# Natural Disasters, Interest Rates Dynamics, and Economic Activities

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September 8, 2022 – Version 0.5
*Preliminary and Incomplete*

**Abstract**

We present novel evidence regarding the impact of natural disasters on the dynamics of interest rates and their influence on real economic activities. Using the universe of bank loans in India, we find that local branches exposed to natural disasters increase loan interest rates for all kinds of borrowers. We also observe a decline in credits. Importantly, these effects persist for at least three years. These results are critical because the local branches are the ones with the soft information. We link rising interest rates to increased default risks of the borrowers and find multiple patterns that corroborate this assertion. Firms respond to natural disasters by increasing their interest expenses and decreasing bank debts. These effects also endure for a number of years. Additionally, cross-sectional spike in interest rates results in a decline in nightlight based real economic activity as well as firm level R&D expenditures. It suggests a novel financial intermediation channel through which natural disaster shocks transmit to the real economy.

**Keywords:** natural disasters, climate change, bank branches, interest rates, loan pricing, bank debt, R&D, real activities, India
**JEL Codes:** G21, Q54, O16, G12, G31

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# 1 Introduction

Sharing and transferring risk is perhaps the most important task of the financial market. This article examines the extent to which financial intermediaries in India share and transfer risks to borrowers in response to natural disasters. This question is of utmost importance because climate change will have a profound impact on future economic activities. It is likely that climate change will increase the frequency of natural disasters (Hsiang and Kopp, 2018). There is a strong likelihood that natural disasters increase the risk of default among borrowers. The underlying objective is to understand whether such an increase in default risk is factored into the pricing of bank loans. If risks are reflected in lending rates, it may increase the financial constraints of the borrowers. Economic activities could decline if borrowers are unable to replace bank funding. However, banks are distinct in that they place a significant emphasis on relationship lending (Beck, Degryse, De Haas and Van Horen, 2018). Investors in the public financial market are rarely privy to the amount of hard and soft information banks possess (Liberti and Petersen, 2019). Thus, the direction of the effect is not *ex ante* clear. Banks may assist firms in mitigating the disaster's impact. On the other hand, banks might have a better understanding of the potential increase in default risk.

This article demonstrates that bank branches raise interest rates in the aftermath of a disaster shock, and that the increased rates persist for at least three years. Our evidence extends well beyond firm financing, as we observe the universe of bank loans. The extant literature focuses primarily on the firm side (see Giglio, Kelly and Stroebel (2021a) for a review). Instead, our data enable us to investigate loan pricing across industries. We interpret this as a supply side response to natural disasters. This is especially crucial in low-income contexts where access to the public debt market is minimal. In the context of India, the private debt market, and banks in particular, are the most significant and in many instances possibly the only source of financing.[1] Banks in India have also historically served developmental and social objectives (Burgess and Pande, 2005; Burgess, Pande and Wong, 2005). Developing countries frequently exhibit a distinct variety of financial frictions (Ranasinghe and Restuccia, 2018; Abuka, Alinda, Minoiu, Peydró and Presbitero, 2019; Itskhoki and Moll, 2019). Furthermore, developing countries are especially susceptible to these extreme weather events (Mani, Bandyopadhyay, Chonabayashi and Markandya, 2018). Consequently, our context also renders the analysis meaningful.

Our analysis builds on prior work documenting that climate risks are priced in the financial market (Engle, Giglio, Kelly, Lee and Stroebel, 2020; Bolton and Kacperczyk, 2021; Giglio, Kelly and Stroebel, 2021a; Ilhan, Sautner and Vilkov, 2021; Sautner, van Lent, Vilkov and Zhang, 2022a; Sautner, Van Lent, Vilkov and Zhang, 2022b). Several studies report the impact of climate risk on a number of asset classes, primarily equities, but also a number of fixed income instruments, with an emphasis on estimating the long-run discount rates. To the best of our knowledge, there is no evidence on the dynamics of branch-level credit rates. This may be primarily due to the lack of branch-level granular credit data, which impedes a thorough bank-side analysis of natural disasters. Importantly, the soft information is something that the local branches hold. In developing countries, this type of data is rarely accessible. We leverage on a universe of bank loans with branch-level granularity. The branch-level data allow us to understand the bank side behavior in detail when branches are exposed to disaster shocks. Additionally, the branch-level analysis permits us to account for unobserved bank-specific factors.

Another aspect that has not been studied in the literature is how disaster shock affects real activities through the financial intermediation channel. While recent literature investigates the real effects of bank shocks, particularly credits and deposits (Chodorow-Reich, 2014; Paravisini, Rappoport, Schnabl and Wolfenzon, 2015; Greenstone, Mas and Nguyen,

[1] The most pertinent alternative is the informal moneylenders who charge extremely high rates of interest.

2020; Mian, Sufi and Verner, 2020; Majilla and Das, 2021), we examine the real effects of branch-level disaster exposure. If disaster shocks increase riskiness and this risk is priced into lending rates, borrowers, firms in particular, may be compelled to abandon potential projects with positive NPV. This is especially crucial in low-income contexts where access to the public debt market is limited. Such a demand-side effect may lead to a decline in economic activity. It is important to note that the aforementioned channel is a *second-order* effect of disaster shocks transmitted through financial intermediaries.

We use a proprietary data on the universe of bank loans in India. We match branch level data with natural disasters at the $1^0 \times 1^0$ latitude-longitude level. To control for unobserved factors at the branch level, we control for branch fixed effects. In addition, we control for year-fixed effects to account for the state of the economy as a whole. Thus, our identification permits us to observe branch-specific loan pricing that accounts for unobserved branch-specific factors. We observe a 20 basis point increase in average branch-level interest rates following a natural disaster. This result is significantly stronger than previous research indicating that the financial market does account for climate risks.

Next, we investigate the interest rate dynamics. Using the local projection method, we estimate impulse response functions (Jordà, 2005). The ability to obtain impacts at different horizons using the same estimation framework is a key advantage of this method. Intriguingly, the increase in loan rates persists for a minimum of three years. We observe a rise in interest rates across all industries. Agriculture, business, and personal loan portfolios exhibit an identical pattern. It is significant because it demonstrates the potential for disaster shocks to have longer-term economy-wide effects. Therefore, financial constraints at the demand side may become more severe.

We observe that disaster shocks reduce the amount of credits. In particular, the total loan outstanding decreases and then increases in the two years following a natural disaster. In particular, the loan decreases by approximately 5 percent in the two years following the natural disaster, then begins to rise in the third year and returns to its initial level in the fourth year. Agriculture, business, and personal loan portfolios all exhibit a comparable pattern.

To understand the mechanisms, we refer to the classic asset pricing theory, which illustrates the effect of default risk on asset pricing.[2] While we cannot test the internal assessment of default risk by bank branches or identify borrower characteristics, three specific results allow us to link an increase in interest rates with an increase in default risk. First, we do not observe an increase in interest rates for loans originated from affected branches but destined for use in distinct regions. Second, we examine the effect of negative rainfall shocks. In accordance with a common definition, we define a negative rainfall shock as precipitation in a given year that falls below the 20th percentile of the historical precipitation for that spatial resolution. Reassuringly, we observe a rise in interest rates as a result of a negative rainfall shock. In particular, a negative rainfall shock increases interest rates by 50 basis points. A similar effect in response to rainfall shocks as in natural disasters may rule out the potential role of transition risk related to climate disasters, i.e. the risk to cash flow resulting from the transition to a low-carbon economy. Lastly, interest rates steadily rise in tandem with the severity of natural disasters. We tend to interpret pricing of increased default risk as the principal mechanism.

While in theory branches could simply raise prices and continue to offer credits, a decline in credits may indicate a loss of local (soft) information or a decrease in demand for credits. Our data do not permit us to dissect the particulars.

After analyzing the effect of natural disasters on the dynamics of interest rates, we examine how firms react to natural disasters. The overarching objective is to identify the effects

[2] See Bakshi, Gao and Zhong (2022) for a review.

of an increase in interest rates on real economic activities. While the branch-level analysis indicates that natural disasters increase interest rates across all sectors, we focus on the firm sector because we lack sufficient information to comprehend the behavior of other agents.

We spatially connect firms from the CMIE Prowess database.[3] We utilize a comparable dynamic framework. According to our local projections estimates, firms reduce their longer-term bank debts, a trend that persists for three years. While short-term debt increases in the aftermath of the disaster, it starts to decline in the second year and returned to its initial level in the third. Importantly, two years after the natural disaster, the interest rate expense increases by approximately 9 percent, then begins to decline in the third year and returns to its initial level in the fourth year. Reassuringly, we observe similar pattern when we examine total interest expense/total capital ratio instead of total interest expense.

The firm-side analysis indicates the existence of a potential financial intermediation channel. While we are unable to determine whether or not firms source bank credits locally, voluminous literature documents a local bias in bank credit sourcing (Petersen and Rajan, 2002; Granja, Leuz and Rajan, 2022). In fact, branches have an incentive to offer local credit due to the availability of soft information.

Next, we investigate the effect of increased lending rates on the real economy. Our analysis distinguishes the initial effects of natural disasters. Specifically, we use the heterogeneous response of bank branches and their respective market powers to identify spaces with a heterogeneous effect. This results in a cross-sectional variation in the response of interest rates to disaster shocks. This design closely resembles shift-share design. We find that branch-level interest rate increases, weighted by market size, are negatively associ-

[3]The database is one of the primary sources of accounting data for Indian companies (both listed and unlisted) and has been utilized in a number of prior studies (Vig, 2013; Siegel and Choudhury, 2012; Gopalan, Mukherjee and Singh, 2016).

ated with firm-level R&D expenditures and spatial nightlight luminosity.

Overall, we demonstrate that financial intermediaries do account for natural disaster shocks when pricing loans. The increase in interest rates depends on the severity of the natural disaster. In addition, the interest rate spike transmits to the demand side, causing firms to incur high interest expense and issue fewer bank debts. We also identify a link between an increase in interest rates and a decline in firm-level R&D expenditures and nightlight-based real economic activities.

*Related Literature* - We contribute to the two strand of literature. The first and foremost, we add to the limited but expanding literature on the effect of climate risk on financial outcomes (see Giglio, Kelly and Stroebel (2021a) for a review). This literature has focused primarily on long-term assets, such as stocks, municipal bonds, and real estate. Recently, investors have begun to price projected long-term sea level rise in municipal bonds (Ramelli, Wagner, Zeckhauser and Ziegler, 2018; Goldsmith-Pinkham, Gustafson, Lewis and Schwert, 2019; Addoum, Ng and Ortiz-Bobea, 2020; Engle, Giglio, Kelly, Lee and Stroebel, 2020; Albert, Bustos and Ponticelli, 2021; Bolton and Kacperczyk, 2021; Giglio, Maggiori, Rao, Stroebel and Weber, 2021b; Ivanov, Kruttli and Watugala, 2021; Bolton and Kacperczyk, 2022; Correa, He, Herpfer and Lel, 2022; Sautner, van Lent, Vilkov and Zhang, 2022a; Sautner, Van Lent, Vilkov and Zhang, 2022b). The primary focus of Engle, Giglio, Kelly, Lee and Stroebel (2020) is the development of climate risk hedging techniques for portfolios. Ramelli, Wagner, Zeckhauser and Ziegler (2018) find that investors reward businesses that make efforts to mitigate climate change. Addoum, Ng and Ortiz-Bobea (2020) conclude that extreme temperatures currently have no effect on businesses.

We focus primarily on the bank side, i.e. the response of local bank branches. In addition, we investigate the firm-side response and its potential effects on real economic activities. In particular, we investigate how the heterogeneous responses of intermediaries to disaster shocks translate into firm and real economic activity. Correa, He, Herpfer and Lel (2022) analyze the firm side effect of the disaster shock on unaffected U.S. firms, comes closest to our paper. They, like us, find that climate disasters widen the loan spread among unaffected firms. In addition, they observe a decline in investment and an increase in cash reserve buffers. Ivanov, Kruttli and Watugala (2021) estimate the impact of the California cap-and-trade bill, which is essentially a carbon pricing policy, on bank credits to polluting companies. They, like us, find that banks charge higher interest rates.

According to our knowledge, our paper is the first study to document the response of branch-level credit rates to disaster shocks and its dynamics.

In addition, our work contributes to the active literature on the real effect of bank shocks that has emerged in recent years (Chodorow-Reich, 2014; Paravisini, Rappoport, Schnabl and Wolfenzon, 2015; Di Maggio and Kermani, 2017; Greenstone, Mas and Nguyen, 2020; Mian, Sufi and Verner, 2020; Majilla and Das, 2021). Existing research has established the transmission of bank credit shocks to the real economy. We introduce a novel disaster exposure channel that influences credit supply and prices. Real economic activities decline when economic agents experience interest rates hike. Though, credit rates, not credit amounts, are our primary mechanism.

This paper unfolds as follows. Section 2 explains the context and identification strategy. Section 3 explains data construction and summary statistics. Section 4 and 5 explain our main results and potential mechanisms, respectively. Section 6 and 7 examine the impact of natural disaster induced increase in loan rate on firms, and real activities, respectively. Section 8 concludes.

