting increased credit risk. Non-banks also disproportionately lend to borrowers without credit histories or prior relationships, highlighting their role in extending financial access during periods of heightened liquidity need. Methodologically, the paper advances the disaster-credit literature by aligning high-frequency credit originations with granular, zip-level disaster exposure, enabling a product-level view of supply dynamics beyond mortgages and coarse geographies. Substantively, our findings offer the first large-scale evidence of non-banks' countercyclical, last-mile role in disaster recovery—an insight increasingly relevant as climate risks rise and timely credit becomes critical for household and firm resilience.

APPENDIX

A Figures

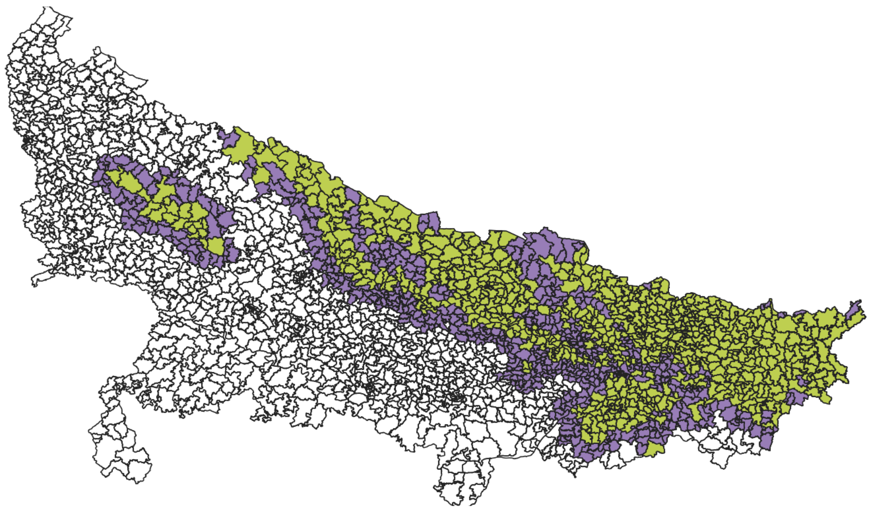
Figure 5: Disasters in India (Source: EM-DAT)



