Does Bank Vulnerability Impact The Firm-Level Crash Risk During Economic Stress Period?

Krishnakanta Maity

Department of Computer Science
Ramakrishna Mission Vivekananda Educational and Research Institute
Belur Math, Howrah
Pin - 711 202, West Bengal

A thesis submitted to
Ramakrishna Mission Vivekananda Educational and Research Institute
in partial fulfillment of the requirements for the degree of
MSc in Big Data Analytics
2021-2023

Acknowledgements

I am honored to present my project, and I would like to express my sincere gratitude to all those who have supported me during the process.

First and foremost, I would like to thank my project supervisor *Prof. Prasenjit Chakrabarti*, for his invaluable guidance, support, and encouragement throughout the course of this project. His insight and expertise have been instrumental in shaping my work and helping me stay on track.

I would also like to thank *MJ Mrinmoy*, for his helpful suggestions and constructive feedback on my project. His contributions have been invaluable and have helped me to improve the quality of my work.

Additionally, I would like to express my appreciation to Department of Computer Science, RKMVERI for providing me with the necessary resources and support to complete my project. Without their help, this project would not have been possible.

Finally, I would like to thank my family and friends for their love and support throughout this journey. Their encouragement and motivation have kept me going when things got tough.

I am grateful to everyone who has played a role in the success of this project. Thank you all.

Ramakrishna Mission Vivekananda Educational and Research Institute, Belur Math, West Bengal

Krishnakanta Maity

January 21, 2023

CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled *'Analysis of the Impact of COVID19 Outbreak on the Indian Banking System'* submitted by *Mr. Krishnakanta Maity*, who has been registered for the award of MSc in Big Data Analytics degree of Ramakrishna Mission Vivekananda Educational and Research Institute, Belur Math, Howrah, West Bengal is absolutely based upon his own work under the supervision of *Prof. Prasenjit Chakrabarti* of Department of Accounting and Finance, Indian Institute of Management Ranchi (IIM Ranchi) and that neither his thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.

Prof. Prasenjit Chakrabarti
Assistant Professor
Department of Accounting and Finance
Indian Institute of Management Ranchi (IIM Ranchi)
Prabandhan Nagar, Ranchi 834004, Jharkhand, India

Abstract

This study aims to examine the relationship between bank vulnerability and firm-level crash risk in the Indian market during COVID period. The research will employ historical data and econometric methods to analyze the effect of bank-specific factors such as MES (Marginal Expected Shortfall) and firm-specific factors such as industry type on the crash risk of individual firms in India. By focusing on the Indian market, the study will provide a unique perspective on how bank vulnerability impacts firm-level risk in an emerging economy. The results of this study will offer valuable insights for policymakers, regulators, investors, and other stakeholders in understanding the transmission of financial stress from the banking sector to the real economy in India. The findings can also inform decisions on financial stability in the Indian market, especially during economic stress periods.

Contents

Chapter 1

Introduction

Banks provide a range of financial services to firms, including lending, deposit-taking, and facilitating payment. This financial relationship allows firms to access the capital they need to invest, grow and innovate, which in turn drives economic growth and development. On the other hand, the performance and stability of firms can also affect the financial stability of banks, as a large portion of banks' assets is typically in the form of loans to firms. Therefore, when firms experience financial stress, it can lead to loan defaults and increased risk for banks. This relationship between banks and firms is dynamic and can be influenced by a range of factors such as economic conditions, regulations, and policies.

During economic stress periods, such as recessions or financial crises, the relationship between banks and firms can change significantly. As economic conditions deteriorate, firms may experience financial stress and struggle to meet their financial obligations, including loan payments to banks. This can lead to an increase in loan defaults, which can negatively impact the financial stability of banks.

In response to this increased risk, banks may become more cautious in their lending practices and may tighten credit standards, making it more difficult for firms to access the capital they need to invest and grow. This can further exacerbate the economic downturn, as firms may struggle to access the capital they need to survive and recover.

Additionally, during economic stress periods, the government and regulatory authorities may implement policies and regulations aimed at addressing the financial crisis. These policies may include measures to stabilize the banking sector, such as providing financial assistance to banks or implementing stricter regulations on their operations. These policies may also affect the relationship between banks and firms, as banks may become subject to stricter regulations, which can further restrict their ability to lend to firms.

