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Author
Ray, Rohini

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Essays on the Effects of Climate Shocks on Liquidity and Systemic Risk

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy

in

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by

Rohini Ray

Committee in charge:

Professor Johannes Wieland, Chair
Professor Juan Herreno
Professor Munseob Lee
Professor Steve Wu

2024

The dissertation of Rohini Ray is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

2024

DEDICATION

To my Ma.

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VITA

2010-2014	Bachelor of Arts in Economics and Physics, Smith College
2015	Research Associate,The Indian School of Business (ISB)
2015-2018	Research Analyst, The International Monetary Fund (IMF)
2020	Short-Term Expert, The International Monetary Fund (IMF)
2021	Technical Advisor, The Bank for International Settlements (BIS)
2022	PhD Intern, The International Monetary Fund (IMF)
2018-2024	Teaching Assistant, University of California San Diego (UCSD)
2018-2024	Doctor of Philosophy, University of California San Diego (UCSD)

ABSTRACT OF THE DISSERTATION

Essays on the Effects of Climate Shocks on Liquidity and Systemic Risk

by

Rohini Ray

Doctor of Philosophy in Economics

University of California San Diego, 2024

Professor Johannes Wieland, Chair

This dissertation consists of three chapters focusing on the effect of an unexpected climate shock on liquidity and systemic risk in the Indian Economy. The causal effects are identified using the exogenous nature of the shock, spatial variation in exposure, and the granular dataset I constructed.

Chapter 1. Unexpected climate shocks are increasing in frequency and magnitude. However, there is limited evidence on quantifying the impact of these shocks on firms and the interlinkages with the financial sector. This is augmented in Emerging market contexts that are more vulnerable to this shock and can face additional market constraints. In this chapter, I estimate the effect of an unexpected flooding shock on firm liquidity and explore the mechanisms

through which they smooth their liquidity needs. I find firms located in the flood zip code face a net decrease in their sales driving the contraction in their operating cash flow. However, the increase in overall cash flow for these firms indicates they are obtaining external financing. While they have access to different margins for adjustment, I document the lack of insurance use and a limited use of Deferred Tax Assets. Credit is the most significant source as exposed firms almost double their volume of new loans compared to unexposed firms. Exploring the credit supply channel, I find branches of local credit institutions are providing credit by lending larger loan volumes, despite being exposed to the shock as well. But there is an there is an intermediation channel from Banks via Non-Bank Financial Institutions to firms, that emerges to provide liquidity after the shock. These results emphasize the necessity of external financing for firms impacted by climate shocks amidst liquidity contractions. While traditional macro-development papers emphasize financial frictions in emerging markets, this chapter demonstrates the presence of external liquidity and firms' diverse access to it.

Chapter 2. Aggregate local shocks impact agents differently, especially in the presence of financial frictions. Analyzing these heterogeneous effects can reveal if the allocation of resources is going to the firms that have a higher credit need. Chapter 1 finds the average firms exposed to the unexpected climate shock face a contraction in their liquidity and increase their borrowing from credit markets. This chapter examines examines how vulnerability to climate shocks varies for different types of firms, and what that implies for their access to external financing and credit risk. Manufacturing and younger firms are more susceptible to these shocks and face a liquidity crunch, thereby needing more external financing. Credit markets allocate larger loan volumes to them. High-credit-risk firms also face a reduction in their liquidity and can access more credit. These firms also restructure a significant number of these loans issued in future periods. The results show that the firms with characteristics that make them more vulnerable to this climate shock require larger loans. Credit markets are working well on this dimension: they are allocating loans to the firms requiring it most. Surprisingly even the high-risk firms are not driven out and can increase their borrowing.

Chapter 3. After the 2008 Great Financial Crisis, Bank Regulators increased capital requirements to make the banking sector more resilient to economic shocks and reduce their impact on the real economy. A key Basel requirement was Bank Capital Adequacy Ratio (CAR) to build in the buffers. In Chapter 1, I find credit institutions exposed to an unexpected climate shock increase their lending to the real economy. In this chapter, I evaluate if more capitalized Banks, i.e. those with better buffers, are better able to supply credit after a climate shock crisis. I find bank branches with higher capitalization increase lending overall, particularly to firms in the real sector. Decomposing the CAR into its components, Tier 1 capital i.e. the bank's core capital and its primary safeguard against losses, is driving these results. Tier 2 capital i.e. the supplementary capital, has no effect. Exposed branches with lower core capital (Tier 1) and higher supplementary capital (Tier 2) increase lending to Non-Bank Financial Institutions (NBFIs) to maximize their risk-adjusted returns while responding to market liquidity needs. Thus, credit flowing from stronger capitalized banks to the real sector during a crisis aligns with macro-financial risk mitigating policies: banks with greater loss absorption capacity are providing liquidity after a shock. However, this capital play by banks that is catalyzing the intermediation channel via NBFIs can potentially augment risk in the system. NBFIs have been documented to reach for yield in their lending practices, which is supported by the relatively less stringent regulatory framework they are subjected to.

Chapter 1

Climate Shocks and Liquidity Smoothing Mechanisms: Evidence from Indian Firms

Extreme climate shocks re disruptive to economic activity and can constrain multiple economic agents simultaneously. Emerging Markets are projected to require up to $300 billion a year by 2030 in climate financing to mitigate the effects of these shocks (IMF GFSR 2022 and UNEP 2021).[1] In this chapter I quantify the effects of the 2015 flooding disaster in South India, on firms cash flows and evaluate the mechanisms through which they can smooth their ensuing liquidity needs. To estimate these effects I build a unique data set that combines transaction level firm-branch[2] credit data with high resolution climate data all at the zip code level. This rich granular data structure combined with the exogenous nature of the shock and spatial variation in exposure identifies the causal effect.

I find that effected firms faced a 1.69 percentage points loss in operating cash flow[3] and a 3.12 percentage points increase in overall cash flow[4]. As the overall cash flow is the sum from

[1] India specifically ranks 7^{th} in Global Climate Risk Index 2021 for County's facing climate risk.

[2] Branches include all Financial Intermediates: Banks and Non-Bank Financial Institutions

[3] The average operating cash flow as a share of assets, for firms in the sample in the financial year prior to the shock is 0.93 percent.

[4] The average cash flow as a share of assets, for firms in the sample in the financial year prior to the shock is 2.24

operations, investing, and financing, the relative increase in overall cash flow relative to the fall in operating cash flow indicates access to external financing. Exposed firms relatively increased their deferred tax assets by 2.68 percentage points and their loan volumes by $9.472 million USD[5]. As the loan volumes almost doubled despite local branches also being subject to the same shock, I evaluate the sources of credit supply. The credit institution branches that were also exposed to the shock, reduced their lending to firms in the region by $4.54 million but they increased lending to non-bank financial institutions (NBFIs) by $10.60 million USD [6]. And the exposed firms borrowed relatively more from NBFIs. These results highlight that financial intermediation via NBFIs plays a significant role in the liquidity provisioning channel to firms after exposure to climate shocks. [7] At a broader level these results show that there is substantive liquidity available in credit markets in India that firms can avail off.

Heavy unexpected rains in November and December 2015, caused severe flooding of unprecedented levels, in various parts of the Indian states of Andhra Pradesh, Tamil Nadu, and the Union Territory of Puducherry. The region is one of the most industrialized in the country and contributed to 13.77% of National GDP in 2015. Thus, India's Nikkei Manufacturing Purchasing Manager's Index (PMI) in Figure 1.1 shows a sharp contraction in business activity at the end of 2015, which managers attributed to this shock. These rains, occurring after the traditional monsoon season, are attributed to the El Niño climate change phenomenon. Since the shock was unanticipated economic agents in the region have not been documented to have prepared against this shock ahead of time. I use this exogenous nature of the shock and the spatial variation in exposure to identify the causal effect.

To conduct the empirical analysis, I combine annual Firm Financial Statement Data

percent.

[5]The average annual borrowing by a firm in the sample is 74.87 Million USD in the financial year prior to the shock.

[6]The average annual lending between a branch-firm pair in the sample is 29.57 Million USD in the financial year prior to the shock.

[7]While there are benefits from this intermediation, it is important to note that there are differences in regulation for NBFIs compared to traditional banks.

compiled by the Center for Monitoring the Indian Economy, with monthly climate data from the University of Delaware Climate Center at the zip code level by creating a geospatial map between firm zip codes and the grid coordinates. I further integrate a proxy credit register with transaction-level data on credit loans between firms and financial institution branches to use of credit, to the firm data by creating a bridge between datasets using forensic methods. In India due to Banking Secrecy Laws, credit providers aren't allowed to disclose information on their borrowers. However, the Ministry of Corporate Affairs maintains a dataset where firms self-report their borrowing information. The biggest challenges associated with creating this high-dimensional dataset came from creating the bridges between datasets and cleaning the data. I used web-based mapping services to create the map between Indian zip codes and their geospatial coordinates. For the mapping between firm financial data and their credit data, I utilized a Levinstein matching algorithm to match firm names. However, due to manual self-reporting of these datasets, the innumerable changes to the addresses and zip codes in Indian cities, and the multiplicity in the method of spelling the same firm or credit institution name, I manually clean the data to account for these errors. Additionally, to identify branches, the same data-cleaning method is applied to the self-reported branch address' from which I extrapolate the branch identity. To my knowledge, this is the first paper that builds such a spatially granular dataset, with high-resolution climate data and high-frequency financial data between institutions.

My results show that exposed firms experiences a reduction in liquidity. On investigating the determinants of the decrease in liquidity, I find it is significantly driven by a contraction in product demand. On average, sales dropped by 14.82 percentage points, which was more significant than the decline in wages which only decreased by 6.28 percentage points[8]. These firm mitigate these effects by using deferred tax assets and borrowing.

It's important to consider that credit institutions in local branches could be constrained

[8]The average net sales as a share of assets, for firms in the sample in the financial year prior to the shock is 11.91 percent. The average wages as a share of assets, for firms in the sample in the financial year prior to the shock is 3.50 percent.

in their lending when climate shocks affect multiple economic agents. [9]. To determine where affected firms can borrow from, I adapt the model developed by Khwaja-Mian (2008) to estimate the lending channel of credit to firms after a climate shock. Extending the model to utilize more granular relationships between firm-credit institution branches, the identification strategy relies on comparing the change in loans between firm-branch pairs where the branch has been exposed vis-a-vis another firm-branch pair of the same firm, but with an unexposed branch. The firm fixed effect absorbs the demand effects.

Although firms that were exposed to climate shocks increased their borrowing, local branches of credit institutions that were also exposed did not provide these loans. These branches reduced their lending to all firms in the region by 4.54 million USD and by 9.16 million USD to the exposed firms. This pattern was observed in both public and private credit institutions, but it was more pronounced in credit institutions with national networks than in local credit institutions. However, these branches increased their lending to NBFIs by 10.60 million. And exposed NBFIs increased lending to exposed firms by 9.3 million USD.

This redirection of credit supply through NBFIs after a climate shock is plausible due to their unique advantages over traditional banks. NBFIs have broader market reach, faster disbursement processes, and a greater risk tolerance, which can make them particularly advantageous in allocating credit among various economic entities in the aftermath of a climate shock. Banks also benefit from lower-risk exposure on their balance sheet from lending to NBFI's who then lend to firms, rather than lending directly. NBFIs can engage in more risky lending, including post-shock, as they are subject to more lenient regulations.

This chapter contributes to the growing literature on how firms respond to climate shocks. Giroud et al. (2012), Bloesch and Gourio (2015), and Collier et al. (2017) have found that despite the temporary effects of such shocks they can have significant impacts on firms. However, these firms use liquidity management tools to counteract these effects. While some firms have used

[9]When banks are under strain, they are less able to help their clients through difficult times. (BIS)

internal cash holdings, Dessaint and Matray (2017) and other studies suggest that local banks play a vital role in mitigating the impact of natural disasters on firms. Berg and Schrader (2012) provide empirical support for this demand-related phenomenon among businesses in Germany. Similarly, Cortes and Strahan (2017) identify a similar impact on mortgage borrowers in the United States. Brown et al. (2020) found that small businesses in the United States increased their borrowing activities following cash flow disruptions resulting from harsh winter weather conditions. Collier et al. (2017) also found that US firms recovering from Hurricane Sandy took on debt rather than claiming insurance. Rampini and Viswanathan (2010, 2013) explain the choice of credit as a risk management tool by firms over the use of insurance. There model finds the cost of frictions associated with the credit markets is lower than the opportunity costs of insurance.

My findings are consistent with this literature, which suggests that firms affected by climate shocks use some form of credit access to smooth out their liquidity. However, my research is set in an Emerging Market Economy (EME) in India, whereas literature predominantly focuses on Advanced Economy settings. Despite the evidence of high levels of financial friction in EMEs from traditional macro-development studies, my research suggests that firms in India also have remarkable access to external financing to mitigate the impact of climate shocks. Furthermore, my research also documents an additional source of smoothing used by these firms: Deferred Tax Assets. The limited use of insurance as a climate finance tool is also consistent across these markets.

This chapter also adds to the vast literature on the role on the effect of shocks on credit supply. The literature on the role of credit in responding to shocks has found bank credit to be the ideal provider of liquidity (Kashyap, Rajan, and Stein (2002), Gatev and Strahan (2006)). However, Paravisini (2008), Khwaja and Mian (2008), Hereno (2023), and many other papers that study financial shocks to banks have found that increased constraints on banks have a negative effect on the aggregate supply of credit. Bernanke (1983) and Gilchrist et al. (2014) have also found that the ability or willingness of credit institutions to lend aftershocks that tighten aggregate financial constraints reduces credit availability. Ivanov et al (2020) shows that this is also true in local markets after natural disasters. However, they establish that bank networks allow for a spatial transfer of funds within banks. There is notable heterogeneity based on the type of bank providing the credit: Cortes (2014) contrasts the lending reactions of local and national banks in the face of natural disasters. Chavaz (2016) examines how recent US hurricanes impact lending activities among diversified banks. Schuwer et al. (2018) investigate the impact of Hurricane Katrina on the lending practices of community banks. And Dlugosz et al. (2019) analyze the influence of natural disasters on the deposit pricing strategies employed by community banks. While I also find that banks can provide credit post-climate shocks, the mechanism I find differs. In the US, banks are the primary provider, and they smooth across branch networks. Whereas in the Indian context, there appears to be an intermediation role of NBFIs in providing liquidity to firms' post-exposure to a climate shock.

1.1 Institutional Background

As the research design of this chapter exploits a natural experiment that occurs in India, this section provides the Institutional Context to understand: (1) The experimental setting of the South Indian Floods of 2015; and (2) Review how Indian Financial Markets Function.

1.1.1 South India Floods of 2015

In November and December of 2015, the Indian states of Andhra Pradesh, Tamil Nadu, and Union Territory of Puducherry.[10] received historically unprecedented levels of rainfall that stalled economic activity for over 17 days. It was the highest recorded amount in over 100 years and was attributed to the 2014-2016 El Niño phenomenon. The aggregate loss is estimated to

[10] Union Territories are an administrative division in India under the governance of the Central Government with limited local autonomy.

range between 3 billion USD to over 13 billion USD. Several firms struggled to navigate the challenging business environment due to the resource limitations posed by this extreme weather event. This spell of rainfall took place over 4 episodes during the two months. However, the entire region was not subject to the shocks. Locations in the low-lying areas were more adversely hit and more parts of this region remain unaffected by the shock. Thus, this creates a natural experimental setting due to the spatial variation in exposure within the given region.

This region is an important economic center contributing to 13.77% of aggregate GDP in the 2015-2016 financial year. Tamil Nadu is especially vital as one of the most industrialized and developed states in India.[11] This is attributed to the concentration of high-productivity industries within Tamil Nadu: auto-motives, textiles, information technology, software, construction, and real estate. This region also houses several Special Economic Zones (SEZ).[12] Thus disruption to such firms can have significant economic implications.

1.1.2 Indian Financial Markets

Credit serves as the primary external source of financing for firms in the Indian economy and generally acts as the first point of access for institutional finance. Annually, credit to the corporate sector accounts for 60% of financial flows and holds a stock value of around 165% of GDP[13]. And given India's relatively closed capital account, most of this bank credit is sourced domestically (Sutton, 2021). Even with the development of capital markets like the corporate bond market, access is very relatively limited and predominantly restricted to larger firms and financial institutions (Ganguly, 2019).[14] Credit is particularly important for firms during aggregate

[11] Tamil Nadu is the second largest contributing state to national output, accounts for 25% of national automotive production and 40% of total manufacturing.