B Additional results

B.1 Robustness check: proximate controls

Figure 6: Control and Treated zipcodes



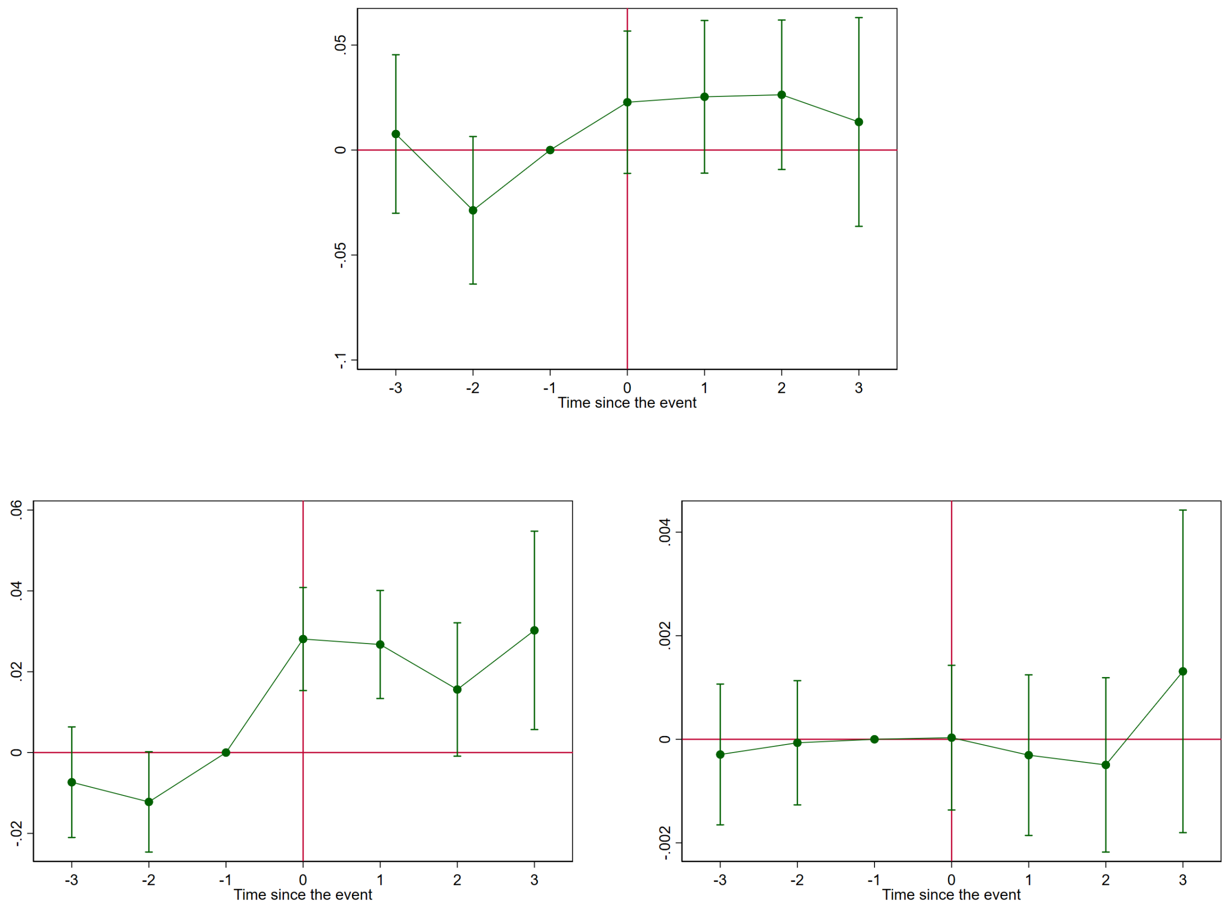
Notes: This map covers the Indian states of Uttar Pradesh and Bihar. Each polygon depicts one zipcode. Polygons in green are treated zipcodes, while polygons in purple are proximate control zipcodes - located within 30 kilometres of flood-affected areas.

As a robustness check, we re-estimate the difference-in-differences and event-study specifications using an alternative control sample restricted to zip codes located within 30 kilometers of treated (flood-affected) areas (Figure 6).

Figure 7 presents event-study estimates for the number of loan accounts, total loan amounts, and delinquency rates, respectively, using the nearby control group (analogous to Figure 4). The dynamic treatment effects closely mirror those in the baseline specification: there is no discernible pre-trend, and non-bank lending again rises sharply relative to banks while delinquency rates remain statistically unchanged.

Table 15 reports the core difference-in-differences estimates corresponding to Table 2 of the main text. The coefficient on Shock $\times$ non-bank remains positive and statistically significant, indicating that non-banks increase loan volume and new loans relative to banks by roughly the same magnitude as in the baseline sample. Table 16 presents results for delinquency rate, confirming that expanded lending does not compromise portfolio qual-

Figure 7: Event study: effect on credit amount (top), number of accounts (left), and delinquency rate (right).



Notes: These graphs present the relative impact of the August 2017 flood on non-bank lending in flood-affected districts compared to traditional bank lending in an event-study specification (Equation 1). The control group for all panels is the set of zipcodes within 30 kilometres of the flood-affected zipcodes. The dependent variables in the top, left, and right panels are loan amounts, number of loans, and delinquency rates. For all panels, Y-axis represents time in quarters relative to the flood event.

Table 15: Baseline Results: banks vs. non-banks

	(1)	(2)	(3)	(4)
	Loan amounts			No. of accounts
Shock X NBFC	0.0391***	0.0391***	0.0489***	0.0429***
	(0.013)	(0.013)	(0.013)	(0.008)
Observations	1415447	1415447	1384104	1404129
R-squared	0.0980	0.0980	0.401	0.248
Lender FE	No	Yes	No	No
Date-Zip FE	Yes	Yes	No	No
Date-Zip-Product FE	No	No	Yes	Yes
Date-Lender-Product FE	No	No	Yes	Yes
Zip-Lender-Product FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The control group is limited to zipcodes within 30 kilometres of the affected zipcodes. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of loans issued. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

ity.

