Bridges Over Troubled Waters: Banking Responses to Flood Disaster

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Abstract

This study examines the causal impact of the 2015 Tamil Nadu floods on district-level banking outcomes using a difference-in-differences framework. Exploiting variation between flood-affected and unaffected districts, we estimate how credit and deposit flows responded to the disaster across multiple sectors, including agriculture, industry, trade, transport, and personal loans. Results show that flood exposure significantly increased credit allocation to indirect agricultural finance and retail trade, reflecting both farmers' recovery needs and heightened reconstruction-related demand. However, deposit levels in affected districts did not exhibit significant changes, suggesting households primarily drew on savings for immediate consumption and relocation costs. Heterogeneity analysis reveals distinct responses by banking offices: in districts with fewer bank offices, credit flows rose for agriculture and professional services but declined for housing loans, highlighting liquidity constraints and prioritisation of short-term recovery needs. In contrast, districts with dense banking networks experienced broader increases spanning agriculture, manufacturing, transport, and personal loans, alongside significant deposit growth. Event study and trend analyses confirm the parallel trends assumption, while robustness checks excluding neighbouring districts validate the findings. Overall, the study shows that banks act as critical stabilisers during disasters, with their institutional reach shaping the capacity to mobilise deposits and sustain credit flows.

Keywords: Credit availability; Natural disasters; Developing economies; Aggregate activity.

JEL Classifications : E23, G21, O13, Q14, Q54

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1. Introduction

The accelerating pace of climate change has intensified the occurrence and severity of natural disasters, posing a major threat to global stability. Rising temperatures, shrinking glaciers, and sea-level rise are not only reshaping ecosystems but also increasing the likelihood of sudden economic and political disruptions. Evidence shows a clear upward trend in the frequency and strength of extreme weather events over recent decades, with studies demonstrating a strong link between climate change and disaster risk (Coronese et al., 2019; Bevacqua et al., 2024). The Intergovernmental Panel on Climate Change (IPCC, 2014) warns that these shifts carry profound socioeconomic consequences, including crop losses, heightened wildfire danger, infrastructure failures, resource scarcity, and pressure on political systems. These impacts are particularly severe in developing countries, where high dependence on agriculture, limited adaptive capacity, and weaker infrastructure amplify the economic damage of disasters. As a result, similar events often result in disproportionately higher losses, recovery costs, and livelihood disruptions compared to developed economies.

In this paper, we empirically examine the effect of climate-induced natural disaster, coastal flooding on bank credit in a developing economy context, focusing on India over the period 2002-2022. We first investigate the extent to which coastal flooding influences overall bank credit in the aftermath of the disaster. We then analyze its differentiated effects across key loan categories, including agricultural credit, personal loans, and trade-related lending, to better understand sectoral vulnerabilities. By assessing disaster-induced changes in bank lending behavior, this paper contributes to understanding the financial sector's resilience and its role in disaster response in developing economies.

The relationship between natural disasters and banking outcomes has been studied in multiple country contexts, offering significant insights. For example, Nguyen et al. (2024) find that natural disasters significantly reduce deposit ratios but show no immediate effect on liquidity, credit risk, profitability, or default risk. Similarly, Gramlich et al. (2023), using a dataset covering 9,928 banks across 149 countries, demonstrate that disaster damages negatively affect capital ratios, with the extent of impact depending on bank location, capitalization, and business model. In the Indian context, Boungou and Gupta (2024) show that natural disasters impair profit-earning assets of commercial banks, highlighting their vulnerability. Despite these contributions, there remains limited understanding of how disasters influence bank credit dynamics over time, particularly in developing economies where banking systems are critical

to recovery. Few studies assess the long-term, post-disaster credit response examining whether lending recovers, stagnates, or becomes more risk-averse in the years following a disaster. Moreover, existing research rarely disaggregates credit into categories (such as agricultural, personal, and trade loans) to uncover sector-specific vulnerabilities. Our study addresses these gaps by analyzing district-level flood exposure and detailed bank credit data for India, providing a comprehensive examination of both short-term and persistent effects of natural disasters on credit allocation and banking resilience.

Natural disasters influence bank credit through multiple interconnected channels that affect both borrowers' and lenders' balance sheets. The physical destruction of capital highlighted in Input-Output and Computable General Equilibrium (CGE) frameworks reduces firms' and households' collateral, erodes repayment capacity, and increases the demand for liquidity (Botzen et al., 2020). At the same time, disasters damage bank infrastructure and raise uncertainty, constraining lending exactly when demand surges. The Bank of Japan survey emphasizes that disasters suppress credit supply in affected areas and may spill over to unaffected regions as banks reallocate resources; these effects are stronger for undercapitalized banks. Ivanov et al. (2022) further demonstrate this spillover using syndicated lending data: capital-constrained banks meet disaster-driven credit demand locally by cutting credit to distant borrowers, reducing corporate credit in unaffected regions by about 3%. This underscores how lending networks propagate shocks across geographies. Moreover, disasters alter risk perceptions, increasing provisioning requirements, tightening lending standards, and reducing long-term credit availability (Gramlich et al., 2023). These dynamics create a paradox: while reconstruction lending or government-backed relief schemes may temporarily boost credit flows, the medium-term trajectory often reflects heightened risk aversion and declining credit quality. Understanding these mechanisms is vital for assessing systemic risk, especially in agriculture-intensive economies like India, where rural banking networks are deeply intertwined with disaster-prone sectors.

Severe economic losses from disasters often prevent households from repaying outstanding loans on time, leading to higher default rates and increased financial strain. Research shows that disasters lower household income while raising essential expenses, pushing families to borrow more to meet immediate needs and rebuild their lives (Sawada & Takasaki, 2017). In rural areas, where agriculture is the primary livelihood, floods and cyclones can destroy crops, livestock, and farm infrastructure, further weakening repayment capacity. This cycle of

reduced income, higher borrowing, and collateral damage makes agricultural loans especially vulnerable, placing added stress on cooperative banks and rural credit institutions that already operate with thin margins and limited capital buffers.

Our results indicate that flooding affects businesses not only through direct physical damage, but also by worsening their financial conditions, notably by increasing their cost of capital, and by jeopardising their ability to service their debt obligations. Hence, while the full impact of climate change is expected to materialise in the long run, climate-related disasters and extreme weather events may disrupt firm operations in the short and medium term, not only in a direct way, but also through the financial channel. This effect is exacerbated by the high reliance of SMEs on bank funding, and their limited access to capital markets, which reduces the possibility of substituting away from bank credit (Iyer et al., 2014). Intensification of climate disasters due to climate change may become an important source of financial vulnerability for European small and medium-sized businesses, and for the banks financing them. A number of studies document that natural hazards bring about an increase in the demand for credit for reconstruction purposes (Berg and Schrader, 2012; Cort´es and Strahan, 2017).

The remainder of the paper is structured as follows. Section 2 reviews the existing literature and elaborates on the contribution of this study alongside the conceptual framework. Section 3 presents the data and empirical strategy, including the difference-in-differences setup and event study methodology. Section 4 provides descriptive analysis, empirical results, and heterogeneity analysis through sub-sample analysis based on banking office density. Section 5 performs robustness checks, including tests of the parallel trends assumption and an alternate treatment group definition. Section 6 presents the conclusion, followed by Section 7, which discusses policy implications.

2. Literature Review and Framework

Several studies have examined the impact of natural disasters on banks, focusing on profitability, performance, and deposits. Walker et al. (2022), using a sample of 187 large-scale U.S. disasters and 2,891 banks from 2000 to 2014, investigate how damages affect bank profitability and solvency. Their results show that disasters significantly influence net income, impaired loans, and return on assets. Solvency measures such as the equity ratio and tier-1 capital ratio also respond, though effects differ across bank types: regional banks often benefit from increased deposits related to recovery payments and insurance inflows, while local and

national banks show negative impacts. Nguyen et al. (2024) study East Asian banks between 1999 and 2014 and find that natural disasters reduce deposit ratios in the short run but have little immediate effect on liquidity, credit risk, or profitability. However, one year later, deposits tend to rise while liquidity falls, reflecting delayed adjustments. Importantly, cross-border banking claims, particularly from regional Asian lenders, help to cushion these shocks in the aftermath of disasters.

Additionally, Barth et al. (2024) provide further evidence from U.S. bank branches (2008-2017), showing both direct and indirect effects of disasters on deposit rates. Directly exposed branches raise deposit rates modestly, but the larger adjustment occurs through spillovers to neighboring, unaffected branches, driven by competition and social connectedness. Their study finds that indirect effects account for up to two-thirds of the total impact, underscoring how disasters shape deposit markets not only locally but also through competitive linkages.