# 2 Context and Empirical Specification

## 2.1 Context: Bank-Credit Driven Financing in India

For any economy, timely and adequate availability of credit is sine qua non to achieve economic development and India is no different. However, what differentiates India from other developed economies is the dependence of various sectors of the economy on bank credit as a primary source of finance, despite the market-based sources of finance gaining importance in the last decade.[4] Both in terms of reach and access banks, remain the focal point of the source of finance in the Indian financial system.

As per RBI (Indian central bank) data, the share of commercial banks' credit in the total outstanding credit by all institutions increase significantly from 58.7 % in 1991 to 78.2 % in 2006 (RBI, 2007). All the major sectors (agriculture, industry, and services) of the Indian economy rely heavily on bank credit to meet their financing needs. The reliance of the informal sector and small-scale industries (SME), which constitute an important segment of the economy, on bank credit to meet both short and long-term capital needs makes it an important driver of economic activity. Soft information at the banks' branch level plays a particularly important role in credit appraisal of small and medium businesses because these firms are traditionally very opaque. The frequent interaction of branches' loan officers and borrower enables banks to collect this private information over time, allowing branches to get a complete picture of borrowers' credit health than what is available through public information (Liberti and Petersen, 2019). The difficulty in transferring this soft information out of a branch makes them even more important in credit allocation decisions.Taken together any exogenous shock to the pricing of loans by banks can have an important bearing on almost all sectors of the economy.

[4] Apart form commercial banks a wide range of financial institutions exist in India that provide credit to different sectors of the economy. These include non-banking financial companies (NBFCs), different types of cooperatives banks, primary agriculture credit societies, etc.

## 2.2 Empirical Strategy

To empirically examine the impact of natural disasters on loan rates, we estimate how loan rates at the branch level respond to the previous years' local ($1^0 \times 1^0$ latitude-longitude level) natural disaster shocks. As loan rate data are reported by banks at the end of the financial year, i.e March of every year, our baseline analysis estimates the effect of natural disasters reported in a calendar year on the loan rate reported in the March of next year. We estimate the regression model mentioned below:

$$Y_{i,b,lt,lo,t} = \beta\, S_{lt,lo,t-1} + \gamma_i + \delta_t + \epsilon_{i,b,lt,lo,t} \tag{1}$$

where, $Y_{i,b,lt,lo,t}$ represents a vector of dependent variables for branch $i$ of bank $b$ at latitude $lt$ and longitude $lo$ reported in year t. In our baseline analysis, we consider two main dependent variables - natural logarithm of equally-weighted ($Log(Equally\ Weighted\ Loan\ Rate)$), and loan outstanding weighted ($Log(Loan\ Outstanding\ Weighted\ Loan\ Rate)$) loan rates. The term $S_{lt,lo,t-1}$ represents $Natural\ Disaster\ Dummy$ which is a binary variables that becomes one when latitude ($lt$), and longitude ($lo$) experiences a natural disaster in year $t-1$ and zero otherwise. $\gamma_i$ and $\delta_t$ are branch and year level fixed effects. The use of branch fixed effects in the model absorbs fixed observed and unobserved branch level characteristics. Similarly, year fixed effects controls for any economic wide shock. In alternate specifications, we also use bank and bank-year level fixed effects to control for bank and bank-year specific factors. Standard errors are clustered at the latitude-longitude level.

$\beta$ is our variable of interest. Our identification relies on the assumption that natural disaster shocks are exogenous. If loan rates at the branch level are sticky and are nonresponsive to the increased risk profile of borrowers in the event of natural disaster, then we expect $\beta = 0$. Whereas, if branches increase loan rate in response to natural disasters to compensate for risk, then $\beta > 0$.

## 2.3 Local Projection Model

The static analysis gives us an idea about the transitory effect of natural disasters on loan rates. To better understand the long-term impact of natural disasters, we use the local projection (henceforth LP) framework (Jordà, 2005) to estimate the change in loan rate and total loan outstanding following a natural disaster shock. The LP framework accommodates a panel structure, it is less sensitive to misspecification when compared to VAR models because it does not constrain the shape of impulse response functions (Montiel Olea and Plagborg-Møller, 2021).[5] Throughout, we present the four-year dynamic response of loan rate and total loan outstanding following natural disaster shock. We estimate the following LP model for different time horizon (h = 0,1,..,4):

$$Y_{i,b,lt,lo,t+h} - Y_{i,b,lt,lo,t} = \zeta_i + \beta_h S_{lt,lo,t} + \gamma X_{i,b,lt,lo,t} + \epsilon_{i,b,lt,lo,t+h} \tag{2}$$

where, $Y_{i,b,lt,lo,t+h}$ denote a vector of dependent variables for branch $i$ of bank $b$ at latitude $lt$ and longitude $lo$ reported in year $t+h$. Similar to the static analysis, we use two dependent variables - natural logarithm of equally-weighted ($Log(Equally\ Weighted\ Loan\ Rate)$) loan rate, and total loan outstanding ($Log(Total\ Loan\ Outstanding)$). $h$ denotes the horizon considered which is four in the current case. $X_{i,b,lt,lo,t}$ denotes a vector that contains three lags of yearly changes in the dependent variable. $\zeta_i$ is branch-level fixed effects. The impulse responses are constructed based on the estimated $\beta_h$ coefficients at each horizon. The 90 percent confidence bands are based on the respective estimated standard errors clustered at the latitude-longitude level.

We estimate the above model for our full sample (Bank-Branch Panel), and also for sectoral loan subsamples - agriculture, business, and personal. The latter would inform us about

[5] Various previous studies have used LP to examine the dynamics of macroeconomic variables (Auerbach and Gorodnichenko, 2012; Jordà and Taylor, 2016; Born et al., 2020; David et al., 2022)

the heterogeneity in the response of bank branches in the event of natural disasters across major sectors.

# 3 Data

We use five different datasets in the study: the population of all the loans disbursed by banks' branches (Bank-Branch Data), natural disaster data, gridded rainfall, firm-level data, and nightlights data. The details of cleaning, geocoding and merging the datasets are explained in Appendix B.

### 3.0.1 Bank-Branch Data

Our primary data source is a proprietary administrative data from the Reserve Bank of India (RBI) on the universe of bank loans. A few previous studies have used this dataset (Cole, 2009; Das et al., 2019; Kumar, 2020; Majilla and Das, 2021). One major advantage of branch-level analysis is the ability to identify loans across industries. We are able to geocode branch locations, which is a vital aspect of our data. The data has two main parts - Basic Statistical Return (BSR) 1, and Basic Statistical Return (BSR) 2.[6] The study uses BSR 1 dataset, which contains granular loan-level data for all banks' branches at a yearly frequency. All the credit accounts with credit limit of over 0.2 million INR are reported in the data set, making it a near universe of loans. In addition to the loan rate, the dataset also reports the account level data of loan amount outstanding, location of usage of the loan, and the borrowers' sector (agriculture, business, personal, etc), among other things. It does not provide loan-level or borrower-level identifiers so one can't trace a particular loan over its lifetime. We aggregate the loan-level granular data at the branch-year level

[6]The BSR 2 contains information on the deposits at the branch level with break-up available for current, savings, and term deposits. Additionally, it also reports the number of accounts owned by females, and other branch characteristics like staff strength, gender composition, etc.

and branch-sector-year level. Specifically, we estimate all the variables (loan rate, and total loan outstanding) both at branch-year and branch-sector-year levels. Our final datasets are unbalanced panels at the branch and branch-sector level at a yearly frequency, which spans from 2000 to 2012.[7] The branch-level panel has 111,106 branches with more than 113 million loans outstanding, when aggregated at branch year level gives us 0.9 million observations. Based on the borrowers' sector, we categorize loans into agriculture, business, personal, and other sectors. The aggregated data at branch-sector-level is an unbalanced panel comprising more than 2.2 million observations.[8]

Panel A of Table 1 reports the summary statistics of bank-branch data. The average equally weighted loan rate (loan outstanding weighted loan rate) charged by banks' branches is 1245.96 (1257.12) bps. As can be seen, the average loan rate, both equally and loan outstanding weighted, charged on business (personal) loans is the greatest (lowest) amongst all the four sectors. On average the loan rate charged on business sector loans is 1317.51 bps, the same value for agriculture and personal loans are 1220.26 and 1171.93 bps. The average total loan outstanding at the branch-year level is 122,146,287 INR, as expected the distribution is highly positively skewed. At the branch-sector level, the average total loan outstanding is highest (lowest) in the business (agriculture) sector among all the four sectors. On average the total loan outstanding in the business sector is 72,451,462 INR, the same value for agriculture and personal loans are 22,031,538 and 32,128,717 INR.

#### 3.0.2 Natural Disaster

The natural disaster data is obtained from open access repository of natural disasters from the Center for Research on the Epidemiology of Disasters' (CRED) Emergency Events

[7]The panel is unbalanced because some branches went out of business and some new branches were opened in the considered period.

[8]Not all bank branches in our dataset lend to all four sectors. To remove the effect of small branches that lend to only one sector we removed them from our dataset.

Database (EM-DAT) (Rosvold and Buhaug, 2021b,a). The data is a geocoded disasters (GDIS) dataset which comprises 39,953 locations for 9,924 disasters that took place across the world between 1960 to 2018. The dataset includes all floods, storms (including typhoons and monsoons), earthquakes, landslides, droughts, volcanic activity, and extreme temperatures that were reported in EM-DAT over these 58 years. The data also has a column that categorizes disasters into three different levels (Level 1, 2, and 3) based on the severity of the disaster.

In the paper, we use a subset of the GDIS dataset that reports the natural disaster events that occurred in India in the time span of 2000 to 2012. This gave us a total of 2,253 disaster events occurring at the different latitude-longitude levels. As reported in Panel A of Table 1 around 24.68% observations in our bank-branch sample experienced a natural disaster in the time span considered in the study.

#### 3.0.3 Rainfall Shock

The rainfall data used in the study is collected by the University of Delaware[9], it is monthly gridded rainfall data. We consider rainfall distribution data for a given latitude and longitude pair spanning from 1980 to 2012. Our rainfall shock variable is defined at the latitude-longitude level. Following the approach in the literature, we categorize a latitude-longitude-year as a rainfall shock if in that year the total rainfall at that latitude-longitude level is below the 20th percentile of the previous 20 years' rainfall distribution at the same latitude-longitude level (Kaur, 2019; Jayachandran, 2006; Majilla and Das, 2021). In some sense, our rainfall shock year can be simply a drought year. As reported in Panel A of Table 1 around 15.46% observations in our branch-year level data experience rainfall shock.

[9]The data can be downloaded from http://climate.geog.udel.edu/~climate/html_pages/download.html

#### 3.0.4 Firm Panel

We prepare our firm-level panel by obtaining data from the Centre for Monitoring Indian Economy (CMIE) database - CMIE $Prowess_{dx}$.[10] The database is one of the primary source of accounting data of Indian firms (both listed and unlisted), and used by various previous studies (Vig, 2013; Siegel and Choudhury, 2012; Gopalan et al., 2016). The database reports, both at yearly and quarterly frequency, balance sheet and income statement items along with other useful information about the firms such as pin code of firms' registered office, firms' industry category, year of incorporation, etc. The balance sheet data has a detailed breakup of firms' borrowing, which helps us to identify the total borrowing from banks and the nature of borrowing (short or long-term). The database also reports the details of firms' expenses including total R&D expenses.

As mentioned, CMIE $Prowess_{dx}$ provides data of both listed and non-listed Indian firms. It covers a total of 52,157 Indian firms. In our analysis, we restrict our sample to only non-financial firms. Our firm-level panel is an unbalanced panel dataset at firm-year frequency. For our purpose, we extract the pin code of the firms' registered office[11], total interest expense (in INR million), short-term bank debt (in INR million), long-term bank debt (in INR million), and total R&D expense (in INR million). Due to missing values in some of the variables, the sample size differs in different analyses done using firm-level data. We winsorize all the branch-year, and branch-sector-year level data at the 1% and 99% to minimize the effects of outliers. Panel B of Table 1 reports the summary statistics of our firm-year panel. The average total interest paid for firms in our sample is 78.34 million INR, and the same value for short and long-term bank debt is 278.08 and 401.06 million INR. The average R&D expenditure done by firms in our sample is 37.06 million INR.

[10] https://prowessdx.cmie.com/

[11] We use firms' registered office pin code to identify its latitude-longitude.

#### 3.0.5 Nightlights Data

The nightlights data is obtained from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG). It collects data from the National Oceanic and Atmospheric Administration (NOAA). The data is available at an annual frequency from 1994 to 2013 at the latitude-longitude level and reports max-light intensity, total-light intensity, and calibrated-light intensity (Asher and Novosad, 2020). We use total-light intensity observed at the latitude-longitude level between 2000 to 2012 in our study.

### 3.1 Univariate Results

Figure 1 shows how the total credit weighted loan rate responds to the natural disaster. Panel A and B report the equally weighted and loan outstanding weighted loan rate (in bps), respectively. When a latitude-longitude pair is hit by natural disasters (level 3) in a year, the banks' branches in that region increase loan rates. The equally weighted (loan outstanding weighted loan) loan rate increases on an average by 21.26 (3.19) bps in years when a latitude-longitude pair is hit by natural disasters (level 3) vis-à-vis normal years. This indicates that loan rates are responsive to natural disasters unconditionally.