[12] An SEZ is an area within a country that is designed to generate positive economic growth It is often associated with lower regulations and better tax incentives to promote economic prosperity.

[13] This is compared to its Emerging Market Economy counterparts.

[14] Medium and Small Sized Firms primarily rely on credit as they have limited access to capital markets. And they constitute a substantive part of the Indian Economy: 40% of the workforce, 45% of manufacturing output, and 30% of GDP.

and idiosyncratic shocks as private investors are less likely to lend during such episodes, which can even reverse their past lending. Regulatory Forbearance in India also allows banks to continue operations despite the capital depletion bank balance sheets face.

While there are no regulatory restrictions on the location of a branch from which a firm can borrow, there are incentives that promote local banking. Local branches are the primary source of credit distribution due to lending quotas and annual targets that are set at the branch level (Rao 2023). This applies to all scheduled banks regardless of their size, branch network depth, ownership structure, or geographic presence. Local banking is preferred because it offers familiarity, reduced information asymmetry, knowledge of local economic conditions, and lower transaction costs. Local branches are better able to assess a firm's creditworthiness, and loan interest rates are determined by the issuing bank branch rather than at the aggregate bank level. Although firms can access credit from any bank branch, there are clear benefits to banking locally. Interpersonal banking relationships between firms and branches can lead to better interest rates and borrowing terms, especially during crises.

Financial intermediaries, also known as Non-Bank Financial Institutions (NBFIs), have become an important source of credit over the past decade. NBFIs are financial institutions that do not accept deposits but provide credit and investments to individuals and firms, and include micro-finance agencies. While all banks in India are regulated under the Banking Companies Act, NBFIs are regulated by the Companies Act of 1956 and are subject to less stringent regulation. NBFIs have certain advantages over banks, such as more flexible approval standards for loans, the ability to issue larger loans, and lower collateral requirements and documentation. They also have quicker disbursement speeds through digital processes, greater financial inclusion, and competitive rates, making them an attractive source of funding[15].

Additionally, since NBFIs can take on greater risk exposure on their balance sheet compared to banks, banks can benefit from lending to them. If a bank lends to a NBFI which in

[15] https://poonawallafincorp.com/blogs/why-choose-nbfc-over-banks-for-business-loan-in-india.php

turn lends to a firm, the risk-weighted assets are smaller on the bank's balance sheet than if it directly lent to the firm. This is because NBFIs can take on more risk exposure on their balance sheet, thus making it a preferable option for banks (Subramanium et. al. 2019). Therefore, it is important to closely examine the sources of supply in credit markets due to the local nature of credit markets and the regulatory arbitrage between different sources of lending.

1.2 Data

To empirically evaluate the effect of the natural disaster described above, I construct a novel data set that combines high-frequency firm-branch data with Geo-spatial and climate data. Given the sample of firms and bank branches, the data set provides the following information: For a firm f located at zip code z, has annual financial data $X_{f \in z,T}$ for the financial year ending at T and the average credit risk measured using their Credit Rating $CR_{f \in z,T}$. They borrow credit from multiple institutions such that the loan from a given institution B with branch b located at zip code z', $b \in z'$, from which the $f \in z,T$ borrows is $L_{f \in z - b^B \in z',t}$, at any given point in time t. And the locations z and z' are exposed to monthly $\tilde{t}$ rainfall levels of $r_{\tilde{t}}$.

1.2.1 Climate Data

The University of Delaware maintains global historic databases on gridded climate data. I use the *Terrestrial Precipitation 1900-2017 Gridded Monthly Time Series (V 5.01) data archives* dataset. They compute the rainfall and temperature measures for a latitude-longitude node by combining data from 20 nearby weather stations using an interpolation algorithm based on the spherical version of Shepard's distance-weighting method to create a 0.5-degree latitude by 0.5-degree longitude grid node. The extreme floods that occurred in South India between November and December of 2015 will be climate shock studied in this Chapter.To construct the climate shock indicators $shock_g$, I aggregate the total rainfall over November and December for every year at each 0.5 degrees by 0.5 degrees latitude-longitude node g. Using this indicator of rainfall level, I construct the percent Deviation (pd) at each node g, for the year 2015 from its historic average:

$$shock_g^{pd} = \frac{rain_g - \bar{rain}_g^{30}}{\bar{rain}_g^{30}}$$

Using the Meteorological Survey of India's definition of extreme rainfall episodes I create the categorical variables for analysis. Based on the percent deviation from the historic mean data, $< 20\%$ is defined as a drought level[16]; Range between -20% and 20% is normal level; 20% to 60% represent excess rain; $> 60\%$ is an extreme excess level. Finally, I collapse the categorical variables into an indicator variable that takes the value of 1 if the given location g receives rainfall in the excess or extreme excess range for November and December 2015. It takes a value of 0 if the location g receives rainfall in the normal range during that time frame. For the main analysis of the chapter, I use this extensive margin to define the shock.

For robustness, I also estimate the effects using an intensive margin measure for exposure to the shock based on the Volatility Adjusted Deviation of rainfall. I begin by calculating the volatility of rainfall over the past 30 years at each node $\hat{rain}_g^{30}$. Using these indicators of rainfall level, I construct the Volatility Adjusted Deviation (vad) from the historic average at each node g, for the year 2015 from it's historic average:

$$shock_g^{vad} = \frac{rain_g - \bar{rain}_g^{30}}{\hat{rain}_g^{30}}$$

By harvesting data from web-based mapping services I create a dataset that matches geospatial coordinates to zip code z. Then using a spatial reference system that minimizes the geodetic distance between two geospatial coordinates g and g':

[16] For this chapter, given the method of defining the one-time climate shock, I count these observations to be part of the control group along with those that experience normal levels of rainfall.

$$min\sqrt{(latitude_g - latitude_{g'})^2 + (longitude_g - longitude_{g'})^2}$$

I map each zip code to its closest geospatial coordinate. This allows me to construct the climate shock at the zip code level.To construct the climate shock indicators $shock_g$, I aggregate the total rainfall over November and December for every year at each 0.5 degrees by 0.5 degrees latitude-longitude node g.

1.2.2 Firm Data

The Prowess dataset compiled by the Center for Monitoring the Indian Economy (CMIE) contains the annual financial statements for about 38,000 Indian Firms.[17] for a comprehensive list of Indian firms from 1989-2019. The firms contribute to more than 70% of industrial output, 75% of corporate taxes, and more than 95% of excise taxes collected by the Government of India (CMIE). The set includes the universe of publicly traded firms and a large sub-sample of unlisted firm that register within the formal sector. They are all medium to large firms as the dataset doesn't include any small or micro-enterprises. Along with financial variables such as assets, cash flows, sales, borrowing, and incomes, it also includes information on firm characteristics, such as industry, age, ownership, and location. It is the most comprehensive dataset for firm-level analysis. I exclude the financial firms from the sample in this analysis. And I restrict the sample to firms located in Andhra Pradesh, Tamil Nadu, and Puducherry and the statements for the financial year ending 2014-2016.[18]. I use the cash flow and operating cash flows as the liquidity measures for the firm, and other balance sheet variables as controls $X_{f \in z,T}$. I match the final data with the climate data based on the basis on zip code z.

[17]Financial Statements include Income Statement, Profit/ Loss, Statement of cash flows, and the Balance Sheet The 1956 Companies Act mandates firms to disclose data on their capacity production, and sales in their annual reports.

[18]The financial year in India spans from April of a given year to March of the next year.

1.2.3 Credit Data

The Ministry of Corporate Affairs (MCA) maintains a historic data set of transaction-level collateralized loans borrowed by firms across India. Banking Secrecy laws in India prohibit banks and other financial institutions from disclosing information about their borrowers[19]. However, firms can self-disclose their lender information. The dataset contains information on the date of loan issuance t, issuing bank (B), address of the issuing station, and total loan amount[20] L_{f-b^B} and the date of any modification that has taken place. Using the address of issuing station parameter I extract the bank branch location ($b \in z'$) from which the loan is issued. I then, create a unique identification number for each bank branch[21].

The self-reporting nature of this data set creates a few caveats to be accounted for. First, there is no formal audit made on this information. Thus, there is the threat of underestimating any effects using this data, as there is the potential of under reporting. Second, the address of the issuing stations or bank branch is nearly fully populated whereas there are some missing values for the bank name. I impute the names of the banks for which it was possible using either of the following techniques: (1) The bank name is included at the beginning of the address variable; (2) The bank names which could be found when searching against the address on a web-based search engine and then cross-checked against the bank's bank branch locator web page. Third, numerous errors are owing to the lack of standardized reporting practice and manual entry process of the data. As the bank branch level and its zip code location are key to my analysis, I manually checked and corrected for the address and zip codes of the bank branches using the bank's web directory on the bank branch locator. As the bank parameter does have a unique identifier in this data set, there are multiplications in both the bank name and bank address' which are cleaned.[22]

[19]The Banking Regulation Act 1949 includes in its regulations and standards, privacy principles aimed at governing the acquisition, retention, and safeguarding of customer data. The Public Financial Institutions Act of 198: Obligation as to Fidelity and Secrecy, prevents public financial institutions from disclosing any details regarding their clients.

[20]All loan amounts are in INR units, unlike the data in Prowess which are in Millions of USD.

[21]All addresses have the zip code and two-digit state code at the end.

[22]BANK EXAMPLE; Bank Example; BANK EXP; bank exp; Bank EXP; BANK exp; bank EXP; Bank EXP. ;

To integrate this data I create a bridge that matches the Company Identification Number (CIN) from the loan data to firm indicator in the Prowess data set using forensic methods. I use the Levenshtein distance matching on firm names, followed by manual checking. To harmonize the difference in frequency between the loans data and Prowess data, I map all transactions within a given financial year to that corresponding financial year. For instance, if a firm borrows a loan in November 2014, it will be considered a part of the 2014-2015 financial year. The prowess variables for this financial year will be issued in their March 2015 statement.

1.3 The Effect of Climate Shocks on Firms

Using the aggregate firm-level variables from the constructed data set, I estimate the effect of the climate shock on firm outcomes.

1.3.1 Identification and Estimation Equation

The identification strategy for this section relies on the nature of the extreme climate event that occurs. As the shock is a random phenomenon, I assume it is orthogonal to the firms-branch fundamentals by construction (Brown 2021). Owing to its transient nature I assume that the shock did not have any structural effects on the firms such as changing their value or creditworthiness. Furthermore, its unexpected nature rules out any anticipation effects that the firm could have hedged against before exposure. Based on the exogeneity of the shock, I can estimate the differential effect of the shock on firms in the region that are exposed compared to those that are not, due to the spatial variation in exposure. The variation across the region is illustrated in Figure 1.2. This is done by using the following cross-sectional regression:

$$\Delta y_{f\in z} = \alpha + \beta shock_{f\in z} + \tau L.X_{f\in z} + \varepsilon_{f\in z} \tag{1.1}$$

banc exp; bankexp;. . . .

where $f \in z$ is firm f located in zip code z. The climate shock $shock_{f\in z}$ takes a binary value of 1 if the given zip code within which the firm operates has been exposed, and 0 otherwise. The dependent variable is constructed by taking the difference in the value between the beginning and end of the financial year within which the shock occurs.[23] These outcomes have been normalized using lagged assets. The coefficient of interest β, measures the differential effect on the firms. [24] The firm controls $X_{f\in z,T-1}$ are lagged by one unit to avoid contemporaneous effects. The standard errors are clustered at the city level.

1.3.2 Effect on Firm Liquidity

I analyze the liquidity position of firms by using the operating cash flow and overall cash flow variables, which are found in a firm's Statement of Cash Flow. The operating cash flow measures the cash that a company generates through its normal business operations. This metric is a good indicator of a company's ability to produce a favorable cash flow that is sufficient to sustain and expand its operations. Table 1.1 reports the effects computed for the effect on liquidity estimated using equation (1.1). Column (1) shows that the average exposed firm experiences an operating cash flow contraction of 1.69 percentage points compared to an unexposed firm in the same region [25]. In the event of a shortfall, the company might require external financing. However, despite the operating cash flow decrease, I find that exposed firms' overall cash flow increased by 3.12 percentage points[26]. Thus, this suggests that despite facing a liquidity shortage, firms are drawing on some source of financing to smooth over the shock.

Decomposing the operating cash flow liquidity measure into sub-components sales and

[23] In this case it is the change between the values in March 2016 and April 2015.

[24] For robustness I also assess the intensive measure of the shock: volatility adjusted deviation from historic mean at each zip code. It is a continuous variable that ranges from 0-3 thus, the higher the score, the greater the firm's exposure to the shock.

[25] Operating cash flow serves as an indicator of whether a company can generate a consistently positive cash flow to sustain and expand its operations, or if it will need external financing to do so.

[26] The cash flow indicator captures the net financing of firms. Cash Flow = Operating cash flow + Investing cash flow + Financing cash flow.

wages[27], I evaluate the channels that are potentially driving the contraction in liquidity.[28]. I find that the slowdown in demand for products is causing a decrease in sales for the average exposed firm by 14.82, as shown in Column (2). However, wages only saw a fall of 6.28 percentage points. Although the fall in sales and wages have opposite effects on Net Income and thereby on Operating Cash flows, the larger magnitude of the sales slowdown outweighs the reduced spending on wages. While payments on wages could have been suspended during the period of complete shutdown due to water logging, increased uncertainty in the region led to a more prolonged contraction in sales.

The non-parametric trends in the cash flow variables are presented in Figure 1.3 (operating cash flow) and Figure 1.4 (cash flow). The results support the extensive margin findings from but also provide additional intensive margin evidence: The more a firm is exposed, the greater the contraction in liquidity. Table 1.2 estimates this effect by regressing these liquidity outcomes on equation (1.1) but using the intensive margin measure i.e. the volatility-adjusted deviation measure of the shock. Column (1) finds that for a one standard deviation increase in exposure, firms face a contraction in operating cash flow of 0.96 percentage points, and an overall cash flow increase of 1.53 percentage points. Decomposing the cash flow covariate further, sales contracts by 8.48 percentage points as seen in column (2) and wages by 2.99 percentage points in column (3). Therefore, the contraction in cash flow from operations, emanating from the decline in sales, is counteracted by a reduction in investment activity or an increase in financing.

Firms that are located in the zip codes that were flooded face a contraction in their sales and consequently a decrease in their operating cash flow. But as their overall cash flow increases, it is indicative that are able to access external financing.

[27]Both Sales and Wages are also constructed as a share of lagged assets

[28]Due to limited data availability for the non-headline numbers components of the operating cash flow, I am unable to test for all the comprehensive accounting decomposition of the cash flow metrics.

1.3.3 Liquidity Smoothing Margins

In this section I evaluate the sources of external financing firms access.

Insurance and Deferred Tax Assets

The Prowess Database contains data on the firms' use of Deferred Tax Assets and Insurance claims. Deferred Tax Assets are generated when a company's taxable income is less than its accounting income, which reduced future tax obligations. They represent future tax benefits that a company can use when it generates taxable income in the future[29]. The unforeseen expenses incurred due to climate shocks can create deferred tax assets for a firm[30]. Insurance is another risk sharing tool for firms. In the dataset, the insurance claims refer to the total amount of insurance payment a firm has received upon the realization of a shock. To assess the use of these tools, I construct a binary variable that takes a value of 1 if the firm has declared a higher amount on their balance, in the year of the climate shock (2015-2016) than the previous financial year.

Table 1.3 shows the use of these smoothing tools by the exposed firms. Column (1) indicates that firms facing liquidity crunches increases deferred tax assets by 3 percentage points points more than those that don't. Column (2) shows no significant difference in the use of insurance claims. Evaluating the trends using the intensive margin of exposure, Figure 1.5, shows a clear upward trend in the creation of deferred tax assets the more exposed a firm is. Insurance, however, shows an inverted U shape, indicating that while some exposed firms may use it, it's not significant. Table 1.4 confirms that the creation of deferred tax assets increases by 1 percentage points for every 1 SD increase in exposure, while the use of insurance remains insignificant.

