



**Economic Honors Dissertation**

*Impact of Natural Disasters on Financial Development:*

*Evidence from Indian States*

**Arjun Grover**

Assisted & mentored by

Prof. Yashobanta Parida

FLAME University

6<sup>th</sup> May, 2022

## The Authors

The author is a student studying at FLAME University - Arjun Grover (Economics Honours). This paper is a final submission as a part of the honours thesis dissertation.

## Acknowledgements

I would like to acknowledge Prof. Yashobanta Parida for his support and guidance through the course of this research project. His prior research in this field coupled with the passion and fervour with which he teaches has been an invaluable contribution. I would also like to acknowledge all my professors over the course of my economics degree, who have taught me different aspects of this subject, dealt with my questions and doubts with patience and respect – and most of all have been a guiding light in my academic journey. A special thank you to Prof. Reshmi Sengupta & Prof. Debasis Rooj for teaching me the very basics of econometrics & data analysis.

## Keywords

Natural disasters, economic development, financial development, floods, banking

## Bibliographical Information

Grover, A. (May 2022). Impact of Natural Disasters on Financial Markets: Evidence from Indian States. India, FLAME University.

## **Abstract**

This paper focuses on the impact of natural disasters on financial development from both a short-term and long-term perspective – taking evidence from Indian states. An empirical study – it uses the Credit-Deposit Ratio as a proxy for financial development (national and agricultural) and uses flood damage data from India as a proxy for natural disasters. The study finds that the national CDR is negative (decreases) over the long run, thereby implying relatively poor credit growth compared with deposit growth. This slows down financial development. On the other hand, the agricultural CDR is positive (increases) over the long run, thereby implying a slightly faster pace of financial development. The short-term findings of this study are inconclusive due to varying results across different Indian states.

## Table of Contents

	Topic	Page No.
i.	<a href="#">List of Abbreviations</a>	5
ii.	<a href="#">List of Figures &amp; Tables</a>	6
1	<a href="#">Introduction</a>	7
2	<a href="#">Review of Literature</a>	13
3	<a href="#">Research Objectives</a>	19
4	<a href="#">Data Description &amp; Research Methodology</a>	20
5	<a href="#">Empirical Model</a>	24
6	<a href="#">Results: OLS Model</a>	26
7	<a href="#">Trend Analysis: Further Discussion from OLS Results</a>	30
9	<a href="#">Conclusion (Limitations, Findings &amp; Policy)</a>	34
iii.	<a href="#">References</a>	37
iv.	<a href="#">Appendix</a>	40

## **List of Abbreviations**

RBI Reserve Bank of India

CDR Credit-Deposit Ratio

GDP Gross Domestic Product

GSDP Gross State Domestic Product

SCB Scheduled Commercial Banks

RRB Regional Rural Banks

CWC Central Water Commission

PCI Per-Capita Income

NPA Non-Performing Assets

## List of Figures & Tables

### List of Figures

Figure 1: Average flood fatalities per million population over 1980-2011.....	9
Figure 2: Average state-wise damage over GSDP from 2001-2019.....	10
Figure 3: Average state-wise population affected per million from 2001-2019.....	11
Figure 4: Average state-wise CDR (%) from 2001-2019.....	12
Figure 5: Trend Analysis of Kerala CDR over a period of 2004 to 2021.....	32
Figure 6: Trend Analysis of Gujarat CDR over a period of 2004 to 2021.....	33
Figure 7: Average state-wise area affected per million hectares from 2001-2019.....	40

### List of Tables

Table 1: Descriptive Statistics.....	22
Table 2: Regression Tests.....	26
Table 3: OLS Regression Results.....	27
Table 4: <i>Credit-Deposit Ratios of Kerala &amp; Gujarat</i> .....	30
Table 5: Endogeneity Test Results.....	42

## Introduction

Businesses and homeowners in India are experiencing increasingly frequent and severe natural disasters. Reviving economic growth in areas hit by natural disasters often relies on bank lending due to the incompleteness of insurance markets. This raises the question: who continues to lend in the aftermath of a disaster?

We conjecture that banking market structure plays a key role in determining the rate of economic recovery from a disaster. Banks – play a particularly important role in the process of economic recovery from natural disasters. When banks suffer physical or capital damage as a result of a natural disaster, they may not be able to provide sufficient funds at the same interest rates as before. In frictionless financial markets, firms should be able to offset such a negative shock to their funding by switching from a damaged to an undamaged bank, or raising funds from the financial markets. In practice, however, switching may involve substantial costs or time due to the role played by private information on customers' creditworthiness, potentially making it difficult for users to obtain funds from alternative sources in a timely and cost-efficient manner.

While there is a considerable body of literature examining banks' role in providing funding during normal times and times of financial crisis, there are relatively few studies that examine how impairment of banks' functioning in the wake of a natural disaster affects economic activity. The aim of this thesis paper is to examine the impact of such on banks failures, focusing on credit-deposit rate, lending & borrowing. Moreover, this area of focus has not been covered with emphasis on India.

In this thesis, we have chosen floods as our proxy for natural disaster. This has been for the following main reasons:

- Floods are the most frequent & impactful natural disasters occurring in India;
- Floods are the most financially damaging disaster in India;
- Flood data is more widely available in India.

### **Flood Profile of India**

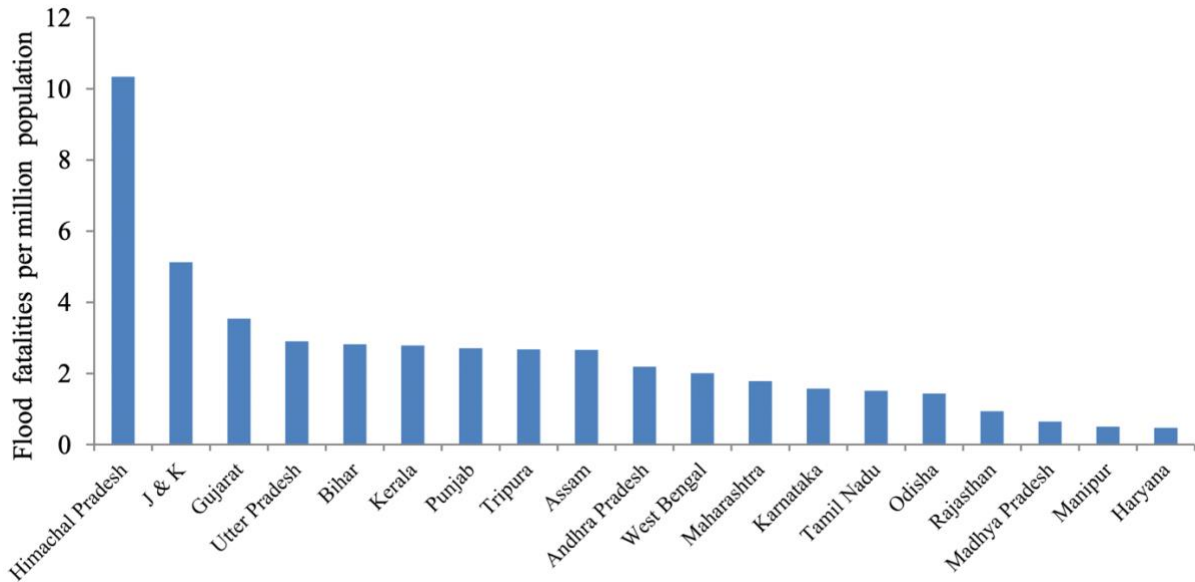
India is one of the most flood-affected nations globally after China (Emergency Events Database, EM-DAT). India's geo-climatic conditions have caused higher flood fatalities and damages. Other factors such as high-risk flood-prone areas, irregular rainfall, higher population density, deforestation, illegal constructions, and environmental degradation, too, have contributed to increasing flood damage in Indian states. According to EM-DAT, 194 floods occurred in China, the highest, followed by India (190), Indonesia (126), Philippines (109), and Bangladesh (69) over the period 1980-2011 (Parida, 2019).