The COVID-19 pandemic has had a significant impact on the global economy and the relationship between banks and firms. The sudden and severe economic shock caused by the pandemic has led to a significant increase in financial stress for firms, which in turn has affected the financial stability of banks.

One of the main ways in which the bank-firm relationship has changed during the COVID-19 pandemic is through the increased stress on firms' finances. Many firms have experienced a significant drop in revenue as a result of lockdowns and other measures to slow the spread of the virus. This has led to an increased difficulty for firms in repaying loans and other forms of debt, which has increased the risk for banks.

Additionally, many banks and other financial institutions have also taken steps to provide liquidity and capital support to firms, such as by providing payment holidays or debt forgiveness. This has helped firms to manage their finances during the pandemic and avoid defaults on loans.

In summary, The COVID-19 pandemic has led to a significant increase in financial stress for firms, which in turn has affected the financial stability of banks. Banks have played a critical role in providing liquidity and capital support to firms, as well as administering government-backed loan programs and providing loans to firms. Additionally, many banks and other financial institutions have also taken steps to provide liquidity and capital support to firms, such as by providing payment holidays or debt forgiveness.

Our analysis aims to shed light on the various factors that have contributed to the vulnerability, and how these factors have changed as a result of the pandemic. We have focused on the firms that have taken loans from vulnerable banks and compared their crash risk to that of firms that have taken loans from non-vulnerable banks. Through this study, we aim to provide insights into the challenges faced by the Indian banking industry and offer suggestions for mitigating the impact of future crises.

Chapter 2

Literature Review/ Related Works

This work is influenced by the article *Goverment Guarantees and Bank Vulnerability During a Crisis from an Emerging Market* [1]. In this article, they analyze the performance of Indian banks during 2007–09 relative to their vulnerability to a crisis measured using pre-crisis data. Using bank branch-level regulatory data, we exploit geographic variation in the exposure to state-owned banks to show that vulnerable private sector bank branches in districts with greater exposure to state-owned banks experienced deposit withdrawals and a shortening of deposit maturity. In contrast, nearby vulnerable state-owned bank branches grew their deposit base and increased loan advances but with the poorer ex-post performance of loans. Our evidence suggests that access to stronger government guarantees during aggregate crises allows even vulnerable state-owned banks to access and extend credit cheaply despite their underperformance, and this renders private sector banks especially vulnerable to crises.

The article "Government guarantees and bank vulnerability during a crisis: Evidence from an emerging market" authors examines the relationship between government guarantees and bank vulnerability during a crisis in an emerging market. The authors find that government guarantees create a moral hazard, as they give banks an incentive to take on more risk, knowing that they will be bailed out by the government if things go wrong. This can lead to a build-up of non-performing loans and a lack of accountability for bad lending decisions. The study argues that in order to mitigate this risk, governments should take steps to strengthen their banking sectors and increase transparency and oversight, such as by imposing stricter regulations and implementing effective supervisory frameworks.

Chapter 3

Methodology/ Hypothesis

3.1 Vulnerability

Marginal expected shortfall (MES) is a measure of the risk of a portfolio or investment. It represents the expected loss in value of the portfolio that would result from a given decline in the market, over and above the normal level of volatility that the portfolio is already expected to experience.

MES can be used to understand [6] the vulnerability of banks, as it provides a way to quantify the potential losses that a bank might incur due to market movements. By calculating MES for a bank's portfolio of assets, analysts can determine how much the bank's value is likely to decline under different market conditions, and can use this information to assess the bank's overall risk profile. MES can be a useful tool for helping to understand the potential impact of market events on a bank's financial health, and can be used to inform risk management and investment decisions.

It estimates [2] the negative of the average stock return for a given financial firm in the worst 5 percent days of the market index for a particular past period (6 months preceding a crisis in our case). Intuitively, the greater the MES, the more vulnerable is the firm to aggregate downturns or crises.

3.2 Crash Risk

Crash risk [5] refers to the probability that a firm will experience a significant decline in its financial performance or go bankrupt. During times of economic crisis, such as the COVID-19 pandemic, firms may be more vulnerable to crash risk due to reduced demand for their products or services, supply chain disruptions, and other factors. In this context, the crash risk of a firm may be related to the vulnerability of the bank from which it has taken a loan.