Tables 17 to 20 disaggregate these effects by collateralization type. Tables 21 to 23 reproduce the product-level estimates. Non-banks continue to expand both collateralized and uncollateralized lending in flood-affected areas, with particularly strong responses in agricultural and consumption segments. Delinquency rates show no significant deterioration - in fact, some coefficients reflect that non-banks obtain better (lower) delinquency rates on their loans.

Table 16: Baseline Results: banks vs. non-banks - Delinquency Rates

	(1)	(2)	(3)
		Delinquency rate	
Shock X NBFC	0.00184***	0.00184***	0.00000714
	(0.000)	(0.000)	(0.000)
Observations	734457	734457	708905
R-squared	0.0426	0.0426	0.133
Lender FE	No	Yes	No
Date-Zip FE	Yes	Yes	No
Date-Zip-Product FE	No	No	Yes
Date-Lender-Product FE	No	No	Yes
Zip-Lender-Product FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 17: Banks vs. non-banks: Collateralized Lending

	(1)	(2)	(3)	(4)
		Loan amounts		No. of accounts
Shock X NBFC	0.545***	0.545***	0.0456	0.0645***
	(0.026)	(0.026)	(0.028)	(0.022)
Observations	146918	146918	146913	146913
R-squared	0.485	0.485	0.514	0.601
Lender FE	No	Yes	No	No
Date-Zip FE	Yes	Yes	Yes	Yes
Date-Lender FE	No	No	Yes	Yes
Zip-Lender FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of loans issued. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 18: Banks vs. non-banks: Delinquency rates for Collateralized Lending

	(1)	(2)	(3)
	Delinquency rate		
Shock X NBFC	-0.0515***	-0.0515***	-0.0374***
	(0.006)	(0.006)	(0.011)
Observations	137711	137711	137694
R-squared	0.363	0.363	0.390
Lender FE	No	Yes	No
Date-Zip FE	Yes	Yes	Yes
Date-Lender FE	No	No	Yes
Zip-Lender FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 19: Banks vs. non-banks: Non-collateralized Lending

	(1)	(2)	(3)	(4)
	Loan amounts			No. of accounts
Shock X NBFC	-0.0660**	-0.0660**	0.188***	0.201***
	(0.026)	(0.026)	(0.043)	(0.027)
Observations	183504	183504	183502	183502
R-squared	0.481	0.481	0.503	0.562
Lender FE	No	Yes	No	No
Date-Zip FE	Yes	Yes	Yes	Yes
Date-Lender FE	No	No	Yes	Yes
Zip-Lender FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of loans issued. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 20: Banks vs. non-banks: Delinquency rates for Non-collateralized Lending

	(1)	(2)	(3)
		Delinquency rate	
Shock X NBFC	0.176***	0.176***	0.0510***
	(0.008)	(0.008)	(0.011)
Observations	170549	170549	170529
R-squared	0.365	0.365	0.409
Lender FE	No	Yes	No
Date-Zip FE	Yes	Yes	Yes
Date-Lender FE	No	No	Yes
Zip-Lender FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 21: Banks vs. non-banks: Lending by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	0.172***	-0.388	-0.0744***	0.0848	0.127***	-0.00930
	(0.032)	(0.255)	(0.028)	(0.146)	(0.034)	(0.218)
Observations	90835	9175	99826	17192	182524	3015
R-squared	0.520	0.790	0.732	0.543	0.543	0.756
Date-Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable is the logarithm of loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 22: Banks vs. non-banks: Extensive Margin by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	0.169***	-0.432**	-0.00850	0.183*	0.174***	0.0192
	(0.030)	(0.174)	(0.022)	(0.096)	(0.023)	(0.155)
Observations	91059	9211	99893	17851	183502	3229
R-squared	0.494	0.799	0.810	0.590	0.554	0.657
Date-Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable is the logarithm of the number of loans. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC_l variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 23: Banks vs. non-banks: Delinquency rates by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	-0.0496***	0.200*	-0.0341***	0.0316	0.0584***	-0.0185
	(0.018)	(0.112)	(0.012)	(0.043)	(0.011)	(0.081)
Observations	67279	4835	84181	9174	170529	905
R-squared	0.467	0.545	0.543	0.521	0.404	0.615
Date-Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to the total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Delinquency rates for business loans are winsorized at the 1% level. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 24: Robustness: heterogeneity by prior relationship