The cumulative frequency of natural disasters in India was 53 per cent for floods, followed by cyclones (21 per cent), landslides (10 per cent), cold wave conditions (6.4 per cent), earthquakes (4.2 per cent), and droughts (2 per cent) over the same period. Floods have been reported as India's costliest disaster accounting for 68 per cent of economic losses, besides being the second most lethal disaster after earthquakes (Parida, 2019).

Recurrent floods adversely affect both household socioeconomic conditions and economic development directly and indirectly. Floods contribute to an imminent loss of human lives, disruption to public utilities, and crop damage. India lost around 0.46 per cent of gross domestic



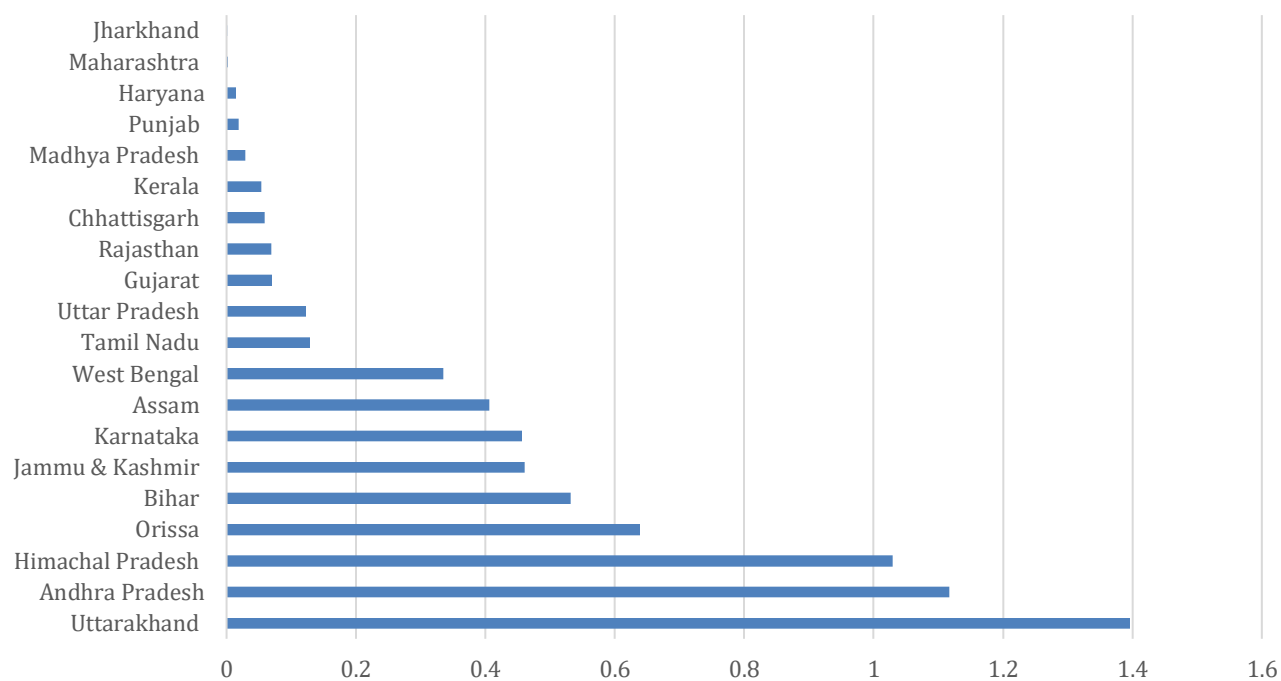
product (GDP); crop damage was around 0.18 per cent of GDP, 1.6 million houses were damaged, damage to public utilities occurred at around 0.21 per cent of GDP, and 6 per cent of the rural population was affected due to floods annually (Parida and Dash, 2019; Parida et al., 2020b).



**Figure 1:** Average flood fatalities per million population over 1980-2011

Source: (Parida, 2019)

### Average Damage over GSDP: 2001 to 2019



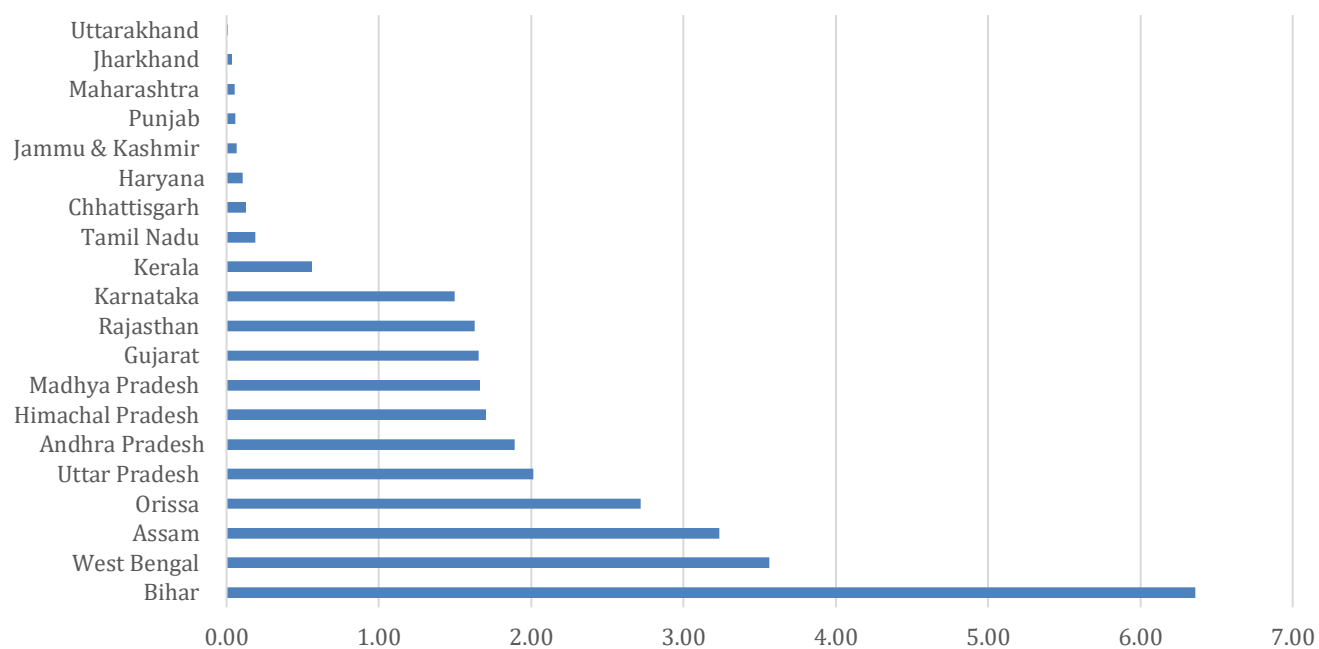
**Figure 2:** Average state-wise damage over GSDP from 2001-2019

Source: Author's Calculation

Uttarakhand and Andhra Pradesh have been the most affected Indian states, whereas Jharkhand and Maharashtra have been least affected when we look at average damage over GSDP over an 18-year period.

Damage over GSDP has been calculated by dividing the overall damage in lakhs (Rs.) by the overall by the current GSDP also in lakhs (Rs.).