Firms that borrow from vulnerable banks may be perceived as being at greater risk of default, which could increase the likelihood of a crash. Vulnerable banks may be more likely to experience financial distress, which could affect their ability to support their borrowers in the event of a crisis. On the other hand, firms that borrow from non-vulnerable banks may be viewed as being more financially stable, as these banks are less likely to experience financial distress and therefore more able to support their borrowers. This relationship between bank vulnerability and firm crash risk is not necessarily causal, and other factors may also influence a firm's crash risk.

Literature uses four measures of firm-specific weekly returns, estimated as the residuals from the market model (*Chen et at., 2001* [3]). In our study, we use two of these measures viz. NSKEW and DUVOL. The following expanded market model regression is the starting point for calculating crash risk:

$$r_{j,\tau} = \alpha_j + \gamma_{1,j} r_{m,\tau-2} + \gamma_{2,j} r_{m,\tau-1} + \gamma_{3,j} r_{m,\tau} + \gamma_{4,j} r_{m,\tau+1} + \gamma_{5,j} r_{m,\tau+2} + \epsilon_{j,\tau} \tag{3.1}$$

Where $r_{j,\tau}$ be the return of j th firm in τ th day, $r_{m,\tau}$ be the return of Nifty50 in τ th day, $\epsilon_{j,\tau}$ be the error term of j th firm in τ th day.

The firm-specific daily return for a firm j in day τ is calculated as the natural logarithm of one plus the residual return from equation (3.1).

$$w_{j,\tau} = \ln(1 + e_{j,\tau}) \tag{3.2}$$

The second measure of crash risk is based on skewness (NSKEW). This measure captures the asymmetry of the return distribution and is frequently used in the literature. Negative (positive) values for the skewness indicate data that are skewed to the left (right). NSKEW is calculated by taking the negative of the third moment of firm-specific weekly returns for each year and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for each firm j in year τ, NSKEW is calculated as:

$$NSKEW_{j,\tau} = -\frac{n(n-1)^{3/2}\sum_\tau w_{j,\tau}^3}{(n-1)(n-2)(\sum_\tau w_{j,\tau}^2)^{3/2}} \tag{3.3}$$

The third measure of crash risk is DUVOL (Down-to-Top Volatility). This is the down-to-top volatility measure of the crash likelihood. A higher value of the DUVOL indicated greater crash risk. DUVOL does not involve third moments and hence is less likely to be overly influenced by extreme daily returns.

$$DUVOL_{j,\tau} = \log\left(\frac{(n_u - 1)\sum_{Down} w_{j,\tau}^2}{(n_d - 1)\sum_{Up} w_{j,\tau}^2}\right) \tag{3.4}$$

3.3 DID Panel Data Regression

The basic idea behind the difference in difference (DID) regression [4] is that it uses a "before-and-after" approach to estimate the effect of the treatment by comparing the change in the outcome variable for the treatment group to the change in the outcome variable for the control group. The method is based on the assumption that both groups would have experienced similar trends in the outcome variable if not for the treatment.

DID regression is particularly useful in situations where a random assignment of the treatment is not possible or practical. It can be used to estimate the causal effect of a policy change, a natural experiment, or a program intervention on a specific outcome variable. The method is widely used in various fields such as economics, epidemiology, and political science.

In summary, DID regression is a statistical method that allows estimating the causal effect of an intervention or treatment on an outcome variable by comparing the change in the outcome variable for a treatment group with the change in the outcome variable for a control group. It is a popular method in many fields, especially when random assignment is not possible or practical. The difference in difference (DID) panel data regression is a statistical method used to estimate the effect of a treatment or intervention on an outcome variable. It involves comparing the change in the outcome variable for a treatment group to the change in the outcome variable for a control group over time. The DID approach involves using panel data, which is data that is collected for the same subjects (e.g., individuals, firms, countries) at multiple points in time. By comparing the change in the outcome variable for the treatment group to the change in the outcome variable for the control group, DID regression allows researchers to control for other factors that may influence the outcome variable, such as time-invariant characteristics of the subjects or time-varying factors that are not affected by the treatment. DID panel data regression can be a powerful tool for evaluating the effectiveness of interventions or policies, as it allows researchers to account for both within-subject changes over time and between-subject differences.

DID panel data regression model is given below,

$$CR = \alpha + FE + \beta_1 MES_{firm} + \beta_2 Post + \beta_3 Post * MES_{firm} + \epsilon \tag{3.5}$$

Where α be the intercept, Fixed effects (FE) are bank, industry and bank*industry, MES_{firm} be the marginal expected shortfall measure of banks, $Post$ a dummy variable, indicate the time, $Post * MES_{firm}$ be the interaction effect, β's are unknown coefficients and ϵ be the error component.