In the Indian context, most of the existing work has focused on household-level impacts of natural disasters. Lahiri and Biswas (2022) show that flood-affected households hold fewer illiquid assets and shift toward more liquid financial assets in the post-flood period, reflecting a change in balance sheet composition. At the same time, disasters raise indebtedness, largely driven by borrowing for essential expenditures. Similarly, Beyer et al. (2022), studying the 2018 Kerala floods, find reduced borrowing for consumption but increased debt for housing and medical needs in the short run. They also report lower household income and expenditure, alongside a shift in savings from banks and gold to post office deposits. While these studies highlight the significant effects of disasters on households, the evidence on how natural disasters influence banking activities in India is still limited but growing. Boungou and Gupta (2024), analyzing the 2001 Gujarat earthquake, find that banks in affected cities reduced loan volumes, increased their holdings of safer securities, and adopted more conservative lending strategies. They also document a decline in banks' overall risk-taking, reflecting a shift in portfolio composition under heightened uncertainty. Taken together, these studies highlight that while natural disasters impose significant costs on households, they also reshape banking behavior though comprehensive evidence on how disasters affect bank credit, particularly agricultural lending, is still lacking.

2.1 Study context

India is widely recognized as one of the most climate risk–prone regions in the world, frequently exposed to natural disasters such as floods, cyclones, and droughts. The Global Climate Risk Index consistently ranks India among the top countries most affected by extreme weather events, reflecting both its high exposure and limited adaptive capacity (Eckstein et al., 2021). Among these hazards, floods are the most recurrent and damaging, accounting for nearly half of all natural disasters in the country over the past two decades (National Disaster Management Authority, 2020). These events not only cause large-scale destruction of infrastructure and livelihoods but also exert significant strain on the financial system, especially in rural and agriculture-dependent areas.

Within India, the coastal states are particularly vulnerable, as they face the dual risks of heavy monsoon rainfall and cyclonic storms. Tamil Nadu, Kerala, and Karnataka have experienced frequent episodes of intense rainfall and flooding in recent years, leading to severe damages in agriculture, housing, and local infrastructure. The 2015 floods in Chennai, the 2018 Kerala floods, and the recurrent monsoon floods in coastal Karnataka illustrate the rising frequency and severity of such disasters. These regions are highly dependent on agriculture and fisheries, with banking institutions playing a central role in financing household consumption, farm activities, and small-scale trade. As a result, floods in these states not only disrupt local economies but also directly impact the operations and lending behavior of banks, making them critical sites for studying the links between natural disasters and bank credit.

In late 2015, Tamil Nadu and the neighboring Union Territory of Puducherry experienced one of the most severe flood events in recent decades. During November and December, Chennai alone recorded over 1,000 mm of rainfall, accompanied by strong winds that uprooted more than 900 trees (GCC, 2017). Toward the end of November, another low-pressure system, linked to the El Niño phenomenon, brought additional downpours, further aggravating the situation. Experts noted that rising temperatures may have contributed to the intensity of rainfall across the coastal belt. The National Institute of Disaster Management reported that several districts including Tiruvallur, Chennai, Kancheepuram, Villupuram, Cuddalore, and Nagapattinam in Tamil Nadu, as well as Puducherry and Karaikal in the Union Territory, were among the worst affected, suffering widespread damage to infrastructure, housing, and livelihoods.

The scale of destruction during the 2015 floods was unprecedented, particularly in Chennai, where 165 out of 200 wards were submerged under water. Basic services collapsed as power supply, schools, airports, and railway networks were brought to a halt, while even hospitals

struggled to function during the peak of the disaster (GCC, 2017). Prolonged rainfall caused several water bodies to overflow, and the Government of India officially declared Chennai a disaster zone. Household surveys indicated that nearly 30% of families in Chennai suffered economic losses ranging from ₹2 lakhs to ₹20 lakhs, while the city's industrial sector faced damages estimated at around ₹14,000 crores (Express News Service, 2015[3]). The surrounding districts were also heavily impacted. In Kancheepuram, floodwaters reached the second floor of many buildings, while in Cuddalore, eight villages were inundated following the overflow of the Paravanar river, prompting the administration to relocate entire communities (District Disaster Management Plan Cuddalore, 2021). Agricultural land was severely affected, with approximately 720 acres destroyed in Cuddalore alone. In Villupuram district, nearly 4,500 residents had to be evacuated from submerged areas. The neighboring Union Territory of Puducherry also faced widespread losses, with Ariyanpukkam town particularly hard-hit. Municipal records estimate damages of ₹486.6 million to local infrastructure, while the agriculture, power, and revenue departments together reported losses of nearly ₹130 million (Times of India, December 3, 2015[4]).

2.2 Conceptual framework

The conceptual framework shown in Figure 1 illustrates the multi-channel pathways through which the 2015 Tamil Nadu floods may have impacted district-level and sectoral banking outcomes.

[Figure 1]

The framework begins with the flood as an exogenous shock that could generate immediate impacts across three dimensions: (i) physical destruction of infrastructure and assets, (ii) economic disruption through business interruptions and supply chain breakdowns, and (iii) financial distress as households and firms faced liquidity constraints and debt-servicing difficulties. These immediate impacts could be transmitted through multiple banking channels. On the one hand, there may be increased credit demand for reconstruction activities, particularly in agriculture and retail trade. On the other hand, banks could face deteriorating credit risk profiles due to loan defaults and information asymmetries, funding pressures from deposit withdrawals and higher borrowing costs, and capital constraints arising from greater provisioning requirements. The relationship between disaster impacts and banking outcomes

[3] https://www.newindianexpress.com/cities/chennai/2015/Dec/27/flood-hit-industrial-belts-clamour-for-aid-861032.html
[4] https://timesofindia.indiatimes.com/topic/chennai-floods

may also be mediated by critical institutional factors. These could include policy responses such as the RBI's disaster relief guidelines, which relaxed lending standards and facilitated alternative documentation; variations in banking infrastructure density across districts, which may determine institutional capacity to absorb shocks; and the availability of alternative financial institutions such as cooperatives and microfinance organizations. The culmination of these channels could produce heterogeneous banking outcomes. Sector-specific credit patterns may emerge, with increases in indirect agricultural finance and retail trade credit. Aggregate deposit levels may remain relatively stable despite initial withdrawal pressures. District-level differences could further matter: banking penetration may be a key determinant, with high-density banking districts demonstrating greater capacity for diversified credit expansion and deposit mobilization compared to areas with limited formal banking infrastructure.

3. Data and Empirical Strategy

3.1 Data

We leverage the Basic Statistical Returns (BSR) of Scheduled Commercial Banks in India, sourced from the Reserve Bank of India, covering the period 2002–2022. The BSR provides detailed information on credit disbursement by occupation category, including Agriculture (Direct and Indirect Finance); Industry (Mining & Quarrying, Manufacturing & Processing, Electricity, Gas & Water, Construction); Transport Operators; Professional and Other Services; Personal Loans (Durables, Housing, and Other Personal Loans); Trade (Wholesale and Retail); Finance; All Others; and Total Bank Credit (Artisans, Village & Tiny Industries, and Other Small-Scale Industries). Except for 2005 and 2013, we construct a balanced panel dataset for all districts. Alongside credit data, we extract district-level deposits, number of bank accounts, and number of bank offices from the BSR. To proxy local economic activity and electrification in the absence of reliable time-series data, we incorporate gridded night-time lights—aggregated and calibrated annually across DMSP and VIIRS platforms from SHRUG's database[5].

3.2 Empirical strategy

To estimate the causal impact of the 2015 flood on the district-level banking outcomes in Tamil Nadu we employ a difference-in-differences (DD). The DD framework is a quasi-experimental research design that allows identification of the causal effect of treatment on treated units

[5] It is an open access repository currently comprising dozens of datasets covering India's over 500,000 villages and 8000 towns over a span of 25 years, all linked together with a set of common geographic identifiers.

relative to control units, under the assumption that, in the pre-treatment period, treated and control districts differ only in their baseline levels. This method calculates the treatment effect by comparing the average change in outcome variables across treated and control districts over time and is widely used to assess the effects of exogenous shocks or policy interventions.

In our analysis, the outcome variables are the district-level credits extended by banks across multiple sectors: total agriculture (total,direct finance, indirect finance) industry (comprising mining & quarrying, manufacturing & processing, electricity, gas & water, construction), transport operators, professional and other services, personal loans (loans for purchase of consumer durables, loans for housing), trade (wholesale trade, retail trade), finance, and others. Formally, we estimate:

$$Y_{dt} = \alpha + \beta_1 Disaster_d + \beta_2 Post_t + \beta_3 (Disaster_d \times Post_t) + \gamma X_{dt} + \delta_d + \lambda_t + \varepsilon_{dt} \quad (1)$$

Where Y_{dt} represents the district-level credit outcomes described above. $Disaster_d$ is an indicator for districts affected by the 2015 flood, $Post_t$ denotes the post-flood period (2015), and the interaction term ($Disaster_d \times Post_t$) identifies the treated districts after the disaster. This coefficient captures the causal effect of the flood on district-level credit outcomes.