### Average Population Affected per Million: 2001 to 2019



**Figure 3:** Average state-wise population affected per million from 2001-2019

Source: Author's Calculation

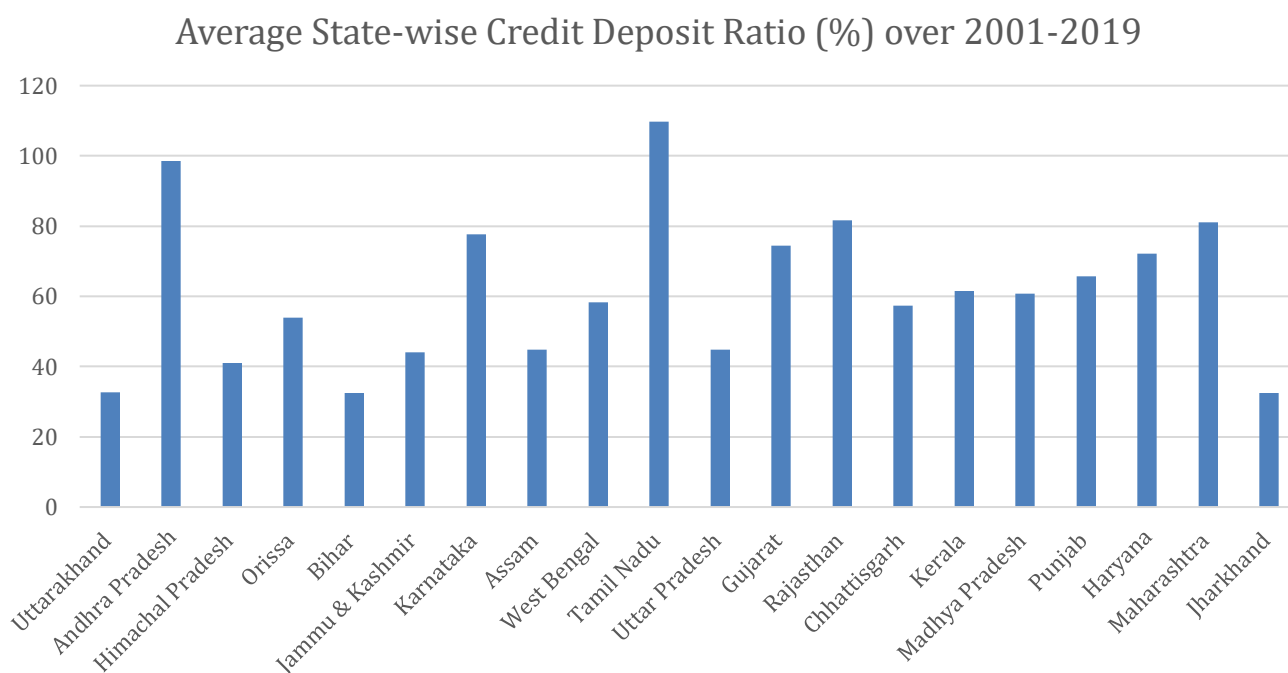
In terms of average population per million affected by the impact and damage of floods, Bihar is at an overwhelming 6.3 while the next closest are West Bengal & Assam at 3.5 & 3.25 respectively. Interestingly, Uttarakhand which is the most affected state in damage over GSDP has an extremely low population affected.

The graph for average area affected per million hectares (Appendix 1) also follows the same pattern as Figure 3 above.

## Financial Development in India

In order to capture a complete picture, we need to consider different aspects of financial development, for instance, whether the financial sector is dominated by banks or the stock market or both. However, our prime objective is to investigate the long-run relationships. This is why we look at regression data over a time-span of approximately 18 years. Therefore, we use bank-based financial proxies due to the unavailability of long-span time series data for the stock market.

The bank based financial proxy we have chosen is the **State-wise Credit Deposit ratio** - which tells us how much of the money banks have raised in the form of deposits has been deployed as loans.



**Figure 4:** Average state-wise CDR (%) from 2001-2019

Source: Indiatat (2022)

## Review of Literature

Since our thesis majorly focuses on "Financial Development" as a whole – we identified the fact that financial development comes perfectly in the middle of two polarising terms: Economic Development (broad) & banking (narrow).

Thus, we utilise a broad to narrow approach to conduct our literature review because it is important to gain thorough insight from a larger economic point of view as well as a more specific bank-based approach as our research focuses on Indian states.

*(Parida & Dash, 2019)* evaluated the effect of floods and the role of financial development on per capita gross state domestic product (GSDP) growth, controlling for growth-enhancing factors across Indian states. The paper uses the pooled mean group (PMG) method using state-level panel data for 19 Indian states over the period 1981-2011. The PMG estimate shows that floods (effect of floods on the mean of economic losses, population affected & area affected) negatively affect the per capita GSDP growth in the long run. The paper also finds that Indian states with better financial development experience a higher per capita GSDP growth, supported by additional capital expenditure, enrolment in higher education, better road infrastructure and higher urbanization. This paper will be a valuable reference for my thesis as it is the only other paper that focuses on an Indian perspective.

*(Botzen et al, 2019)* found that economic losses from natural disasters have been increasing in recent decades. This has been attributed mainly to population and economic growth in disaster-prone areas. Future natural disaster losses are expected to increase due to a continued increase in economic exposure and climate change. A rapidly expanding literature has estimated the direct

(e.g., property damage) and indirect (e.g., gross domestic product growth, trade) economic impacts of natural disasters. This article reviews this emerging literature. Based on 25 primary studies, they conclude that natural disasters have a significant negative effect on growth, an effect that increases over time and is strongest for climatic disasters in developing countries. Moreover, there are significant short-run declines in economic growth for climatic and geological disasters for which long-run effects are insignificant. Being a developing country, India becomes an interesting analysis because most studies point towards a long-run negative impact while this study confirms our initial hypothesis.

(Klomp, 2016) studied data based on satellite images of the night-time light intensity in a specific country or region which is shown to be highly correlated with income per capita. After testing for the sensitivity of the results, the main findings of the study suggests that natural disasters reduce the amount of lights visible from outer space significantly in the short run. However, in the long run most of the disaster effect has disappeared. Finally, the impact of a disaster depends partly on the size and scope of the natural catastrophe, the geographical location, the degree of financial development of a country and the quality of the political institutions present.

*(Keerthiratne et al, 2017)* estimates the impact of natural disasters on financial development proxied by private credit. They employ country level panel data set of natural disasters and other economic indicators covering 147 countries for the period from 1979 to 2011 - finding that companies and households get deeper into debt after a natural disaster. This effect is stronger in poorer countries whilst the effect is weaker in countries where agriculture is more important. However, it is important to note that private credit is only one dimension of financial

development and financial markets are less well developed in poor countries which are more vulnerable to disasters such as India. Thus, the immediate impact of natural disasters is better interpreted as households getting (further) into debt rather than as financial development, but the longer term impacts indicate an expansion of credit availability (positive).

*(Zhang et al, 2020)* studied pacific small island states and investigated how natural disasters affect sustainable development in these states, with a highlight on the role of financial development in alleviating the negative impacts of natural disasters on the local economic growth. Using natural disasters as an exogenous variable, they empirically estimate the direct and indirect roles of financial development on these states and explicitly distinguish the economic effects from a battery of measures of financial development. They find that natural disasters impose substantial negative impacts on economic growth in this region in the short-run.

*(Khan et al, 2019)* set out with an objective to examine the impact of natural disasters on external migration, price level, poverty incidence, health expenditures, energy and environmental resources, water demand, financial development, and economic growth in a panel of selected Asian countries for a period of 2005–2017. The results find that natural disasters in the form of storm and flood largely increase migration, price level, and poverty incidence, which negatively influenced a country's economic resources, including enlarge healthcare expenditures, high energy demand, and low economic growth. This study failed to provide any evidence on short or long run impact.

*(Klomp, 2014)* use data for more than 160 countries in the period 1997–2010 to explore the impact of large-scale natural disasters on the distance-to-default of commercial banks. The financial consequences of natural catastrophes may stress and threaten the existence of a bank by

adversely affecting their solvency. After extensive testing for the sensitivity of the results, the main findings of the study suggest that natural disasters increase the likelihood of a banks' default. More precisely, it concludes that geophysical and meteorological disasters reduce the distance-to-default the most due to their widespread damage caused. In addition, the impact of a natural disaster depends on the size and scope of the catastrophe, the rigorous-ness of financial regulation and supervision, and the level of financial and economic development of a particular country. This is an extremely important insight as how each state in India is equipped to not just handle, but recover from certain natural disasters such as floods or cyclones will greatly affect its financial development.