In Figure 2, we report how the total credit weighted loan rate responds to rainfall shock. As before, Panel A and B report the equally weighted and loan outstanding weighted loan rate (in bps), respectively. When a latitude-longitude pair experiences a rainfall shock in a year the banks' branches in that region charge higher loan rates. The equally weighted (loan outstanding weighted loan) loan rate increases on an average by 21.38 (44.47) bps in years when a latitude-longitude pair experiences rainfall shock vis-à-vis normal years. This indicates that loan rates are responsive to rainfall shock unconditionally. Taken together, the above univariate results suggests that banks' branches increase loan rate in response to natural disasters and rainfall shock.

# 4 Results

## 4.1 Main Results

### 4.1.1 Natural Disaster and Loan Rate

Table 2 reports the estimated coefficients of Eq. (1), when independent variable is natural disaster dummy. In columns (1) to (3), we find that natural disasters positively impact equally weighed loan rates at the branch level. The effect is economically significant. In our baseline specification with branch and year fixed effects, we find on average a banks' branches at a latitude-longitude level that experiences a natural disaster increase the loan rate by 0.2 percentage points.

Columns (4) to (6) report the results when the dependent variable is loan outstanding weighed loan rates at the branch level. We find a similar pattern as seen in the case of the equally weighted loan rate. A natural disaster at a latitude-longitude level leads to an increase of 0.1 percentage points in the loan rates charged by local banks' branches. The estimated effect is slightly lower as compared to the estimated effect on the equally weighted loan rate, but remains economically significant.

Taken together, the above evidence suggests that banks' branch-level loan rates are responsive (in the upward direction) to the natural disaster shocks. Also, the empirical pattern is consistent across specifications. As we discuss later, the results can be interpreted in light of branches compensating for the change in the risk profile of the borrowers in the event of a natural disaster.

## 4.2 Local Projection Results

### 4.2.1 Full Sample

Next, we examine the dynamics of loan rate and total credit in the periods after a natural disaster. We begin by reporting the impulse response of loan rate (equally weighted loan rate) obtained from local projection estimates in Eq. (2).[12] Panel A of figure 3 displays the cumulative change in the natural logarithm of equally weighted loan rate, measured in bps.[13] We find that in periods following a natural disaster at a latitude-longitude level, banks' branches increase their loan rates for the first two years and reduce afterwards. The increase in loan rate is both economically and statistically significant. Specifically, the loan rate increases on an average by 62 bps ($1245.96 \times 0.05$) in two years period after the natural disaster, and starts to decline from the third year onwards to return to starting level in the fourth year.

Next, we report the impulse response of total loan outstanding obtained from Eq. (5). Panel B of figure 3 displays the cumulative change in the natural logarithm of total loan outstanding, measured in INR thousand. We find that in periods following a natural disaster, total loan outstanding decreases for the first two years and increase afterwards. The decrease in total loan outstanding is both economically and statistically significant in the first two years. Specifically, the loan outstanding decreases on average by 6,107 thousand INR ($122{,}146{,}287 \times 0.05$) in two years period after the natural disaster, and starts to increase from the third year onwards to return to starting level in the fourth year.

[12]We also checked the dynamics of loan rate using loan outstanding weighted loan rate. We find qualitatively similar results

[13]The 90 percent confidence bands are based on the respective estimated standard errors.

### 4.2.2 Sectoral Analysis

The previous section reports the dynamics of loan rate and total credit in the periods after a natural disaster for our full bank-branch level sample. In this section, we examine the dynamics of the same variables for different sectoral subsamples - agriculture, business, and personal. For that, we estimate Eq. (2) separately for subsamples of loans given to a particular sector at branch-level.[14]

We start with reporting the impulse response function of loan rate (equally weighted loan rate) and total loan outstanding for the agriculture sector estimated from Eq. (2). Panel A and B of figure 4 display the cumulative change in the natural logarithm of equally-weighted loan rate, and total loan outstanding, respectively. We find that in periods following a natural disaster at a latitude-longitude level, loan rates (total loan standing) increase (decrease) for the first two years and decrease (increase) thereafter. The change in loan rate and total loan outstanding is both economically and statistically significant. Specifically, the loan rate (total loan outstanding) increases (decreases) by close to 5% (7%) in two years period after the natural disaster, and starts declining (increase) from the third year onwards to return to starting level in the fourth year.

Next, we report the impulse response function of loan rate (equally weighted loan rate) and total loan outstanding for the business sector estimated from Eq. (2). Panel A and B of figure 5 display the cumulative change in the natural logarithm of the equally weighted loan rate, and total loan outstanding, respectively. We find that in periods following a natural disaster at a latitude-longitude level, loan rates (total loan standing) increase (decrease) for the first two years and decrease (increase) afterward. The increase in loan rate is both economically and statistically significant, whereas the decrease in loan outstanding is statistically significant only only in the first year and economically small. The loan rate

[14] Not all branches in our sample provide loan to all the three sectors considered in the study.

increases by close to 4.5% in two years period after the natural disaster, and starts to decrease from the third year onwards to return to starting level in the fourth year. The loan outstanding in the same period first decreases by a small amount (2%) and then increases after returning to the starting level.

Lastly, we report the impulse response function of loan rate (equally weighted loan rate) and total loan outstanding for personal loans estimated from Eq. (2). Panel A and B of figure 6 display the cumulative change in the natural logarithm of equally weighted loan rate, and total loan outstanding, respectively. Same as earlier, We find that in periods following a natural disaster at a latitude-longitude level, the loan rates increase for the first two years and decrease thereafter. The increase in loan rate is both economically and statistically significant. Specifically, the loan rate increases by close to 5% in two years period after the natural disaster, and starts to fall from the third year onwards to return to starting level in the fourth year. The loan outstanding shows a decreasing trend, although not monotonic, following the natural disaster. The cumulative change in loan outstanding is statistically insignificant, except in period two.

Our results show that the dynamics of loan rates are qualitatively similar across sectors. However, loan outstanding dynamics show heterogeneity across sectors. The loan outstanding decreases sharply in the agriculture sector, whilst business and personal loans show only a moderate decline.

# 5 Potential Mechanisms

The most immediate possible mechanism is the pricing of increased default risk. When economic agents are exposed to a disaster shock, their default risk increases, and such risks are reflected in the loan pricing (See Bakshi, Gao and Zhong (2022) for a review). However, at least two alternative mechanisms exist. One of the competing explanations is the uncertainty resulting from transition risk – the risk to cash flow associated with the future path of economic activity and the future evolution of the climate. A further alternative explanation is that disaster exposures may have increased the risk aversion of branches. In other words, branches increase credit rates even if the default risk has not changed.

One caveat is that we do not observe the branch's internal assessment of the default risks of the borrowers. Additionally, we do not observe borrower characteristics. However, there are few findings that indicate default risk may be the primary underlying mechanism.

First, we examine if the pricing of loans originated from branches that are affected by natural disaster but destined for use at a location that is not affected by natural disaster differs from those to be used at locations affected by natural disaster. This analysis is important to understand the mechanism through which natural disaster influences loan pricing. If an increase in the default risk of borrowers is the primary mechanism by which natural disasters influence loan pricing, then we would not expect to observe an increase in interest rates for loans originated from affected branches but destined for use in distinct regions not affected by natural disaster.

To test this, we first estimate the average loan rate, both equally and loan amount weighted, for each of the different districts separately where loans offered by a branch are used.[15] Next, we create three dummy variables; $Diff.\ Dist.$, $ND$, and $Org.\ Dist.$. The first variable takes the value one for districts where the loans are used is not the one where the branch is located and zero otherwise. The second variable becomes one if the district in which the loans are used has not experienced natural disaster in a year (rainfall shock) and zero otherwise. Whereas, the third variable becomes one for all the districts where

[15] We estimate loan rates at district level and not at latitude-longitude level because our data allows us to identify usage of loans at district level only.

loans are used if the district in which loan offering branch is located has experienced a natural disaster (rainfall shock).[16] We estimate the regression model mentioned below:

$$Y_{i,b,d,t} = \beta \; Diff. \; District \times ND \times Org. \; District + \gamma_i + \delta_t + \epsilon_{i,b,d,t} \tag{3}$$

where, $Y_{i,b,d,t}$ represents a vector of dependent variables for branch $i$ of bank $b$ at district $d$ reported in year t. The variable of interest is $\beta$. $\gamma_i$ and $\delta_t$ are branch and year fixed effects. Standard errors are clustered at district level. If banks' branches increase loan rate to compensate for increase in default risk of the borrowers due to natural disaster, then we would not expect to observe an increase in loan rates if loans are destined for use in distinct regions not affected by natural disaster.

Table 3 reports the estimated coefficients of Eq. (3). In all the columns, we find that the coefficient of triple interaction is negative and statistically significant. On an average an affected banks' branch charges 0.3 (0.7) percentage point less on loans if it is used at a location not affected by natural disaster (rainfall shock). We observe that loans originated in affected branches but destined for use in unaffected regions do not experience an increase in interest rates.

Second, we examine the impact of negative rainfall shocks. For that, we re-estimate Eq (1) with $Rainfall \; Shock \; Dummy$ which a binary variables that becomes one when latitude ($lt$), and longitude ($lo$) experiences a (negative) rainfall shock in year $t-1$ and zero otherwise. Table 4 reports the estimated coefficients of Eq. (1), when independent variable is rainfall shock dummy. In columns (1) to (3), we find that rainfall shock positively impacts equally

[16]For example, if a branch $i$ located in district $D_1$ has offered loans that are used in three different districts $D_1$, $D_2$, and $D_3$. Then, we estimate average loan rate for all the loans originated by branch $i$ to be used in $D_1$, $D_2$, and $D_3$ separately. If districts $D_1$ and $D_2$ have experienced a natural disaster (rainfall shock), and district $D_3$ has not. Then $Diff \; Dist.$ will be one for $D_2$ and $D_3$, and zero for $D_1$. $ND$ will be one for $D_3$ and zero for $D_1$ and $D_2$. Lastly, $Org. \; Dist.$ dummy will be one for all the three ($D_1$, $D_2$, $D_3$) because loan offering branch's district $D_1$ experience natural disaster (rainfall shock). Thus, only for loans used in district $D_3$ $Diff \; Dist.$, $ND$, and $Org. \; Dist.$ dummy variables would be one.

weighed loan rates at the branch level. The effect is economically significant. On average, a banks' branches that experience a natural disaster increase their loan rate by 50 basis points.

Columns (4) to (6) report the results when the dependent variable is loan outstanding weighed loan rates at the branch level. We find a similar pattern as seen in the case of the equally weighted loan rate. A rainfall shock leads to an increase of 0.5 percentage points in the loan rates charged by local banks' branches. The estimated effect is economically significant.

The above evidence suggests that banks' branch-level loan rates are responsive (in the upward direction) to rainfall shock. The results can be interpreted in light of branches compensating for the change in the risk profile of the borrowers in the event of rainfall shock. It may rule out the potential role of transition risk associated with climate disasters, i.e., the risk to cash flow resulting from the transition to a low-carbon economy.[17]

Lastly, we examine the heterogeneous increase in interest rates in response to the intensity of disaster shocks. The results so far show that banks' branches in the natural disaster hit latitude-longitude pair increase loan rates. They may do it to compensate for increase in the risk profile of the borrowers. Thus, the relationship between change in the loan rate and natural disasters should be heterogeneous, with a large increase in the case of areas hit by more severe natural disasters. To test this conjecture, we allow natural disasters to be discrete. Specifically, a latitude-longitude pair can encounter no natural disaster, very mild level of natural disaster ($ND\ Level$ 1), medium level of natural disaster ($ND\ Level$ 2), and severe level of natural disaster ($ND\ Level$ 3): $S^{dis}_{lt,lo,t-1} \in$

[17] To show that our baseline results are not driven only by rainfall shocks. In one of the robustness checks, we removed all the latitude-longitude-year combinations that have experienced both natural disaster and rainfall shock from our sample. We re-estimate our baseline model (Eq. 1) on this subsample. Table A1 shows coefficients of Eq (1) estimated on this reduced subsample. We find qualitatively similar results as in baseline specification reported in Table 2.

$\{S^{No}_{lt,lo,t-1}, S^{L1}_{lt,lo,t-1}, S^{L2}_{lt,lo,t-1}, S^{L3}_{lt,lo,t-1}\}$. We create three binary variables $ND\ Level\ 1$, $ND\ Level\ 2$, and $ND\ Level\ 3$ that become one when $S^{dis}_{lt,lo,t-1}$ is $S^{L1}_{lt,lo,t-1}$, $S^{L2}_{lt,lo,t-1}$, and $S^{L3}_{lt,lo,t-1}$, respectively and zero otherwise. As before, no disaster shock ($S^{No}_{lt,lo,t-1}$) is the base category. We estimate the following regression:

$$\begin{aligned} Y_{i,b,lt,lo,t} = {} & \beta_1\ ND\ Level\ 1_{lt,lo,t-1} + \beta_2\ ND\ Level\ 2_{lt,lo,t-1} + \beta_3\ ND\ Level\ 3_{lt,lo,t-1} \\ & + \gamma_i + \delta_t + \epsilon_{i,b,lt,lo,t} \end{aligned} \tag{4}$$

$\beta_1$, $\beta_2$, and $\beta_3$ are our variables of interest. If banks' branches increase loan rates to compensate for the increase in the risk profile of the borrowers when an area is hit by natural disasters, then we expect the change in loan rate to be positively associated with the severity of the natural disasters. In our model, it would reflect in the form of $\beta_1 < \beta_2 < \beta_3$. In an alternate specification, we also use bank and bank-year fixed effects to control for bank and bank-year specific factors. Standard errors are clustered at latitude-longitude level.