We include district-level controls, X_{dt} such as the number of bank accounts, the number of bank offices, and night-light intensity to account for local economic activity. District fixed effects (δ_d) account for time-invariant characteristics of districts, year fixed effects (λ_t) capture common shocks, and standard errors are clustered at the district level to address within-district correlation. Deposit amounts are measured through aggregated total deposits. Our treatment group comprises the districts of Kancheepuram, Chennai, Thiruvallur, Cuddalore, Nagapattinam, and Villupuram, which were severely affected by the disaster, while all other districts in Tamil Nadu serve as the control group. We construct a binary treatment variable (treatment = 0) and assign a value of one for districts in the treatment group based on district names. To identify the causal impact of the disasters, we employ a difference-in-differences (DiD) strategy, comparing changes in credit and deposit outcomes before and after 2015 between treated and control districts. We also assess parallel trends in pre-treatment years to validate the DiD assumption. To formally assess the validity of the parallel trends assumption required for causal identification, we additionally estimate an event-study specification of the form:

$$Y_{dt} = \alpha + \sum_{k \in K, k \neq -1} \beta_k \, (Disaster_d \times 1_{t-2015=k}) + \gamma X_{dt} + \delta_d + \lambda_t + \varepsilon_{dt} \quad (2)$$

Where, K indexes years relative to the flood (e.g., $k = -9, \ldots., -3, -1, 0, 1, 2, ..$) , excluding years for which data are unavailable (such as 2005 and 2013). $1_{t-2015=k}$ is an indicator for each year k relative to the flood year (2015); $k = -1$ (the pre-flood year) is omitted as the reference period. The coefficients β_k for $k < 0$ measure any pre-flood differences in trends between treated and control districts in each relative pre-treatment year. We jointly test the null hypothesis $H_0: \beta_k = 0 \; for \; all \; k < 0$. Failure to reject H_0 supports the parallel trends assumption, as it indicates no pre-treatment divergence in credit between treatment and control districts. The same set of controls and fixed effects as in the baseline DD are included. The event-study specification also enables us to visualise and quantify the timing and persistence of the flood's impact by tracing the estimated effects year by year before and after the shock.

4. Empirical results

4.1 Descriptive statistics

Table 1 and Table 2 reveal a notable expansion in credit, deposits, and bank infrastructure in both regions post-shock, but with a much larger absolute scale and growth in the affected districts (treatment) group in Tamil Nadu. Specifically, the affected districts experienced substantial increases in outstanding credit across all categories, with industry and personal loans showing the largest post-shock means (26.6 and 18.1 crores, respectively), far exceeding the control group's credit amounts. Similarly, deposit amounts and the number of offices more than doubled in both groups post-shock, but the affected districts maintained a significantly higher scale, having 2.33 million in mean deposits and 622.83 offices post-shock compared to 408 thousand and 289.24 in other districts. Finally, the variability (sd) across all metrics increased notably in the post-shock period for the affected districts, indicating a greater heterogeneity in outcomes after the event. These differences underscore the uneven scale of financial exposure and post-disaster adjustments across districts, which justifies the use of a difference-in-differences strategy to isolate the disaster's impact. Appendix Figures A1 to A6 present the temporal trends in bank credit supply across occupations for affected and unaffected districts of Tamil Nadu. The figures show changes over time, from 2002 to 2022, in the log of credit share, with the red line representing unaffected districts and the blue line representing affected districts.

[Table 1]

[Table 2]

4.2 Main results

Table 3 presents the DD regression estimates for the causal impact of the 2015 flood on district-level bank credits by occupation category. Recovery trajectories vary by economic sector (Rodríguez, 2007). Even when one industry bears the majority of disaster damage—such as from floods or earthquakes—the effects are never homogenous (Rodríguez, 2007). The regressions are controlled for proxies of economic activity and banking penetration, including nighttime lights, the number of bank accounts, and the number of bank offices.

The results reveal a significant increase in credits distributed to the agriculture sector, particularly for indirect finance after the disaster by the banks operating in the flooded districts. This finding suggests that flood-affected districts experienced heightened demand for agricultural credit in the post-disaster period, likely driven by farmers' need to replace damaged crops, livestock, and farming equipment, as well as to finance replanting and restoration activities. This pattern is institutionally supported by the Reserve Bank of India's disaster relief guidelines (RBI, 2017)[6], which explicitly mandate that "banks shall grant fresh crop loan to the affected people based on the scale of finance for the crop and the cultivation area" and stipulate that "credit should not be denied for want of personal guarantees" while "assistance will not be denied merely for want of additional fresh security." The guidelines further facilitate indirect finance by allowing "margin requirements may be waived" and accepting that "in the absence of original title record, a certificate issued by the Revenue Department officials may be accepted for financing to farmers." These relaxed lending norms naturally favor cooperative societies and microfinance institutions that have established relationships with local revenue authorities and can process such alternative documentation more efficiently than formal banking channels

This pattern of increased agricultural credit demand following natural disasters is well-documented by Del Ninno, Dorosh, and Smith (2003) and Dercon (2002) who report similar increases in credit demand following the 1998 floods in Bangladesh, while Rizwan et al. (2020) document heightened agricultural credit demand among flood-affected Pakistani farmers. Additionally, Berg and Schrader (2012), who examine post-disaster lending following a volcanic eruption in Ecuador reported that while natural disasters disproportionately disrupt agricultural credit access, farmers with established relationships with microfinance institutions

[6] https://www.rbi.org.in/commonman/English/scripts/notification.aspx?id=2326

maintain better credit access compared to new borrowers. This relationship effect may explain why indirect finance channels—which involve more personalized lending through cooperatives and self-help groups—show stronger growth in our context. The rapid banking sector response observed in Tamil Nadu is consistent with international evidence showing banks react swiftly to compensate for delayed government intervention. Abedifar et al. (2024) document this phenomenon during Iran's 2019 floods, while Cortés (2014) and Cortés and Strahan (2017) provide similar evidence from the United States, demonstrating that local banks serve as crucial financial intermediaries during critical recovery periods when government assistance faces implementation delays.

We also observe a significant increase in credits to retail trade, which can be attributed to the heightened economic activity during the post-flood reconstruction phase. The disaster likely created increased demand for construction materials, household goods, and daily necessities, prompting retailers to seek additional working capital to replenish inventory and meet surge in consumer demand. This pattern is consistent with the typical economic response following natural disasters, where retail trade experiences temporary growth due to reconstruction-related consumption. Small businesses are predominantly found in the service and retail sectors, which are intensely competitive and experience higher rates of closures and ownership changes even in normal, non-disaster periods (Rodríguez, 2007). Small retail businesses differ from large retailers in that they are directly and indirectly affected by extreme events, yet they possess fewer resources to respond and retain resilience (Ingirige et al., 2008). In a broader context, internal and external vulnerability factors jeopardize the resilience of small retail businesses (Ehlers & Lazenby, 2011). Regulatory frameworks and access to finance are generally regarded as external threats. Identifying idiosyncratic and covariate threats in the broadly informal small retail business sector—especially in light of the observed increase in credit to retail trade during post-disaster reconstruction—enables the development of targeted preventive and response actions that align capital support with firms' most critical vulnerabilities (Kativhu et al., 2018).

The analysis indicates that for occupation categories apart from indirect finance in agriculture and retail trade, there are no significant impacts on district-wise bank credit following the 2015 Tamil Nadu flood. Specifically, sectors such as transport operators, professional and other services, personal loans, industry, and construction do not show significant changes in credit allocation post-shock. These findings are consistent across all examined occupations, and the full set of occupation-wise results is presented in Appendix Table A1 for reference. Existing

literature observes that while some construction-related enterprises may experience a temporary spike in activity following disasters, this does not translate into a significant or lasting impact on credit in the studied context (Dahlhamer & Tierney, 1998; Rodríguez, 2007).

The results for deposits are reported in Appendix Table A2. Regarding deposits, although a decline in total deposits is observed across flood-affected districts, this decrease is not statistically significant. The downward movement in deposits can be attributed to households' immediate liquidity requirements following the disaster—families likely withdrew savings to meet emergency expenses, cover temporary relocation costs, and finance initial reconstruction activities. Additionally, some depositors may have shifted funds to banks in districts unaffected by the flood as a precautionary measure, contributing to the observed reduction in deposit levels within the affected regions. Upon visual inspection of Appendix Figures A1 (agriculture) and A6 (trade), comparing credit differences before and after the shock, we find that the parallel trends assumption appears to be satisfied.