**(Duki et al, 2021)** state the assumption that following a natural disaster, the rate of economic growth recovers faster in less competitive banking markets. A 10% reduction in competition increases the rate of economic growth by 0.3%. In less competitive markets, banks respond to a disaster by increasing the supply of real estate credit by refinancing mortgage loans, but do not lend more to businesses or consumers. Instead, government agencies provide disaster loans to affected businesses and households. This introduces the concept of governance structures and political factors that also attribute to the financial development of a country. This is particularly important in the case of a centre-state democracy like India – which will further be explored in this thesis.

**(Strobl et al, 2019)** constructed a panel of quarterly banking data and historical losses due to hurricane strikes for islands in the Eastern Caribbean to econometrically investigate the impact of these natural disasters on the banking industry. The results suggest that, following a hurricane strike, banks face deposit withdrawals and experience a negative funding shock to which they



respond by reducing the supply of lending and by drawing on liquid assets. There are no signs of deterioration in loan defaults and bank capital. Therefore, the withdrawal and use of deposits rather than an expansion in credit appears to play a significant role in funding post hurricane recovery in the region. This paper is contradictory to an earlier paper by Keerthiratne & Tol – where credit expansion does not seem to play a significant role in post-disaster recovery.

*(Cortés et al, 2017)* **find that** multi-market banks reallocate capital when local credit demand increases after natural disasters. Using property damage as an instrument for lending growth, the authors find credit in unaffected but connected markets declines by a little less than 50 cents per dollar of additional lending in shocked areas. However, banks shield their core markets because most of the decline comes from loans in areas where banks *do not* own branches. Moreover, banks increase sales of more-liquid loans and they bid up the rate on deposits in the connected markets. These actions help lessen the impact of the demand shock on credit supply.

A major trend across most of the studies we have reviewed is that the immediate impact after a natural disaster is presumably and rightfully negative. The financial development aspect of a state/country economy is also hindered in the short-run, and all studies empirical and qualitative in nature agree with the same consensus. While our initial hypothesis based on preliminary research is that we expect positive financial development in the long run based on cost efficiency in businesses & households due to damage - leading to faster recovery & higher economic growth due to credit availability, the study by (Brie, Mohan & Strobl 2019) indicated that this long-run positive growth doesn't actually have much significance with regards to credit availability. Instead, it seems to be geared more towards the withdrawal and use of deposits at banks. Thus, it is my hope through the empirical nature of this thesis to explore the same. The

other interesting factors that have come up during this literature review is the distinction between rural and urban. In a country like India, where Agriculture accounts for over 40% of total employment – it is extremely important to consider different levels of households and firms (for example – MSME's vs Large Organizations). The major gap of our literature review is again India specific factors such as Migration, Urbanization, Forest Land Cover etc. as well as the nature of governance in India as discussed earlier. Due to the democratic nature of governance and the state-centre divide, certain states are better/worse prepared to deal with the economic implications of a natural disaster. However, we will account for the agricultural nature of India's economy in our regression analysis.

## **Research Objectives**

We specify our research study by looking at natural disasters data from India with a focus on damage due to floods. In order to capture a complete picture in India, we need to consider different aspects of financial development, for instance, whether the financial sector is dominated by banks or the stock market or both. However, our prime objective is to investigate the long-run relationships. Therefore, we use bank-based financial proxies due to the unavailability of long-span time series data for the stock market. Thus, we utilize the Credit-Deposit Ratio of Indian banks as our key dependent variable.

Immediate impact increases fiscal pressure on the government through the banks due to outstanding credit loans - is this positive or negative in the long run? Economic downturns lead to cost efficiency in businesses & households - leading to faster recovery & higher economic growth due to credit availability. What is the growth scenario pre-post disaster across Indian states and does it correlate with credit availability is another key question this thesis hopes to explore.

## **Research Gap**

The research gaps this paper seeks to explore is the impact of natural disasters on financial development specifically from an Indian perspective, using data from Indian states over an 18 year time period.

## **Data Description & Research Methodology**

### **OLS Regression**

The empirical study uses data from 20 different Indian states (where more than 95% of natural disasters have taken place in India) over a time period of 2001 to 2019. The data has been compiled into panel series data and statistical analysis has been done using STATA software.

The state-wise flood data used in this study were obtained from the Central Water Commission (2012) report. This dataset provides different flood disaster-related information such as area affected, the population affected, the number of human lives lost, the number of houses damaged and economic losses due to floods.

However, in the CWC dataset, some information is missing. For instance, data on human lives lost are reported for some states for the respective years, but other variables such as area affected and population affected by floods are not reported. To account for the missing data, we have used the DFO and Emergency Events Database (EM-DAT). Also, there are cases of missing observations for the two important outcome variables – flood fatalities and damages due to floods in the CWC dataset. For the flood fatality variable, we matched only an 8 per cent sample of the CWC dataset with the DFO and EM-DAT dataset. Similarly, for the damages due to floods variable, only 6 per cent of the observations of the CWC dataset were matched with the DFO and EM-DAT dataset.

Concerning various explanatory variables used in our study, the gross state domestic product (GSDP), both at current and constant prices, is available from the Ministry of Statistics and Program Implementation, Government of India (GoI). The government total expenditures are

taken from the various volumes of State Finance Reports published by the Reserve Bank of India. The state-wise total population, literate population, and adult population data are taken from various census years, such as 2001 and 2011. The state-wise total populations, literate population, and adult population are linearly interpolated for the years when no census was conducted.

The main proxy for financial development has been chosen as the state wise credit-deposit ratio – the data for which has been obtained from the Indiastat data source website. In order to account for the developing nature of India's economy, it is important to take into consideration that agriculture contributes to a major part of the rural India economy. Thus, we have taken credit to agriculture as an additional dependent variable in one of our multiple linear regression models to see the effect on smaller, rural banks in agriculture dominated states.

The main independent variable – total damage over gross state domestic product – includes the damages to crops, damages to housing & physical structures, damage to public utility & overall monetary value damage.

In order to obtain a more thorough view considering the lack of availability in data for other control variables, we have included other independent variables such as total area affected by damage as well as total population affected by damage. This data has also been obtained from the CWC.

## Trend Analysis

To further confirm the results of our empirical model, we look at state-wise Credit-Deposit Ratio data from specific high flood prone states across two banking segments: Scheduled Commercial Banks & Regional Rural Banks to ascertain the short term/immediate impact on banks in the aftermath of a major natural disaster. This data has been obtained from the Handbook of Indian Statistics, published by the Reserve Bank of India for the year 2021.

**Table 1:** Descriptive Statistics

Variable	No. of Observations	Mean	Standard Deviation	Definition
statewisecdr	380	61.25447	23.44746	Credit-Deposit Ratio (%)
agricredit	380	52.66	28.776	Credit to Agriculture (%)
popaffmill	380	1.478216	3.408481	Total Population affected by disaster
Totaldamage*	380	820.2122	3310.976	Total damage inclusive of damage to crop,

				building & public utility
damageovergsdp	380	0.3492285	1.585827	Total damage divided by the current GSDP
govexp	380	15.75405	4.909647	Total government expenditure due to damage as percentage of GSDP
lnpop	380	17.56836	0.8436779	Log of total population
lnareaaffected	380	0.169362	0.358524	Log of the total area affected by disaster
lnpci	380	11.04553	0.5508358	Log of per capita income

*Source: Authors' Calculation*

*\*Not included in the actual regression model.*

## Empirical Model

For the empirical model, the **OLS regression** model has been used to understand the effect of the above mentioned variables and impact of natural disasters on financial development.