Assessing the margins of adjustment firms can access, Deferred Tax Assets have significant but very minimal. Surprisingly, Insurance has no significant effect. Given that insurance is a

[29] For instance, if a company records accrued expenses in its financial statements that are not currently deductible for tax purposes, it establishes a deferred tax asset. This means the company is likely to have lower tax payments in the future when it eventually deducts these expenses, leading to potential tax savings.

[30] PwC Viewpoint: Accounting and disclosure implications of natural disasters.

risk-sharing tool meant to help agents smooth over negative shocks, it is an important finding that the market is not functioning in this context.

Firm Borrowing

I define the firm borrowing channel as the method used to evaluate the total credit borrowed by a firm. In this approach, the dependent variable of interest is the credit demand by firms. It is calculated by taking the difference in aggregate firm borrowing before and after a shock occurs[31]. All new loans taken from all credit institutions are aggregated to the firm.

In Table 1.5 I find the average exposed firm increased their borrow by 9.47 million USD in the post-shock period compared to an unexposed firm. This represents an almost twofold increase compared to the average loan amount from the previous year's sample. Assess the intensive margin effects, Figure 1.7 shows, that the exposed firms relatively don't change their borrowing post-shock, but unexposed firms face a large contraction. Hence the differential effect for exposed firms is positive. Column (1) of Table 1.6. shows for a one standard deviation increase in shock an exposed firm increased its relative borrowing by 5.93 million USD. Thus, similar to advanced economies, Indian firms also use credit to mitigate the effects of natural disasters. And Indian financial markets have liquidity available for this purpose. Table 1.7 find no effects on the number of loans on the extensive margin. But the number of modifications increase slightly.

Borrowing from credit markets plays a significant role for firms facing a liquidity shortage due to exposure to a climate shock. While the number of loans issued do not significantly increase, the loan amount associated with the new issues increases. These results are robust to the both the extensive and intensive margin definitions of the shock. Thus, the shocks that effects firms in the real sector have implications for the financial sector as well via the use of credit channels.

[31] Pre-shock period is from April 2015 to October 2015 and the post-shock period is from November 2015 to March 2016. This definition of the pre- and post-period is different from the sections above due to the availability of granular credit data.

1.4 Role of Credit Supply in Liquidity Smoothing

A natural progression in inquiry is to assess the supply of credit given that firms exposed to the floods almost doubled their borrowing demand and Credit Institutions are able to provide the liquidity. This is especially relevant given that climate shocks affect local aggregate financing conditions. Therefore, the availability of local credit markets from which these firms can borrow can also affect external liquidity provisioning.

1.4.1 Identification and Estimation Equation

A traditional challenge associated with studying the effect of shocks on credit channels is the inability to distinguish between the firm demand channel and the bank supply channel due to the correlation between a demand shock to the business and a supply shock to the bank. To address this problem, Khwaja-Mian (KM) exploits a given data structure in a fixed-effect regression model. To estimate the sources of credit for the exposed firms I extend the econometric identification strategy developed by KM. In my analysis, I modify the framework to use the branches of credit institutions[32] as my unit of analysis rather than the aggregate bank level. This build on the localized nature of the shock and firm-bank relations in India. The following expands on the econometric design of the regression model used in this section.

The reduced form estimation equation to assess credit supply channel from a given firm f to a branch b is as follows:

$$L_{f-b} = \alpha + \beta_1 shock_b + shock_f + \varepsilon_{f-b}$$

,

where, L_{f-b} is the loan issued from credit institution branch b to firm f, $shock_f$ is shock

[32] Credit Institutions includes Banks and NBFIs

to firm f, $shock_b$ is the shock to branch b, and ε_{f-b} is the idiosyncratic shock. This framework is especially relevant in the case of climate shocks, where the incidence of the shock falls on both firms and banks. But when estimating the role of credit supply in liquidity smoothing, the coefficient of interest is β_1 in the equation above will be biased as follows:

$$\hat{\beta}_1^{ols} = \beta_1 + \frac{cov(shock_b, shock_f)}{var(shock_b)}$$

where, the $cov(shock_b, shock_f) > 0$ for firms and branches that have both been exposed to the shock[33]. KM identifies the credit supply channel by exploiting firms' borrowing from multiple branches which vary in their exposure to the shock. The first difference cross-sectional regression with firm fixed effects will compare loans taken by firms from exposed branches against those from unexposed branches. Will a firm, that borrows from multiple branches experience a difference in borrowing from the exposed branches post the shock? Firm fixed effects in a within-firm comparison effectively account for the specific changes in credit demand within each firm when applied to first difference data. No additional assumptions about the correlation between supply and demand are required. Furthermore, as the shock is unexpected, branches potentially are unable to alter their lending practices preemptively or establish buffers before the shock occurs. This could have otherwise either underestimated or overestimated of the impact of the bank lending channel, contingent on the direction of the adjustments made before the shock. The unbiased coefficient can now be estimated using the following regression:

$$L_{f-b} = \alpha + \beta^{fe} shock_b + \delta_f + \varepsilon_{f-b}$$

where, L_{f-b} is the loan issued from branches b to firm f, $shock_b$ is the shock to branches b, δ_f is the firm fixed effects, and ε_{f-b} is the idiosyncratic shock. And now β^{fe} is unbiased.

Thus the estimation equation to assess the branch lending channel is:

[33] It is equal to 1 in my sample when using the binary definition of the shock.

$$\Delta L_{f \in z - b^B \in z'} = \alpha_{f \in z} + \beta shock_{b^B \in z} + \varepsilon_{f \in z - b^B \in z'} \tag{1.2}$$

where, $f \in z$ is a firm located in zip code z, $b^B \in z'$ is a branch b of credit provider B located in zip code z' and Δ is the difference in the level between April 2015 - October 2015 and November 2015 - March 2016.The dependent variable $\Delta L_{f \in z - b^B \in z'}$ change in the loans between a firm and a branch. The standard errors are clustered at the city level. The branch shock $shock_{b^B \in z}$ takes a binary value of 1 if the given zip code within which the firm operates has been exposed, and 0 otherwise[34]. After applying first-difference to the data, the fixed effects $\alpha_{f \in z}$ are incorporated, effectively assimilating all the shocks related to firm borrowing and credit demand. Therefore, the fixed effects approach serves to examine whether a single firm borrowing from two distinct banks encounters a more pronounced reduction in lending from the bank that confronts a comparatively more substantial decrease in its liquidity supply. The coefficient of interest β measures the ability of a branch in the exposed zone, to extend credit to firms in comparison to those in the unexposed zones. Hence estimating the ability of exposed banks to provide the necessary credit to firms for their liquidity smoothing.

1.4.2 Credit Supply from Exposed branches

The dataset created for this chapter contains information on credit access provided to all firms in the region by financial institutions located both within and outside the region. This means that some branches of financial institutions are exposed to the region, and some are not. By using equation (1.2), we can determine how the lending behavior of an exposed branch differs towards firms in the region. The measure of lending will be calculated by comparing the total volume of loans disbursed before and after the flood shock of 2015 to a particular firm-branch pair. The

[34]For robustness I also assess the intensive measure of the shock: volatility adjusted deviation from historic mean at each zip code. It is a continuous variable that ranges from 0 to 3. Hence higher the score, the greater the exposure of the firm to the shock.

region comprises the States of Tamil Nadu, Andhra Pradesh, and Union Territory of Puducherry which were affected by the flood shock.

In Table 1.8 column (1) I find that exposed branches increase lending to the firms in the region by 2.95 million USD post shock. However, columns (2) and (3) uncover an intermediation channel from firms and towards NBFIs: Exposed branches relatively increase lending to NBFIs by 10.60 million USD, while they decrease lending to firms by 4.54 million USD. This contraction in lending is greater pronounced, 5.17 million USD, within the sub sample of lending to exposed firms. Table1.11 further evaluates this estimation of the number of loans issued, for robustness. Thus, the results are indicative of exposed branches channeling credit liquidity away from firms and towards NBFIs. Table 1.9, shows the exposed NBFI relatively increased lending to all firms in the region by 15 million USD (column 1) and Table 1.12 (column 1) finds the number of loans issued decreases.

This evidence suggests that channeling credit via NBFIs is an optimal response for some banks when it comes to allocating credit among economic agents after a climate shock. These NBFI hold advantages including greater market penetration, less strict and faster disbursement procedures, and a higher capacity for risk-taking[35]. The Banks also benefit from lending to NBFIs instead of directly to firms, as the amount of risk-weighted assets on the bank's balance sheet is lower in this case.

1.4.3 Credit Supply from Exposed branches to Exposed Firms

In this section, I restrict the sample of firms that receive credit to only those were affected by the climate shock. In this section, Equation (1.2) is used to estimates the supply of credit to exposed firms, based and the heterogeneity in branch characteristics. Lending will be measured as the difference between the total volume of loans pre-and post-shock, between a given firm-branch

[35]NBFI's include microfinance institutions that lend to underserved populations who will be most affected by the shock.

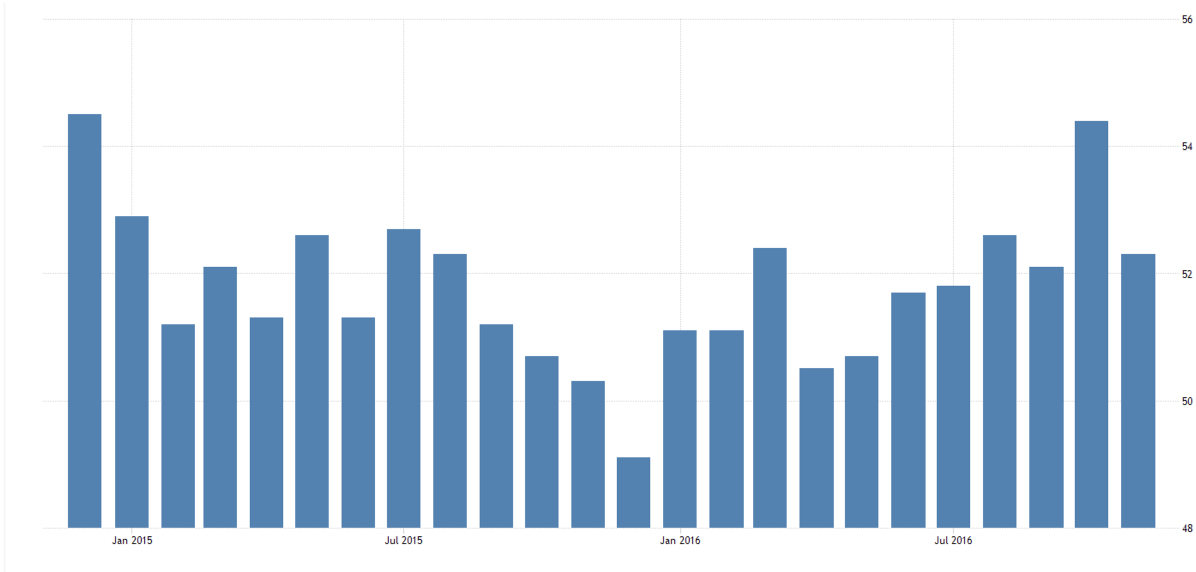
pair.

Table 1.10, Column (1) shows that bank branches that are exposed reduce their lending to exposed firms by 9.16 million USD. In Column (2), it is found that branches that are part of institutions with national networks significantly reduce their lending to exposed firms by 3.55 million USD. But credit from institutions with national networks towards these firms increases by 3.25 million USD. For robustness, Table 1.11 evaluates the estimation for the number of loans issued and it is found that there is no differential effect based on ownership of credit institutions. that need to borrow to smooth out the liquidity crunch may access credit from exposed local/regional bank branches and non-bank financial institutions, or from unexposed banks that are part of national networks. In Table 1.12, I find that conditional on being exposed, NBFIs relatively increase lending to exposed firms in the region by 9.3 million USD, Column 2, and to unexposed firms by 12.73 million USD , Column 3. However the number of loans to exposed firms reduces as indicative in Table 1.12 Column 2 but there is no effect for the unexposed firms.

Thus exposed branches of NBFIs and local banks lend more to exposed firms. These results could be driven by reach for yield that these institutions are seeking when lending to firms.

1.5 Conclusion

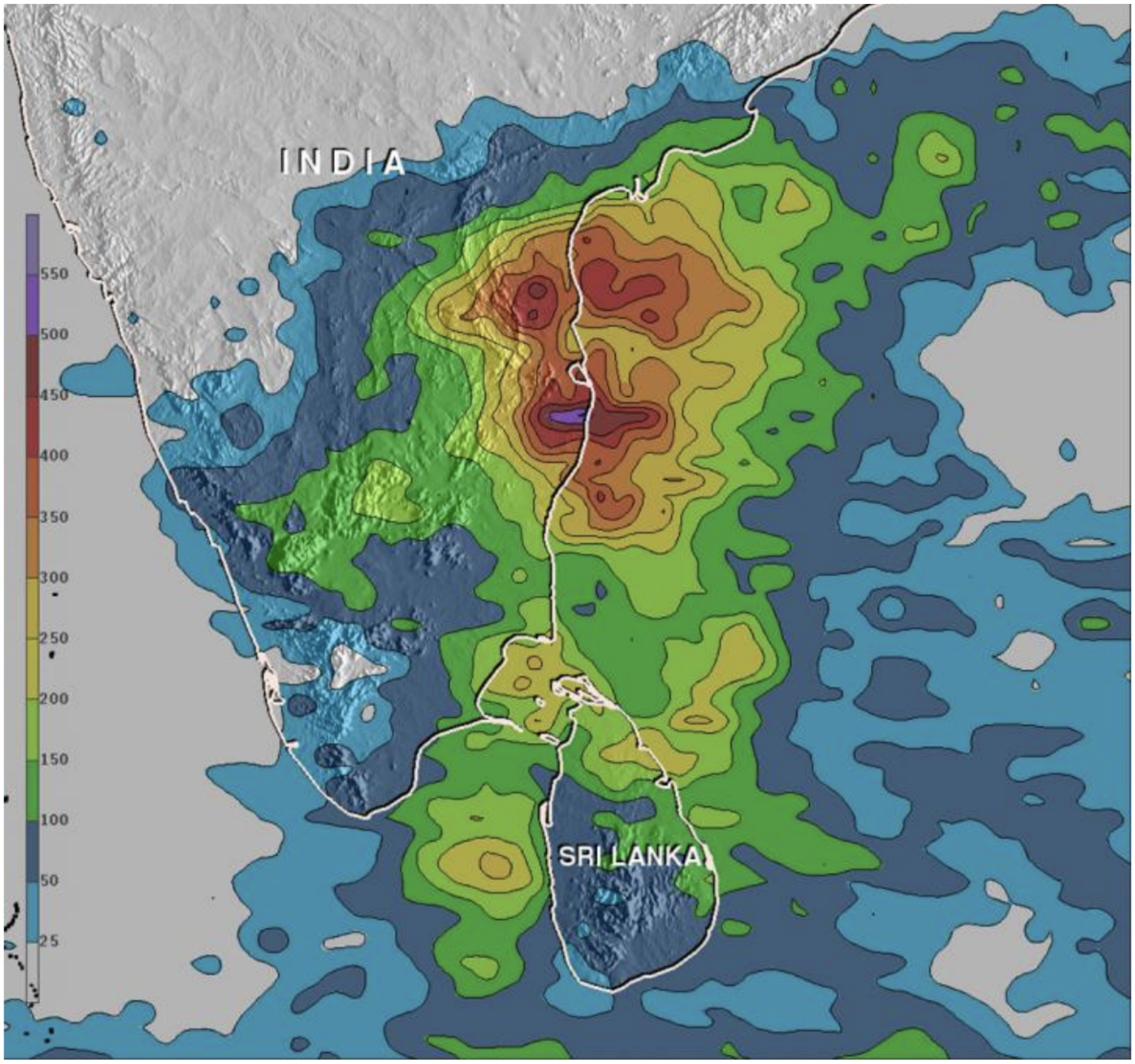
Unexpected climate shocks can have a significant impact on the economy and affect different economic agents simultaneously, resulting in tighter local financial conditions. As these shocks become more frequent and severe, it is crucial to understand their effects and the mechanisms through which they propagate through the economy. This chapter quantifies the impact of climate shocks on firm liquidity and evaluates the methods they use to manage their liquidity needs. The research design is set in the 2015 unexpected extreme floods in Southern India. To estimate the effects, I create a novel high-frequency dataset combining firm balance sheets, credit register data, and climate data at the zip code level. By exploiting the spatial variation in exposure, I find that Indian firms exposed to local flood shocks experience a reduction in liquidity. While traditional macro-development papers find the presence of numerous financial frictions in emerging markets setting, this chapter shows that external liquidity exists, and firms have various sources to access it. Exposed firms uses deferred tax assets to manage its liquidity crunch but insurance claims are not significant.The exposed firms also significantly increase their borrowing from financial institutions. However, local branches do not provide the credit. Local branches redirect credit away from firms and instead lend to NBFIs. As a result, the exposed firms borrow either from NBFIs or from unexposed branches affiliated with national networks. These results highlight the importance of external financing for firms affected by climate shocks and document an intermediation mechanism taking place to supply credit to firms.