Chapter 4

Experimental Evaluation

Our experimental evaluation is following,

4.1 Description of Data

Data collection involves collecting data from different sources to have an accurate analysis. In this case, bank information is taken from the Reserve Bank of India (RBI) website, market data is sourced from Yahoo Finance and firm-specific data can be obtained using the Center for Monitoring Indian Economy's (CMIE) Prowess database. This data is then used to assess the financial performance of banks and firms and to understand market trends. The data collected can be used to make decisions, create forecasts and take actionable steps.

Out of 29 considered banks, 12 are public and remaining 17 banks are private banks. Whole data is collected over time period January 2019 to June 2020 and total time frame is divided into three parts with gap of 6 months each namely (1) Initial phase of COVID (2) Before COVID and (3) After COVID. A total of 2280 companies from 151 production types clusters taken for the analysis.

4.2 Analysis of Results

4.2.1 Exploratory Data Analysis

In exploratory data analysis we found many interesting insights from the data, are following,

- Private sector have more vulnerable bank compared to public sector.
- Public banks gave loan to the more banks.
- In public sector top lending bank is SBI.
- In private sector top lending bank is HDFC.
- Top three industries are fund based financial services, wholesale trading and drugs & pharmaceuticals.
- Most of financial service firms are taken loan from private banks.
- Average ROA is more for the firms who took loan from vulnerable banks.
- Average leverage is quite high for the firms who took loan from private vulnerable banks compared to public vulnerable banks.

4.2.2 DID Panel Data Regression

Controls variables are return of assets (ROA), Leverage of the firms. Using all possible combination of fixed effects, for both the crash risk measures with and without control variable we run total of 28 DID panel data regression models. From each of the models we clearly notice that interaction between MES and Post is significant at 0.01 level of significance. That simply indicate that reduction in the crash risk for those firms that took loan from the vulnerable banks. For the with controls models, crash risk is significantly related to the crash risk at the previous time period.

Table 1: Result for NSKEW measure (Without controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: NSKEW: Crash Risk Measure						
MES		1.939*	3.722			9.472*	
	(0.000)	(1.095)	(3.922)	(0.000)	(0.000)	(4.887)	(0.000)
Post	-0.047	-0.046	-0.044	-0.045	-0.044	-0.044	-0.044
	(0.039)	(0.059)	(0.046)	(0.033)	(0.026)	(0.027)	(0.026)
MES:Post	-8.529***	-8.591***	-8.605***	-8.590***	-8.651***	-8.673***	-8.677***
	(0.734)	(1.048)	(1.096)	(0.864)	(1.067)	(1.044)	(1.047)
Observations	4,203	4,203	4,203	4,203	4,203	4,203	4,203
R2	0.009	0.042	0.125	0.048	0.137	0.145	0.150
Note:	*p<0.1; **p<0.05; ***p<0.01						
Bank-FE	Y	N	N	Y	Y	N	Y
Industry-FE	N	Y	N	Y	N	Y	Y
Bank * Industry-FE	N	N	Y	N	Y	Y	Y
Controls	N	N	N	N	N	N	N

Table 2: Result for NSKEW measure (With controls)

	Dependent variable:						
	NSKEW: Crash Risk Measure						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MES		2.260**	4.735			11.141**	
	(0.000)	(0.977)	(3.757)	(0.000)	(0.000)	(4.777)	(0.000)
Post	-0.047	-0.046	-0.044	-0.045	-0.044	-0.043	-0.043
	(0.037)	(0.066)	(0.044)	(0.032)	(0.026)	(0.027)	(0.027)
ROA	0.002	0.004	0.003	0.004	0.003	0.003	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Leverage	0.0001	-0.00002	0.0001	-0.00004	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.001)	(0.0002)	(0.001)	(0.001)	(0.001)
NSKEW (t-1)	0.092***	0.081***	0.071***	0.083***	0.067***	0.072***	0.070***
	(0.013)	(0.024)	(0.015)	(0.012)	(0.012)	(0.014)	(0.013)
MES:Post	-8.535***	-8.601***	-8.628***	-8.599***	-8.673***	-8.698***	-8.704***
	(0.759)	(1.034)	(1.113)	(0.880)	(1.086)	(1.061)	(1.067)
Observations	4,203	4,203	4,203	4,203	4,203	4,203	4,203
R2	0.019	0.051	0.130	0.057	0.142	0.150	0.155
Note:					*p<0.1; **p<0.05; ***p<0.01		
Bank-FE	Y	N	N	Y	Y	N	Y
Industry-FE	N	Y	N	Y	N	Y	Y
Bank * Industry-FE	N	N	Y	N	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