Table 5 reports the estimated coefficients of Eq. (4). In columns (1) to (3), we find that the severity of the natural disaster is positively associated with equally weighed loan rates. The coefficient of ND Level 3 is the greatest among the three different levels of natural disasters.[18] This indicates that branches in areas most severely impacted by natural disasters increase lending rates more than branches in places where the severity of the natural disaster is less severe. The differences are economically significant. In our baseline model, branches that experienced a level 3 natural disaster raise their loan rates by an average of 0.7 percentage points, whereas levels 1 and 2 natural disasters increase loan rates by 0.3 and 0.1 percentage points, respectively.

Columns (4) to (6) report the results when the dependent variable is loan outstanding

[18] Here, ND Level 3, ND Level 2, and ND Level 1 show the natural disaster of decreasing severity.

weighed loan rates at the branch level. A similar pattern is observed as with the equally weighted loan rate.[19] Broadly our findings indicate that the association between natural disasters and lending rates is heterogeneous, with the strength of the relationship increasing as the severity of the natural disaster increases.

In light of these findings, we tend to interpret an increase in interest rates resulting from an increase in default risk as the primary mechanism. This is consistent with the existing asset pricing framework in climate finance literature (for a review, see Giglio, Kelly and Stroebel (2021a)). Another possibility is an excess credit demand. Nevertheless, it is improbable given that we observe a decline in credits.

Theoretically, the probability of default could have increased for at least two reasons. First, natural disasters may have had a substantial impact on cash flow. Another possibility is if the value of collateral decreases due to the direct effects of disaster shocks or the asset pricing feedback channel, banks may restrict credit or raise interest rates (Stiglitz and Weiss, 1981; Benmelech and Bergman, 2009). It may increase the firm's financial constraints on the demand side. However, our data do not allow us from separating these two channels.

In theory, we may expect a rise in interest rates due to an increased default risk, but a decline in credit may not be immediate. After all, banks are unique, and lending heavily depends on relationships. Additionally, local branches possess a substantial amount of soft information. With an increase in interest rates, branches may be willing to extend more credit. One possibility is that rising interest rates will reduce demand. Loss of soft information is yet another possibility. Natural disasters have increased the informational friction, making branches unwilling to extend credit. While both channels appear plausible, our data do not permit us to dissect the details.

[19] In our baseline model, on average branches that experienced level 3 natural disaster increase loan rate by 0.6 percentage points, while the increase in loan rate at the areas hit by a natural disaster of level 1 and 2 are 0.2 and 0.1 percentage points, respectively. The estimated difference in the increase in loan rate is economically significant.

# 6 Effect on Firms

Next, we examine the borrower's perspective. As only firm-level data are of sufficient quality, we restrict our analysis to the firm level.[20] To understand the influence of bank branches' increase in loan rates in response to natural disasters on firms, we exploit a panel of firm accounting data obtained from CMIE $Prowess_{dx}$. We took the firm's (both listed and unlisted) registered office pin code data from CMIE $Prowess_{dx}$, and matched it with latitude and longitude at $1^0 \times 1^0$ precision.[21] This allowed us to match our firm panel data with the incidence of natural disasters. We examine the dynamics of firms' total interest expense, the short and long-term bank debt amount, and total R&D expenditure following their latitude-longitude pair experience a natural disaster. Our identification strategy is based on the fact that the firms at a particular latitude-longitude level would be dependent on the local banks' branches for financial needs.[22] Hence, any increase in loan rate by banks' branches in response to natural disasters would influence firms' total interest expense, the short and long-term bank debt amount, and total R&D expenditure. Our main conjecture here is that due to increase in loan rates by local banks' branches in response to natural disasters, the firms at the same area would incur high-interest expenses, that in turn can make them reduce short and long-term bank borrowing and R&D expense.

Again, we use the local projection (LP) framework (Jordà, 2005), to study the dynamics of firm-level variables. As earlier, throughout this section, we present the four-year dynamic response of total interest expense, short and long-term bank debt amount, and total R&D expense. We estimate the following LP model for different time horizon (h = 0,1,..,4):

[20] Rarely is demand-side information on household or agricultural finance available at such a granular level.

[21] We consider a sample of 52157 firms for which data is available in the CMIE $Prowess_{dx}$. As mentioned earlier, we restrict our sample to non-finance firms.

[22] Extensive research demonstrates a local bias in credit sourcing (Petersen and Rajan, 2002; Granja, Leuz and Rajan, 2022).

$$Y_{i,lt,lo,t+h} - Y_{i,lt,lo,t} = \zeta_i + \beta_h S_{lt,lo,t} + \gamma X_{i,lt,lo,t} + \epsilon_{i,lt,lo,t+h} \tag{5}$$

where, $Y_{i,b,lt,lo,t+h}$ denote a vector of dependent variables for firm $i$ at latitude $lt$ and longitude $lo$ reported in year $t+h$. In the analysis, we use four dependent variables - natural logarithm of total interest expense, short and long-term bank debt, and total R&D expense. $h$ denotes the horizon considered which is four in the current case. $X_{i,b,lt,lo,t}$ denotes a vector that contains three lags of yearly changes in the dependent variable. $\zeta_i$ is firm-level fixed effects. The impulse responses are constructed based on the estimated $\beta_h$ coefficients at each horizon. The 90 percent confidence bands are based on the respective estimated standard errors.

We begin by reporting the impulse response of total interest expense obtained from Eq. (5). Figure 7 displays the cumulative change in the natural logarithm of total interest expense, measured in INR million. We find that in time periods following a natural disaster, firms tend to incur high total interest expenses.[23] The increase in total interest expense is both economically and statistically significant. Specifically, the interest rate expense increases by close to 9% in two years period after the natural disaster, and starts to decrease from the third year onwards to return to starting level in the fourth year. It is not surprising that the interest expense dynamics are nearly identical to the loan rate dynamics (rise in the first two years, fall thereafter, and return to the initial level in the fourth year) estimated using bank-branch level data (see Figure 3).[24]

Next, we discuss the impulse response of short and long-term bank debt obtained from Eq. (5). Panel A and B Figure A1 show the cumulative change in the natural logarithm of short and long-term bank debt, respectively. We find that in time periods following a

[23]In one of the robustness test, we estimate the impulse response of total interest expense/total capital using Eq. (5). As can be observed in figure A2 the pattern remains qualitatively similar.

[24]It could be another evidence that firms acquire bank debts locally.

natural disaster firms tend to reduce the amount of both short and long-term bank debt. In a four-year period, the reduction in both short and long-term bank debt is economically and statistically significant. In particular, the short-term bank debt first rises and then declines in periods after the natural disaster, at the end of the fourth year it is reduced by around $-7\%$. Similarly, the long-term bank debt has a falling trend (although not monotonic) in the aftermath of the natural disaster; by the end of the fourth year, it has decreased by approximately $-2\%$. Consequently, our data also indicates that enterprises affected by natural disasters reduce both their short- and long-term bank borrowing.

Lastly, we report and discuss the impulse response of total R&D expense obtained from Eq. (5). Figure 8 displays the cumulative change in the natural logarithm of one plus total R&D expense, measured in INR million. In the aftermath of a natural disaster, firms tend to curtail their R&D expenditures. The R&D expense decreases by close to 4% in the first year after a natural disaster; the reduction is both economically and statistically significant. From the second year onwards, it increases and returns to starting level in the fourth year. Our analysis so far signal that, as a result of the increase in lending rates by local bank branches in response to natural disasters, firms in the region pay high-interest expenses, which may prompt them to curtail short- and long-term bank borrowing and R&D expenditures.

# 7 Potential Impact on R&D and Real Activity

In this section, we delve deeper into the potential financial intermediation channel via which natural disasters affect real economic activities. Specifically, we examine the impact of the natural disaster-induced increase in loan rate on firm level R&D and real economic activity proxied by nighlight luminosity of the region. As we argue before, firms depend heavily on bank debts to finance their investment, particularly in India (Kumar, 2020).

Consequently, when branches in a given region increase lending rates following a natural disaster, the increased cost of capital will have a detrimental influence on the firms' investment activity (Frank and Shen, 2016).[25] Similarly, other economic agents, like households, may reduce their economic activities in response to the natural disaster-induced increase in loan rates by banks' branches. Cumulatively, we may observe a decline in regional economic activities.

The response of bank branches to the natural disaster is heterogeneous. Our identification strategy exploits the heterogeneity in the change of loan rate between branches in response to natural disasters weighted by their corresponding market share. This closely mimic a shift-share design (Goldsmith-Pinkham, Sorkin and Swift, 2020). We first estimate the average change in loan rate by banks' branches in response to the natural disaster. We leverage this heterogeneity to estimate interest rate shock at every latitude-longitude-year level by calculating the market share weighted interest rate. Then we relate latitude-longitude-year level interest rate shock to R&D and nighlight based real activities. The specific steps are listed below..

We begin by predicting the change in branch-level interest rates following a natural disaster shock. For that, we estimate the following regression for each branch:

$$Log(Interest\ Rate_{i,b,lt,lo,t}) = \beta_0 + \beta_i S_{lt,lo,t-1} + \epsilon_{i,b,lt,lo,t} \tag{6}$$

where, $Interest\ Rate_{i,b,lt,lo,t}$ is the average loan rate for branch(i) of bank (b) at latitude(lt), and longitude(lo) in year t. In our analysis, we consider two main dependent variables - natural logarithm of equally-weighted ($Log(Equally\ Weighted\ Loan\ Rate)$), and loan outstanding weighted ($Log(Loan\ Outstanding\ Weighted\ Loan\ Rate)$) loan rates. $S_{lt,lo,t-1}$ is dummy variable that takes the value one when a latitude($lt$), and longitude($lo$) pair in

[25] Another potential factor is credit rationing.

year t experiences a natural disaster shock otherwise zero. $\beta_i$ is the average change in the interest rate at branch level if the latitude and longitude pair experiences a natural disaster shock. Estimation of Eq. (6) gives us a vector of average change in the loan rate for all the branches in our sample that have experienced natural disaster.

Next, at every latitude, longitude, and year level we estimate market share weighted change in interest rate ($Interest\ Rate\ Shock_{lt,lo,t}$).

$$Interest\ Rate\ Shock_{lt,lo,t} = \frac{\sum_i \beta_i \times Market\ Shr_{i,b,lt,lo,t}}{\sum Market\ Shr_{i,b,lt,lo,t}} \tag{7}$$

where, $\beta_i$ is the average change in interest rate at branch level in case of natural disaster shock estimated from Eq. (6), $Market\ Shr_{i,b,lt,lo,t}$ is market share of banks' (b) branch (i) at latitude (lt), and longitude (lo) in year t. This gives us two series of interest rate shock: one for equally weighted loan rate ($EW\ Interest\ Rate\ Shock$) and other for loan outstanding weighted loan rate ($LOW\ Interest\ Rate\ Shock$).

The $Interest\ Rate\ Shock$ variable captures the heterogeneity in the change in loan rate by dominant branch[26] in response of natural disaster across the latitude-longitude level. We examine the relation of our interest rate shock measure with firms' R&D and real activities at the same latitude-longitude level. The underlying intuition is that branches respond heterogeneously to natural disasters and that the dominating branches' interest rate changes have a greater effect on the region.

[26]By dominant branches, we mean branches having dominant market share at the latitude-longitude level.

## 7.1 Impact on R&D Activity

We first examine the impact on firm level R&D activity. To do so, we estimate the following regression:

$$Y_{i,lt,lo,t} = \beta\ Interest\ Rate\ Shock_{lt,lo,t} \times S_{lt,lo,t-1} + \gamma_i + \delta_t + \epsilon_{i,lt,lo,t} \quad (8)$$

where, $Y_{i,lt,lo,t}$ represents a vector of dependent variables for firm $i$ at latitude $lt$ and longitude $lo$ reported in year t. In our analysis, we consider natural logarithm of one plus R&D expense (INR million) as dependent variable. The term $S_{lt,lo,t-1}$ represents *Natural Disaster Dummy* that is a binary variables that becomes one when latitude ($lt$), and longitude ($lo$) experiences a natural disaster shock in year $t-1$ and zero otherwise. $Interest\ Rate\ Shock_{lt,lo,t}$ is estimated using Eq. (7). $\gamma_i$, and $\delta_t$ are firm and year-level fixed effects. We add firm fixed effects to control for any firm level time invariant observed and unobserved factors. We also use year fixed effects to absorb any economic wide shock.[27]

Table 6 reports the estimates for Eq. (8). We have two estimates of the interest rate shock, one based on an equally weighted loan rate and the other based on a loan outstanding-weighted loan rate. The column (1) of Table 6 shows that with one percentage point increase in the interest shock exposure when the region experiences a natural disaster there is a drop of 18.5% in R&D investments by firms. The corresponding value in the case of interest shock estimated using the loan outstanding weighted loan rate is 30.1%. The drop in R&D investments by firms is economically significant.

[27] RD investment is known to be positively correlated among firms at a given point in time and across time for a given firm (Klette and Kortum, 2004). Our firm and year level fixed effects control for that.