Dependent variable	*Prior Relationship*	
	0	1
Loan amounts	0.0521***	0.0295
	(0.014)	(0.024)
Loan accounts	0.0486***	0.0386***
	(0.009)	(0.013)
Delinquency rate	0.00000439	-0.0000843
	(0.001)	(0.001)
Observations	484011	193736
R-squared	0.189	0.158
Date-Zip-Product FE	Yes	Yes
Date-Lender-Product FE	Yes	Yes
Zip-Lender-Product FE	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across lender-borrower pairs where the lender did (1) or did not (0) previously lend to the borrower, using estimates derived from Equation (2) where the prior relationship dummy is interacted with the β_2 term. The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 25: Robustness: heterogeneity by CIBIL score

Dependent variable	*CIBIL score band*					
	No score	Subprime	Near prime	Prime	Prime plus	Super prime
Loan amounts	0.0859***	0.0467	0.0955***	0.0567**	0.0149	-0.0551
	(0.021)	(0.044)	(0.030)	(0.026)	(0.046)	(0.114)
Loan accounts	0.102***	0.0458**	0.0446***	0.0549***	0.0334	-0.0135
	(0.014)	(0.023)	(0.016)	(0.015)	(0.025)	(0.046)
Delinquency rate	0.000835	0.000153	-0.00119	-0.00126	-0.000169	0.00460
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)
Observations	242419	48282	99209	151841	43029	5076
R-squared	0.263	0.306	0.258	0.206	0.292	0.164
Date-Zip-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Lender-Product FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across CIBIL score bands, using sample split estimates derived from Equation (2). The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. Each row corresponds to a measure of loan performance. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 26: Robustness: heterogeneity by credit score inquiry

Dependent variable	*Inquiry*	
	0	1
Loan amounts	0.0399*	0.0445***
	(0.023)	(0.016)
Loan accounts	0.0335***	0.0529***
	(0.013)	(0.011)
Delinquency rate	0.00152	-0.000455
	(0.001)	(0.001)
Observations	313035	355822
R-squared	0.223	0.141
Date-Zip-Product FE	Yes	Yes
Date-Lender-Product FE	Yes	Yes
Zip-Lender-Product FE	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across lender-borrower pairs where the lender did (1) or did not inquire (0) about the borrower from the credit union, using split sample estimates derived from Equation (2). The control group is limited to Zipcodes within 30 kilometres of the affected Zipcodes. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 27: Heterogeneity test: collateralized loans

	(1)	(2)	(3)
	Loan amounts	New loans	Delinquency rates
Shock X NBFC	0.0691***	0.0592***	-0.000352***
	(0.012)	(0.008)	(0.000)
Observations	1402260	1410933	786088
R-squared	0.321	0.248	0.200
Date-PIN-Product FE	Yes	Yes	Yes
Date-Lender-Product FE	Yes	Yes	Yes
PIN-Lender-Product FE	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across CIBIL score bands using sample split estimates derived from Equation (2). Each column corresponds to a measure of loan performance. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 28: Heterogeneity test: non-collateralized loans

	(1) Loan amounts	(2) New loans	(3) Delinquency rates
Shock X NBFC	0.0491***	0.0823***	0.0000960
	(0.017)	(0.012)	(0.001)
Observations	1097989	1115410	652775
R-squared	0.375	0.379	0.0851
Date-PIN-Product FE	Yes	Yes	Yes
Date-Lender-Product FE	Yes	Yes	Yes
PIN-Lender-Product FE	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood disaggregated across CIBIL score bands using sample split estimates derived from Equation (2). Each column corresponds to a measure of loan performance. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B.2 Robustness check: faraway controls

Our second robustness check re-estimates the difference-in-differences and event-study specifications using an alternative control sample restricted to zip codes located outside 30 kilometers of treated areas to limit spillovers.