Table 3: Result for DUVOL measure (Without controls)

	Dependent variable:						
	DUVOL: Crash Risk Measure						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MES		-1.165	-3.366			-2.396	
	(0.000)	(0.910)	(2.095)	(0.000)	(0.000)	(2.373)	(0.000)
Post	0.002	0.002	0.004	0.003	0.005	0.005	0.005
	(0.007)	(0.009)	(0.010)	(0.007)	(0.009)	(0.007)	(0.009)
MES:Post	-3.175***	-3.227***	-3.230***	-3.222***	-3.229***	-3.256***	-3.240***
	(0.00004)	(0.364)	(0.889)	(0.00004)	(0.0001)	(0.819)	(0.0001)
Observations	4,203	4,203	4,203	4,203	4,203	4,203	4,203
R2	0.013	0.036	0.134	0.046	0.143	0.148	0.152
Note:					*p<0.1; **p<0.05; ***p<0.01		
Bank-FE	Y	N	N	Y	Y	N	Y
Industry-FE	N	Y	N	Y	N	Y	Y
Bank * Industry-FE	N	N	Y	N	Y	Y	Y
Controls	N	N	N	N	N	N	N

Table 4: Result for DUVOL measure (With controls)

	Dependent variable:						
	DUVOL: Crash Risk Measure						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MES		-0.875	-2.455			-1.076	
	(0.000)	(0.967)	(1.841)	(0.000)	(0.000)	(2.375)	(0.000)
Post	0.002	0.003	0.004	0.003	0.005	0.005	0.005
	(0.007)	(0.009)	(0.011)	(0.007)	(0.009)	(0.008)	(0.009)
ROA	0.001	0.002	0.001	0.002	0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.001*	0.001*	0.001	0.001	0.001	0.001	0.001
	(0.0004)	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.0004)	(0.0004)
DUVOL (t-1)	0.110***	0.098***	0.092***	0.096***	0.087***	0.090***	0.089***
	(0.023)	(0.020)	(0.025)	(0.022)	(0.023)	(0.025)	(0.025)
MES:Post	-3.180***	-3.231***	-3.248***	-3.228***	-3.245***	-3.275***	-3.260***
	(0.0001)	(0.290)	(0.851)	(0.0001)	(0.0001)	(0.794)	(0.0001)
Observations	4,203	4,203	4,203	4,203	4,203	4,203	4,203
R2	0.025	0.046	0.140	0.055	0.149	0.154	0.158
Note:					*p<0.1; **p<0.05; ***p<0.01		
Bank-FE	Y	N	N	Y	Y	N	Y
Industry-FE	N	Y	N	Y	N	Y	Y
Bank * Industry-FE	N	N	Y	N	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

Chapter 5

Discussions

The COVID-19 pandemic has had a significant impact on businesses, with many firms experiencing a reduction in revenue and an increase in financial vulnerabilities. One group that has been particularly affected are those firms that took loans from vulnerable banks, which may have been struggling financially even prior to the pandemic. However, recent data suggests that these firms may have also experienced a reduction in crash risk after the COVID outbreak.

One possible reason is the economic downturn caused by the pandemic. Many businesses have had to cut costs and make difficult decisions in order to survive, which may have included reducing investments in high-risk ventures. Additionally, the uncertain economic environment may have made firms more cautious in their decision-making, leading to a decrease in crash risk.

Another factor to consider is the role of government intervention in mitigating crash risk. Many countries implemented various measures to support businesses and prevent financial instability, such as loan forbearance and financial aid programs. These interventions may have helped to reduce crash risk.

It is important to note that this reduction in crash risk may not be universal, and may vary depending on the specific circumstances of each firm. Some firms may have been able to adapt and pivot to new markets, while others may have struggled to survive the economic downturn.