### 7.2 Impact on Real Activity

Next, we examine the impact on real economic activity using average night light at the latitude-longitude level as its proxy. To do so, we estimate the following regression equation:

$$Y_{lt,lo,t} = \beta \; Interest\ Rate\ Shock_{lt,lo,t} \times S_{lt,lo,t-1} + \gamma_{lt,lo} + \delta_t + \epsilon_{lt,lo,t} \tag{9}$$

where, $Y_{lt,lo,t}$ represents a vector of dependent variables for latitude $lt$ and longitude $lo$ reported in year t. In our analysis, we consider natural logarithm of one plus average night light ($Log(1 + Night\ Light_{lt,lo,t})$) as dependent variable. The term $S_{lt,lo,t-1}$ represents $Natural\ Disaster\ Dummy$ that is a binary variables that becomes one when latitude ($lt$), and longitude ($lo$) experiences a natural disaster shock in year $t-1$ and zero otherwise. $Interest\ Rate\ Shock_{lt,lo,t}$ is estimated using Eq. (7). $\gamma_{lt,lo}$, and $\delta_t$ are latitude-longitude and year-level fixed effects. The latitude-longitude fixed effects absorb observed and unobserved time-invariant characteristics of a location that can impact night light.[28]

Table 7 reports the estimates of Eq. (9). We have two estimates of interest rate shock - one using an equally weighted loan rate and another using loan outstanding weighted loan rate. The column (1) of Table 7 shows that with a one percentage point increase in the interest shock exposure when a region experiences a natural disaster there is a drop of 6.0% in average night light. The corresponding value in the case of interest shock estimated using the loan outstanding weighted loan rate is 9.3%. The drop in economic activity is economically significant.

These results, together, indicate that increase in loan rates by banks' branches in response to natural disasters affects the R&D investments of local firms and also the local economic

[28]One of these features is the spatial configuration of a region; on average, metropolitan regions have higher nightlight luminosity than rural areas. Our latitude-longitude fix would account for this feature.

activity. Overall, the evidence implies a financial intermediary pathway. It is important to note that, the financial intermediation channel is the *second-order* effect of natural disasters on real operations.

# 8 Conclusion

A growing body of literature demonstrates that climate risks influence firm financing. While it is known that climate risks have an impact on firm financing, little is known about how banks respond when their local branches are exposed to natural disasters. We investigate how bank branches price loans in response to natural disasters. This is crucial because it is the local branches who frequently possess a large amount of soft information.

We present direct evidence of the effects of disaster shocks on bank lending and pricing. Our bank-branch-level analysis is not limited to firm loans alone, which is a distinguishing characteristic. We observe that branches exposed to natural disasters have higher interest rates and tend to reduce credit supply. This effect endures for multiple periods. On the demand side, higher interest rates and restricted credit availability are likely to exacerbate existing financial frictions. We observe a rise in interest expenses and a decline in bank debt in affected firms. Similarly, these effects persist for multiple periods. Finally, we link an increase in interest rates with a decline in real economic activity. Specifically, we find that an increase in interest rates, weighted by branch size, is associated with a decline in firm-level R&D and nightlight luminosity.

Climate change will have a significant impact on future economic activities. Due to the multifaceted nature of climate change's effects, it is challenging to quantify the extent to which individual economic agents are impacted. Our paper presents the first empirical evidence that bank branch-level exposure to natural disasters influences lending rates and loan amounts for all borrowers. The pattern we document in this paper has important implications for comprehending the interplay between climate change, the lending market, and the economy.

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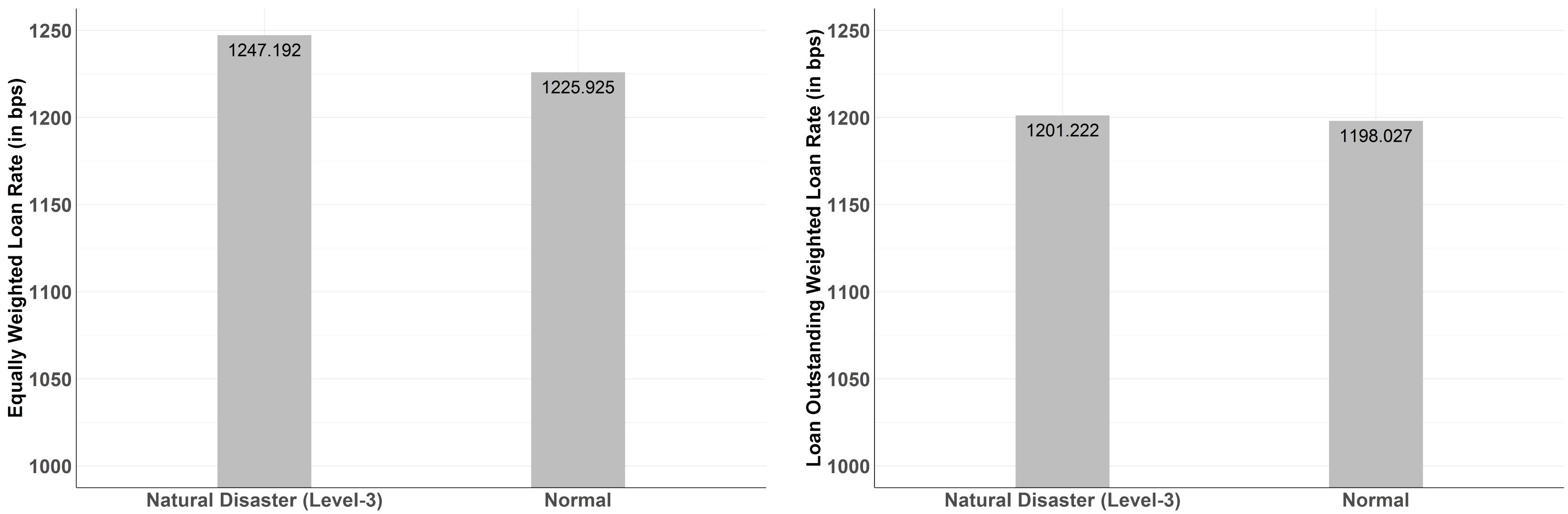
# 9 Figures and Tables

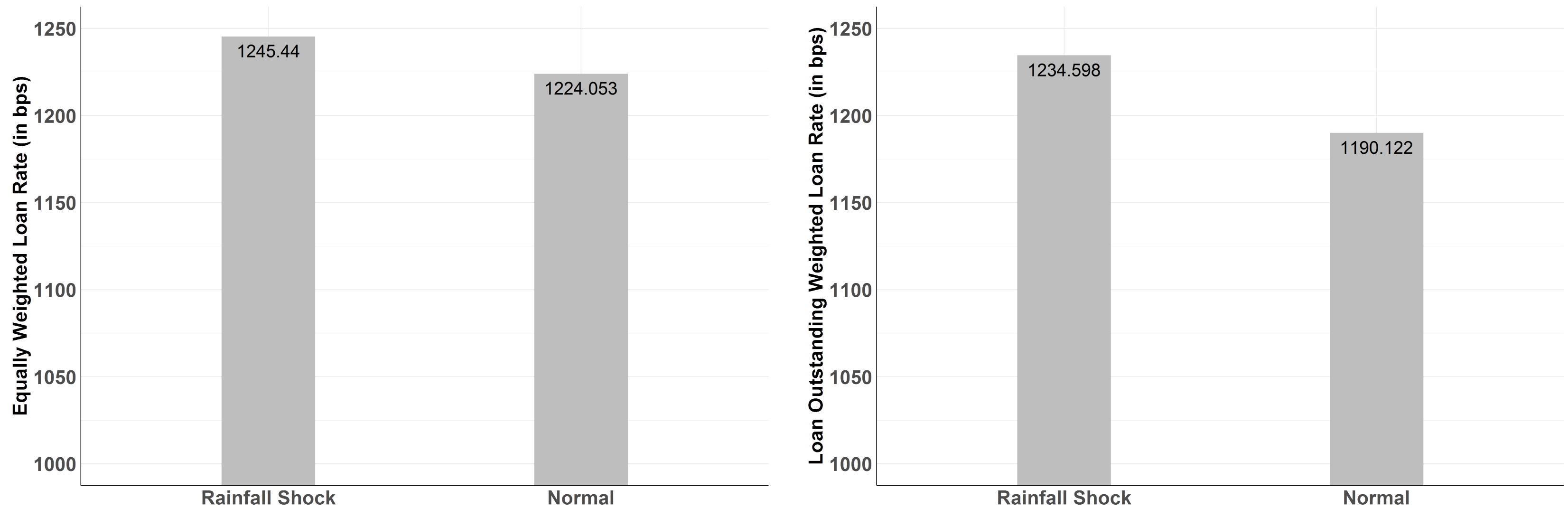



(a) Equally Weighted Loan Rate

(b) Loan Outstanding Weighted Loan Rate

Figure 1: Impact of natural disaster on loan rates

*Notes:* These figures depict the mean value of loan rates (in bps) across branches at a latitude-longitude pair in response to a natural disaster (level-3) and normal year. Panel (a) and (b) represent the mean value of equally weighted loan rate and loan outstanding weighted loan rate respectively. The sample period spans from 2000 to 2012.

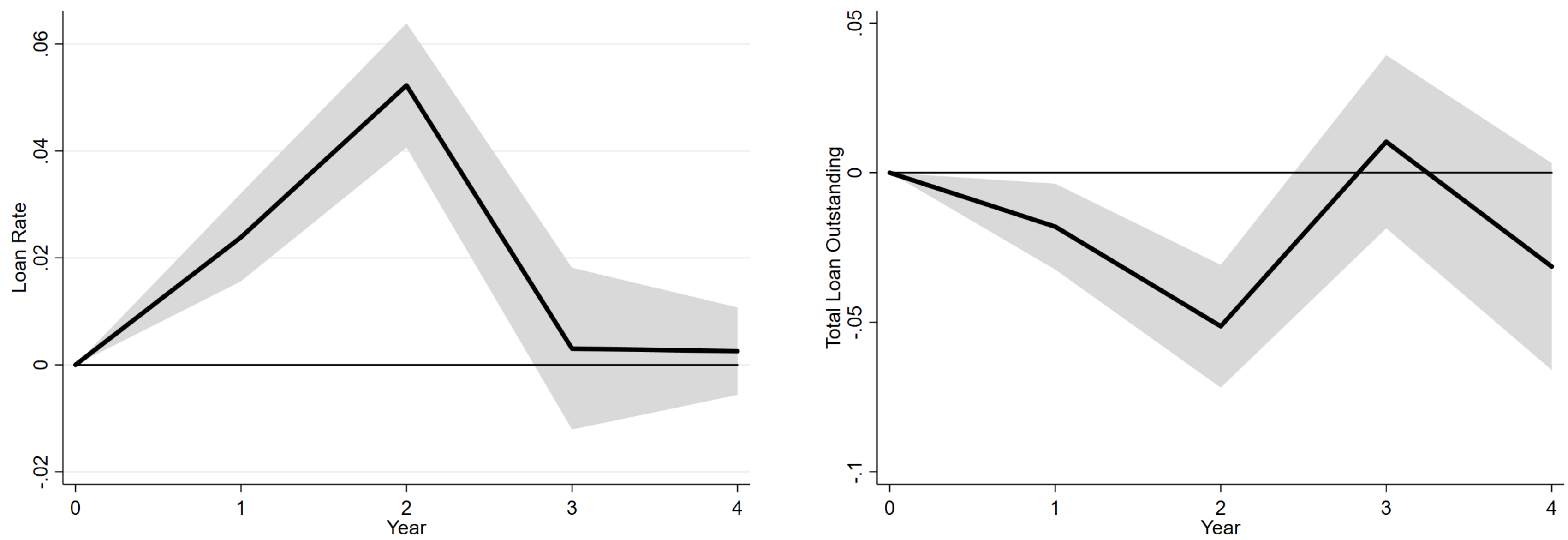



(a) Equally Weighted Loan Rate

(b) Loan Outstanding Weighted Loan Rate

Figure 2: Impact of rainfall shock on loan rates

*Notes:* These figures depict the mean value of loan rates (in bps) across branches at a latitude-longitude pair in response to a rainfall shock and normal year. Panel (a) and (b) represent the mean value of equally weighted loan rate and loan outstanding weighted loan rate respectively. The sample period spans from 2000 to 2012.