Source: Trading Economics

Figure 1.1: Indian Manufacturing PMI

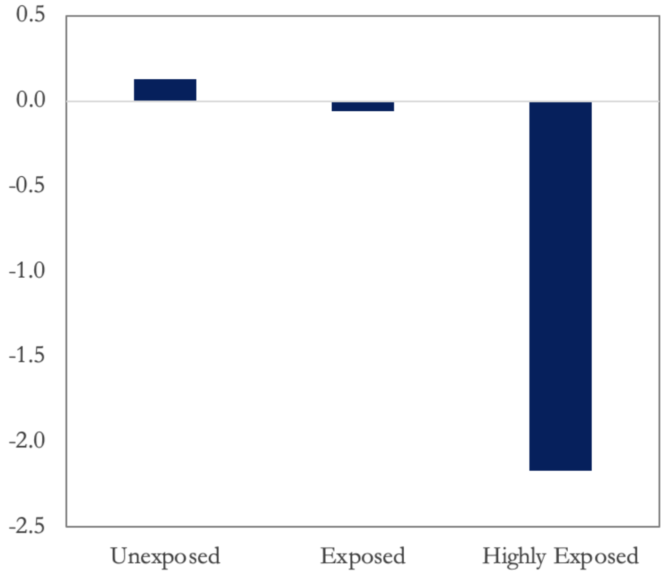
The Nikkei India Manufacturing Purchasing Managers' Index (PMI) is computed using monthly surveys to procurement executives across more than 300 industrial firms. Reports of this Index attribute the sharp decline in December 2015 to the South India Floods of 2015. The report also reveals that the Chennai floods led to a two-year decline in the country's manufacturing performance in December. A summary of this can be found in the news article by Business Today, published on January 4, 2016 titled *Chennai floods pull down Indian manufacturing: Nikkei India PMI survey*



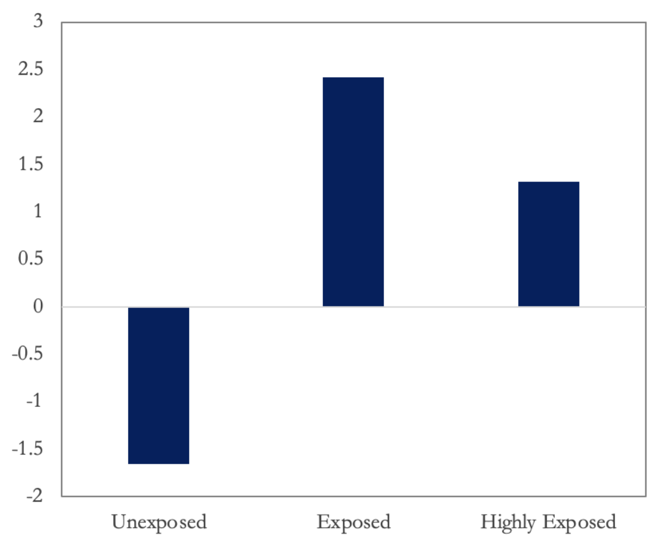
Source: NASA

Figure 1.2: Climate Shock Satellite Image

The figure shows the satellite image over the states of Tamil Nadu, Andhra Pradesh and Union Territory of Puducherry in December 2015. The figure illustrates that there was significant spatial variation in the exposure within the region based on both the extensive margin to exposure and intensive margin.



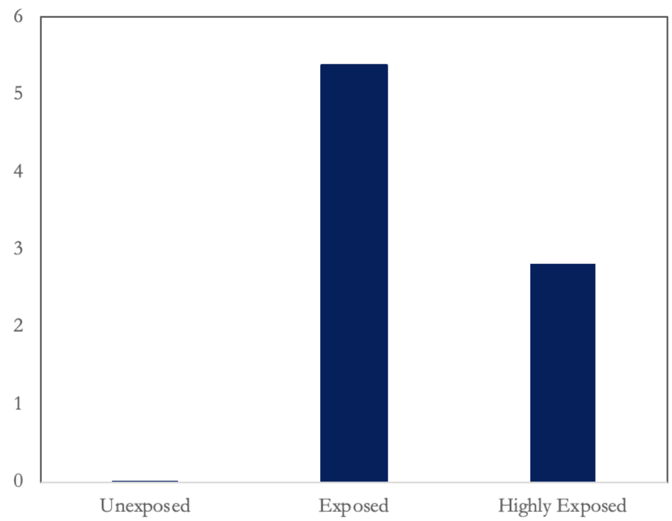
(a) Operating Cash Flow



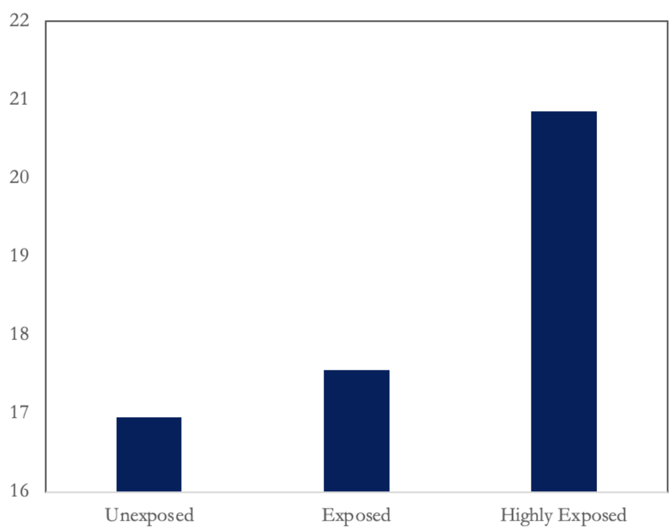
(b) Cash Flow

Figure 1.3: Effect of Climate Shock on Firm Liquidity

This figure shows the change in liquidity measures for firms in the region. The measures include the Net Operating Cash Flow and total Cash Flow The change is computed by taking the difference stated in the financial statement in March 2016 and March 2015. The shock took place in November- December of 2015. The values have been normalized using the firm's lagged assets.



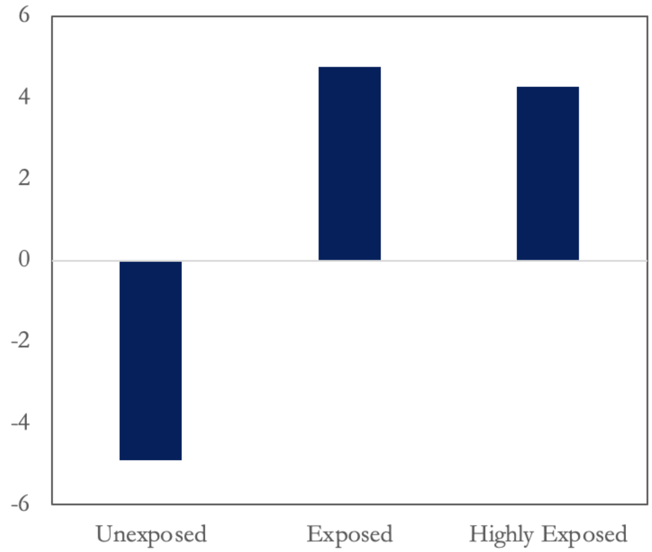
(a) Insurance Claims



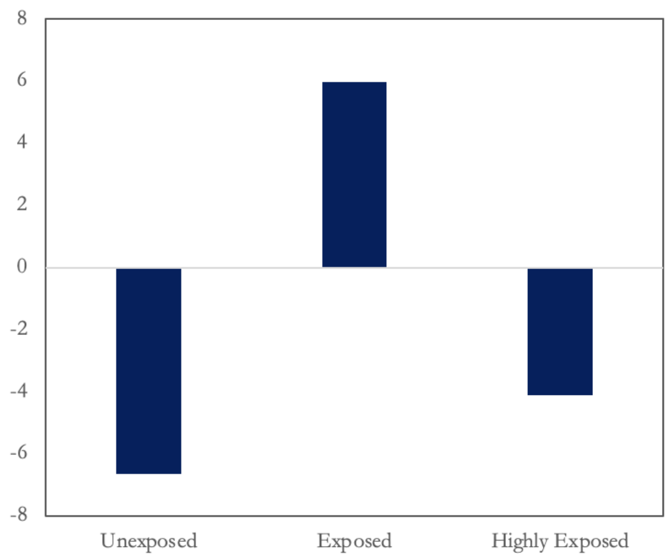
(b) Deferred Taxes

Figure 1.4: Other Liquidity Smoothing Tools

This figure shows the relative change in percent likelihood of using Deferred Taxes and Insurance Claims by firms in the region. The change is computed by taking the difference stated in the financial statement in March 2016 and March 2015. The shock took place in November-December of 2015.



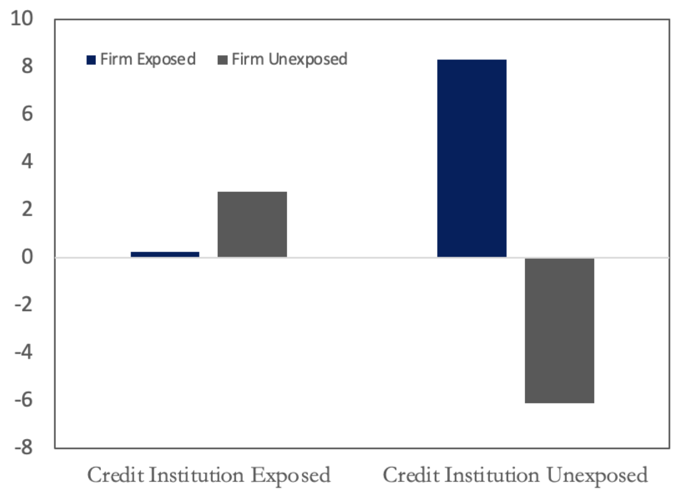
(a) Loan Amount



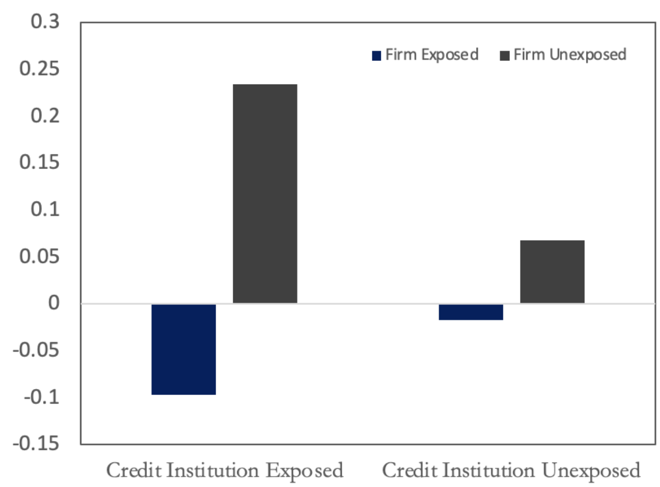
(b) Number of Loans

Figure 1.5: Firm Borrowing Channel for Liquidity Smoothing

This figure shows the relative change in aggregate firm borrowing in the region. The change is computed by taking the difference in the total volume (in million USD) and number of loans (count) taken by a firm post-exposure and pre-exposure. The values have been normalized using the average borrowing volume and average number of loans respectively in the full sample.



(a) Credit Issuance Amount



(b) Credit Issuance Number

Figure 1.6: Credit Supply Channel

This figure shows the relative change in supply of loans: total volume (in million USD) and number of loans (count),between a credit institution branch and firms, in million USD The change is computed by taking the difference in the total volume of loans taken by a firm post-exposure and pre-exposure. Non- Bank Financial Corporations are included in both the Credit giving institutions as well as a firm. The sample of firms are restricted to those in the region and credit institutions include all branches (in the region and nationally) that supply credit. The values have been normalized using the average borrowing volume and average number of loans respectively in the full sample.

Table 1.1: Impact of the Climate Shock on Firm Liquidity

	Operating Cash flow	Determinants of Operating Cash flow		Cash flow
		Sales	Wages	
	(1)	(2)	(3)	(4)
Firm Shock	-1.69***	-14.86***	-6.28***	3.12**
	(0.47)	(4.74)	(1.80)	(1.25)
N	2347	2313	2275	2573
R^2	0.00	0.00	0.01	0.00

This table presents the results of the regression Equation 1.1. The independent variables is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's liquidity. Operating Cash flow includes all cash generated by a firm that is used for it's it's short run operating. Thus it is used as the measure for liquidity of a firm. The operating cash flow can be further decomposed as a difference between incoming cash via sales and outgoing cash via wage expenditure. This is used to understand where the channel driving the changes in operating cash flow. Overall cash flow includes cash from financing and investing a firm receives over the operating cash flow. And thus is used to indicate if there are any adjustment made to counteract changes in operating cash flow.The coefficient of interest measures the differential effect on liquidity for firms that have been exposed to the climate shock compared to those that have not been exposed.The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.2: Impact of the Climate Shock on Firm Liquidity: Intensive Margin in Exposure

	Operating Cash flow	Determinants of Operating Cash flow		Cash flow
		Sales	Wages	
	(1)	(2)	(3)	(4)
Firm Shock	-0.96**	-8.48**	-2.99***	1.53***
	(0.37)	(3.79)	(0.87)	(0.56)
N	2348	2313	2276	2348
R^2	0.009	0.001	0.001	0.000

This table presents the results of the regression Equation 1.1. The independent variable is the intensive margin indicator described above. The location is measured at the zip code level. The dependent variables assess' the impact of the shock on the firm's liquidity. Operating Cash flow includes all cash generated by a firm that is used for its short-run operating. Thus, it is used as the measure of the liquidity of a firm. The operating cash flow can be further decomposed as a difference between incoming cash via sales and outgoing cash via wage expenditure. This is used to understand where the channel driving the changes in operating cash flow. Overall cash flow includes cash from financing and investing a firm receives over the operating cash flow. This is used to indicate if there are any adjustments made to counteract changes in operating cash flow. The coefficient of interest measures the differential effect on liquidity for firms that have been exposed to the climate shock compared to those that have not been exposed. The sample period includes the annual financial data from the reports issued from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.3: Use of Insurance and Deferred tax to Liquidity Smooth

	Deferred Tax (1)	Insurance Claims (2)
Firm Shock	0.03***	0.00
	(0.008)	(0.015)
N	2840	2840
R^2	0.007	0.001

This table presents the results of the regression Equation 1.1. The independent variables is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's use of tools to adjust against the liquidity contraction. Deferred taxes is the measured using a binary indicator that takes the value of 1, if a firm's financial statement shows the creation of a deferred tax asset. The insurance claim similarly is also a binary variable that takes a value of 1 if a firm's financial statement indicates a positive insurance claim. The coefficient of interest measures the differential use of the corresponding instrument for firms that have been exposed to the climate shock compared to those that have not been exposed.The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.4: Use of Insurance and Deferred tax to Liquidity Smooth: Intensive Margin in Exposure

	Deferred Tax	Insurance Claims
	(1)	(2)
Firm Shock	0.01***	0.00
	(0.003)	(0.004)
N	2843	2843
R^2	0.006	0.000

This table presents the results of the regression Equation 1.1. The independent variable is the intensive margin indicator described above. The location is measured at the zip code level. The dependent variables assess' the impact of the shock on the firm's use of tools to adjust against the liquidity contraction. Deferred taxes the measured using a binary indicator that takes the value of 1 if a firm's financial statement shows the creation of a deferred tax asset. The insurance claim similarly is also a binary variable that takes a value of 1 if a firm's financial statement indicates a positive insurance claim. The coefficient of interest measures the differential use of these instruments to smooth liquidity for the firms that have been exposed to the climate shock compared to those that have not been exposed. The sample period includes the annual financial data from the reports issued from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.5: Firm Borrowing to Liquidity Smooth