Therefore, the focus Y variable is ‘statewisecdr’ and the focus X variables are ‘damageoverGSDP’ ‘popaffectedmil’ & ‘lnareaaffected’. The other control variables have been included based upon existing literature and the hypothesis of the study. Moreover, it is essential to consider that the inclusion of too many independent variables can cause overfitting within the model, causing undesirable results. As Prof. Jeffrey Wooldridge noted, over specifying a model can exacerbate multicollinearity problems, decrease the efficiency of estimators, and result in increased variance of estimators.

## Regression Models

### SLR1

$$statewisecdr = \beta_0 + \beta_1 damageovergdp + u.$$

### MLR1

$$statewisecdr = \beta_0 + \beta_1 popaffectedmil + \beta_2 lnpop + \beta_3 lnpci + \beta_4 govexp + u.$$

### MLR2

$$statewisecdr = \beta_0 + \beta_1 lnareaaffected + \beta_2 lnpop + \beta_3 lnpci + \beta_4 govexp + u.$$

### MLR3

$$agricdr = \beta_0 + \beta_1 lnareaaffected + \beta_2 lnpop + \beta_3 lnpci + \beta_4 govexp + u.$$



**Primary Hypothesis:** The negative short-run impact of natural disasters may lead to overall reduction in the pace of financial development due to the creation of NPA's. With an agricultural economy like India, the post-disaster recovery may lead to increased credit that could influence economic growth & financial development (heavy expenditure on infrastructure).

**Secondary Hypothesis:** The increased demand for loans is likely to be a factor. Households and businesses may need credit for rebuilding or to smooth out temporary income disruptions. In addition to alleviating the disaster impacts on borrowers, new "recovery" lending may help offset losses on loans already on the books of banks. Thus, we are likely to see a different in outcomes when comparing overall CDR versus agricultural CDR.

## Results

The results obtained after running the OLS regression are given in Table 3. The tests conducted on our regression model have been summarized in Table 2. On running the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity, a p-value of 0.000 was obtained for all our regression models. Due to the presence of heteroskedasticity, robust regression were run on the model to control for it. The OLS models used passed the Variance Inflation Factor (VIF) Test for collinearity. On running the Ramsey RESET test for omitted variable bias, none of our regression models were observed to have any omitted variable bias. The kdensity test conducted on our regression residuals are approximately normal and fit the assumption of normality (Appendix 2) for all our MLR models. We also conducted the Durbin–Wu–Hausman test for endogeneity and concluded that our regression models were endogenous in nature (Appendix 3).

**Table 2:** Regression Tests

<b>ovtest   <math>H_0</math>: model has no omitted variables   Omitted Variable Bias Test</b>		
<b><i>Model</i></b>	<b><i>Prob &gt; F</i></b>	<b><i>Conclusion</i></b>
SLR1 (Robust)	0.4539	Fail to reject $H_0$
MLR 1(Robust)	0.1173	Fail to reject $H_0$
MLR2 (Robust)	0.1103	Fail to reject $H_0$
MLR3 (Robust)	0.1101	Fail to reject $H_0$
<b>vif   Variance Inflation Factor Test for Collinearity</b>		

<i>Model</i>	<i>Mean VIF</i>	<i>Conclusion</i>
SLR1 (Robust)	-	-
MLR 1(Robust)	1.33	No multicollinearity
MLR2 (Robust)	1.33	No multicollinearity
MLR3 (Robust)	1.73	No multicollinearity

*Source: Authors' Calculation*

**Table 3: OLS Regression Results**

<b>Variables</b>	<b>SLR1: Regressing statewiseCDR (Robust)</b>	<b>MLR1: Regressing statewiseCDR (Robust)</b>	<b>MLR2: Regressing statewiseCDR (Robust)</b>	<b>MLR3: Regressing agricredit (Robust)</b>
damageovergsdp	-0.4941 (0.5363)	-	-	-
popaffectedmil	-	-0.5051** (0.2209)	-	-
lnareaaffected	-	-	-4.4084** (2.859)	0.6740* (0.482)
govexp	-	-0.1746	-0.1877	0.3413***

		(0.2376)	(0.2385)	(0.0509)
lnpop	-	14.8138*** (1.432)	14.886*** (1.441)	2.239*** (0.2375)
lnpci	-	21.8586*** (1.663)	22.083*** (1.656)	4.8871*** (0.304)
<b>_cons</b>	61.4270*** (1.2170)	-436.942*** (38.35)	-440.494*** (38.50)	-95.874*** (7.07)
<b>No. of Obs</b>	<b>380</b>	<b>380</b>	<b>380</b>	<b>380</b>
<b>F(1, 378)</b>	<b>0.85</b>	<b>99.02</b>	<b>98.85</b>	<b>68.84</b>
<b>Prob &gt; F</b>	<b>0.3574</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
<b>R-squared</b>	<b>0.0011</b>	<b>0.4262</b>	<b>0.4254</b>	<b>0.3673</b>
<b>Root MSE</b>	<b>23.465</b>	<b>17.856</b>	<b>17.868</b>	<b>3.1575</b>
<b>Standard Deviations are in parenthesis   Significant at *10%, **5%, ***1%</b>				

*Source: Authors' Calculation*

As visible in Table 3, we begin our analysis with SLR1 - where we find a negative relationship between damage and CDR. From the coefficients observed after running the robust regression, keeping all other factors constant we find that for every unit increase in damageoverGSDP, there is a decrease of 0.4941 units in the credit-deposit ratio. The negative relation is enough to confirm our primary hypothesis that in the long run, the negative CDR leads to relatively poor

credit growth compared with deposit growth. This slows down financial development. However, it is important to notice that this variable is not significant at less than 10%.

Therefore, we build on this theory by replacing our proxy for natural disasters from total damage over GSDP to population affected by natural disasters. In MLR1, we find a negative relationship between  $\text{popaffectedmil}$  &  $\text{statewisecdr}$  - keeping all other factors constant we find that for every unit increase in  $\text{popaffectedmil}$ , there is a decrease of 0.5051 units in the credit-deposit ratio. This relationship is also significant at less than 5%. Meanwhile, the control variables for total population & per capita income display a positive relationship. Highly significant at less than 1%, for every unit increase in total population & PCI, the CDR increases by 14.81 & 21.85 units respectively. Government expenditure when increased by unit drops the CDR by 0.1746 units, but this was also insignificant. The first MLR1 confirms our primary hypothesis, and we build on this foundation by switching out population affected with area affected. Again, we find extremely similar results – hence solidifying our regression results. The models produced an  $R^2$  value of 0.4262 and 0.4254 as well as F-stats at 99.02 and 98.85 respectively, with a  $\text{Prob} > F = 0.000$ , indicating that our models are highly significant.

The third MLR3 model incorporates agricultural credit instead of state wise credit deposit ratio to see if we can mimic the same long run-negative relationship when it comes to rural parts of India where credit is given to agriculture. We find that there is actually a positive relationship between  $\text{agricredit}$  and area affected, where for every unit increase in area affected by damage, the credit to agriculture increases by 0.6740. Moreover, this relationship is significant at less than 10%, which merits further research. Meanwhile, other all control variables also show positive relationships with high significance at less than 10%.

## Discussion – Trend Analysis

Based on the results of our OLS regression, we can statistically confirm our primary and secondary hypothesis. However, our analysis is based on a long term time frame of over 18 years. Thus, it is important to also conduct a thorough analysis of the immediate impact (short-term) and proceed to make a distinction between large, nationalised banks with access to external backing and financial resources as well as regional banks, that may not have the same capacity.

As per our results, the national CDR is negative (reduces) over the long run, thereby implying relatively poor credit growth compared with deposit growth. This slows down financial development. On the other hand, the agricultural CDR is positive (increases) over the long run, thereby implying a slightly faster pace of financial development.