Table 29: Baseline Results: banks vs. non-banks

	(1)	(2)	(3)	(4)
	Loan amounts			No. of accounts
Shock X NBFC	0.0164	0.0164	0.0610***	0.0671***
	(0.015)	(0.015)	(0.011)	(0.008)
Observations	2494843	2494843	2455258	2490792
R-squared	0.140	0.140	0.417	0.302
Lender FE	No	Yes	No	No
Date-PIN FE	Yes	Yes	No	No
Date-PIN-Product FE	No	No	Yes	Yes
Date-Lender-Product FE	No	No	Yes	Yes
PIN-Lender-Product FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The control group is limited to zipcodes outside 30 kilometres of the affected zipcodes. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of loans issued. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 30: Baseline Results: banks vs. non-banks - Delinquency Rates

	(1)	(2)	(3)
		Delinquency rate	
Shock X NBFC	0.000675**	0.000675**	-0.000171
	(0.000)	(0.000)	(0.000)
Observations	1423774	1423774	1390424
R-squared	0.0334	0.0334	0.119
Lender FE	No	Yes	No
Date-PIN FE	Yes	Yes	No
Date-PIN-Product FE	No	No	Yes
Date-Lender-Product FE	No	No	Yes
PIN-Lender-Product FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood, using estimates derived from Equation (2). The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 31: Banks vs. non-banks: Collateralized Lending

	(1)	(2)	(3)	(4)
		Loan amounts		No. of accounts
Shock X NBFC	0.864***	0.864***	0.214***	0.163***
	(0.027)	(0.027)	(0.024)	(0.020)
Observations	219929	219929	219924	219924
R-squared	0.455	0.455	0.485	0.565
Lender FE	No	Yes	No	No
Date-PIN FE	Yes	Yes	Yes	Yes
Date-Lender FE	No	No	Yes	Yes
PIN-Lender FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of loans issued. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 32: Banks vs. non-banks: Delinquency rates for Collateralized Lending

	(1)	(2)	(3)
	Delinquency rate		
Shock X NBFC	-0.0444***	-0.0444***	-0.112***
	(0.006)	(0.006)	(0.009)
Observations	206146	206146	206133
R-squared	0.350	0.350	0.384
Lender FE	No	Yes	No
Date-PIN FE	Yes	Yes	Yes
Date-Lender FE	No	No	Yes
PIN-Lender FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 33: Banks vs. non-banks: Non-collateralized Lending

	(1)	(2)	(3)	(4)
	Loan amounts			No. of accounts
Shock X NBFC	-0.452***	-0.452***	0.305***	0.328***
	(0.028)	(0.028)	(0.036)	(0.026)
Observations	265604	265604	265597	265597
R-squared	0.527	0.527	0.558	0.608
Lender FE	No	Yes	No	No
Date-PIN FE	Yes	Yes	Yes	Yes
Date-Lender FE	No	No	Yes	Yes
PIN-Lender FE	No	No	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable in Columns 1 through 3 is the logarithm of loan amounts. The dependent variable in Column 4 is the logarithm of number of loans issued. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 34: Banks vs. non-banks: Delinquency rates for Non-collateralized Lending

	(1)	(2)	(3)
		Delinquency rate	
Shock X NBFC	0.0842***	0.0842***	0.0803***
	(0.008)	(0.008)	(0.010)
Observations	247234	247234	247215
R-squared	0.393	0.393	0.444
Lender FE	No	Yes	No
Date-PIN FE	Yes	Yes	Yes
Date-Lender FE	No	No	Yes
PIN-Lender FE	No	No	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood for collateralized lending. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 35: Banks vs. non-banks: Lending by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	0.216***	-0.448**	0.0962***	0.109	0.282***	0.177
	(0.027)	(0.181)	(0.025)	(0.113)	(0.030)	(0.181)
Observations	135287	22806	151950	38677	264376	5076
R-squared	0.495	0.834	0.704	0.600	0.570	0.703
Date-PIN FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
PIN-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable is the logarithm of loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $\text{Shock}_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 36: Banks vs. non-banks: Extensive Margin by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	0.243***	-0.425***	0.114***	0.0658	0.308***	0.0211
	(0.026)	(0.136)	(0.021)	(0.079)	(0.024)	(0.128)
Observations	135588	22872	152131	40190	265597	5671
R-squared	0.495	0.817	0.776	0.641	0.587	0.661
Date-PIN FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
PIN-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable is the logarithm of the number of loans. The primary independent variable is an interaction term between the Shock and NBFC variables. The $Shock_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The $NBFC_l$ variable is a dummy indicating that the lender is an NBFC. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 37: Banks vs. non-banks: Delinquency rates by Product