	Loan Amount (1)
Firm Shock	9.47*
	(4.75)
N	2840
R^2	0.004

This table presents the results of the regression Equation 1.1. The independent variables is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable is the change in new loans borrowed by a firm. The change is computed using the difference in aggregate volume of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate volume of new loans issued to a firm between March 2015-October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential use of credit by firms that have been exposed to the climate shock compared to those that have not been exposed.The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.6: Firm Borrowing to Liquidity Smooth: Intensive Margin in Exposure

	Loan Amount	Number of Loans	Number of Modifications
	(1)	(2)	(3)
Firm Shock	5.93***	-0.00	0.01
	(1.20)	(0.02)	(0.01)
N	727	727	727
R^2	0.005	0.103	0.000

This table presents the results of the regression Equation 1.1. The independent variable is the intensive margin indicator described above. The location is measured at the zip code level. The location is measured at the zip code level. The dependent variable is the change in number of new loans borrowed by a firm. And the number of modifications calculates the number of the new loans issued that are restructured at a future date. The change is computed using the difference in aggregate volume of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential use of credit by firms that have been exposed to the climate shock compared to those that have not been exposed. The sample period includes the annual financial data from the reports issued from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.7: Firm Borrowing to Liquidity Smooth: Number of Loans and Number of Modifications

	Number of Loans	Number of Modifications
	(1)	(2)
Firm Shock	0.04	0.05^{***}
	(0.07)	(0.02)
N	727	727
R^2	0.10	0.00

This table presents the results of the regression Equation 1.1. The independent variables is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable in column (1) is the change in new loans borrowed by a firm. The change is computed using the difference in aggregate number of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015-October 2015 (pre-shock). In column (2) the dependent variable measures the number of modifications i.e. the number of the new loans issued that are restructured at a future date.This variable is constructed in the same way as column (1). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential use of credit by firms that have been exposed to the climate shock compared to those that have not been exposed.The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.8: Provision of Credit Supply for Liquidity to Firms

	All	NBFIs	Firms		
			All Firms	Exposed Firms	Unexposed Firms
	(1)	(2)	(3)	(4)	(5)
Branch Shock	2.95**	10.60***	-4.54**	-5.17**	-0.59
	(1.29)	(2.30)	(1.75)	(1.84)	(0.63)
N	1644	434	1210	667	543
R^2	0.17	0.23	0.16	0.31	0.11

This table presents the results of the regression Equation 1.2. The independent variables is a binary indicator that takes a value of 1 for those credit institutions are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable is the change in the volume of the new loans issued by a credit institution branch to a given firm. The change is computed using the difference in aggregate volume of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate volume of new loans issued to a firm between March 2015-October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from an exposed branches to a given firm, compared to the supply from unexposed branched to the firm. The columns focus on lending to given groups of firms. Column (1) estimates the effects for all firms. Column (2) looks at the supply from all credit institution to the subset of Non-Bank Financial Institutions. Columns (3),(4), and (5) focus on the firms in the real sector (services and manufacturing). The sample period includes data from the reports issued in March of 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.9: Provision of Credit Supply for Liquidity from NBFIs to Firms: Loan Amount

	All Firms	Exposed Firms	Unexposed Firms
	(1)	(2)	(3)
Shock to Branches	-10.50**	-7.46**	-6.01**
	(3.51)	(2.56)	(2.58)
NBFI Dummy	-8.46	-0.60	-15.24
	(6.66)	(2.20)	(11.47)
Shock*NBFI Dummy	15.78**	9.37**	12.73*
	(6.39)	(3.87)	(6.09)
N	1210	667	543
R^2	0.222	0.314	0.164

This table presents the results of the regression Equation 1.2. The independent variables is a binary indicator that takes a value of 1 for those credit institutions are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable is the change in the volume of the new loans issued by a credit institution branch to a given firm. The change is computed using the difference in aggregate volume of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate volume of new loans issued to a firm between March 2015-October 2015 (pre-shock). The climate shock took place in November and December of 2015. To assess the differential effect of supplying credit by NBFIs, I include the dummy indicator that takes a value of 0 if the credit institution branch providing the loans is a Bank and 1 if it is a NBFI. The coefficient of interest measures the supply of credit from an NBFI branch, conditional on exposure, to firms. The columns focus on lending to different groups of firms. Column (1) estimates the effects for all firms. Column (2) looks at the Exposed Firms. Column (3) looks at the Unexposed Firms. The sample period includes data from the reports issued in March of 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.10: Heterogeneity in Provision of Credit Supply for Liquidity to Exposed Firms

	Loan Amount		
	(1)	(2)	(3)
Branch Shock	1.87	-1.64**	0.16
	(2.14)	(0.58)	(6.00)
Bank Dummy	0.43		
	(2.27)		
Branch Shock*Bank Dummy	-9.15**		
	(3.67)		
National Network Dummy		3.24***	
		(0.74)	
Branch Shock*National Network Dummy		-3.55**	
		(1.28)	
Public Dummy			-18.18
			(20.99)
Branch Shock*Public Dummy			-9.12
			(26.1)
N	667	667	667
R^2	0.31	0.31	0.32

This table presents the results of the regression Equation 1.2. The independent variables is a binary indicator that takes a value of 1 for those credit institutions are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable is the change in the volume of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in aggregate volume of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate volume of new loans issued to a firm between March 2015-October 2015 (pre-shock). The climate shock took place in November and December of 2015. To assess the heterogeneous effect across different types of credit intuitions I include the following: The Bank Dummy takes a value of 1 if the credit institution branch providing the loans is a Bank and 0 if it a NBFC; The National Network Dummy takes a value of 1 if the credit institution branch providing the loans is part of a national network across the country, and 0 if it a local or region institution; The Public Dummy takes a value of 1 if the credit institution branch providing the loans is a Government owned, and 0 if Privately owned.The sample period includes data from the reports issued in March of 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.11: Provision of Credit Supply for Liquidity to Firms: Number of Loans

	Lending	NBFIs	Firms		
			All Firms	Exposed Firms	Unexposed Firms
	(1)	(2)	(3)	(4)	(5)
Shock to Branches	0.05	0.33***	-0.28**	-0.18**	-0.51*
	(0.06)	(0.10)	(0.09)	(0.07)	(0.26)
N	1644	434	1210	667	543
R^2	0.14	0.161	0.138	0.122	0.28

This table presents the results of the regression Equation 1.2. The independent variables is a binary indicator that takes a value of 1 for those credit institutions are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable is the change in the number of the new loans issued by a credit institution branch to a given firm. The change is computed using the difference in aggregate number of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015-October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from an exposed branches to a given firm, compared to the supply from unexposed branched to the firm. The columns focus on lending to given groups of firms. Column (1) estimates the effects for all firms. Column (2) looks at the supply from all credit institution to the subset of Non-Bank Financial Institutions. Columns (3),(4), and (5) focus on the firms in the real sector (services and manufacturing). The sample period includes data from the reports issued in March of 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 1.12: Provision of Credit Supply for Liquidity from NBFIs to Firms: Number of Loans

	All Firms	Exposed Firms	Unexposed Firms
	(1)	(2)	(3)
Shock to Branches	0.03	0.40	-0.62**
	(0.22)	(0.34)	(0.200)
NBFI Dummy	0.68**	1.55***	-0.04
	(0.24)	(0.48)	(0.22)
Shock*NBFI Dummy	-1.10***	-1.90***	-0.09
	(0.26)	(0.44)	(0.53)
N	1210	667	543
R^2	0.123	0.106	0.291

This table presents the results of the regression Equation 1.2. The independent variables is a binary indicator that takes a value of 1 for those credit institutions are located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level.The dependent variable is the change in the number of the new loans issued by a credit institution branch to a given firm. The change is computed using the difference in aggregate volume of new loans issued to a firm between November 2015-March 2016 (post-shock) and the aggregate volume of new loans issued to a firm between March 2015-October 2015 (pre-shock). The climate shock took place in November and December of 2015. To assess the differential effect of supplying credit by NBFIs, I include the dummy indicator that takes a value of 0 if the credit institution branch providing the loans is a Bank and 1 if it is a NBFI. The coefficient of interest measures the supply of credit from an NBFI branch, conditional on exposure, to firms. The columns focus on lending to different groups of firms. Column (1) estimates the effects for all firms. Column (2) looks at the Exposed Firms. Column (3) looks at the Unexposed Firms. The sample period includes data from the reports issued in March of 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Chapter 2

The Cross-Section Effect of Climate Shocks on Firms and Credit Risk

Aggregate local shocks can affect firms unevenly, especially in the presence of financial frictions like limited credit access and high borrowing costs. Analyzing these heterogeneous effects is crucial to understanding economic implications for resource allocation and risk. Chapter 1 reveals that firms exposed to an unexpected climate shock typically experience a liquidity contraction and increase their borrowing from credit markets. In this chapter, I examine whether certain firms within the cross-section are more vulnerable to climate shocks and what this vulnerability implies for their access to external financing.

I explore this question by exploiting the November-December 2015 South India Floods, which affected the highly industrialized region spanning Andhra Pradesh, Tamil Nadu, and Puducherry. Unexpected heavy rainfall after the monsoon season caused widespread flooding in various parts of the area. This led to an immediate halt in economic activities for around 17 days and subsequent disruptions that impeded operations. To empirically investigate this question, I assemble a novel dataset containing firms' annual financial statements, firm credit rating, transaction-level credit issuance between firms and financial institution branches, geographic coordinates of each firm and bank branch, and corresponding weather data for each zip code. By exploiting the unexpected nature of the shock and spatial variations in exposure to in a cross-sectional regression setting, I estimate how the credit risk distribution for firms that borrow changes.

I find that firms with characteristics that make them more vulnerable, do in fact experience a decline in operating cash flow, driven by contraction sales. and liquidity issues due to shocks need more external financing. Credit markets allocate larger volumes of loans to these firms that require more at the margin. Thus even in the cross-section, liquidity is provided where it is most required. High credit risk firms also face a greater liquidity crunch and increase borrowing. Traditional literature in this are, finds borrowers with the lowest credit quality cannot utilize credit lines to address external liquidity shocks (Brown, 2021). And borrowers with low to medium credit risks can depend on bank financing for liquidity support but high credit risk borrowers may find it challenging to access such assistance, even in the presence of non-fundamental liquidity shocks, as highlighted (Diamond, 1991). Thus, it is an interesting finding that credit markets are allocating funds to those firms that require the liquidity, and high risk firms are able to access the financing. However, unlike the other types of firms, firms with high credit risk that face a decrease in their operating cash flow are not seeing a decline in their sales. On the contrary they see an increase in their sales. Hence these firms could be more vulnerable to climate shocks indirectly due to the lower margin of safety they hold, due to which they also face higher credit risk. Thus allocation to such firms helps meet their liquidity needs, it may be a source of risk in future periods as climate shock become more prevalent.

Given the rising occurrence and intensity of climate-related disruptions, these findings highlight the significance for businesses, particularly those facing tighter financial limitations or elevated credit risks, to cultivate a broader array of risk-management approaches. This could entail establishing precautionary reserves or investing in insurance to alleviate the impact of such shocks.

2.1 Data

To empirically evaluate the effect of the natural disaster described above, I construct a novel data set that combines high-frequency firm-branch data with Geo-spatial and climate data. Given the sample of firms and bank branches, the data set provides the following information: For a firm f located at zip code z, has annual financial data $X_{f\in z,T}$ for the financial year ending at T and the average credit risk measured using their Credit Rating $CR_{f\in z,T}$. They borrow credit from multiple institutions such that the loan from a given institution B with branch b located at zip code z', $b \in z'$, from which the $f \in z, T$ borrows is $L_{f\in z-b^B\in z',t}$, at any given point in time t. And the locations z and z' are exposed to monthly $\tilde{t}$ rainfall levels of $r_{\tilde{t}}$.

2.1.1 Climate Data

The University of Delaware maintains global historic databases on gridded climate data. I use the *Terrestrial Precipitation 1900-2017 Gridded Monthly Time Series (V 5.01) data archives* dataset. They compute the rainfall and temperature measures for a latitude-longitude node by combining data from 20 nearby weather stations using an interpolation algorithm based on the spherical version of Shepard's distance-weighting method to create a 0.5-degree latitude by 0.5-degree longitude grid node. The extreme floods that occurred in South India between November and December of 2015 will be climate shock studied in this Chapter.To construct the climate shock indicators $shock_g$, I aggregate the total rainfall over November and December for every year at each 0.5 degrees by 0.5 degrees latitude-longitude node g. Using this indicator of rainfall level, I construct the percent Deviation (pd) at each node g, for the year 2015 from its historic average:

$$shock_g^{pd} = \frac{rain_g - \bar{rain}_g^{30}}{\bar{rain}_g^{30}}$$

Using the Meteorological Survey of India's definition of extreme rainfall episodes I create the categorical variables for analysis. Based on the percent deviation from the historic mean data, $< 20\%$ is defined as a drought level[1]; Range between -20% and 20% is normal level; 20% to 60% represent excess rain; $> 60\%$ is an extreme excess level. Finally, I collapse the categorical variables into an indicator variable that takes the value of 1 if the given location g receives rainfall in the excess or extreme excess range for November and December 2015. It takes a value of 0 if the location g receives rainfall in the normal range during that time frame. For the main analysis of the chapter, I use this extensive margin to define the shock.

By harvesting data from web-based mapping services I create a dataset that matches geospatial coordinates to zip code z. Then using a spatial reference system that minimizes the geodetic distance between two geospatial coordinates g and g':

$$min\sqrt{(latitude_g - latitude_{g'})^2 + (longitude_g - longitude_{g'})^2}$$

I map each zip code to its closest geospatial coordinate. This allows me to construct the climate shock at the zip code level.

2.1.2 Firm Data

Firm Financial Data

The Prowess dataset compiled by the Center for Monitoring the Indian Economy (CMIE) contains the annual financial statements for about 38,000 Indian Firms.[2] for a comprehensive

[1]For this chapter, given the method of defining the one-time climate shock, I count these observations to be part of the control group along with those that experience normal levels of rainfall.

[2]Financial Statements include Income Statement, Profit/ Loss, Statement of cash flows, and the Balance Sheet The 1956 Companies Act mandates firms to disclose data on their capacity production, and sales in their annual

list of Indian firms from 1989-2019. The firms contribute to more than 70% of industrial output, 75% of corporate taxes, and more than 95% of excise taxes collected by the Government of India (CMIE). The set includes the universe of publicly traded firms and a large sub-sample of unlisted, but registered within the formal sector, firms They are all medium to large firms as the dataset doesn't include any small or micro-enterprises. Along with financial variables such as assets, cash flows, sales, borrowing, and incomes, it also includes information on firm characteristics, such as industry, age, ownership, and location. It is the most comprehensive dataset for firm-level analysis. I exclude the financial firm from the sample in this analysis. And restrict the sample to firms located in Andhra Pradesh, Tamil Nadu, and Puducherry and the statements for the financial year ending 2014-2016.[3]. I use the cash flow and operating cash flows as the liquidity measures for the firm, which is located in zip code z, and other balance sheet variables to add as controls $X_{f \in z,T}$ I match the final data with the climate data based on the basis on zip code z.

Firm Credit Rating Data

The Centre for Monitoring Indian Economy (CMIE), Prowess database, also contains Credit Ratings data issued by the main Credit Rating Agencies in India: CRISIL, ICRA, CARE, India Ratings and Research Private Limited (FITCH), and Brickwork Ratings. The ratings assess the creditworthiness of the firms by evaluating their ability to repay debt. The database covers credit ratings for firms predominantly in the real sector from 1991. For a given firm the ratings are based on different credit instruments held by the firm from two broad categories: market-based instruments or capital market debt instruments such as bonds, debentures and bank-based instruments including loan facilities from the bank such as term loans, cash credit, bank guarantee, etc. Data on bank-based instruments is available from 2008 onwards, following the prudential guidelines for implementing the new capital adequacy framework for banks issued by the Reserve Bank of India in April 2007.

reports.