[Table 3]

[Table 4]

[Table 5]

4.3 Heterogeneity analysis

Studies suggest that banking infrastructure density may moderate the relationship between natural disasters and credit allocation. Districts with varying levels of banking penetration likely exhibit different financial intermediation capacities and institutional responses to external shocks. Areas with dense banking networks may have greater capacity to absorb deposit outflows while simultaneously expanding credit supply, whereas districts with limited banking infrastructure may rely more heavily on informal or semi-formal financial intermediaries. Additionally, policy relevance motivates this analysis as understanding heterogeneous effects across different banking environments provides crucial insights for targeted policy interventions. Examining how treatment effects vary across districts with different banking densities can help in understanding whether effects operate primarily through formal banking channels or through alternative financial intermediaries.

To examine whether the impact of the floods varies by banking infrastructure density, we conduct heterogeneity analysis based on district-level bank size, measured by the number of bank offices. We categorise districts using bank office percentiles based on the distribution of bank branches within Tamil Nadu in 2022. Districts are classified into three categories: those

with bank offices at or below the 25th percentile (≤197 offices), between the 25th and 75th percentiles (197-460.5 offices), and above the 75th percentile (≥460.5 offices). For analytical purposes, we combine the first two categories to create a "below 75th percentile" group and compare it with the "above 75th percentile" group.

Our categorisation based on the 75th percentile of bank offices is methodologically sound as the percentile-based approach ensures sufficient sample size in both subgroups while capturing meaningful variation in banking infrastructure. Using 2022 data for categorisation provides a contemporary measure of banking infrastructure that reflects the modern financial landscape.

Table 4[7] presents the sub-sample analysis for districts with relatively lower banking office density (below 75th percentile). The results indicate that in these districts, there is a significant increase in credit supply to indirect finance within the agriculture sector following the flood. This suggests that areas with limited banking offices rely more heavily on cooperative societies, self-help groups, and other intermediary financial institutions for agricultural credit distribution. Additionally, we observe a surge in credit supply for professional and other services, reflecting the increased demand for reconstruction-related professional services in these areas. Interestingly, there is a decline in loans provided for personal housing in these districts, which may indicate that households in areas with limited banking infrastructure prioritize immediate recovery needs over long-term housing investments. Consistent with our baseline regression results, we find an increase in loans provided to the retail sector. Regarding deposits, Appendix Table A4 reports no significant change in bank deposits in below 75th percentile bank size districts during the post-shock period.

In contrast, the sub-sample analysis for large bank size districts (above 75th percentile), reported in Table 5, reveals an increase in credit allocation across multiple sectors[8]. These districts experience increased credit to indirect finance for agriculture, manufacturing and processing activities, transport operators, and personal loans overall, with loans for housing showing particular growth. Both wholesale and retail trade sectors received an increase in credit following the shock. However, we observe a decline in loans provided to the electricity, gas, and water subsector within the industry category. Appendix Table A6 demonstrates that, in districts characterized by larger bank sizes and greater numbers of bank offices, household deposits with banks increase significantly in the period following a flood shock, in contrast to

[7] For detailed estimates across the occupation category refer to Appendix Table A3
[8] For detailed estimates across the occupation category refer to Appendix Table A5

districts with smaller bank networks.

These findings corroborate those of Lahiri and Biswas (2024) and Beyer et al. (2022). Lahiri and Biswas document that, in Tamil Nadu, flood-affected households augment both bank deposits and retirement funds while reducing holdings of gold—evidence of a portfolio shift toward liquid financial assets in line with experiential learning and precautionary savings theories. Beyer et al. similarly observe that households in Kerala increase participation in post-office savings schemes but curtail fixed and recurring bank deposits and gold investments, which they attribute to the need to finance property repairs. Collectively, these results imply that larger banking presences are capable of accommodating heightened credit demand in the aftermath of a disaster while simultaneously maintaining or enhancing their deposit bases, owing to their superior deposit-mobilisation capacity and more sophisticated liquidity management.

To further assess the validity of the parallel trends assumption, we estimate an event-study specification; the resulting graphs in Appendix Figures 7 and 8 confirm that pre-treatment trends are satisfied in indirect agricultural finance and retail trade credit. Additionally, we estimate the following regression using only the pre-flood period ($t < 2015$):

$$Y_{dt} = \alpha + \beta_1(\lambda_t) + \beta_2(Disaster_d) + \beta_3(\lambda_t \times Disaster_d) + \gamma' X_{dt} + \delta d + \varepsilon_{dt} \quad (3)$$

where $Disaster_d$ is a binary indicator for treated (flood-affected) districts, and λ_t is a continuous year variable interacted with $Disaster_d$. Note that the main effect of $Disaster_d$ (β_2) is absorbed by the district fixed effects δd and therefore not separately identified, as district treatment status is time-invariant. However, the coefficient of primary interest, β_3, which captures the interaction between the linear time trend and treatment status, remains identified and provides a direct test of differential pre-treatment trends. The estimate of interest is the interaction term(s) between year and treatment, β_3 which tests whether the trend in outcomes differs between treated and control districts in the pre-shock years. The same set of covariates and district fixed effects as in the main specification are included, and standard errors are clustered at the district level. If the coefficients on the interaction terms are statistically insignificant, we infer that the trends in outcomes between treatment and control districts do not differ prior to the flood—providing empirical evidence in support of the parallel trends assumption. This approach complements the event study analysis and offers a robustness check for causal identification. Appendix Table A7 (credits) and Appendix Table A8 (deposits)

report the estimates for the parallel trends assumption. The results indicate that the assumption holds for all categories of credit supply (except for categories such as Electricity, gas & water and Finance), but not for deposits.

5. **Robustness Checks**

The robustness check addressing spillover effects is essential for causal identification in our difference-in-difference framework. Natural disasters often generate economic effects that extend beyond directly affected areas through several channels: (1) migration spillovers occur when displaced populations move to neighbouring districts, potentially affecting local credit demand and deposits; (2) supply chain disruptions may impact economic activity in adjacent areas that serve as suppliers or customers to affected regions; (3) precautionary behaviour in neighbouring districts may lead to changes in saving and borrowing patterns as residents anticipate potential future shocks. By excluding neighbouring districts from our control group, we address the Stable Unit Treatment Value Assumption (SUTVA), which requires that the treatment of one unit does not affect outcomes for other units. Violation of SUTVA would bias our difference-in-difference estimates by contaminating the control group with treatment effects, leading to an underestimation of the true causal impact.

As a robustness check, we refine our treatment definition by excluding neighbouring districts of the disaster-affected areas from the control group to address potential spillover effects. The new treatment group comprises the directly affected districts within Tamil Nadu, specifically Kancheepuram, Chennai, Thiruvallur, Cuddalore, Nagapattinam, and Villupuram. The refined control group excludes adjacent districts and includes only those districts that were geographically distant from the flood-affected areas: Coimbatore, Dindigul, Erode, Kanniyakumari, Karur, Krishnagiri, Madurai, Namakkal, Pudukkottai, Ramanathapuram, Sivaganga, The Nilgiris, Theni, Thoothukkudi, Tiruchirappalli, Tirunelveli, Tiruppur, and Virudhunagar.

Our geographic exclusion strategy is methodologically rigorous because it creates spatial separation between treatment and control districts, reducing the likelihood that control units are indirectly affected by the disaster. The selection of distant districts as controls ensures these areas are sufficiently removed from the disaster zone to be unaffected by migration flows, supply chain disruptions, or precautionary behavioural changes.

The results reported in Table 6[9] and Appendix Table A10 from this robustness specification confirm our main findings for credit and deposits respectively. We continue to observe a significant increase in credit for indirect finance within the agriculture sector and retail trade within the trade sector following the flood. Consistent with our baseline results, we do not find a significant impact on deposits with banks after the shock, reinforcing the validity of our main conclusions and suggesting that our results are not driven by spillover effects to neighbouring districts.

The fact that our main results remain statistically significant after this more conservative specification strengthens our confidence in the causal interpretation. This consistency suggests that our baseline findings are not artefacts of spillover contamination but rather reflect genuine treatment effects of the flood on banking outcomes in directly affected districts. Furthermore, the robustness check enhances external validity by demonstrating that our results are not sensitive to specific control group definitions, increasing confidence that our findings would generalise to similar disaster contexts and strengthening the policy relevance of our conclusions.