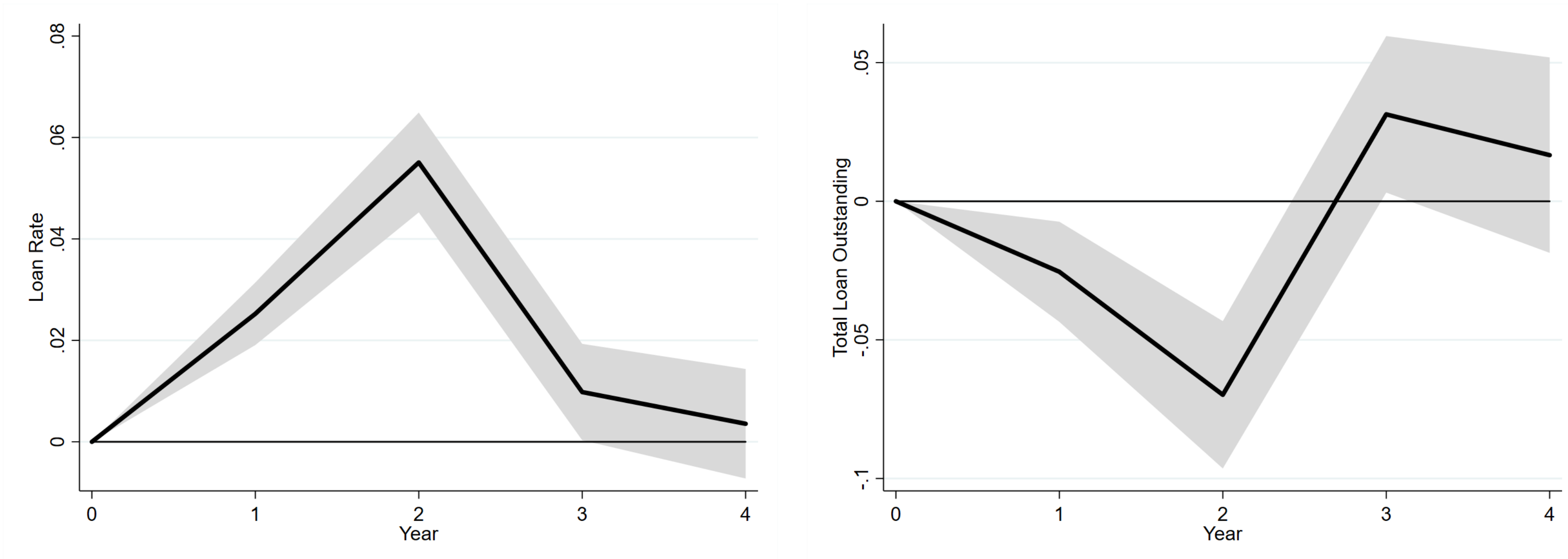



(a) Equally Weighted Loan Rate

(b) Total Loan Outstanding

Figure 3: Response of loan rate and total loan outstanding to natural disaster (Full Sample)

*Notes:* These figures show the impulse response obtained from Eq. (2) for full sample. The shaded regions indicate the 90 percent confidence intervals based on standard errors estimated by clustering errors at latitude-longitude level. Panel (a) and (b) show the cumulative change in natural logarithm of equally weighted loan rate and total loan outstanding, respectively after the occurrence of natural disaster. Both the variable are estimated using Bank-Branch panel data. The sample period spans from 2000 to 2012.

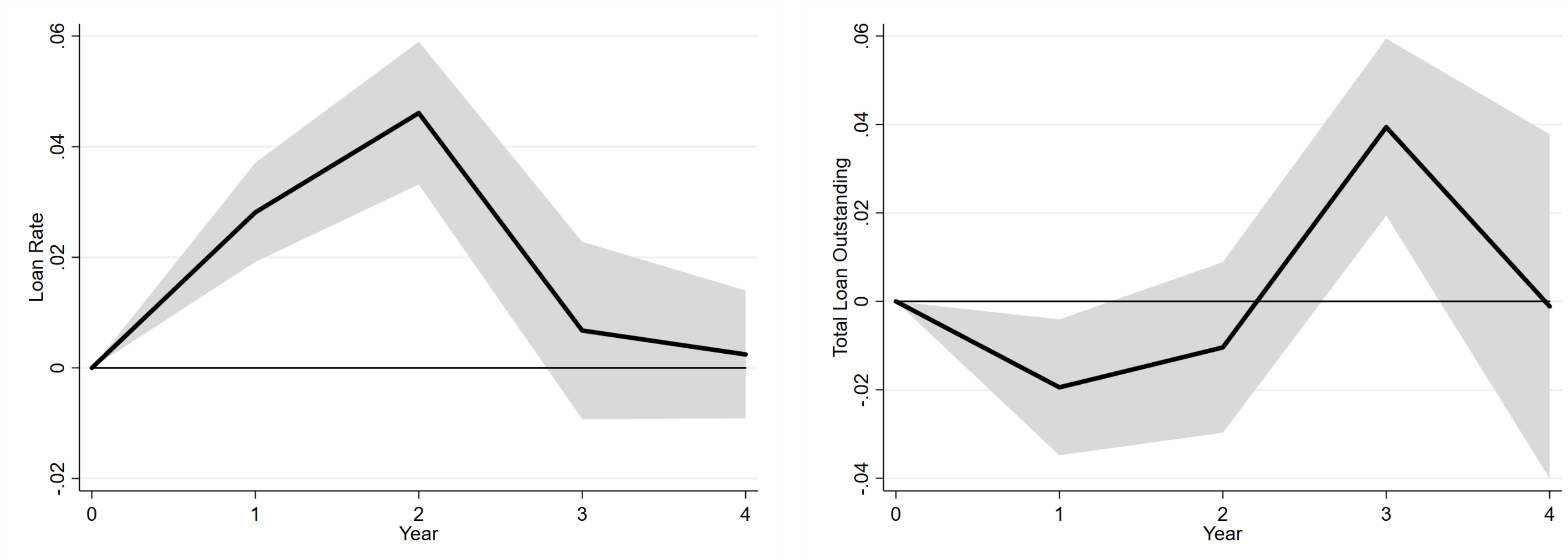



(a) Equally Weighted Loan Rate

(b) Total Loan Outstanding

Figure 4: Response of loan rate and total loan outstanding to natural disaster (Agriculture Sector)

*Notes:* These figures show the impulse response obtained from Eq. (2) for agriculture sector loans. The shaded regions indicate the 90 percent confidence intervals based on standard errors estimated by clustering errors at latitude-longitude level. Panel (a) and (b) show the cumulative change in natural logarithm of equally weighted loan rate and total loan outstanding, respectively after the occurrence of natural disaster. Both the variable are estimated using Bank-Branch panel data. The sample period spans from 2000 to 2012.

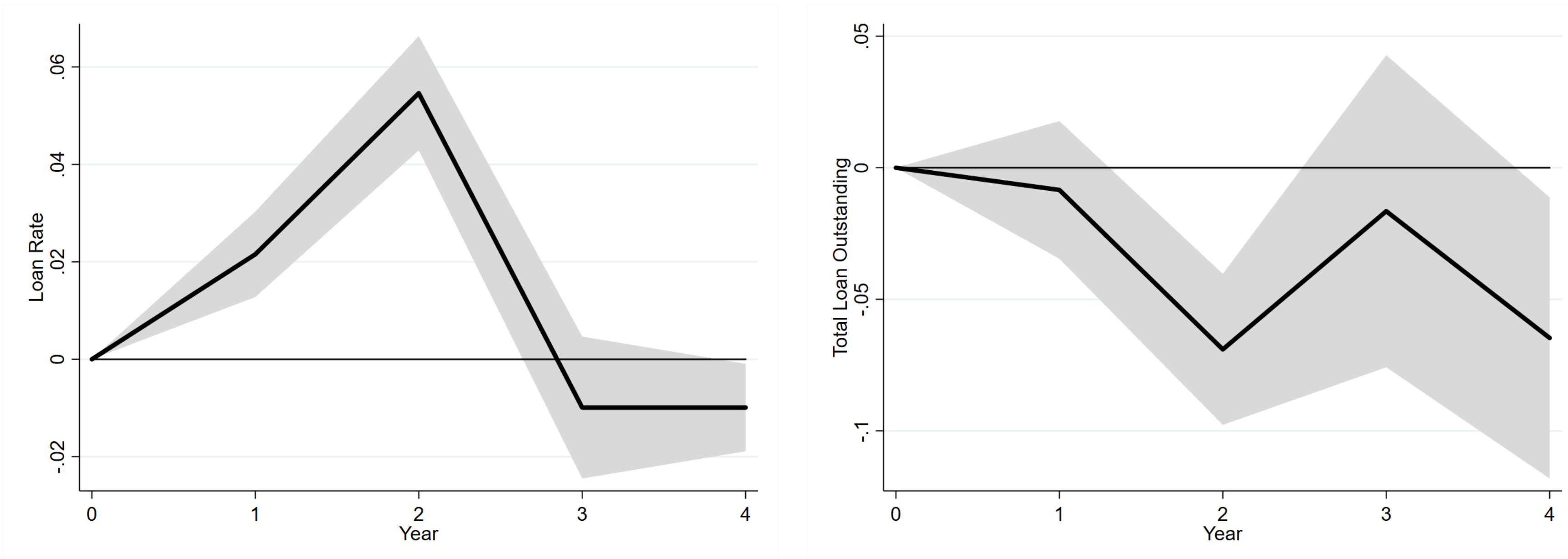



(a) Equally Weighted Loan Rate

(b) Total Loan Outstanding

Figure 5: Response of loan rate and total loan outstanding to natural disaster (Business Sector)

*Notes:* These figures show the impulse response obtained from Eq. (2) for business sector loans. The shaded regions indicate the 90 percent confidence intervals based on standard errors estimated by clustering errors at latitude-longitude level. Panel (a) and (b) show the cumulative change in natural logarithm of equally weighted loan rate and total loan outstanding, respectively after the occurrence of natural disaster. Both the variable are estimated using Bank-Branch panel data. The sample period spans from 2000 to 2012.




(a) Equally Weighted Loan Rate

(b) Total Loan Outstanding

Figure 6: Response of loan rate and total loan outstanding to natural disaster (Personal Loans)

*Notes:* These figures show the impulse response obtained from Eq. (2) for personal loans. The shaded regions indicate the 90 percent confidence intervals based on standard errors estimated by clustering errors at latitude-longitude level. Panel (a) and (b) show the cumulative change in natural logarithm of equally weighted loan rate and total loan outstanding, respectively after the occurrence of natural disaster. Both the variable are estimated using Bank-Branch panel data. The sample period spans from 2000 to 2012.

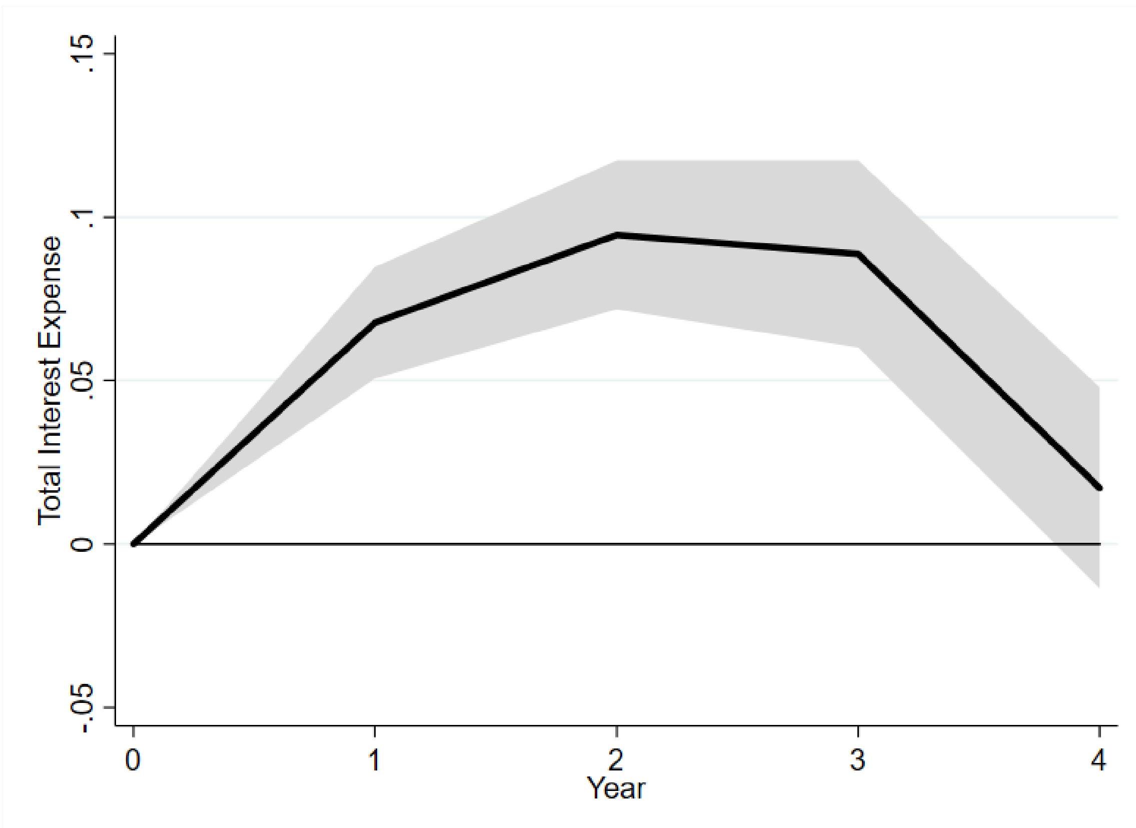



Figure 7: Response of firm level total interest expense to natural disaster
*Notes:* The figure shows the impulse response obtained from Eq. (5). The shaded regions indicate the 90 percent confidence interval. The figure displays the cumulative change in natural logarithm of total interest expense, after the occurrence of natural disaster. The variable is estimated using firm-level panel. The sample period spans from 2000 to 2012.