[3]The financial year in India spans from April of a given year to March of the next year.

Ratings are designated to an instrument within a firm and represented by an alphabetic or alphanumeric symbol. Each rating symbol indicates the level of credit risk linked with the rated instrument or entity. For the empirical analysis, the credit ratings issued by different agencies have been harmonized and numerically encoded using the rating grade definition in the data set[4]. The baseline is set to the highest safety rating and is given a score of 0. Following, the score increases as the risk of default increases: High Safety gets a score of 1, Moderate Safety gets 2, Adequate Safety gets 3, Inadequate Safety gets 4, Substantial Risk gets 5, High Risk gets 6 and Default gets 7. I aggregate the credit risk metric to the overall firm level for a given financial year[5] using two methods: (i) simple average across all securities; (ii) weighted average, where the weight corresponds to the share of the monetary amount that is raised by that security rated compared to the total amount raised by the firm across all rated securities in that financial year. I merge this rating data with the firm financial data using the common unique firm code identifier used in Prowess' Financial Statement data.

2.1.3 Credit Data

The Ministry of Corporate Affairs (MCA) maintains a historic data set of transaction-level collateralized loans borrowed by firms across India. Banking Secrecy laws in India prohibit banks and other financial institutions from disclosing information about their borrowers.[6] However, firms can self-disclose their lender information. The dataset contains information on the date of loan issuance t, issuing bank (B), address of the issuing station, and total loan amount.[7] L_{f-b^B} and the date of any modification that has taken place. Using the address of issuing station parameter I extract the bank branch location ($b \in z'$) from which the loan is issued. Also, create a unique

[4]Most of the ratings in the sample fall within the investment rating category.

[5]FY2015: April 2014-March 2015; This is consistent with other annual variables in the dataset.

[6]The Banking Regulation Act 1949 includes in its regulations and standards, privacy principles aimed at governing the acquisition, retention, and safeguarding of customer data. The Public Financial Institutions Act of 198: Obligation as to Fidelity and Secrecy, prevents public financial institutions from disclosing any details regarding their clients.

[7]All loan amounts are in INR units, unlike the data in Prowess which are in Millions of USD.

identification number for each bank branch[8].

The self-reporting nature of this data set creates a few caveats to be accounted for. First, there is no formal audit made on this information. Thus, there is the threat of underestimating any effects using this data, as there is the potential of underreporting. Second, the address of the issuing stations or bank branch is nearly fully populated whereas there are some missing values for the bank name. I impute the names of the banks for which it was possible using either of the following techniques: (1) The bank name is included at the beginning of the address variable (2) The bank names which could be found when searching against the address on a web-based search engine and then cross-checking it against the bank's bank branch locator web page. Third, numerous errors are owing to the lack of standardized reporting practice and manual entry process of the data. As the bank branch level and its zip code location are key to my analysis, I manually checked and corrected for the address and zip codes of the bank branches using the bank's web directory on the bank branch locator. As the bank parameter does have a unique identifier in this data set, there are multiplications in both the bank name and bank address' which are cleaned.[9]

To integrate this data with the rest I create a bridge that matches Company Identification Number (CIN) here to firm indicator in the Prowess data set using forensic methods. I use the Levenshtein distance matching on firm names, followed by manual checking. Thus, the match takes place by firm. To harmonize the difference in frequency between the loans data and prowess data, I map all transactions within a given financial year to that corresponding financial year. For instance, if a firm borrows a loan in November 2014, it will be considered a part of the 2014-2015 financial year. The prowess variables for this financial year will be issued in their March 2015 statement.

[8] All addresses have the zip code and two-digit state code at the end.

[9] BANK EXAMPLE; Bank Example; BANK EXP; bank exp; Bank EXP; BANK exp; bank EXP; Bank EXP. ; banc exp; bankexp;. . . .

2.2 Empirical Framework

2.2.1 Identification

The identification strategy for this section relies on the nature of the extreme climate event that occurs. In November-December 2015, heavy rainfall hit Indian states Andhra Pradesh, Tamil Nadu, and the Union Territory of Puducherry, causing a historic economic slowdown lasting over 17 days. This rainfall, the highest in over a century, was linked to the El Niño phenomenon of 2014-2016. Economic losses ranged from 3 billion USD to over 13 billion USD. Many businesses struggled due to limited resources amidst the extreme weather. The rainfall occurred in four episodes over two months, affecting low-lying areas more severely. This regional variation offers a natural experimental setting for studying the impact of such events.

As the shock is a random phenomenon, I assume it is orthogonal to the firms-branch fundamentals by construction (Brown 2021). Owing to its transient nature I assume that the shock did not have any structural effects on the firms such as changing their value or creditworthiness. And since it was unexpected it rules out any anticipation effects that the firm could have hedged against prior to exposure. Building on this exogeneity of the shock, I use the spatial variation in the exposure to estimate the differential effect of the shock between firms in the region that are exposed and those that are not.

2.2.2 Estimation Equation

$$\Delta y_{f\in z} = \alpha + \beta_1 shock_{f\in z} + \beta_2 C_{f\in z} + \beta_3 shock_{f\in z} * C_{f\in z} + \tau L.X_{f\in z} + \varepsilon_{f\in z} \tag{2.1}$$

where $f \in z$ is firm f located in zip code z. The climate shock $shock_{f\in z}$ takes a binary value of 1 if the given zip code within which the firm operates has been exposed, and 0 otherwise. The dependent variable $Deltay_{f \in z}$ is constructed by taking the difference in the value between the beginning and end of the financial year within which the shock occurs For all the Annual Balance Sheet indicators the change is taken between the values in March 2016 and April 2015. For the high-frequency credit indicators, the change is taken between the pre and post period: Pre-shock period is from April 2015 to October 2015 and the post-shock period is from November 2015 to March 2016.. These outcomes have been normalized using lagged assets.

$C_{f \in z}$ is the indicator variable to define the firm characteristics. It used on different covariates such as sector, age, size and credit rating. The coefficient of interest β_3 measures the interaction between the firm's exposure to the climate shock and the characteristic of interest.The firm controls $X_{f \in z, T-1}$ are lagged by one unit to absorb contemporaneous effects. The standard errors are clustered at the city level.

2.3 Results in the Cross-Section

In this section I evaluate the empirical estimates that measure the effects of the climate shock within the cross-section of firms. I first assess the impact of firms with time-invariant characteristics that have the potential to make them more vulnerable to the shock: (1) Sector; (2) Size and (3) Age. Following, I assess the effects across the credit risk distribution of firms.

2.3.1 Static Firm Characteristics

Sector

The data include firms that belong to the manufacturing and service sector. However, manufacturing firms have the potential to be more susceptible to be affected by flooding than those in the service industry. Table 2.1 tabulates the heterogeneous effects of climate shocks on firms based on sector. Exposed manufacturing firms experience a more pronounced reduction in liquidity by 4.81 percentage points (column 1). This is primarily attributed to a substantial decline in sales by 16.38 percentage points (column 4), and in wage expenses by 8.16 percentage points (column 7). However, these firms see an increase in overall cash flow by 6.80 percentage points (column 10).

These firms, however, also seem to be 2.91 percent points more likely to insurance claims, unlike the average firm which shows no such significant result. Manufacturers also borrow more by $19.55 million. Thus, not only do the financial markets in this context have enough liquidity to finance firms, but the manufacturing firms that are more exposed are also accessing more credit.

Size

Firms belonging to the higher size deciles are larger and should have better access to credit markets. In table 2.4 I find larger firms experience an no significant change in liquidity. Their relative sales grow by 4.35 percentage points and their wage bill also increases by 3.26 percentage points. But their cash flow does not significantly change. Thus table 2.5 find's no difference in deferred asset creation or insurance claims. However, the larger firms increase their relative borrowing by3.13 million USD as seen in table 2.6. Despite being unaffected by these shocks, they are able to access more credit for the market.

Age

Older firms are more established and are often better equipped to mitigate the effects of exogenous shocks. Table 2.7, column (1) shows older exposed firms experience an increase in their cash flow by 0.018 percentage points. Sales grow by 0.91 percentage points and wages by 0.39 percentage points . Their overall cash flow also faces an increase of 0.33 percentage points.

As these firms do not face a liquidity crunch they should not have a need for external financing. And they do not see any significant use of deferred asset or insurance as indicated in Table 2.8. They also borrow less by 0.48 USD million as seen in table 2.9 column 1. Hence these firms may have better risk management practices developed over the years to be better prepared to counter random shocks.

2.3.2 Firms Credit Risk

The credit risk covariate measures the annual aggregate credit risk for a firm across all securities issued by that firm in that year. It is a discrete variable with the lowest value associated with the least risk and the higher the value moves closer to default. The credit risk for a firm is taken at the begin of the period. Conditional on being exposed, table 2.10 estimates that firms with higher credit risk face a contraction in their operating cash flow off 0.83 percentage points. Unlike the average treatment effect, the contraction is not associated with a decrease in their sales. Their sales actually increase by 7.70 percentage points and wages also increase by 7.03 percentage points. Thus the main driving force for the fall in liquidity does not seem to affect these firms. their cash flow increases so there is some financing going on.

Table 2.11 establish that these firms do not use deferred tax assets or insurance claims. Table 2.12 estimates the change in a firm's credit risk that demands credit when exposed to an unexpected climate shock. The annual credit risk is computed using a simple average across all securities rated for a given firm, in that given year. Column (1) evaluates change in the total volume of new loan issuances. While exposed firms significantly reduce their borrowing demand by $42.16 million, and safer firms i.e. lower credit risk on average borrow $10.27 million USD more, exposure to the shock relatively increases the share of more risky firms demanding credit by 11.79 million USD. These results indicate that firms with high credit risk firms require more external financing when exposed to climate shocks via larger volumes borrowed. These firms also restructure a significant number of these loans issued in future periods.

The results show that the firms with characteristics that make them more vulnerable to this climate shock require larger loans.This can be attributed to their lower shock absorption capacity i.e. their margin of safety is very low. Thus any cash flow variability (e.g. working capital, payments, timeline or cost increase) can affect their cash flow. They have very little maneuverability which is why their debt service capability is low hence high credit risk. Thus it is important to evaluate in future work, what is driving their operating cash flow shortage and increased borrowing. This is would be especially important when considering an inter-temporal dimension to risk as the number of loans restructured increases and could be converted into Non-Performing Loans on the Balance Sheet.

2.4 Conclusion

I explore the impact of climate shocks on the risk profile of firms seeking credit. Exogenous factors like policy shifts, crises, and global credit cycles have been shown to reshape the composition of firms accessing external funding. These changes may result in riskier firms obtaining credit. Exploiting the natural experimental conditions set up by the unprecedented severe floods in Southern India in 2015, I compare how the risk composition of firms demanding credit changes when exposed to the shock. In a cross-sectional regression framework, I conducted empirical analysis using a unique high-frequency dataset that integrates firm balance sheets, credit register data, and climate data at the zip code level. Firms more vulnerable to shocks, experiencing sales declines and liquidity crunches, need more external financing. Credit markets allocate larger loans to these firms. However, high credit risk firms, despite increasing sales, also face liquidity issues and borrow more. These findings highlight the importance for firms, especially those with tighter financial constraints to develop a wider range of risk management strategies especially are vulnerabilities to climate shocks increase.

Table 2.1: Firm Sector and the Impact on Firm Liquidity

	Operating Cash flow	Determinants of Operating Cash flow		Cash flow
		Sales	Wages	
	1	2	3	4
Shock	1.12***	-4.96	-11.04***	-0.84***
	(0.28)	(3.76)	(2.71)	(0.20)
Manuf.	-0.07**	9.14***	1.45***	-6.66***
	(0.03)	(2.32)	(0.42)	(2.17)
Shock*Manuf.	-4.81***	-16.38*	8.16***	-6.80***
	(1.04)	(9.45)	(2.71)	(2.41)
N	2347	2313	2275	2371
R^2	0.002	0.001	0.001	0.002

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To measure the heterogeneous effect across different sectors, the shock is interacted with an indicator variable on firm type. Manf. is a binary variable taking the value of 1 for those firms in the sector.The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's liquidity. Operating Cash flow includes all cash generated by a firm that is used for it's it's short run operating. Thus it is used as the measure for liquidity of a firm. The operating cash flow can be further decomposed as a difference between incoming cash via sales and outgoing cash via wage expenditure. This is used to understand where the channel driving the changes in operating cash flow. Overall cash flow includes cash from financing and investing a firm receives over the operating cash flow. And thus is used to indicate if there are any adjustment made to counteract changes in operating cash flow. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.2: Firm Sector and the Use of Insurance and Deferred Tax

	Deferred Tax	Insurance Claims
	(1)	(2)
Shock	0.03	-0.01
	(0.02)	(0.00)
Manf.	-0.02	0.01***
	(0.02)	(0.00)
Shock*Manf.	0.02	0.03***
	(0.02)	(0.00)
N	2840	2840
R^2	0.007	0.007

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To measure the heterogeneous effect across different sectors, the shock is interacted with an indicator variable on firm type. Manf. is a binary variable taking the value of 1 for those firms in the sector. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's use of tools to adjust against the liquidity contraction. Deferred taxes is the measured using a binary indicator that takes the value of 1, if a firm's financial statement shows the creation of a deferred tax asset. The insurance claim similarly is also a binary variable that takes a value of 1 if a firm's financial statement indicates a positive insurance claim. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.3: Firm Sector and Borrowing

	Loan Volume	Number of Loans	Number of Modifications
Firm Shock	-14.41	-0.04	0.08
	(10.1)	(0.12)	(0.06)
Manuf.	-10.43**	-0.01	-0.06
	(4.48)	(0.01)	(0.07)
Shock*Manuf.	19.55**	-0.03	-0.04
	(9.51)	(0.15)	(0.09)
N	727	727	727
R^2	0.037	0.003	0.012

This table represents the results of the regression Equation 2.1. The independent variable is a binary indicator that takes a value of 1 for those firms located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level. To measure the heterogeneous effect across different sectors, the shock is interacted with an indicator variable on firm type. Manf. is a binary variable taking the value of 1 for those firms in the sector. The sample period includes the annual financial data from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.4: Firm Size and the Impact on Firm Liquidity

	Operating Cash flow	Determinants of Operating Cash flow		Cash flow
		Sales	Wages	
	1	2	3	4
Shock	-1.56	-34.67***	-19.35***	8.86**
	(1.92)	(12.06)	(4.97)	(4.31)
Size	-0.28***	0.35*	-0.28**	0.36*
	(0.07)	(0.19)	(0.11)	(0.19)
Shock*Size	-0.03	4.35**	3.26***	-0.28
	(0.37)	(2.00)	(0.76)	(0.19)
N	2347	1530	2275	2371
R^2	0.001	0.001	0.002	0.003

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To measure the heterogeneous effect across different sizes, the shock is interacted with an indicator variable on firm type. Size is a categorical variable on the decile group that a given firm belongs to. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's liquidity. Operating Cash flow includes all cash generated by a firm that is used for it's it's short run operating. Thus it is used as the measure for liquidity of a firm. The operating cash flow can be further decomposed as a difference between incoming cash via sales and outgoing cash via wage expenditure. This is used to understand where the channel driving the changes in operating cash flow. Overall cash flow includes cash from financing and investing a firm receives over the operating cash flow. And thus is used to indicate if there are any adjustment made to counteract changes in operating cash flow. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.5: Firm Size and the Use of Insurance and Deferred Tax

	Deferred Tax (1)	Insurance Claims (2)
Shock	-0.00	-0.02
	(0.02)	(0.02)
Size	-0.03***	-0.01***
	(0.00)	(0.00)
Shock*Size	0.01	0.01**
	(0.01)	(0.00)
N	2840	2840
R^2	0.033	0.009

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To measure the heterogeneous effect across different sizes, the shock is interacted with an indicator variable on firm type. Size is a categorical variable on the decile group that a given firm belongs to.The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's use of tools to adjust against the liquidity contraction. Deferred taxes is the measured using a binary indicator that takes the value of 1, if a firm's financial statement shows the creation of a deferred tax asset. The insurance claim similarly is also a binary variable that takes a value of 1 if a firm's financial statement indicates a positive insurance claim. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.6: Firm Size and Borrowing