[Table 6]

6. Conclusion

This study examines the causal impact of the 2015 Tamil Nadu floods on district-level credit supply across various sectors: agriculture (total, direct, and indirect finance), industry (total, mining, manufacturing, utilities, construction), transport services, personal loans (total, consumer durables, housing), trade (total, wholesale, retail), finance, and others. We also investigate the effect on deposits. Using a difference-in-differences approach, comparing flood-affected districts with unaffected ones, our aim is to analyse how banks smooth credit and deposit in the event of a natural disaster. We find evidence of increase in credit supply in response to local shocks created by exposure to flood for indirect agricultural finance and retail trade after the flood while deposits show no significant overall change.

Districts with fewer bank offices respond to the shock by significantly increasing credit to agriculture sector especially for indirect finance. These districts also exhibit increased credit to professional services, reflecting demand for reconstruction, and a decline in housing loans, suggesting priority on immediate recovery over long-term investments. Retail sector credit

[9] For detailed estimates across the occupation category refer to Appendix Table A9

increases here as well, particularly benefiting small businesses and micro, small, and medium enterprises, which are critical for local recovery but tend to be severely impacted by flood shocks and infrastructure disruptions.

Conversely, districts with larger banking offices respond by increasing credit across multiple sectors, including indirect agricultural finance, manufacturing, transport, personal loans, housing, wholesale, and retail trade. However, loans to the electricity, gas, and water subsectors decline. These districts also experience a notable post-disaster increase in deposits, in contrast to their counterparts. These patterns are consistent with findings by Lahiri and Biswas (2024) and Beyer et al. (2022), which document a shift in household portfolios toward liquid financial assets and increased savings after disasters. Overall, a stronger banking presence supports better credit flow and deposit mobilization during recovery. Together these adjustments not only show that banks play a key stabilizing role in smoothing local economic shocks, but also highlight the importance of institutional reach and capacity for equitable and timely post-disaster recovery.

7. Policy Implications

Different economic sectors are exposed to disaster shocks in varied ways, with agriculture, industry, trade, and personal loans each experiencing distinct impacts that require sector-specific recovery strategies. Therefore, a tailored policy approach is essential for effective shock mitigation and economic revival—since a one-size-fits-all policy may not sufficiently address the unique needs and vulnerabilities of each sector. The policy implications of these findings are clear: enhancing the presence and capacity of formal banking institutions in disaster-prone and underserved areas should be a top priority to ensure timely credit access in the aftermath of natural disasters. This includes scaling up bank branches and mobile banking services, promoting rapid disbursement and restructuring of loans—especially for agriculture, MSMEs, and the retail sector—and ensuring deposit mobilization and liquidity support during recovery phases. Tailored financial products and targeted outreach, alongside deployment of alternative service channels like mobile ATMs, are essential to both protect vulnerable small businesses and accelerate local economic recovery. A robust contingency framework involving central and local policymakers, as well as active insurance claim coordination, will further strengthen financial resilience and inclusiveness in disaster response.

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Appendix

Table A1: Impact on credit

Variables	(1) Total agriculture	(2) Direct finance	(3) Indirect finance	(4) Industry	(5) Mining & quarrying	(6) Manufacturing & processing	(7) Electricity gas & water	(8) Construction	(9) Transport operators	(10) Professional and other services	(11) Personal loans	(12) Loans for purchase of consumer durables	(13) Loans for housing	(14) Trade	(15) Wholesale trade	(16) Retail trade	(17) Finance	(18) All others
Post	3.935***	3.959***	4.077***	1.909***	2.787***	1.831***	2.581**	3.449***	3.455***	3.305***	3.674***	0.647***	3.964***	3.000***	2.965***	3.139***	3.425***	1.186***
	(0.121)	(0.111)	(0.337)	(0.236)	(0.450)	(0.245)	(0.952)	(0.266)	(0.299)	(0.256)	(0.154)	(0.203)	(0.214)	(0.222)	(0.287)	(0.210)	(0.454)	(0.206)
Disaster×Post	0.0223	0.00701	0.266*	-0.00905	0.403	0.133	-0.949	-0.195	0.207	0.112	0.0492	-0.0235	-0.0209	0.118	0.103	0.150**	0.0151	0.0728
	(0.0918)	(0.0901)	(0.137)	(0.0880)	(0.534)	(0.149)	(0.832)	(0.241)	(0.147)	(0.0814)	(0.109)	(0.159)	(0.128)	(0.156)	(0.209)	(0.0642)	(0.187)	(0.0718)
Constant	14.50***	14.19***	12.17***	14.25***	9.934***	14.33***	8.568***	10.19***	10.89***	12.28***	13.84***	10.41***	12.45***	13.41***	12.15***	12.78***	10.21***	13.07***
	(0.312)	(0.224)	(0.456)	(0.221)	(0.471)	(0.260)	(0.808)	(0.252)	(0.490)	(0.358)	(0.319)	(0.238)	(0.311)	(0.269)	(0.346)	(0.237)	(0.399)	(0.190)
Observations	626	626	626	626	618	626	604	626	626	626	626	626	626	626	626	626	626	626
R-squared	0.978	0.980	0.898	0.923	0.823	0.921	0.692	0.912	0.943	0.959	0.976	0.887	0.972	0.911	0.911	0.965	0.886	0.918
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Impact on deposits

VARIABLES	(1) Deposits (without clustering)
Post	-2.222***
	(0.0811)
Disaster×Post	0.00389
	(0.0657)
Constant	11.61***
	(0.144)
Observations	626
R-squared	0.995
Year FE	YES
District FE	YES
Covariates	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Impact on credit (below 75 percentile bank size)

VARIABLES	(1) Total agriculture	(2) Direct finance	(3) Indirect finance	(4) Industry	(5) Mining & quarrying	(6) Manufacturing & processing	(7) Electricity, gas & water	(8) Construction	(9) Transport operators	(10) Professional and other services	(11) Personal loans	(12) Loans for purchase of consumer durables	(13) Loans for housing	(14) Trade	(15) Wholesale trade	(16) Retail trade	(17) Finance	(18) All others
Post	3.743***	3.762***	3.840***	1.839***	2.679***	1.643***	3.142**	3.482***	3.418***	3.282***	3.614***	0.433	3.936***	2.948***	2.916***	3.148***	3.735***	0.987***
	(0.114)	(0.102)	(0.377)	(0.280)	(0.626)	(0.281)	(1.370)	(0.372)	(0.415)	(0.338)	(0.181)	(0.257)	(0.258)	(0.307)	(0.373)	(0.288)	(0.565)	(0.266)
Disaster×Post	0.0369	0.0318	0.258**	-0.000350	0.858	0.224	-1.131	-0.418	0.117	0.206**	-0.0684	0.0378	-0.190**	-0.0533	-0.152	0.126**	-0.263	0.123
	(0.0440)	(0.0424)	(0.121)	(0.132)	(0.723)	(0.217)	(1.278)	(0.333)	(0.134)	(0.0918)	(0.0610)	(0.271)	(0.0890)	(0.216)	(0.290)	(0.0571)	(0.185)	(0.0938)
Constant	13.49***	13.40***	10.63***	13.21***	8.040***	12.92***	9.301***	9.824***	10.10***	11.62***	13.10***	9.272***	11.80***	12.56***	11.26***	12.01***	10.61***	11.92***
	(0.204)	(0.190)	(0.642)	(0.539)	(1.139)	(0.550)	(1.600)	(0.650)	(0.654)	(0.323)	(0.316)	(0.568)	(0.450)	(0.366)	(0.483)	(0.286)	(0.747)	(0.403)
Observations	466	466	466	466	458	466	444	466	466	466	466	466	466	466	466	466	466	466
R-squared	0.986	0.986	0.898	0.881	0.744	0.888	0.557	0.845	0.930	0.938	0.970	0.837	0.967	0.860	0.867	0.950	0.791	0.812
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Impact on deposits (below 75 percentile bank size)

VARIABLES	(1) Below 75 percentile bank size	(2) Above 75 percentile bank size
Post	-2.350***	-2.111***
	(0.116)	(0.203)
Disaster×Post	-0.0487	0.212**
	(0.0637)	(0.0852)
Constant	11.03***	12.75***
	(0.184)	(0.221)
Observations	466	160
R-squared	0.993	0.995
Year FE	YES	YES
District FE	YES	YES
Covariates	YES	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Impact on credit (Above 75 percentile bank size)