	(1) Agriculture	(2) Gold	(3) Vehicle	(4) Business	(5) Consumption	(6) Microfinance
Shock X NBFC	-0.0925***	0.0701	-0.112***	0.0329	0.0870***	0.0460
	(0.015)	(0.096)	(0.010)	(0.036)	(0.010)	(0.083)
Observations	103274	14843	131649	23383	247215	1746
R-squared	0.444	0.533	0.545	0.497	0.440	0.652
Date-PIN FE	Yes	Yes	Yes	Yes	Yes	Yes
Date-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
PIN-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood at the product level. The control group is limited to Zipcodes outside 30 kilometres of the affected Zipcodes. The dependent variable is the ratio of delinquent loan amounts to the total loan amounts. The primary independent variable is an interaction term between the Shock and NBFC variables. The $Shock_{t,z}$ variable is a dummy indicating a flood shock in a given Zipcode z at time t. The NBFC variable is a dummy indicating that the lender is an NBFC. Delinquency rates for business loans are winsorized at the 1% level. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B.3 Differential effect: split sample results

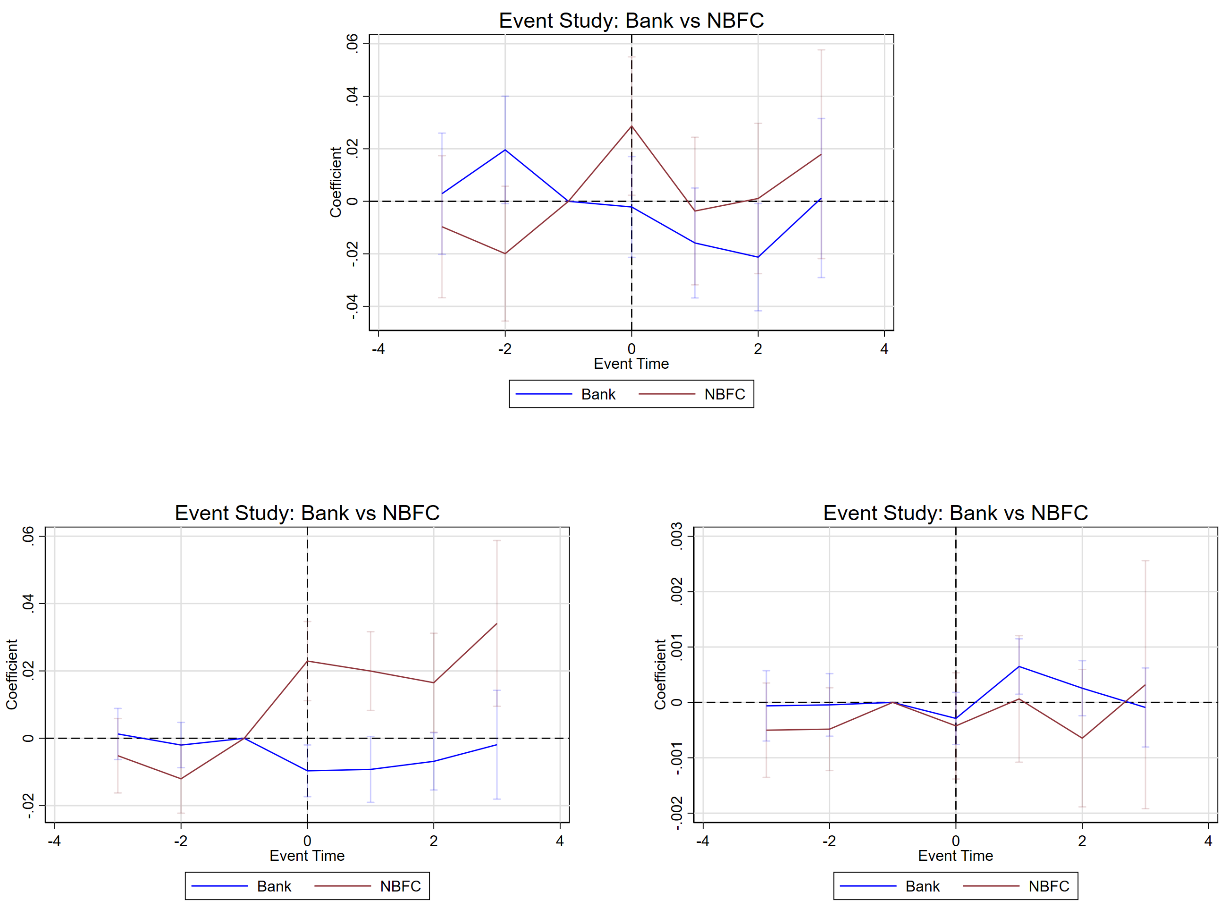
The differential effect on credit can also be identified by splitting the sample and estimating separate event-study models for banks and NBFCs. Splitting the sample allows the coefficients to capture the time-varying effects of the flood shock within each lender type, isolating the temporal adjustment patterns of each group.