	Loan Volume	Number of Loans	Number of Modifications
Firm Shock	0.55	-0.05	0.09*
	(7.80)	(0.14)	(0.03)
Size	-2.20	-0.00	0.01
	(1.85)	(0.03)	(0.00)
Shock*Size	3.13*	0.03	-0.01
	(1.73)	(0.04)	(0.01)
N	727	727	727
R^2	0.005	0.104	0.003

This table represents the results of the regression Equation 2.1. The independent variable is a binary indicator that takes a value of 1 for those firms located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level. To measure the heterogeneous effect across different sizes, the shock is interacted with an indicator variable on firm type. Size is a categorical variable on the decile group that a given firm belongs to. The sample period includes the annual financial data from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.7: Firm Age and the Impact on Firm Liquidity

	Operating Cash flow	Determinants of Operating Cash flow		Cash flow
		Sales	Wages	
	1	2	3	4
Shock	-4.27***	-35.85***	-15.19***	2.07
	(1.17)	(11.71)	(4.44)	(1.63)
Age	-0.00**	0.31*	0.05*	0.06
	(0.00)	(0.17)	(0.03)	(0.04)
Shock*Age	0.18***	0.91**	0.39***	0.33*
	(0.03)	(0.36)	(0.12)	(0.16)
N	2347	2313	2275	2371
R^2	0.002	0.004	0.002	0.001

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To measure the heterogeneous effect by the time duration the firm has been operating, the shock is interacted with an indicator variable on Age. Age is the continuous variable.The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's liquidity. Operating Cash flow includes all cash generated by a firm that is used for it's it's short run operating. Thus it is used as the measure for liquidity of a firm. The operating cash flow can be further decomposed as a difference between incoming cash via sales and outgoing cash via wage expenditure. This is used to understand where the channel driving the changes in operating cash flow. Overall cash flow includes cash from financing and investing a firm receives over the operating cash flow. And thus is used to indicate if there are any adjustment made to counteract changes in operating cash flow.The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.8: Firm Age and the Use of Insurance and Deferred Tax

	Deferred Tax	Insurance Claims
	(1)	(2)
Shock	0.01	0.00
	(0.02)	(0.02)
Age	0.00	0.00***
	(0.00)	(0.00)
Shock*Age	0.00	-0.00
	(0.00)	(0.00)
N	2840	2840
R^2	0.012	0.006

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To measure the heterogeneous effect by the time duration the firm has been operating, the shock is interacted with an indicator variable on Age. Age is the continuous variable. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's use of tools to adjust against the liquidity contraction. Deferred taxes is the measured using a binary indicator that takes the value of 1, if a firm's financial statement shows the creation of a deferred tax asset. The insurance claim similarly is also a binary variable that takes a value of 1 if a firm's financial statement indicates a positive insurance claim. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.9: Firm Age and Borrowing

	Loan Volume	Number of Loans	Number of Modifications
Firm Shock	18.62*	0.07	0.04
	(9.55)	(0.09)	(0.03)
Age	0.53*	-0.01*	-0.00
	(0.30)	(0.00)	(0.00)
Shock*Age	-0.48*	-0.01*	-0.00
	(0.31)	(0.00)	(0.00)
N	727	727	727
R^2	0.007	0.112	0.003

This table represents the results of the regression Equation 2.1. The independent variable is a binary indicator that takes a value of 1 for those firms located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level. To measure the heterogeneous effect by the time duration the firm has been operating, the shock is interacted with an indicator variable on Age. Age is the continuous variable. The sample period includes the annual financial data from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively. end

Table 2.10: Credit Risk and the Impact on Firm Liquidity

	Operating Cash flow	Determinants of Operating Cash flow		Cash flow
		Sales	Wages	
	1	2	3	4
Shock	4.10***	-39.93***	-35.49***	-3.29***
	(1.29)	(12.72)	(11.39)	(1.05)
Credit Rating	-0.01	0.11	0.11	0.01
	(0.01)	(0.10)	(0.09)	(0.01)
Shock*CR	-0.83***	7.70***	7.03***	0.66***
	(0.26)	(2.50)	(2.24)	(0.21)
N	1035	1069	1051	1040
R^2	0.004	0.004	0.004	0.004

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone.To assess firm riskiness associated with borrowing, the independent variable interacts with a discrete metric that measures the firm's annual aggregate credit risk before exposure to the shock. The firm risk is calculated using a simple average across all securities held by the firm that have been rated. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's liquidity. Operating Cash flow includes all cash generated by a firm that is used for it's it's short run operating. Thus it is used as the measure for liquidity of a firm. The operating cash flow can be further decomposed as a difference between incoming cash via sales and outgoing cash via wage expenditure. This is used to understand where the channel driving the changes in operating cash flow. Overall cash flow includes cash from financing and investing a firm receives over the operating cash flow. And thus is used to indicate if there are any adjustment made to counteract changes in operating cash flow. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.11: Credit Risk and the Use of Insurance and Deferred Tax

	Deferred Tax	Insurance Claims
	(1)	(2)
Shock	0.02	-0.01
	(0.04)	(0.03)
Credit Rating	-0.02***	-0.00
	(0.01)	(0.00)
Shock*CR	-0.00	0.00
	(0.01)	(0.00)
N	1194	1194
R^2	0.022	0.006

This table presents the results of the regression Equation 2.1. The independent shock variable is a binary indicator that takes a value of 1 for those firms are located in the flood zone, and 0 if not in the flood zone. To assess firm riskiness associated with borrowing, the independent variable interacts with a discrete metric that measures the firm's annual aggregate credit risk before exposure to the shock. The firm risk is calculated using a simple average across all securities held by the firm that have been rated. The location is measured at the zip code level.The dependent variables assess' the impact of the shock on the firm's use of tools to adjust against the liquidity contraction. Deferred taxes is the measured using a binary indicator that takes the value of 1, if a firm's financial statement shows the creation of a deferred tax asset. The insurance claim similarly is also a binary variable that takes a value of 1 if a firm's financial statement indicates a positive insurance claim. The sample period includes the annual financial data from the reports issued in March of 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 2.12: Credit Risk and Borrowing

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Firm Shock	-42.16**	-0.21	-0.09*
	(16.07)	(0.23)	(0.05)
Credit Rating	-10.27***	-0.04	-0.03***
	(3.38)	(0.03)	(0.01)
Shock*Credit Rating	11.79***	0.01	0.03*
	(3.60)	(0.06)	(0.02)
N	382	382	382
R^2	0.044	0.012	0.014

This table represents the results of the regression Equation 2.1. The independent variable is a binary indicator that takes a value of 1 for those firms located in the flood zone, and 0 if not in the flood zone. The location is measured at the zip code level. To assess firm riskiness associated with borrowing, the independent variable interacts with a discrete metric that measures the firm's annual aggregate credit risk before exposure to the shock. The firm risk is calculated using a simple average across all securities held by the firm that have been rated. The sample period includes the annual financial data from March 2014 to March 2016. The cross-sectional regression takes the difference between the dependent variable metric issued in March 2016 and March 2015. I include a prior year's data to normalize all continuous variables by lagged assets. The climate shock took place in November and December of 2015. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Chapter 3

Climate Shocks, Banking Capital and Provision of Liquidity to Firms

A bank's capacity to absorb losses is measured by its capital reserves. Policymakers aim to promote credit growth while maintaining macro-financial stability through Basel Regulations, which set Banking Capital Requirements. Banks with stronger capitalization are better equipped to absorb losses without depleting their assets, and therefore tend to offer less risky credit. During the Global Financial Crisis (GFC), capital holdings had a significant impact on banks' ability to absorb losses from mortgage portfolios, influencing their ability to provide credit to the real sector. Extreme natural disaster events can expose vulnerabilities and disrupt credit markets. In this chapter, I examine whether banks' capital adequacy ratios affect their ability to provide credit to firms that need external liquidity following exposure to a climate shock.

I empirical evaluate this question by using the natural experiment of the South India Floods in November-December 2015. These floods affected the highly industrialized region that includes Andhra Pradesh, Tamil Nadu, and Puducherry. Unanticipated heavy rainfall after the monsoon season led to widespread flooding in different parts of the area. This, in turn, caused an immediate halt in economic operations for approximately 17 days, leading to disruptions that impeded economic activity.

I construct an innovative dataset comprising annual financial statements of firms, bank balance sheet data and transaction-level credit issuance between firms and financial institution branches, geographical coordinates of each firm and bank branch, and corresponding weather data for each zip code. Identification is based on the unexpected nature of shock, leveraging the spatial variation in exposure to the shock and the data structure. I adapt the empirical firm-fixed effects model outlined in Khwaja-Mian (2008) to assess the supply of credit channel from branches exposed and explore the connection between this provisioning of credit and bank capital requirements.

In this context, I find bank capital itself does not play a significant role in determining credit supply. This result is consistent with many studies in the literature. For instance, Berrospide et al. (2010) found that bank capital had only a minimal effect on lending adjustments. Likewise, Jiménez et al. (2010) and Albertazzi et al. (2010) used Spanish credit register data to show how low bank capitalization restricts credit supply. Studies based on US syndicated loan level data, such as Santos and Winton (2010) and Elliot (2010), also indicate reduced effects of bank capital on credit supply.

However, when exposed to a climate shock, branches within more capitalized banks tend to increase overall lending. Banks with higher capitalization increase their lending to firms in the real sector but decrease their lending to Non-Bank Financial Institutions (NBFIs). These results hold even when I look at the effects based on only Tier 1 capital levels. Tier 1 capital represents the bank's core capital and serves as the primary protection against losses. Tier 2 capital, the supplementary capital that isnt aimed to create buffers for the bank, has no significant effect on branch lending to the real sector. Branches of banks with lower capital adequacy ratios as well and lower individual levels of Tier 1 and high levels of Tier 2 capital are increase their lending to NBFIs post the shock.

The credit flow from well-capitalized banks to real sector firms after being exposed to climate shocks aligns with macro-financial risk mitigating policies. This is because banks with greater loss absorption capacity are providing liquidity. In contrast, banks with lower core capital and higher supplemental capital are lending more to NBFIs. This can be profitable for these banks (Agarwal, 2023) and reduce their risk exposure (Irani et al., 2021). Future work can investigating the risk-return trade-offs of this intermediation channel given that the regulatory frameworks[1], operational restrictions, and requirements vary significantly between the Banks and NBFIs.

3.1 Data

To empirically evaluate the effect of the natural disaster described above, I construction a novel data set that combines high frequency firm-branch data with Geo-spatial and climate data. Given the sample of firms and bank branches, the data set provides the following information: For a firm f located at zip code z, has annual financial data $X_{f \in z,T}$ for the financial year ending at T. They borrow credit from multiple institutions such that the loan from a given institution B with branch b located at zip code z', $b \in z'$, from which the $f \in z, T$ borrows is $L_{f \in z - b^B \in z', t}$, at any given point in time t. The balance sheet financial data of these institutions are at the annual aggregate level B_T. And the locations z and z' are exposed to monthly $\tilde{t}$ rainfall levels of $r_{\tilde{t}}$.

3.1.1 Climate Data

The University of Delaware maintains comprehensive databases on global climate data. I utilize the "Terrestrial Precipitation 1900-2017 Gridded Monthly Time Series (V 5.01) data archives" dataset. They calculate rainfall and temperature measures for a specific location by combining data from 20 nearby weather stations using an interpolation algorithm based on the spherical version of Shepard's distance-weighting method. This creates a 0.5-degree latitude by

[1]NBFIs do not fall under Basel regulations

0.5-degree longitude grid node. In this chapter, I define a climate shock as an extreme rainfall event that occurred in November and December of 2015. To create the climate shock indicators $shock_g$, I add up the total rainfall for each year in November and December and do this for each 0.5 degrees by 0.5 degrees latitude-longitude node g. I then use this rainfall indicator to calculate the percent deviation (pd) at each node g for the year 2015 from its historical average:

$$shock_g^{pd} = \frac{rain_g - \bar{rain}_g^{30}}{\bar{rain}_g^{30}}$$

Using the Meteorological Survey of India's definition of extreme rainfall episodes I create the categorical variables for analysis. Based on the percent deviation from the historic mean data, $< 20\%$ is defined as a drought level[2]; Range between -20% and 20% is normal level; 20% to 60% represent excess rain; $> 60\%$ is an extreme excess level. Finally, I collapse the categorical variables into an indicator variable that takes the value of 1 if the given location g receives rainfall in the excess or extreme excess range for November and December 2015. It takes a value of 0 if the location g receives rainfall in the normal range during that time frame. For the main analysis of the chapter, I use this extensive margin to define the shock.

By harvesting data from web-based mapping services I create a dataset that matches geospatial coordinates to zip code z. Then using a spatial reference system that minimizes the geodetic distance between two geospatial coordinates g and g':

$$min\sqrt{(latitude_g - latitude_{g'})^2 + (longitude_g - longitude_{g'})^2}$$

I map each zip code to it's closest geospatial coordinate. This allows me to construct the climate shock at the zip code level.

[2]For this chapter, given the method of defining the one-time climate shock, I count these observations to be part of the control group along with those that experience normal levels of rainfall.

3.1.2 Firm Financial Data

The Prowess dataset compiled by the Center for Monitoring the Indian Economy (CMIE) contains the annual financial statements for about 38,000 Indian Firms.[3] for a comprehensive list of Indian firms from 1989-2019. The firms contribute to more than 70% of industrial output, 75% of corporate taxes, and more than 95% of excise taxes collected by the Government of India (CMIE). The set includes the universe of publicly traded firms and a large sub-sample of unlisted, but registered within the formal sector, firms They are all medium to large firms as the dataset doesn't include any small or micro-enterprises. Along with financial variables such as assets, cash flows, sales, borrowing, and incomes, it also includes information on firm characteristics, such as industry, age, ownership, and location. It is the most comprehensive dataset for firm-level analysis. I exclude the financial firm from the sample in this analysis. And restrict the sample to firms located in Andhra Pradesh, Tamil Nadu, and Puducherry and the statements for the financial year ending 2014-2016.[4]. I use the cash flow and operating cash flows as the liquidity measures for the firm, which is located in zip code z, and other balance sheet variables to add as controls $X_{f \in z,T}$ I match the final data with the climate data based on the basis on zip code z.

3.1.3 Credit Data

The Ministry of Corporate Affairs (MCA) maintains a historic data set of transaction-level collateralized loans borrowed by firms across India. Banking Secrecy laws in India prohibit banks and other financial institutions from disclosing information about their borrowers.[5] However, firms can self-disclose their lender information. The dataset contains information on the date of

[3]Financial Statements include Income Statement, Profit/ Loss, Statement of cash flows, and the Balance Sheet The 1956 Companies Act mandates firms to disclose data on their capacity production, and sales in their annual reports.

[4]The financial year in India spans from April of a given year to March of the next year.

[5]The Banking Regulation Act 1949 includes in its regulations and standards, privacy principles aimed at governing the acquisition, retention, and safeguarding of customer data. The Public Financial Institutions Act of 198: Obligation as to Fidelity and Secrecy, prevents public financial institutions from disclosing any details regarding their clients.

loan issuance t, issuing bank (B), address of the issuing station, and total loan amount.[6] L_{f-b^B} and the date of any modification that has taken place. Using the address of issuing station parameter I extract the bank branch location ($b \in z'$) from which the loan is issued. Also, create a unique identification number for each bank branch[7].

The self-reporting nature of this data set creates a few caveats to be accounted for. First, there is no formal audit made on this information. Thus, there is the threat of underestimating any effects using this data, as there is the potential of under reporting. Second, the address of the issuing stations or bank branch is nearly fully populated whereas there are some missing values for the bank name. I impute the names of the banks for which it was possible using either of the following techniques: (1) The bank name is included at the beginning of the address variable (2) The bank names which could be found when searching against the address on a web-based search engine and then cross-checking it against the bank's bank branch locator web page. Third, numerous errors are owing to the lack of standardized reporting practice and manual entry process of the data. As the bank branch level and its zip code location are key to my analysis, I manually checked and corrected for the address and zip codes of the bank branches using the bank's web directory on the bank branch locator. As the bank parameter does have a unique identifier in this data set, there are multiplications in both the bank name and bank address' which are cleaned.[8]

To integrate this data with the rest I create a bridge that matches Company Identification Number (CIN) here to firm indicator in the Prowess data set using forensic methods. I use the Levenshtein distance matching on firm names, followed by manual checking. Thus, the match takes place by firm. To harmonize the difference in frequency between the loans data and prowess data, I map all transactions within a given financial year to that corresponding financial year. For instance, if a firm borrows a loan in November 2014, it will be considered a part of the 2014-2015 financial year. The prowess variables for this financial year will be issued in their March 2015

[6]All loan amounts are in INR units, unlike the data in Prowess which are in Millions of USD.