VARIABLES	(1) Total agriculture	(2) Direct finance	(3) Indirect finance	(4) Industry	(5) Mining & quarrying	(6) Manufacturing & processing	(7) Electricity gas & water	(8) Construction	(9) Transport operators	(10) Professional and other services	(11) Personal loans	(12) Loans for purchase of consumer durables	(13) Loans for housing	(14) Trade	(15) Wholesale trade	(16) Retail trade	(17) Finance	(18) All others
Post	4.070***	4.228***	3.303***	0.793**	0.932*	0.769	0.123	2.307***	2.987***	2.904***	3.316***	0.615*	3.630***	2.577***	2.282***	2.698***	2.729***	1.041***
	(0.347)	(0.316)	(0.745)	(0.320)	(0.487)	(0.411)	(1.135)	(0.475)	(0.609)	(0.281)	(0.321)	(0.317)	(0.442)	(0.250)	(0.325)	(0.247)	(0.489)	(0.240)
Disaster×Post	0.397*	0.293	0.667**	0.318*	0.192	0.340*	-0.822**	0.525	0.756**	0.291	0.556***	0.173	0.522**	0.551***	0.655**	0.493***	0.509	0.298*
	(0.204)	(0.218)	(0.250)	(0.144)	(0.483)	(0.145)	(0.288)	(0.369)	(0.217)	(0.168)	(0.153)	(0.266)	(0.172)	(0.121)	(0.207)	(0.118)	(0.307)	(0.130)
Constant	15.74***	15.01***	14.15***	16.21***	11.86***	16.41***	10.44***	11.95***	12.86***	14.21***	15.64***	11.83***	14.24***	15.01***	13.94***	14.44***	12.24***	14.37***
	(0.428)	(0.243)	(0.728)	(0.276)	(0.518)	(0.316)	(0.703)	(0.257)	(0.913)	(0.577)	(0.496)	(0.387)	(0.423)	(0.411)	(0.603)	(0.252)	(0.178)	(0.285)
Observations	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160
R-squared	0.968	0.974	0.898	0.942	0.914	0.925	0.876	0.952	0.952	0.965	0.974	0.917	0.977	0.969	0.949	0.973	0.947	0.945
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Impact on deposits (Above 75 percentile bank size)

VARIABLES	(1) Deposits (with clustering)
Post	-2.111***
	(0.203)
Disaster×Post	0.212**
	(0.0852)
Constant	12.75***
	(0.221)
Observations	160
R-squared	0.995
Year FE	YES
District FE	YES
Covariates	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A7: Alternate specification for parallel trends (Credit)

VARIABLES	(1) Total agriculture	(2) Direct finance	(3) Indirect finance	(4) Industry	(5) Mining & quarrying	(6) Manufacturing & processing	(7) Electricity, gas & water	(8) Construction	(9) Transport operators	(10) Professional and other services	(11) Personal loans	(12) Loans for purchase of consumer durables	(13) Loans for housing	(14) Trade	(15) Wholesale trade	(16) Retail trade	(17) Finance	(18) All others
Trend	0.282***	0.272***	0.338***	0.135***	0.198***	0.138***	0.235***	0.228***	0.264***	0.241***	0.228***	0.149***	0.139***	0.217***	0.182***	0.207***	0.255***	0.0449***
	(0.00718)	(0.00608)	(0.0258)	(0.0212)	(0.0436)	(0.0230)	(0.0560)	(0.0205)	(0.0155)	(0.0186)	(0.00839)	(0.0313)	(0.0294)	(0.0170)	(0.0197)	(0.0107)	(0.0387)	(0.0158)
Disaster×Trend	-0.00323	-0.00550	0.00453	-0.0237	-0.0414	-0.00219	-0.162*	0.0317	0.00339	0.000738	0.0267	0.0352	0.0233	0.0201	0.0110	-0.0153	-0.0683**	0.00873
	(0.0109)	(0.0124)	(0.0531)	(0.0271)	(0.0422)	(0.0283)	(0.0875)	(0.0419)	(0.0277)	(0.0287)	(0.0192)	(0.0277)	(0.0264)	(0.0189)	(0.0429)	(0.0189)	(0.0322)	(0.0127)
Constant	-548.7***	-528.2***	-667.0***	-247.7***	-371.2***	-261.2***	-396.8***	-457.7***	-519.0***	-470.5***	-453.5***	-303.3***	-272.7***	-429.1***	-355.7***	-395.1***	-475.0***	-80.41**
	(15.01)	(12.69)	(58.41)	(40.55)	(83.78)	(44.93)	(106.8)	(43.39)	(32.21)	(37.87)	(19.32)	(63.32)	(60.95)	(30.74)	(43.02)	(22.65)	(71.97)	(29.92)
Observations	370	370	370	370	362	370	348	370	370	370	370	370	370	370	370	370	370	370
R-squared	0.971	0.970	0.841	0.881	0.761	0.883	0.662	0.865	0.915	0.946	0.965	0.501	0.561	0.848	0.860	0.945	0.847	0.869
Year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Alternate specification for parallel trends (Deposits)

VARIABLES	(1) Deposits
Trend	-0.0543***
	(0.00945)
Disaster×Trend	0.0465**
	(0.0214)
Constant	102.4***
	(22.22)
Observations	370
R-squared	0.750
Year FE	NO
District FE	YES
Covariates	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Impact on credits (excluding neighbouring districts)

VARIABLES	(1) Total agriculture	(2) Direct finance	(3) Indirect finance	(4) Industry	(5) Mining & quarrying	(6) Manufacturing & processing	(7) Electricity gas & water	(8) Construction	(9) Transport operators	(10) Professional and other services	(11) Personal loans	(12) Loans for purchase of consumer durables	(13) Loans for housing	(14) Trade	(15) Wholesale trade	(16) Retail trade	(17) Finance	(18) All others
Post	3.977***	4.019***	3.951***	1.847***	2.852***	1.785***	2.948**	3.403***	3.225***	2.898***	3.577***	0.636**	3.854***	2.793***	2.651***	2.962***	3.002***	1.004***
	(0.161)	(0.145)	(0.409)	(0.284)	(0.542)	(0.301)	(1.159)	(0.283)	(0.308)	(0.179)	(0.155)	(0.230)	(0.207)	(0.234)	(0.249)	(0.226)	(0.538)	(0.219)
Disaster×Post	0.0375	0.0235	0.281*	-0.0397	0.371	0.108	-1.234	-0.170	0.206	0.156	0.0342	0.0131	-0.0640	0.119	0.127	0.156*	0.0157	0.132
	(0.0987)	(0.0953)	(0.157)	(0.0995)	(0.532)	(0.156)	(0.802)	(0.261)	(0.182)	(0.0949)	(0.118)	(0.170)	(0.140)	(0.158)	(0.210)	(0.0865)	(0.212)	(0.0838)
Constant	14.58***	14.22***	12.48***	14.77***	10.31***	14.87***	9.164***	10.38***	11.24***	12.76***	14.12***	10.57***	12.79***	13.84***	12.67***	13.13***	10.67***	13.35***
	(0.334)	(0.229)	(0.522)	(0.214)	(0.529)	(0.238)	(0.954)	(0.261)	(0.521)	(0.340)	(0.336)	(0.235)	(0.278)	(0.240)	(0.292)	(0.230)	(0.413)	(0.215)
Observations	469	469	469	469	464	469	457	469	469	469	469	469	469	469	469	469	469	469
R-squared	0.975	0.978	0.897	0.937	0.825	0.936	0.694	0.915	0.944	0.964	0.979	0.906	0.978	0.898	0.912	0.967	0.880	0.924
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Table A10: Impact on deposit (excluding neighbouring districts)

VARIABLES	(1) Deposits
Post	-2.214***
	(0.0791)
Disaster×Post	0.0345
	(0.0702)
Constant	11.78***
	(0.155)
Observations	469
R-squared	0.995
Year FE	YES
District FE	YES
Covariates	YES

Robust standard errors in parentheses are clustered at the district level
*** p<0.01, ** p<0.05, * p<0.1