Formally, the specification is:

$$Y_{t,z,p} = \alpha + \sum_{k \neq -1} \beta_k D_{t,z} + \delta_{z,p} + \eta_{t,p} + \epsilon_{t,z,p} \tag{3}$$

The estimated coefficients are plotted in Figure 8. The results reveal clear divergence in post-flood lending behavior. For banks (blue), coefficients remain flat throughout the event window, indicating limited adjustment in either loan amounts or borrower coverage after the floods. In contrast, NBFC coefficients (red) show a pronounced and sustained increase beginning in the flood quarter and persisting for several quarters thereafter. This pattern is visible for both loan amounts (top panel) and number of accounts (bottom-left panel), suggesting that NBFCs expanded credit supply on both the intensive and extensive margins. The delinquency panel (bottom-right) shows no significant rise in default rates for either group, implying that NBFC expansion was not accompanied by higher default rates.

Figure 8: Event study: effect on credit amount (top), number of accounts (left), and delinquency rate (right).



Notes: These graphs present the relative impact on non-bank lending (compared to bank lending) of the August 2017 flood in an event-study specification (Equation 3). The sample is split for banks (blue) and non-banks (red) and estimated separately. The dependent variables in the top, left, and right panels are loan amounts, number of loans, and delinquency rates. For all panels, Y-axis represents time in quarters relative to the flood event.

C Data Appendix

C.1 CIBIL

We use loans and credit score data from **TransUnion CIBIL**, India's oldest credit bureau. Our working dataset is aggregated at the **zip code** × **credit score band** × **product category** × **lender type** × **inquiry status** × **prior relationship** level. Below, we describe the construction and meaning of each variable.

Zip Code. Refers to the Indian Postal Index Number (zip) corresponding to the borrower's location. zip codes serve as the geographic identifier, enabling alignment with flood exposure data.

Credit Score Band. Borrowers are classified by TransUnion CIBIL into five score bands based on their credit history and repayment behavior:

1. *No credit score*
2. *Subprime*
3. *Near Prime*
4. *Prime*
5. *Prime Plus*
6. *Super Prime*

Product Category. Loan products are grouped into six broad categories:

1. **Vehicle Loan** – credit used for the purchase of automobiles or two-wheelers.
2. **Consumption Loan** – unsecured household borrowing for durable or nondurable consumption.
3. **Business Loan** – working capital and small-enterprise credit extended to individuals or proprietorships.

4. **Gold Loan** – secured lending backed by household gold collateral.

5. **Agricultural Loan** – credit for farm inputs, machinery, or other agri-related purposes.