While the reasons for this reduction may be varied, it is clear that the economic downturn and government intervention have played a role in mitigating risk. Further research is needed to fully understand the long-term effects of the pandemic on these firms and the broader economy.

Chapter 6

Conclusions and Future Scope

The results of this study suggest that firms who took loans from vulnerable banks after the COVID-19 outbreak experienced a significantly lower crash risk compared to firms who took loans from non-vulnerable banks. This finding is consistent with the idea that firms who are able to secure financing from financially stable sources are less likely to experience financial distress.

This study contributes to the existing literature on the relationship between firm-level financial stability and crash risk by using difference-in-differences panel data regression to control for potential confounders. Future research could expand upon these findings by examining other potential determinants of crash risk, such as firm size, industry, and management quality.

There are several directions in which this research could be expanded in the future. One possibility is to investigate the impact of other types of financial support, such as government-backed loans or equity injections, on firm-level crash risk. It would also be interesting to examine the role of firm-level characteristics, such as size, industry, and management quality, in moderating the relationship between access to stable financing and crash risk.

Additionally, this study focused on the impact of financing on crash risk in the context of the COVID-19 pandemic. Future research could explore the generalizability of these findings to other economic downturns or to more stable periods.

Appendix A

Additional Diagram

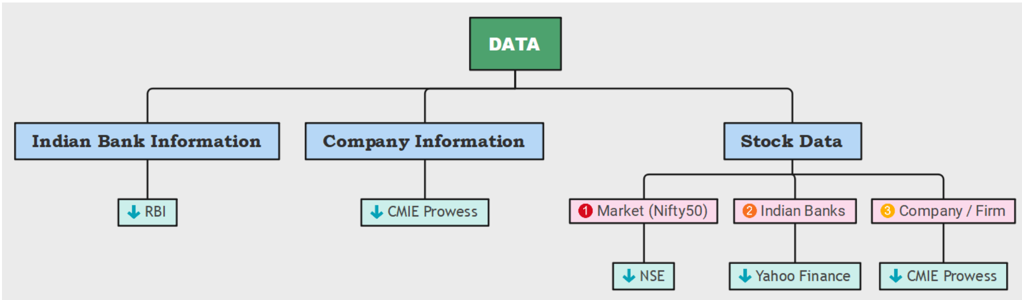

Figure A.1: Data Source

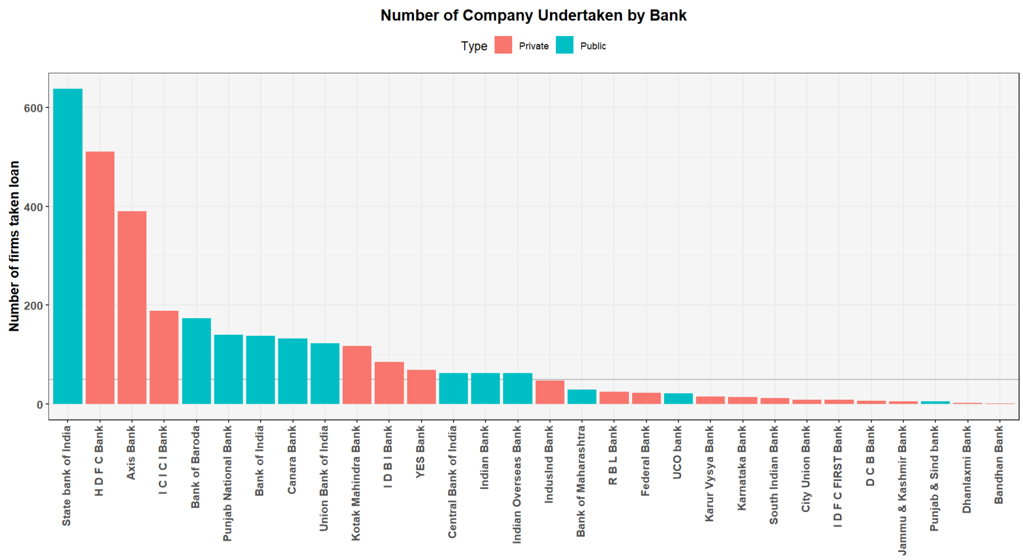

Figure A.2: Number of company undertaken by bank

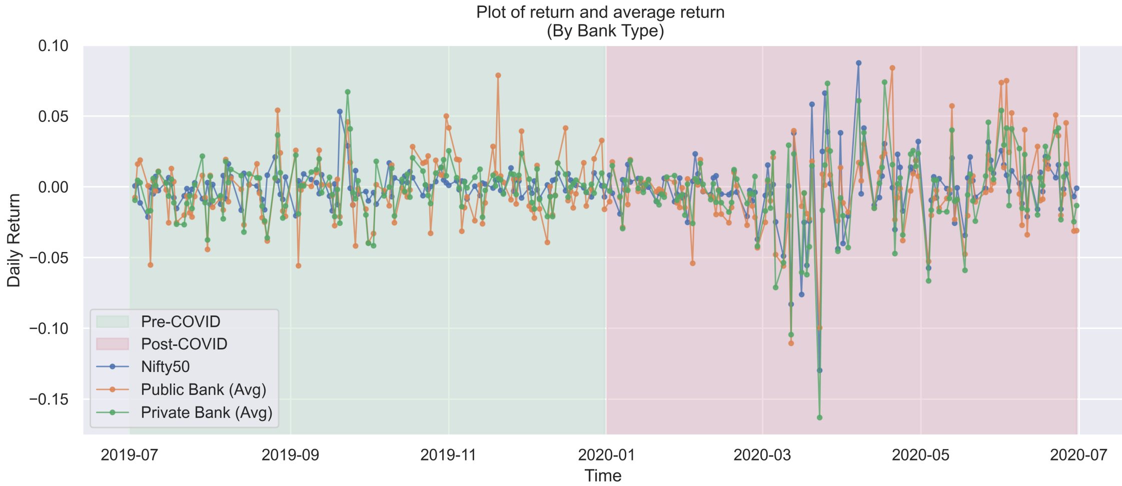

Figure A.3: Return by bank type

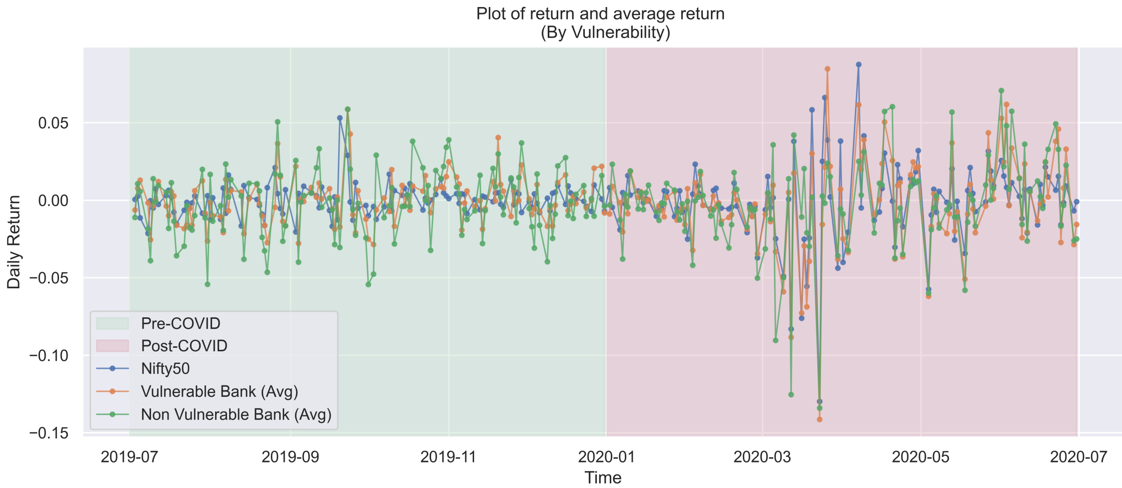

Figure A.4: Return by vulnerability

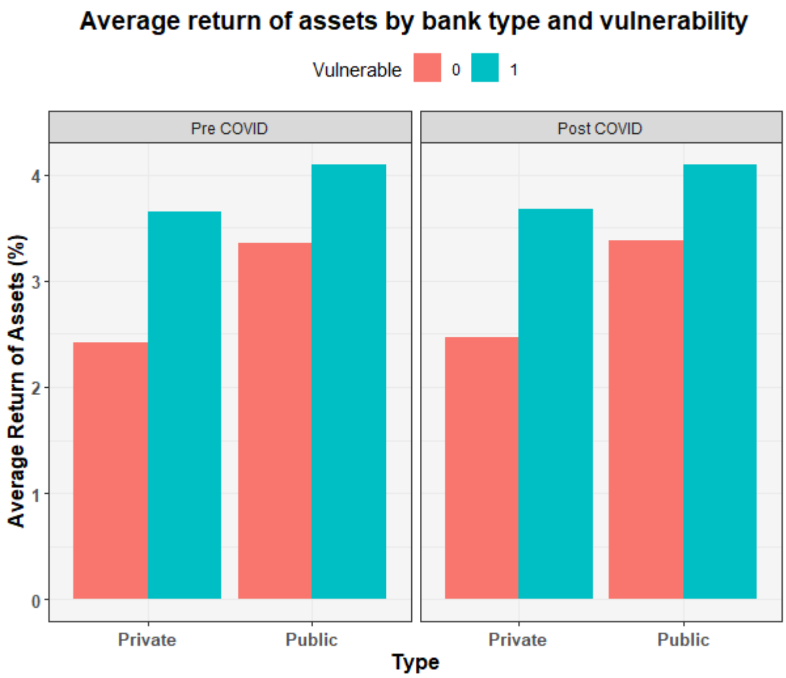

Figure A.5: Average ROA by bank type and vulnerability

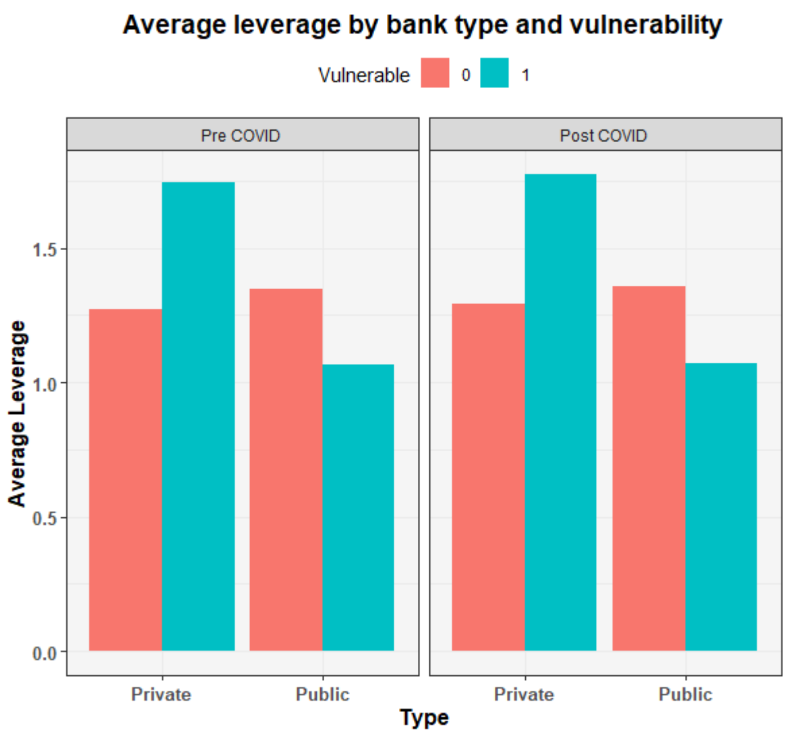

Figure A.6: Average leverage by bank type and vulnerability

Bibliography

[1] Viral V Acharya and Nirupama Kulkarni. Government guarantees and bank vulnerability during a crisis: Evidence from an emerging market. Technical report, National Bureau of Economic Research, 2019.

[2] Juan-Juan Cai, John HJ Einmahl, Laurens de Haan, and Chen Zhou. Estimation of the marginal expected shortfall: the mean when a related variable is extreme. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 77(2):417–442, 2015.

[3] Joseph Chen, Harrison Hong, and Jeremy C Stein. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of financial Economics*, 61(3):345–381, 2001.

[4] Jamie R Daw and Laura A Hatfield. Matching and regression to the mean in difference-in-differences analysis. *Health services research*, 53(6):4138–4156, 2018.

[5] Ahsan Habib, Mostafa Monzur Hasan, and Haiyan Jiang. Stock price crash risk: review of the empirical literature. *Accounting & Finance*, 58:211–251, 2018.

[6] Julien Idier, Gildas Lamé, and Jean-Stéphane Mésonnier. How useful is the marginal expected shortfall for the measurement of systemic exposure? a practical assessment. *Journal of Banking & Finance*, 47:134–146, 2014.