**For this case study, we have taken the flood prone states Gujarat & Kerala – Table 4 below details the year-wise CDR of both SCB's & RRB's for both states. Please note that the highlighted years are important because they directly succeed a major disaster event in each respective state.**

*Table 4: Credit-Deposit Ratios of Kerala & Gujarat*

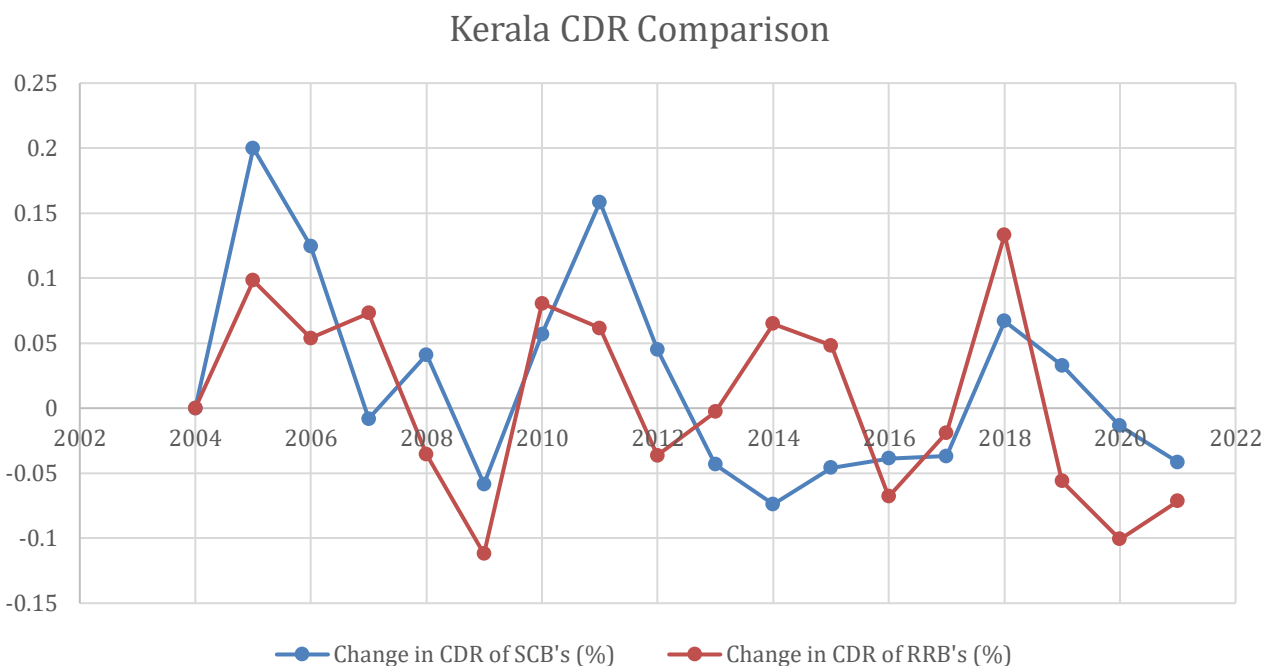
Year	Kerela SCB's CDR	Kerela RRB's CDR	Gujurat SCB's CDR	Gujurat RRB's CDR
2004	45.5	94.6	42.2	45.5
2005	54.6	103.9	46.5	46.4
2006	61.4	109.5	55.6	50.2
2007	60.9	117.5	63.7	54.1

<b>2008</b>	63.4	113.3	66.5	55.1
<b>2009</b>	59.7	100.6	63.7	49.1
<b>2010</b>	63.1	108.7	65.3	46.6
<b>2011</b>	73.1	115.4	66.2	44.3
<b>2012</b>	76.4	111.2	70.4	46.2
<b>2013</b>	73.1	110.9	72.8	52.2
<b>2014</b>	67.7	118.1	74.7	53.7
<b>2015</b>	64.6	123.8	72.7	54.3
<b>2016</b>	62.1	115.4	75.4	56.3
<b>2017</b>	59.8	113.2	68.9	53.9
<b>2018</b>	63.8	128.3	75.6	59.5
<b>2019</b>	65.9	121.1	78.8	61.7
<b>2020</b>	65	108.9	74.8	61.5
<b>2021</b>	62.3	101.1	69.9	61.7

Source: RBI – Handbook of Indian Statistics (2021)

\*Highlighted years indicate years succeeding a major natural disaster over a benchmark of population affected & area affected

The different events that have occurred through the past two decades in Kerala & Gujarat include the 2004 Indian Ocean Floods & Tsunami that inflicted severe damage on both Kerala & Gujarat; 2005 Gujarat floods that left approximately 176,000 people homeless; 2015 Deep Depression Gujarat Cyclone that caused damages of over 70 billion rupees; The 2017 Gujarat monsoon flooding that cause over 300 deaths; the 2018 Kerala floods that killed over 500 people and caused damages in excess of 40,000 crore rupees & the 2019 Kerala floods further exasperated this effect adding on another 300 deaths.



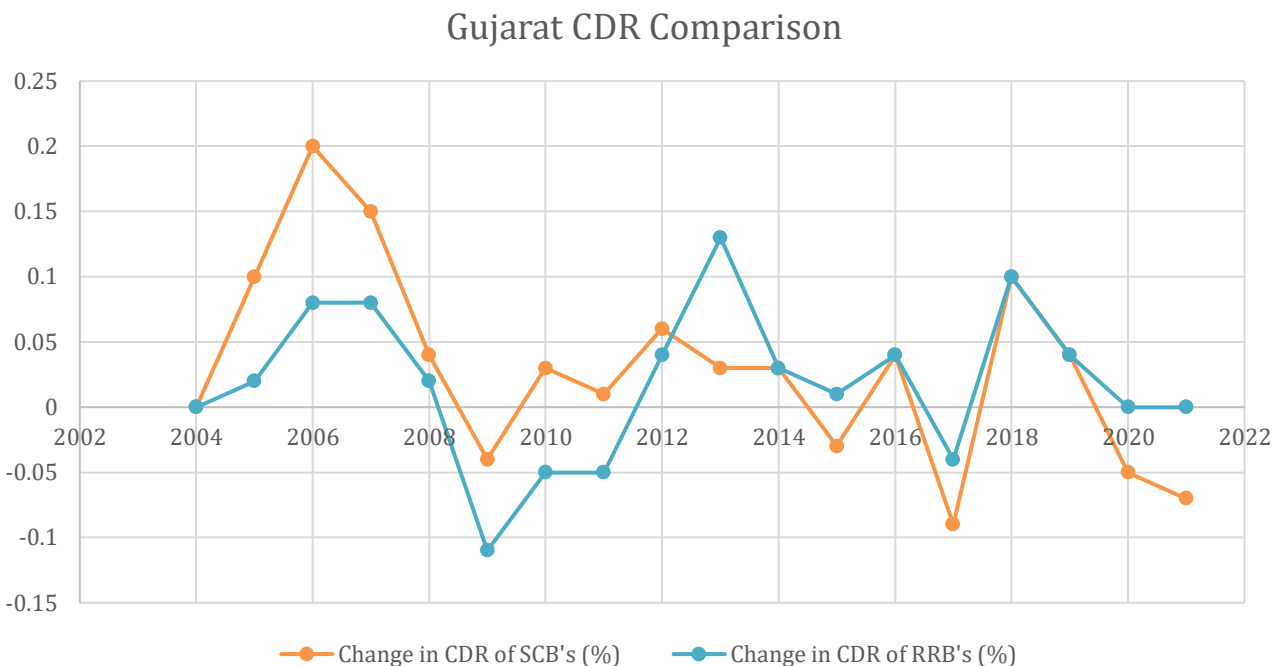
**Figure 5:** Trend Analysis of Kerala CDR over a period of 2004 to 2021

Source: (Handbook of Indian Statistics, 2021)

Observing Kerala, the first major event happens in 2005, proceeding which the CDR of both RRB's and SCB's dips. However, in 2007 – while the CDR continues to dip for RRB's, it starts to climb back up in the case of SCB's – though not yet at the level it used to be. Hence, we see a marginal increase in CDR levels.