[7]All addresses have the zip code and two-digit state code at the end.

[8]BANK EXAMPLE; Bank Example; BANK EXP; bank exp; Bank EXP; BANK exp; bank EXP; Bank EXP. ; banc exp; bankexp;. . . .

statement.

3.1.4 Bank Balance Sheet Data

The Reserve Bank of India (RBI) maintains the Annual Bank Statistical Returns (BSR) available on the Database on the Indian Economy (DBIE) platform. The open-source section of this database contains aggregate bank-level balance sheet variables including industry classification, credit, deposits, non-performing loans, cost of funds, cost of deposits, and Capital Adequacy Ratios (CARs). In 2015, the Indian banking system comprised 27 public sector banks, 21 private sector banks, and 49 foreign banks. Public sector banks dominated with nearly 70% of the total market share, while private sector banks held around 23%, leaving foreign banks with the remaining 7%.

I integrate the data from this RBI dataset with the MCA credit data by creating a unique bridge between the bank names in the two datasets and merging the datasets on that basis. The main variable of interest in this chapter is the Bank's Capital Adequacy Ratio (CAR). The CAR of Indian banks in 2015 varied among institutions but they all maintained the minimum CAR of 9% of risk-weighted assets in compliance with the Basel III guidelines and the RBI directive [9]. I recode the continuous values of the CAR into the following categories: (1) The baseline, 0, is set to the lowest tier of capitalized banks lower than the 25^{th} percentile or those that have a CAR less than 11.75; (2) Banks with a CAR between 11.76 and 12.60 or between the 25^{th} and 50^{th} percentile get a score of 1; (3) Banks with a CAR between 12.69 and 16.78 or between the 50^{th} and 75^{th} percentile get a score of 2; (4) Banks with a CAR above 16.79 or higher than the 75^{th} percentile get a score of 3.

[9] International Standard set by Basel III requires all Banks to maintain a 8% Capital Adequacy Ratio. However, the RBI mandated a higher regulatory threshold of 9% in 2015, intending to fortify financial stability and minimize risks.

3.2 Empirical Framework

3.2.1 Identification

The identification strategy for this section relies on the nature of the extreme climate event that occurs. In November-December 2015, heavy rainfall hit Indian states Andhra Pradesh, Tamil Nadu, and the Union Territory of Puducherry, causing a historic economic slowdown lasting over 17 days. This rainfall, the highest in over a century, was linked to the El Niño phenomenon of 2014-2016. Economic losses ranged from 3 billion to over 13 billion USD. Many businesses struggled due to limited resources amidst the extreme weather. The rainfall occurred in four episodes over two months, affecting low-lying areas more severely. This regional variation offers a natural experimental setting for studying the impact of such events. The causal identification is based on three assumptions: (1) Given the random nature of the shock, it is orthogonal to Bank fundamentals by construction (Brown 2021); (2) Owing to its transient nature the shock does not affect any structural changes for the Banks; (3) The unexpected nature rules out any anticipation effects that the firm could have hedged against prior to exposure.

In this study, I build upon the exogeneity of the shock and extend the econometric identification strategy developed by Khwaja-Mian (KM). The traditional challenge associated with studying the effect of shocks on credit channels is the difficulty in differentiating between the firm demand channel and the bank supply channel. This is because of the correlation between demand shock to the firm and supply shock to the bank. To address this challenge, KM exploits a given data structure in a fixed-effect regression model. KM identifies the bank lending channel by examining firms' borrowing from multiple bank branches that vary in their exposure to the shock.

To compare the loans taken by firms from banks that are exposed compared to from the unexposed banks, a first difference cross-sectional regression with firm fixed effects is run on this data. The coefficient obtained from this regression shows whether a firm that borrows from multiple banks will experience a difference in borrowing from the exposed bank branches post the shock. Firm fixed effects in a within-firm comparison effectively account for the specific changes in credit demand within each firm when applied to first difference data. No additional assumptions about the correlation between supply and demand are required.

Furthermore, as the shock is unexpected, banks are unable to alter their lending practices preemptively or establish buffers before the shock occurs. This could have otherwise either underestimated or overestimated the impact of the bank lending channel, contingent on the direction of the adjustments made before the shock. The unbiased coefficient can now be estimated using the regression formula.

3.2.2 Estimation Equation

$$\Delta L_{f\in z-b^B\in z'} = \alpha_{f\in z} + \beta_1 shock_{b^B\in z} + \beta_2 CAR_B + \beta_3 shock_{b^B\in z} * CAR_B + \tau L.X_B \varepsilon_{f\in z-b^B\in z'} \quad (3.1)$$

where, $f \in z$ represents a firm located in a particular zip code, $b^B \in z'$ is a branch of a credit provider located in another zip code z', and Δ is the difference between the levels of loans between April 2015 - October 2015 and November 2015 - March 2016. The dependent variable is denoted as $\Delta L_{f\in z-b^B\in z'}$. CAR_B measures the level of capitalization of the bank, with values ranging from 0 to 4. A value of 0 represents the least capitalized banks, while 4 represents the most capitalized ones. The branch shock $shock_{b^B\in z}$ is a binary variable that takes a value of 1 if the zip code in which the firm operates has been exposed and 0 otherwise. To account for firm borrowing and credit demand shocks, I use the first-difference of the data, and firm fixed effects $\alpha_{f\in z}$ are incorporated. The fixed effects approach helps to determine whether a single firm borrowing from two different banks experiences a more pronounced reduction in lending from the bank that faces a more substantial decrease in its liquidity supply. The coefficient of interest

β_3 measures the interaction between the branch's ability to extend credit to firms in the exposed zone and the level of capitalization of the bank. The Bank controls are lagged by one period. The standard errors in the study are clustered at the city level.

3.3 Results

3.3.1 Capital Adequacy Ratio

The capital adequacy ratio (CAR) measures a bank's ability to absorb losses and reflects its financial health. The CAR measure is estimated by dividing the bank's total capital (Tier 1 capital + Tier 2 capital) by its risk-weighted assets (RWAs). Regulators such as the Basel Committee and the Reserve Bank of India set CAR requirements to enable banks to cover losses, protect depositors, and maintain financial sector stability.

In Table 3.1, Column (1) shows that bank branches exposed to climate risks reduce lending to exposed firms by 9.16 million USD. Unconditionally Capital does not appear to be a significant factor in determining credit supply. However, when examining the interaction between branch exposure and bank capital, it is found that branches within more capitalized banks increase their supply of credit to firms and NBFIs by 13.85 million USD, conditional on being exposed to climate risks. Although the effect is significant for the volume of new loans supplied, Column (2) and Column (3) find no significant impact on the number of loans or the number of modifications made. Thus, capital acts as a buffer for the Banks against the shock.

When examining the results between firms in the real sector and NBFIs, there is a difference in the mechanism. In Table 3.2, more capitalized banks conditional on being exposed, relatively increase their lending to firms in the real sector by 36.33 million USD. Conversely, Table 3.3 shows that more capitalized banks conditional on being exposed, relatively decrease their lending to NBFIs by 3.95 million USD. Thus, bank branches with higher level of capital are buffered against the shock and increase lending to the real sector of the economy.

3.3.2 Tier 1 Capital

Decomposing the affect of the CAR into it's components, Tier 1 and Tier 2 capital, in this section I evaluate the effects based on Tier 1 capital levels. Tier 1 capital is considered to be a bank's core capital. It serves as the serving as the first defense against losses. Regulators also focus on Tier 1 capital to boost a bank's financial health and to maintain overall stability. Table 3.4, 3.5 and 3.6 shows the estimates hold the same as in the overall CAR indicator: they are in the same direction but the magnitude is smaller. Conditional on being exposed to the climate shock, branches with higher CAR increase overall lending by 7.76 million USD. They increase lending to real sector firms by 29.36 million USD but reduce lending to NBFIs by 5.73 million USD.

Banks with higher safeguards are increasingly lending directly to the real sector. This aligns with the Basel regulations to boost buffer capital to support credit provision during crises.

3.3.3 Tier 2 Capital

Tier 2 capital is the supplementary capital held by a bank. It is less important for regulators to target to build in buffers as it includes securities that are harder to liquidate and more volatile.The results in Table 3.8 and Table 3.7 show that Tier 2 capital doesn't have any significant effect on the supply of credit from exposed branches, especially to the firms in the real sector. Conversely, Table 3.9 (Column 1) shows that exposed branches of banks with higher Tier 2 capital increase lending to NBFIs by 9.42 million USD.

Given the supplementary nature of Tier 2 capital, it is not surprising that it does not impact the branches lending decisions to the real sector during crisis. But the increased lending to NBFIs can speak to the need of banks to take on less risk on their balance sheet. On the asset side it is less risky to lend to NBFIs than real firms. And with higher Tier 2 capital that cant be liquidated that easily this would minimize a mismatch.

3.4 Conclusion

Capital held by Banks is an important indicator of its financial strength as it determines its loss absorption capacity. Research to understand the relationship between capital held by Banks and the amount of credit it supplies became especially vital in the post the Great Financial Crisis. In this chapter, I investigate how the degree of bank capitalization, as measured by the capital adequacy ratio, impacts credit provision following exposure to the 2015 extreme flood climate shock in Southern India.

Extending the Khwaja-Mian 2008 firm-fixed-effects model on a high-frequency, spatially granular credit dataset, I find banks with higher capital levels tend to increase lending, particularly to firms in the real sector, following such shocks. Conversely, branches with lower core capital and higher supplementary capital level lend more to Non-Bank Financial Institutions (NBFIs). These results have important policy implications in signaling potential risk build-up due to the regulatory arbitrage between Banks and NBFIs.

Table 3.1: Capital Adequacy Ratio and Overall Credit Supply

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-22.86***	0.05	-0.08
	(7.21)	(0.16)	(0.09)
Capitalization	-12.22	-0.10	0.01
	(9.64)	(0.14)	(0.03)
Shock*Capitalization	13.85 ***	0.06	0.01
	(3.66)	(0.08)	(0.02)
N	876	876	876
R^2	0.32	0.22	0.36

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR covariate is a discrete variable corresponding to the quartile within which the Bank's capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from exposed branches to both real sector firms and NBFIs, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.2: Capital Adequacy Ratio and Credit Supply to Firms

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-71.42**	-0.38	-0.04
	(25.47)	(0.21)	(0.05)
Capitalization	-18.81	-0.15	0.02
	(13.99)	(0.16)	(0.03)
Shock*Capitalization	36.33**	0.25***	-0.00
	(16.29)	(0.08)	(0.02)
N	650	650	650
R^2	0.33	0.23	0.48

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR covariate is a discrete variable corresponding to the quartile within which the Bank's capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from an exposed branch to real sector firms, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.3: Capital Adequacy Ratio and Credit Supply to NBFIs

	Loan Amount (1)	Loan Count (2)	Loan Modifications (3)
Branch Shock	15.03**	0.50**	-0.16
	(4.26)	(0.13)	(0.11)
Capitalization	0.05	0.02	-0.07
	(1.43)	(0.11)	(0.05)
Shock*Capitalization	-3.95***	-0.16	0.06
	(1.06)	(0.08)	(0.05)
N	226	226	226
R^2	0.34	0.17	0.23

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR covariate is a discrete variable corresponding to the quartile within which the Bank's capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from exposed branches to NBFIs, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.4: Tier 1 Capital Adequacy Ratio and Overall Credit Supply

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-9.02	0.14	-0.06
	(5.27)	(0.09)	(0.08)
CAR T1	-4.77	-0.09	0.01
	(4.15)	(0.14)	(0.03)
Shock*CAR T1	7.76*	0.01	-0.00
	(3.88)	(0.05)	(0.01)
N	876	876	876
R^2	0.320	0.224	0.364

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR Tier 1 covariate is a discrete variable corresponding to the quartile within which the Bank's Tier 1 capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from exposed branches to both real sector firms and NBFIs, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.5: Tier 1 Capital Adequacy Ratio and Credit Supply to Firms

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-49.38**	-0.20	0.018
	(18.57)	(0.13)	(0.04)
CAR T1	-8.72	-0.16	0.056***
	(6.29)	(0.17)	(0.015)
Shock*CAR T1	29.36*	0.15**	-0.04**
	(16.30)	(0.07)	(0.02)
N	650	650	650
R^2	0.327	0.228	0.486

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR Tier 1 covariate is a discrete variable corresponding to the quartile within which the Bank's Tier 1 capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from an exposed branch to real sector firms, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.6: Tier 1 Capital Adequacy Ratio and Credit Supply to NBFIs

	Loan Amount (1)	Loan Count (2)	Loan Modifications (3)
Branch Shock	15.86**	0.48***	-0.17
	(4.66)	(0.07)	(0.10)
CAR T1	0.74	0.03	-0.13
	(1.64)	(0.10)	(0.08)
Shock*CAR T1	-5.73***	-0.17***	0.09**
	(1.15)	(0.04)	(0.02)
N	226	226	226
R^2	0.35	0.17	0.23

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The Tier 1 CAR covariate is a discrete variable corresponding to the quartile within which the Bank's Tier 1 capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from exposed branches to NBFIs, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.7: Tier 2 Capital Adequacy Ratio and Overall Credit Supply

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-26.37	-0.10	-0.12
	(17.76)	(0.18)	(0.13)
CAR T2	-13.63	-0.13***	-0.01
	(8.79)	(0.04)	(0.03)
Shock*CAR T2	15.00	0.16	0.04
	(9.95)	(0.12)	(0.06)
N	876	876	876
R^2	0.325	0.224	0.365

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR Tier 2 covariate is a discrete variable corresponding to the quartile within which the Bank's Tier 2 capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from exposed branches to both real sector firms and NBFIs, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.8: Tier 2 Capital Adequacy Ratio and Credit Supply to Firms

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-36.17	-0.25	-0.14
	(25.71)	(0.23)	(0.10)
CAR T2	-15.86	-0.14**	-0.03
	(11.41)	(0.05)	(0.03)
Shock*CAR T2	15.30	0.19	0.06
	(11.22)	(0.12)	(0.04)
N	650	650	650
R^2	0.327	0.228	0.485

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The CAR Tier 2 covariate is a discrete variable corresponding to the quartile within which the Bank's Tier 2 capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from an exposed branch to real sector firms, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 3.9: Tier 2 Capital Adequacy Ratio and Credit Supply to NBFIs

	Loan Amount	Loan Count	Loan Modifications
	(1)	(2)	(3)
Branch Shock	-6.02	0.20	0.06
	(4.17)	(0.16)	(0.16)
CAR T2	-7.93***	-0.08	0.07
	(1.59)	(0.06)	(0.06)
Shock*CAR T2	9.42**	0.06	-0.06
	(2.69)	(0.08)	(0.08)
N	226	226	226
R^2	0.347	0.164	0.227

This table presents the results of the regression Equation 3.1. The independent variable is a binary indicator that takes a value of 1 for those credit institutions located in the flood zone and 0 if not in the flood zone. The location is measured at the zip code level. The Tier 2 CAR covariate is a discrete variable corresponding to the quartile within which the Bank's Tier 2 capital adequacy ratio falls within the sample. Higher the value of the covariate is associated with more capitalization. The dependent variable is the change in the number of new loans issued by a credit institution branch to a given firm exposed to the shock. The change is computed using the difference in the aggregate number of new loans issued to a firm between November 2015 and March 2016 (post-shock) and the aggregate number of new loans issued to a firm between March 2015 and October 2015 (pre-shock). The climate shock took place in November and December of 2015. The coefficient of interest measures the differential supply of credit from exposed branches to NBFIs, conditional on how capitalized the aggregate bank is. The sample period includes data from the reports issued from March 2015 to March 2016. Firm Fixed Effects are included to absorb the demand side effects. Lagged Bank Controls have been included. Standard errors, in parentheses, have been clustered at the city level. ***, ** and * denote significance at 1%, 5% and 10% respectively.

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