Figure A1

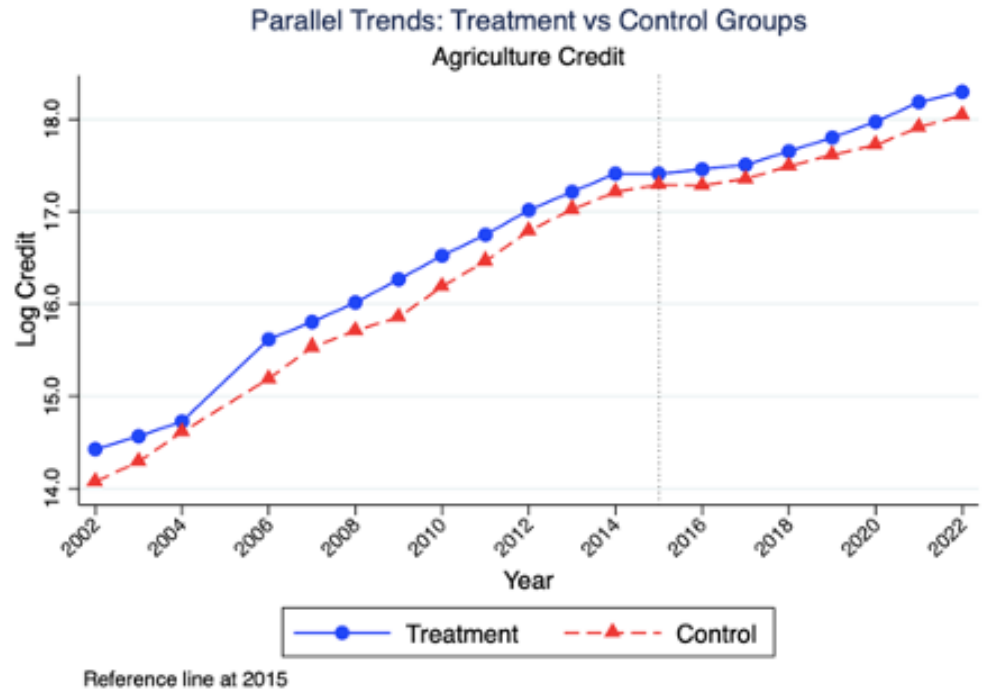


Figure A2

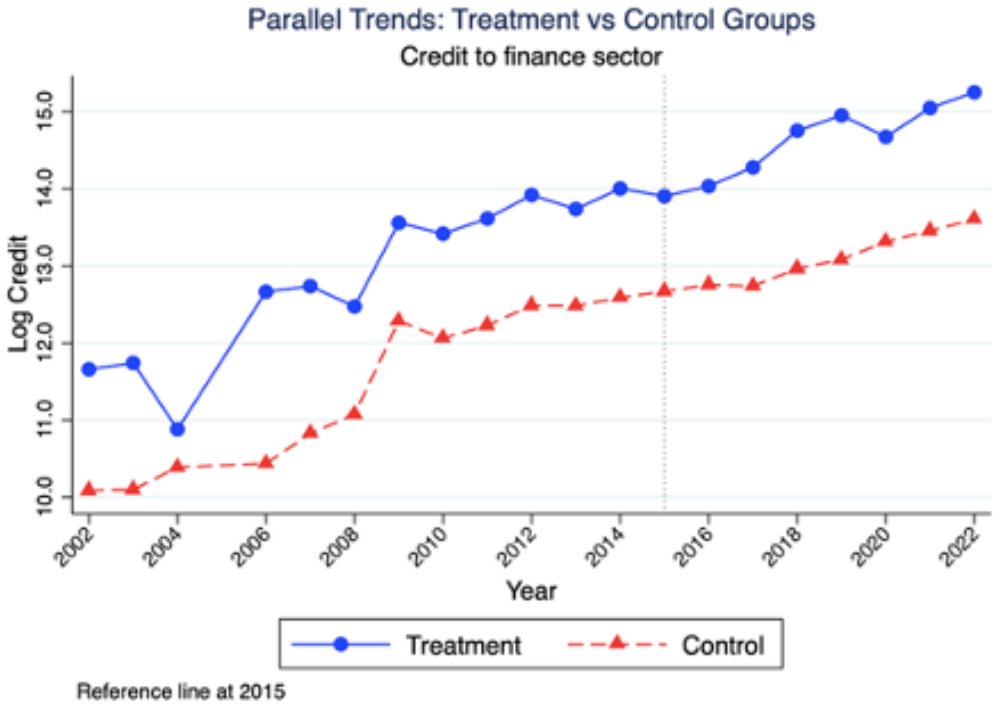


Figure A3

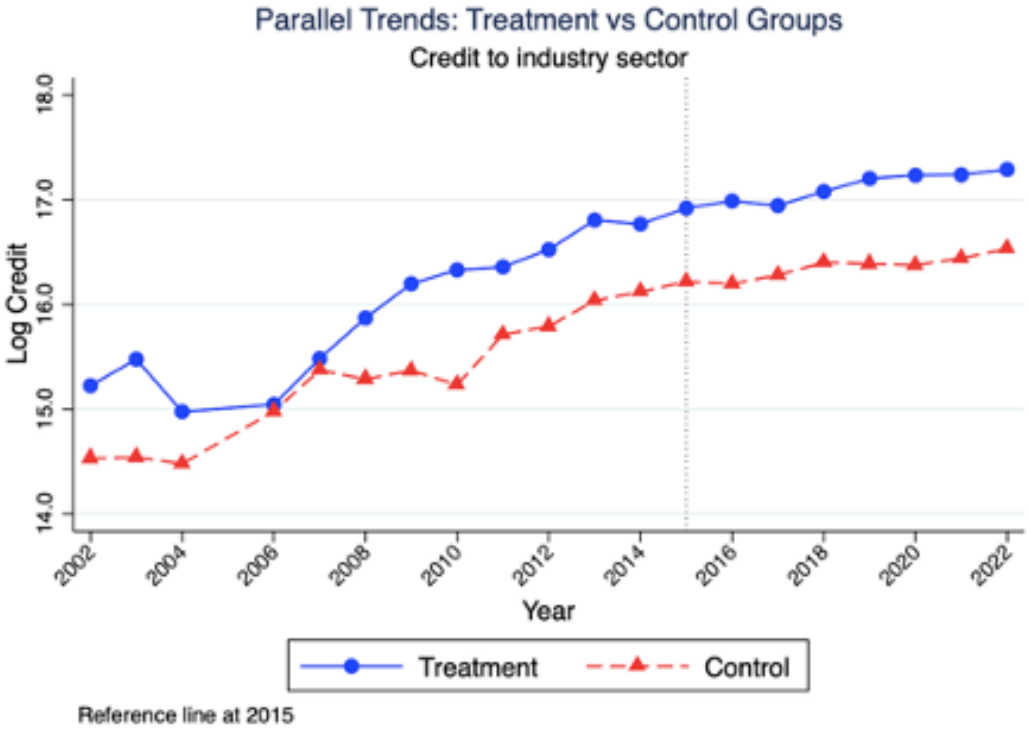


Figure A4

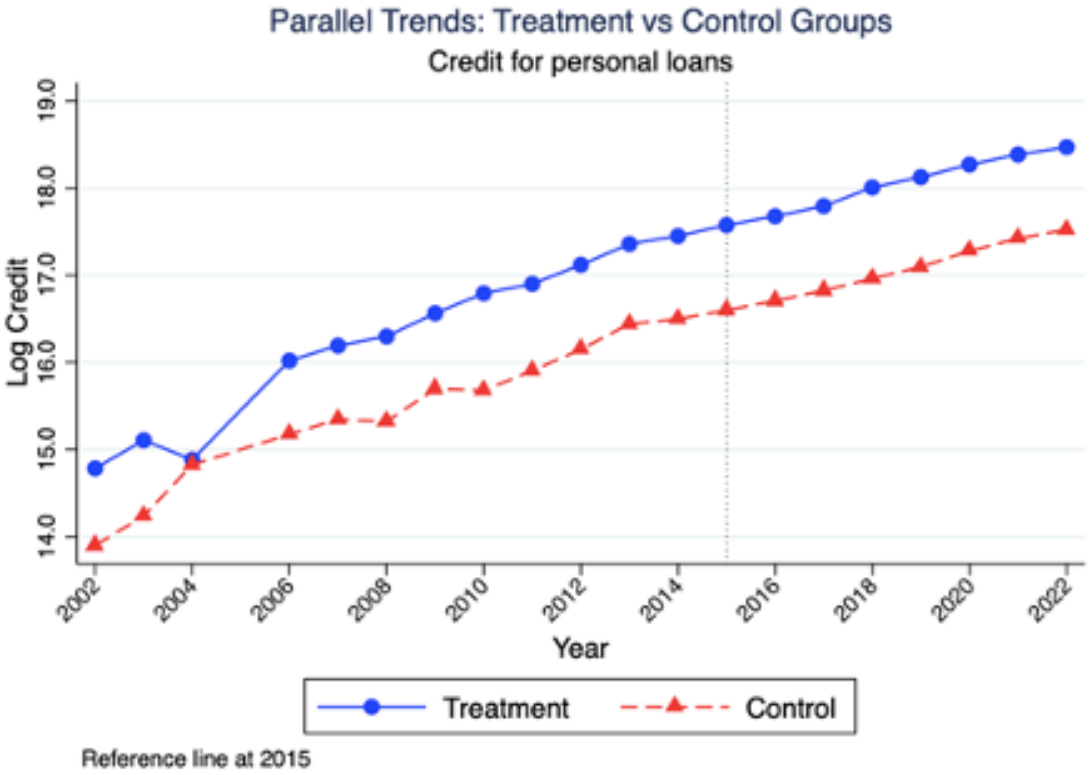


Figure A5