Interestingly, when we skip to the next significant levels in 2018, we find extremely intuitive results. By 2018, the CDR rate has been increasing at a steady level, to a point where it eclipses it's previous high. On the other hand, the SCB's are unable to reach back to its initial levels over the long run, briefly touching it's previous high in 2010 and then again marginally in 2018.





**Figure 6:** Trend Analysis of Gujarat CDR over a period of 2004 to 2021

Source: (Handbook of Indian Statistics, 2021)

The first major event takes place in 2004, after which we unexpectedly observe a continuous upward trend in both RRB's & SCB's. Between 2005 and 2007, the change in CDR is positive despite a major tsunami in the Indian Ocean, hinting at mass destruction and perhaps, many loans being taken in order to cope with the financial strain. This case study shows us that perhaps the short-run impact may not always be negative.

Another observation is that over the course of the next decade and a half, we see more positive changes in RRB's, whereas we see more negative changes in SCB's – thereby confirming the results of our empirical analysis regarding long term impact of natural disasters.

## **Conclusion**

### **Limitations**

Before we reach our main conclusions, it is important to acknowledge some of the limitations of our study. The presence of endogeneity in our regression models is a limitation of the study.

Although our model did not have any omitted variable bias, in the presence of endogeneity, OLS can produce biased and inconsistent parameter estimates. Hypotheses tests can be seriously misleading. Although a possible solution would be to use an alternative dependent variable that is exogenous, that may prove a difficult task considering the nature of the study and the lack of available, consistent and accurate data. Therefore, we suggest that an additional model be conducted using instrumental variables (IV) techniques to control for endogeneity.

The second major limitation of the study was the lack of an updated census. Currently, population estimates were calculated using interpolated figures from 2011, but updated estimates would prove useful to not just this study, but any future studies in India to provide more accurate and updated research estimates across a variety of subjects.

Lastly, the damage data for other natural disasters such as earthquakes, draughts & cyclones was limited. Although I began this research study with the hope that I could ascertain the impact of natural disasters on financial development – unfortunately due to a lack of available data – the study was focused on flooding data.

## **Findings**

A major endogenous factor that might mitigate disaster effects on banks is increased demand for loans. Households and businesses may need credit for rebuilding or to smooth out temporary income disruptions. In addition to alleviating the disaster impacts on borrowers, new "recovery" lending may help offset losses on loans already on the books. Consistent with that premise, we find that overall, when we look at CDR across the country – we see a long term negative impact on financial development due to natural disasters. The national CDR is negative (reduces) over the long run, thereby implying relatively poor credit growth compared with deposit growth. This slows down financial development. On the other hand, the agricultural CDR is positive (increases) over the long run, thereby implying a slightly faster pace of financial development.

As we come to the short-run impact – although our hypothesis and literature review believes that the short run impact on both a national as well as rural front would immediately be negative, our trend analysis in Gujarat says the opposite while our trend analysis in Kerala agrees. Thus, we find our study to be inconclusive with regards to the short-term impact of natural disasters on financial development. We believe that with agricultural loans, the short-run impact could perhaps be extremely positive in order to support and alleviate the heavy losses of farmers in rural parts of India.

## **Policy Implications & Recommendations**

Large, nationally operating banks tend to be well diversified both geographically and in terms of their product offerings. Small, locally operating banks, however, are increasingly at risk – particularly if they operate in disaster-prone areas. Current banking regulations generally do not

factor natural disaster risks into their capital requirements. To avoid the next big financial crisis, regulators such as the RBI may want to adjust their reserve requirements by taking this growing risk exposure into consideration – especially in a disaster prone country like India.

## References

- Keerthiratne, Subhani & Tol, Richard. (2017). Impact of Natural Disasters on Financial Development. *Economics of Disasters and Climate Change*. 1. 10.1007/s41885-017-0002-5.
- Zhang, Dayong. (2020). Financial development, natural disasters, and economics of the Pacific small island states. *Economic Analysis and Policy*. 66. 10.1016/j.eap.2020.04.003.
- Duqi, Andi, McGowan, Danny, Onali, Enrico and Torluccio, Giuseppe, (2021), Natural disasters and economic growth: The role of banking market structure, *Journal of Corporate Finance*, 71, issue C, number S0929119921002236, <https://EconPapers.repec.org/RePEc:eee:corfin:v:71:y:2021:i:c:s0929119921002236>.
- Parida, Yashobanta & Dash, Devi. (2019). Rethinking the effect of floods and financial development on economic growth: Evidence from the Indian states. *Indian Growth and Development Review*. ahead-of-print. 10.1108/IGDR-05-2019-0044.
- Botzen, W. & Deschenes, Olivier & Sanders, Mark. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*. 13. 167-188. 10.1093/reep/rez004.
- Khan, Khawar & Zaman, Khalid & Shoukry, Alaa & Sharkawy, Abdelwahab & Gani, Showkat & Sasmoko, Sasmoko & Ahmad, Jamilah & Khan, Associate Prof. Dr. Aqeel & Sanil, Hishan. (2019). Natural disasters and economic losses: controlling external migration, energy and environmental resources, water demand, and financial development for global prosperity. 26. 10.1007/s11356-019-04755-5.

- Klomp, Jeroen. (2014). Financial Fragility and Natural Disasters: An Empirical Analysis. *Journal of Financial Stability*. 13. 10.1016/j.jfs.2014.06.001.
- Klomp, Jeroen. (2016). Economic development and natural disasters: A satellite data analysis. *Global Environmental Change*. 36. 67-88. 10.1016/j.gloenvcha.2015.11.001.
- Brei, Michael & Mohan, Preeya & Strobl, Eric. (2019). The Impact of Natural Disasters on the Banking Sector: Evidence from Hurricane Strikes in the Caribbean. *The Quarterly Review of Economics and Finance*. 72. 10.1016/j.qref.2018.12.004.
- Cortés, Kristle & Strahan, Philip. (2017). Tracing out Capital Flows: How Financially Integrated Banks respond to Natural Disasters. *Journal of Financial Economics*. 125. 10.1016/j.jfineco.2017.04.011.
- Parida, Yashobanta & Roy Chowdhury, Joyita & Saini, Swati. (2021). Do Income and Government Responsiveness Reduce Flood Damages and Fatalities? Evidence from the Indian States.
- Cortés, Kristle & Strahan, Philip. (2017). Tracing out Capital Flows: How Financially Integrated Banks respond to Natural Disasters. *Journal of Financial Economics*. 125. 10.1016/j.jfineco.2017.04.011.
- Hosono, K., Miyakawa, D., Uchino, T., Hazama, M., Ono, A., Uchida, H., & Uesugi, I. (2016). NATURAL DISASTERS, DAMAGE TO BANKS, AND FIRM INVESTMENT. *International Economic Review*, 57(4), 1335–1370.  
<http://www.jstor.org/stable/44280155>
- Parida, Y., & Dash, D. P. (2019). Rethinking the effect of floods and financial development on economic growth. *Indian Growth and Development Review*.

- Parida, Y. (2020). Economic impact of floods in the Indian states. *Environment and Development Economics*, 25(3), 267-290.
- Wooldridge JM (2002) *Econometric Analysis of Cross Section and Panel Data*. Cambridge,MA: MIT Press.
- Strömberg, D. (2007). Natural disasters, economic development, and humanitarian aid. *Journal of Economic perspectives*, 21(3), 199-222.