6. **Microfinance Loan** – group or individual loans extended through microfinance institutions (MFIs).

Lender Type. Lenders are classified according to institutional type:

1. **PSU Banks** – public sector banks.

2. **Private Banks** – privately owned scheduled commercial banks.

3. **NBFCs** – non-bank financial companies.

4. **HFCs** – housing finance companies.

5. **Fintechs** – digitally enabled, technology-based lenders.

This typology allows us to distinguish traditional deposit-taking institutions from non-bank and digital intermediaries. We code items 3, 4, and 5 as non-bank institutions.

Inquiry Indicator. Equals 1 if the lender made a credit inquiry to TransUnion CIBIL regarding a prospective borrower within 90 days prior to the loan origination. This variable proxies for recent loan applications and credit demand.

Prior Relationship Indicator. Equals 1 if the lender had extended a loan to the same borrower within the preceding five years. This variable captures relationship lending and repeat interactions between lender and borrower.

D Data availability

The credit data used in this study are proprietary and subject to institutional confidentiality restrictions. As a result, they are not publicly available.

Table 38: Loan Amounts: by Product Category and Lender Type

	Mean	SD	Median	Obs
Agriculture				
Banks	2.4455	107.0425	0.326	488,720
Non-banks	0.5723	0.6407	0.420	92,270
Consumption				
Banks	0.7165	7.8287	0.250	697,098
Non-banks	0.2431	1.3330	0.0319	303,012
Gold				
Banks	0.2156	0.3981	0.104	81,442
Non-banks	0.3119	1.0532	0.090	99,304
Vehicle				
Banks	1.1046	3.3869	0.457	317,235
Non-banks	1.0281	2.1646	0.435	347,544
Business				
Banks	1.2172	8.4905	0.300	64,131
Non-banks	0.8639	8.2369	0.240	42,513
MFI				
Banks	0.3459	2.5012	0.0800	30,642
Non-banks	1.0673	6.9096	0.0386	331

Notes: Amounts are in million rupees. Numbers are rounded to two decimals. Observation counts may differ due to missing values.

Table 39: Loan Accounts: by Product Category and Lender Type

	Mean	SD	Median	Obs
Agriculture				
Banks	0.00515	0.0307	0.002	488,720
Non-banks	0.00158	0.00164	0.001	92,270
Consumption				
Banks	0.00410	0.0240	0.001	697,098
Non-banks	0.00854	0.0372	0.002	303,012
Gold				
Banks	0.00176	0.00226	0.001	81,442
Non-banks	0.00499	0.0173	0.001	99,304
Vehicle				
Banks	0.00287	0.00864	0.001	317,235
Non-banks	0.00461	0.0129	0.002	347,544
Business				
Banks	0.00143	0.00140	0.001	64,131
Non-banks	0.00243	0.00439	0.001	42,513
MFI				
Banks	0.00347	0.0109	0.001	30,642
Non-banks	0.00187	0.00220	0.001	331

Notes: Number of accounts are in millions. Numbers are rounded to two decimals. Observation counts may differ due to missing values.

Table 40: Delinquency Rates: by Product Category and Lender Type

	Mean	SD	Median	Obs
Agriculture				
Banks	0.015877	3.814228	0	481,343
Non-banks	0.000336	0.0017065	0	92,270
Consumption				
Banks	0.0029791	1.205386	0	688,393
Non-banks	0.0048236	0.0383395	0	302,967
Gold				
Banks	0.0002045	0.002687	0	80,738
Non-banks	0.0285943	4.768780	0	99,304
Vehicle				
Banks	0.000302	0.0022446	0	316,708
Non-banks	0.0004648	0.0023912	0	347,526
Business				
Banks	0.0172723	4.113694	0	59,093
Non-banks	0.0013611	0.0044035	0	42,512
MFI				
Banks	0.001688	0.0626847	0	26,298
Non-banks	0.0007951	0.0079971	0	331

Notes: Delinquency rate is the share of origination amount that becomes 90+ DPD within 12 months. Numbers are rounded to two decimals. Observation counts may differ due to missing values.

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