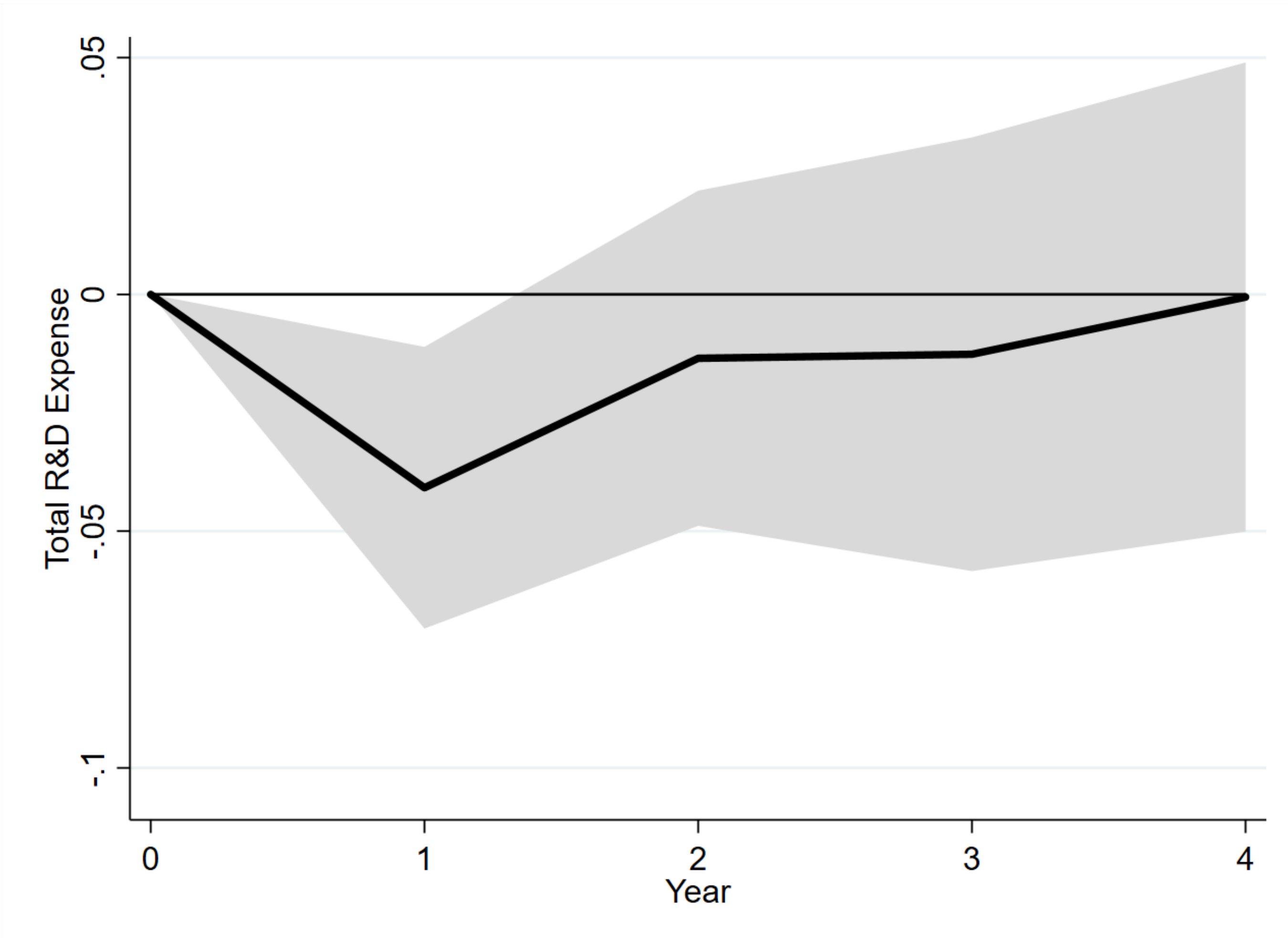



Figure 8: Response of firm level total R&D expense to natural disaster
*Notes:* The figure shows the impulse response obtained from Eq. (5). The shaded regions indicate the 90 percent confidence interval. The figure displays the cumulative change in natural logarithm of one plus total R&D expense, after the occurrence of natural disaster. The variable is estimated using firm-level panel. The sample period spans from 2000 to 2012.

| Variables | Number | Mean | SD |
|---|---|---|---|
| Panel A - Bank-Branch Panel | | | |
| Branch-Year-Level | | | |
| Equally Weighted Loan Rate (bps) | 911238 | 1245.967 | 194.420 |
| Loan Outstanding Weighted Loan Rate (bps) | 911238 | 1257.145 | 196.197 |
| Total Loan Outstanding ('000 INR) | 911238 | 122146.287 | 380011.717 |
| No. of Branch-Year Pairs exposed Natural Disaster (Number) | 224924 | - | |
| No. of Branch-Year Pairs exposed Rainfall Shock (Number) | 140919 | - | |
| Branch-Year-Sector-Level: Agriculture Sector | | | |
| Equally Weighted Loan Rate (bps) | 551335 | 1220.261 | 206.710 |
| Loan Outstanding Weighted Loan Rate (bps) | 551335 | 1229.405 | 206.649 |
| Total Loan Outstanding ('000 INR) | 551335 | 22031.538 | 79444.38 |
| Branch-Year-Sector-Level: Business Sector | | | |
| Equally Weighted Loan Rate (bps) | 688454 | 1317.517 | 182.227 |
| Loan Outstanding Weighted Loan Rate (bps) | 688454 | 1320.917 | 187.464 |
| Total Loan Outstanding ('000 INR) | 688454 | 72451.462 | 195537.36 |
| Branch-Year-Sector-Level: Personal Loans | | | |
| Equally Weighted Loan Rate (bps) | 703716 | 1171.937 | 188.512 |
| Loan Outstanding Weighted Loan Rate (bps) | 703716 | 1163.467 | 195.512 |
| Total Loan Outstanding ('000 INR) | 703716 | 32128.717 | 85879.03 |
| Branch-Year-Sector-Level: Others | | | |
| Equally Weighted Loan Rate (bps) | 295907 | 1285.153 | 222.975 |
| Loan Outstanding Weighted Loan Rate (bps) | 295907 | 1287.092 | 228.902 |
| Total Loan Outstanding ('000 INR) | 295907 | 31019.935 | 132737.28 |
| Panel B - Firm Panel | | | |
| Total Interest Expense (Million INR) | 115,323 | 78.343 | 251.721 |
| Short Term Bank Debt (Million INR) | 93,128 | 278.085 | 790.036 |
| Long Term Bank Debt (Million INR) | 72,578 | 401.067 | 1310.431 |
| Total R&D Expense (Million INR) | 16,394 | 37.066 | 127.686 |

Table 1: Summary statistics

*Notes:* This Table reports the summary statistics of all the variables used in the study. Panel A and B reports summary statistics of variables derived from our bank-branch and firm panel, respectively. Number represents the number of branch-year, and firm-year observations in Panel A and B, respectively. Units of measurement, whenever is applicable, is shown in the parenthesis. The sample period spans from 2000 to 2012.

| *Dependent variable:* | Log(Equally Weighted Loan Rate (bps)) | | | Log(Loan Outstanding Weighted Loan Rate) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Natural Disaster Dummy | 0.002 | 0.003 | 0.003 | 0.001 | 0.003 | 0.003 |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| Branch Fixed Effects | Yes | No | No | Yes | No | No |
| Year Fixed Effects | Yes | Yes | No | Yes | Yes | No |
| Bank Fixed Effects | No | Yes | No | No | No | Yes |
| Bank-Year Fixed Effects | No | No | Yes | No | No | Yes |
| Observations | 911,238 | 910,384 | 911,238 | 911,238 | 910,384 | 911,238 |

Table 2: Effect of natural disaster on loan rate

*Notes:* The table reports the estimated coefficients of Eq. (1). Every column reports a separate linear regression. In columns (1) to (3) and (4) to (6) natural logarithm of equally weighted loan rate (bps) and loan outstanding weighted loan rate (bps) are dependent variables, respectively. Both the variable are estimated using Bank-Branch panel data. Natural Disaster Dummy is a binary variable that takes the value one if a latitude-longitude pair experiences a natural disaster in a year and zero otherwise. Standard errors clustered at latitude-longitude level are reported in the parenthesis. The sample period spans from year 2000 to 2012.

| *Dependent variable:* | Log(Equally Weighted Loan Rate) | | Log(Loan Outstanding Weighted Loan Rate) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Diff. Dist. × ND × Org. Dist. (Natural Dis.) | −0.003 | | −0.008 | |
| | (0.003) | | (0.003) | |
| Diff. Dist. × ND × Org. Dist. (Rainfall Sho.) | | −0.007 | | −0.012 |
| | | (0.002) | | (0.002) |
| Branch Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 1,163,525 | 1,163,352 | 1,163,525 | 1,163,352 |
| Adjusted $R^2$ | 0.565 | 0.565 | 0.534 | 0.534 |

Table 3: Lending in Different District, and Natural Disaster

*Notes:* The table reports the estimated coefficients of Eq. (3). Every column reports a separate linear regression. In columns (1-2) and (3-4) natural logarithm of equally weighted loan rate (bps) and loan outstanding weighted loan rate (bps) are dependent variables, respectively. Both the variable are estimated using Bank-Branch panel data. Diff. Dist. is a dummy that takes the value one for districts where the loans are used is not the one where the branch is located and zero otherwise. ND is a dummy variable that becomes one if the district in which the loans are used has not experienced natural disaster (rainfall shock) in a year and zero otherwise. Org. District variable becomes one for all the districts where loans are used if the district in which loan offering branch is located has experienced a natural disaster (rainfall shock) and zero otherwise. Standard errors clustered at district level are reported in the parenthesis. The sample period spans from year 2000 to 2012.

| *Dependent variable:* | Log(Equally Weighted Loan Rate (bps)) | | | Log(Loan Outstanding Weighted Loan Rate) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Rainfall Shock Dummy | 0.005 | 0.003 | 0.001 | 0.005 | 0.002 | 0.001 |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.002) | (0.001) |
| Branch Fixed Effects | Yes | No | No | Yes | No | No |
| Year Fixed Effects | Yes | Yes | No | Yes | Yes | No |
| Bank Fixed Effects | No | Yes | No | No | No | Yes |
| Bank-Year Fixed Effects | No | No | Yes | No | No | Yes |
| Observations | 910,384 | 910,384 | 910,384 | 910,384 | 910,384 | 910,384 |

Table 4: Effect of rainfall shock on loan rate

*Notes:* The table reports the estimated coefficients of Eq. (1). Every column reports a separate linear regression. In columns (1) to (3) and (4) to (6) natural logarithm of equally weighted loan rate (bps) and loan outstanding weighted loan rate (bps) are dependent variables, respectively. Both the variable are estimated using Bank-Branch panel data. Rainfall Shock Dummy is a binary variable that takes the value one if a latitude-longitude pair experiences less than $20^{th}$ percentile rainfall in a year and zero otherwise. Standard errors clustered at latitude-longitude level are reported in the parenthesis. The sample period spans from year 2000 to 2012.

| *Dependent variable:* | Log(Equally Weighted Loan Rate (bps)) | | | Log(Loan Outstanding Weighted Loan Rate) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ND Level 1 | 0.003 | 0.001 | −0.0001 | 0.002 | 0.001 | −0.0003 |
| | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) | (0.003) |
| ND Level 2 | 0.001 | 0.003 | 0.004 | 0.001 | 0.003 | 0.004 |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) |
| ND Level 3 | 0.007 | 0.012 | 0.011 | 0.006 | 0.009 | 0.008 |
| | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| Branch Fixed Effects | Yes | No | No | Yes | No | No |
| Year Fixed Effects | Yes | Yes | No | Yes | Yes | No |
| Bank Fixed Effects | No | Yes | No | No | No | Yes |
| Bank-Year Fixed Effects | No | No | Yes | No | No | Yes |
| Observations | 910,384 | 911,238 | 911,238 | 910,384 | 911,238 | 911,238 |

Table 5: Heterogeneity in the effect of natural disaster level on loan rate

*Notes:* The table reports the estimated coefficients of Eq. (4). Every column reports a separate linear regression. In columns (1) to (3) and (4) to (6) natural logarithm of equally weighted loan rate (bps) and loan outstanding weighted loan rate (bps) are dependent variables, respectively. Both the variable are estimated using Bank-Branch panel data. ND Level 1, ND Level 2, and ND Level 3 are binary variables that take the value one when a latitude-longitude pair experiences a level 1, level 2, and level 3 natural disaster in a year, and zero otherwise, respectively. Standard errors clustered at latitude-longitude level are reported in the parenthesis. The sample period spans from year 2000 to 2012.

| *Dependent variable:* | Log(1 + R&D Expense) | |
|---|---|---|
| | (1) | (2) |
| EW Interest Rate Shock × Natural Disaster Dummy | −0.185 | |
| | (0.323) | |
| LOW Interest Rate Shock × Natural Disaster Dummy | | −0.301 |
| | | (0.295) |
| Firm Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Observations | 16,125 | 16,125 |

Table 6: Effect of natural disaster on R&D investments

*Notes:* The table reports the estimated coefficients of (8). Every column reports a separate linear regression. In all columns natural logarithm of one plus total R&D expense, which is estimated at firm level, is dependent variables. Natural Disaster Dummy is a binary variable that takes the value one if a latitude-longitude pair experiences a natural disaster in a year and zero otherwise. EW Interest Rate Shock (LOW Interest Rate Shock) is a continuous variable that is estimated by first predicting the average change in equally weighted interest rate (loan outstanding weighted interest rate) given a branch is exposed to natural disaster using Eq. (6), and then estimating the market share weighted average interest rate change at each latitude-longitude pair (see Eq. (7)). Standard errors are reported in the parenthesis. The sample period spans from year 2000 to 2012.

| *Dependent variable:* | Log(1 + Night Light) | |
|---|---|---|
| | (1) | (2) |
| EW Interest Rate Shock × Natural Disaster Dummy | −0.060 | |
| | (0.286) | |
| LOW Interest Rate Shock × Natural Disaster Dummy | | −0.093 |
| | | (0.288) |
| Lat-Long Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Observations | 4,633 | 4,633 |

Table 7: Effect of natural disaster on real activity

*Notes:* The table reports the estimated coefficients of Eq. (9). Every column reports a separate linear regression. In all columns natural logarithm of one plus night light, which is estimated at latitude-longitude pair each year is dependent variables. Natural Disaster Dummy is a binary variable that takes the value one if a latitude-longitude pair experiences a natural disaster in a year and zero otherwise. EW Interest Rate Shock (LOW Interest Rate Shock) is a continuous variable that is estimated by first predicting the average change in equally weighted interest rate (loan outstanding weighted interest rate) given a branch is exposed to natural disaster using Eq. (6), and then estimating the market share weighted average interest rate change at each latitude-longitude pair (see Eq. (7)). Standard errors are reported in the parenthesis. The sample period spans from year 2000 to 2012.