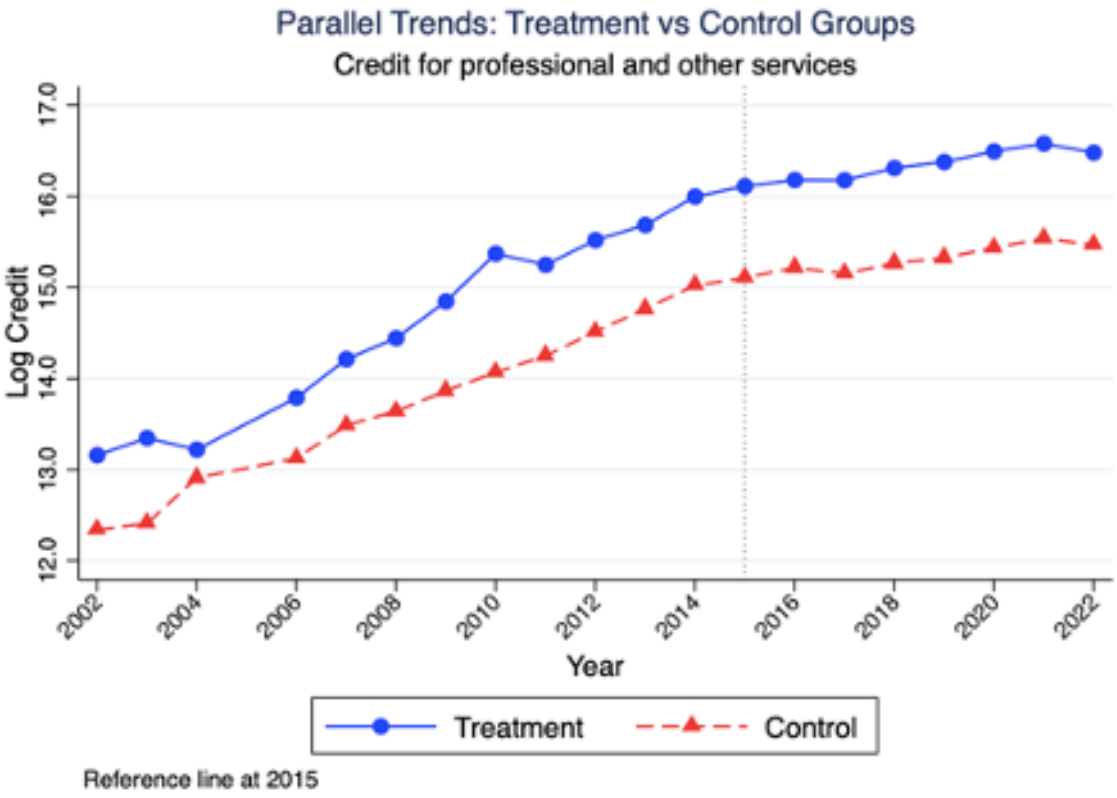


Figure A6

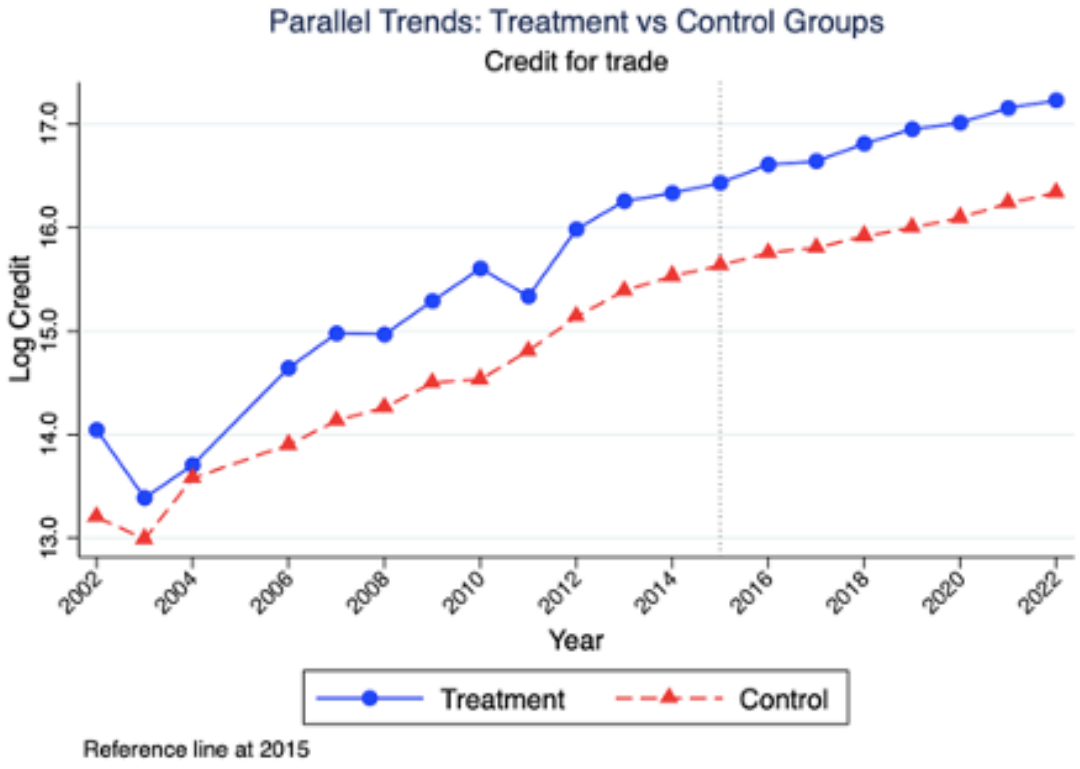


Figure A7: Event study (Indirect finance)

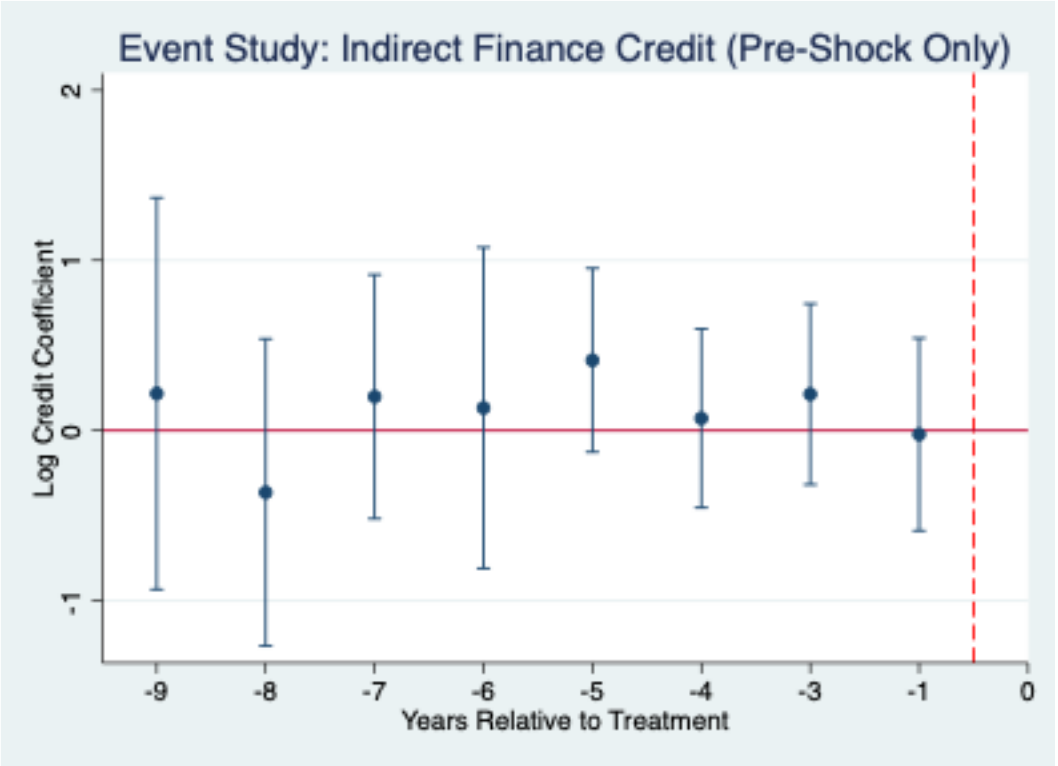


Figure A8: Event study (Retail trade)