# Appendix

## Appendix 1

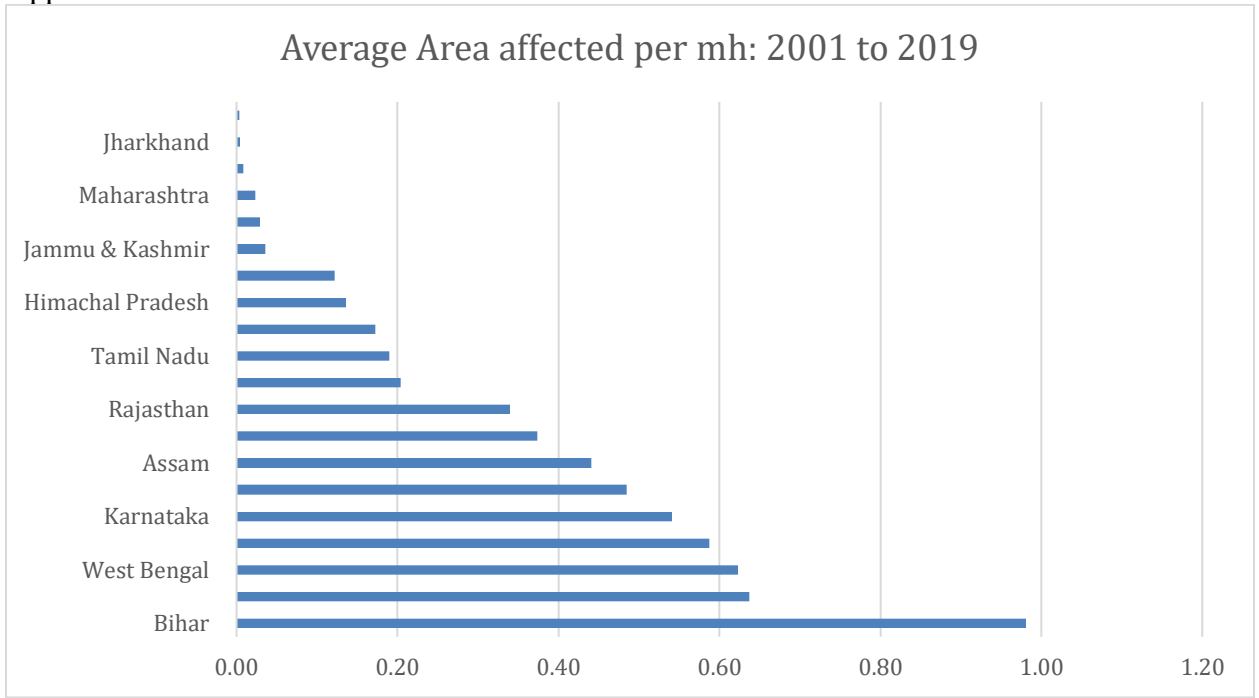
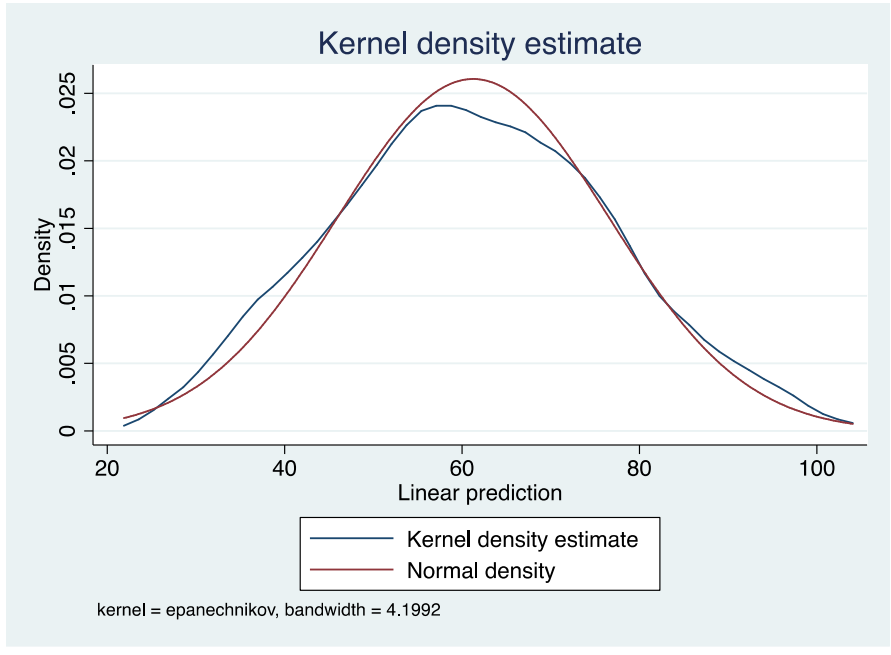


Figure 7: Average state-wise area affected per million hectares from 2001-2019

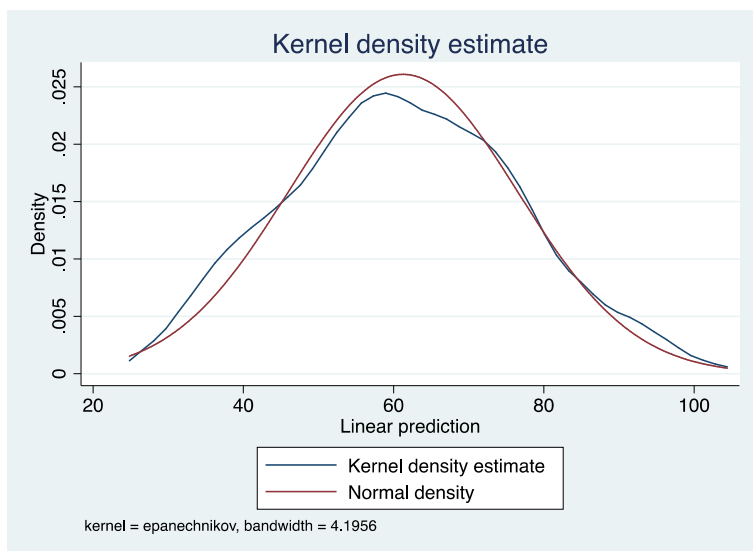
Source: Author's Calculation

## Appendix 2: Source – Author's Calculation

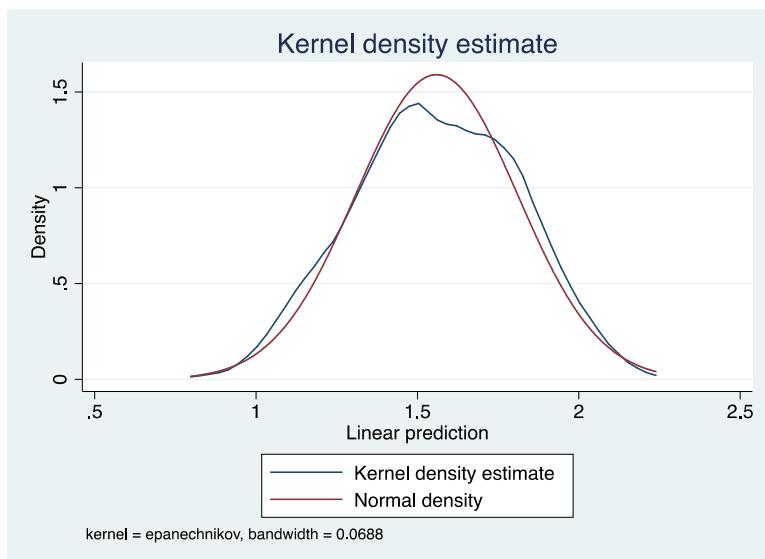




## MLR 1



## MLR 2



## MLR 3

## Appendix 3

**Table 5: Endogeneity Test**

<i>test ehat</i>   Test for endogeneity	
Model	Prob > F
MLR1	0.0000
MLR2	0.0000
MLR3	0.0000
Conclusion: Endogeneity exists	

*Source: Authors' Calculation*