# A Appendix - Figures and Tables

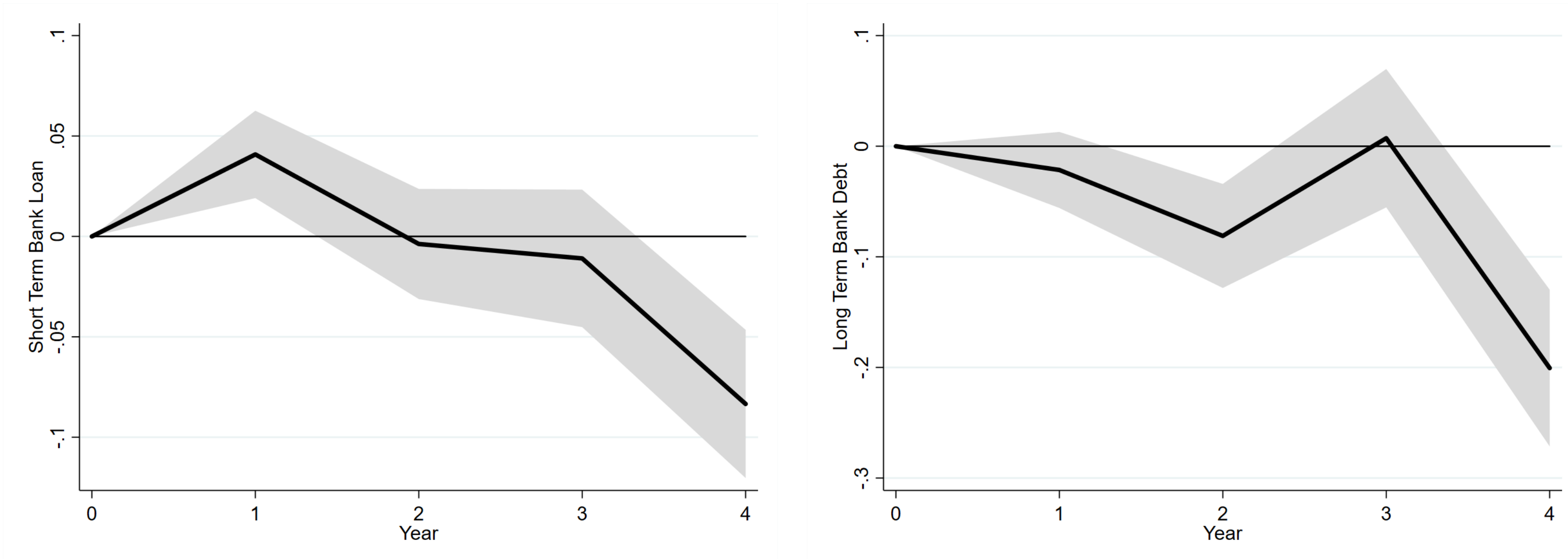



Figure A1 : Response of firm level total short and long term bank debt to natural disaster

*Notes:* These figures show the impulse response obtained from Eq. (5). The shaded regions indicate the 90 percent confidence intervals. Panel (a) and (b) show the cumulative change in natural logarithm of total short and long-term bank debt, respectively after the occurrence of natural disaster. The variable is estimated using firm-level panel. The sample period spans from 2000 to 2012.

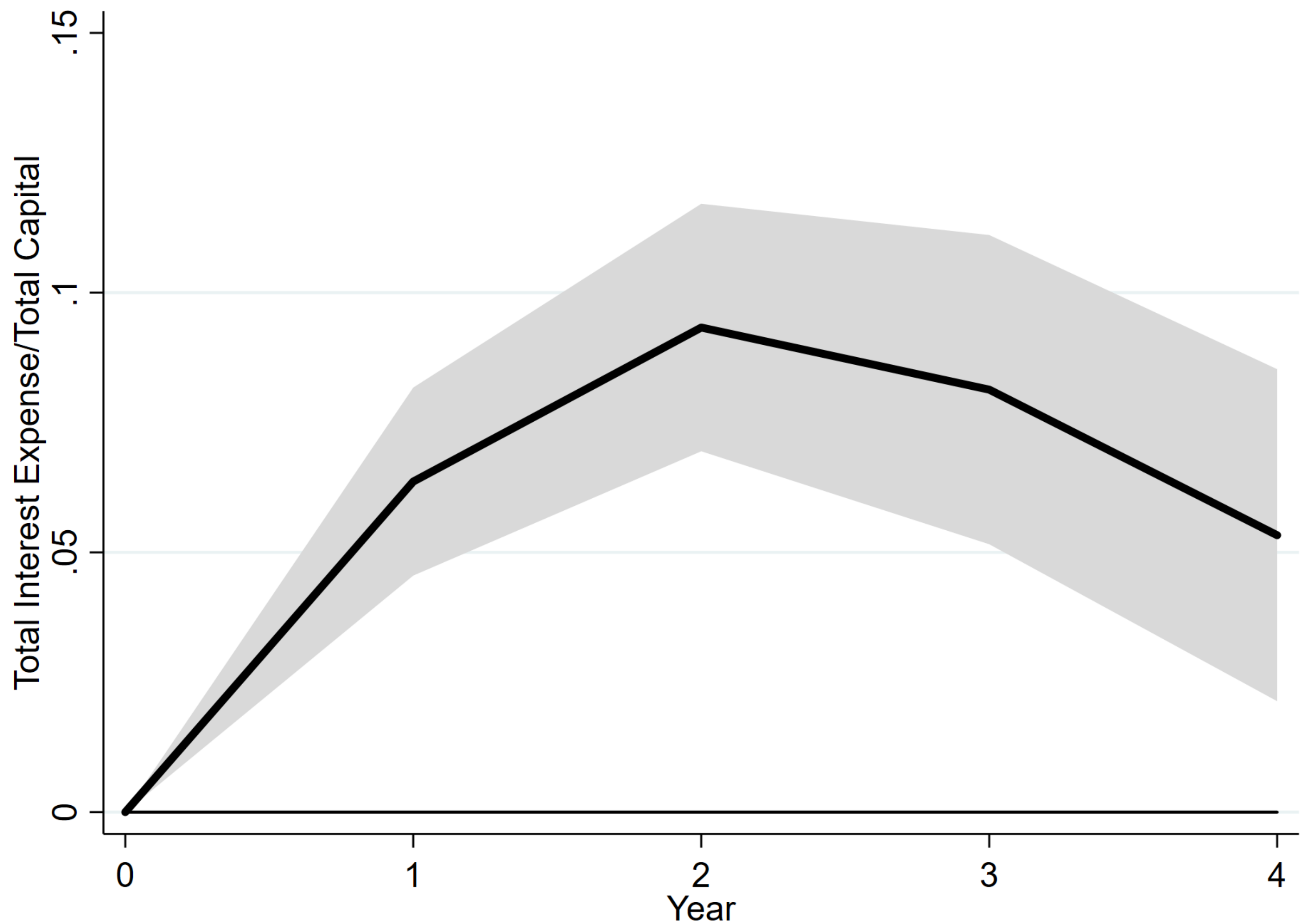



Figure A2 : Response of firm level total interest expense/total capital to natural disaster

*Notes:* The figure shows the impulse response of total interest expense/total capital after the occurrence of natural disaster obtained from Eq. (5). The shaded regions indicate the 90 percent confidence intervals.The variable is estimated using firm-level panel. The sample period spans from 2000 to 2012.

| *Dependent variable:* | Log(Equally Weighted Loan Rate (bps)) | | | Log(Loan Outstanding Weighted Loan Rate (bps)) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Natural Disaster Dummy | 0.001 | 0.003 | 0.003 | 0.001 | 0.003 | 0.003 |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| Year Fixed Effects | Yes | Yes | No | Yes | Yes | No |
| Branch Fixed Effects | Yes | No | No | Yes | No | No |
| Bank Fixed Effects | No | Yes | No | No | Yes | No |
| Bank-Year Fixed Effects | No | No | Yes | No | No | Yes |
| Observations | 884,632 | 883,778 | 884,632 | 884,632 | 883,778 | 884,632 |

Table A1 : Impact of natural disaster on loan rate (without rainfall shock)

*Notes:* The table reports the estimated coefficients of Eq. (1) for a subsample of observations after removing latitude-longitude pair that experienced both natural disaster and rain fall shock in the same year. Every column reports a separate linear regression. In columns (1) to (3) and (4) to (6) natural logarithm of equally weighted loan rate (bps) and loan outstanding weighted loan rate (bps) are dependent variables, respectively. Both the variable are estimated using Bank-Branch panel data. Natural Disaster Dummy is a binary variable that takes the value one if a latitude-longitude pair experiences a natural disaster in a year and zero otherwise. Standard errors clustered at latitude-longitude level are reported in the parenthesis. The sample period spans from year 2000 to 2012.

| *Dependent variable:* | Log(Equally Weighted Loan Rate (bps) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Mkt Share | 0.033 | 0.123 | 0.124 |
| | (0.010) | (0.015) | (0.015) |
| Year Fixed Effects | Yes | Yes | No |
| Branch Fixed Effects | Yes | No | No |
| Bank Fixed Effects | No | Yes | No |
| Bank-Year Fixed Effects | No | No | Yes |
| Observations | 911,238 | 910,384 | 911,238 |

Table A2 : Relationship between market power of branch and loan rate

*Notes:* The table reports the estimated coefficients of regression equation mentioned below:

$$Y_{i,b,lt,lo,t} = \beta \ MktShare_{lt,lo,t-1} + \gamma_i + \delta_t + \epsilon_{i,b,lt,lo,t} \tag{10}$$

where, $Y_{i,b,lt,lo,t}$ represents a vector of dependent variables for branch $i$ of bank $b$ at latitude $lt$ and longitude $lo$ reported in year t, which in this is natural logarithm of equally-weighted ($Log(Equally\ Weighted\ Loan\ Rate)$). Every column reports a separate linear regression. The variable is estimated using Bank-Branch panel data. Mkt Share is the market share of a branch estimate as the ratio of branchs' total credit outstanding and total credit outstanding at latitude-longitude pair. $\gamma_i$ and $\delta_t$ are branch and year level fixed effects. In alternate specifications, we also use bank and bank-year level fixed effects to control for bank and bank-year specific factors. Standard errors clustered at latitude-longitude level are reported in the parenthesis. The sample period spans from year 2000 to 2012.

## B Data Construction

In this section, we explain the steps followed to construct the data. As stated we use data from five different sources to construct the two panels; bank-branch and firm-level panels. The primary analysis unit is $1^0 \times 1^0$ latitude longitude pair.

For branch-level financial outcome data, we use the "directory of bank branches" file available on RBI's website to get information about a unique branch code, the physical address, and the corresponding financial year. Next, we parse the pincodes of each branch and replace a few wrong pincodes with correct ones using the given address by deploying "geopy" python library. Once we have the correct pincode of each branch, we match the pincodes to the latitude and longitude. For that, we use the "geopy" library and did an automated search on "https://www.mapmyindia.com" API section using the scrapping script that gives us the latitude longitude of each branch in our dataset. We merge natural disaster data downloaded from the website of the Center for Research on the Epidemiology of Disasters (CRED) Emergency Events Database (EM-DAT) by using latitude and longitude information available in the dataset at $1^0 \times 1^0$ level. Specifically, we use latitude-longitude-year to identify branches that are exposed to natural disasters in a given year.

For rainfall shock data, we use monthly rainfall data available at latitude and longitude levels. Next, we use the python library "pgeocode" to decode the latitude and longitude corresponding to India. The rainfall shock data available at the latitude-longitude level is then matched to the branch level data using latitude, longitude, and year. For nightlight data, we first fetch data by address. Thereafter, we follow a similar process as done in the case of bank branches; use "geopy" python library to match the address to correct pincodes and a similar automated search to get latitude and longitude.

Lastly, to create our firm-level panel we download pincodes of the firms' registered office from CMIE $Prowess_{dx}$. Next, as done in the previous cases we match pincodes to the respective latitude-longitude level and then use latitude, longitude, and year to identify firms that are exposed to natural disasters in a year.