The Impact of Capital Infusion and Political Connection on Bank Moral Hazard: Evidence from India

A thesis submitted during **2025** to the University of Hyderabad

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by

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CERTIFICATE

This is to certify that the thesis entitled "**The Impact of Capital Infusion and Political Connection on Bank Moral Hazard: Evidence from India"** submitted by **Md Shoeb** bearing Registration Number **20MBPH08** in partial fulfilment of the requirements for award of Doctor of Philosophy in the **School of Management Studies** is a bonafide work carried out by him under my supervision and guidance. This thesis is free from Plagiarism and has not been submitted previously in part or in full to this or any other University or Institution for award of any degree or diploma.

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Further, the student has passed the following courses towards fulfilment of coursework requirement for Ph.D.:

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5.	RESEARCH AND PUBLICATION ETHICS	PH804	2	Pass

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DECLARATION

I, **Md Shoeb**, hereby declare that this thesis entitled "**The Impact of Capital Infusion and Political Connection on Bank Moral Hazard: Evidence from India**" submitted by me under the guidance and supervision of Professor **V. Mary Jessica** and co-supervision of Professor **Vijaya Bhaskar Marisetty** is a bonafide research work. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma. I hereby agree that my thesis can be deposited in Shodhganga/INFLIBNET. A report on plagiarism statistics from the University Librarian is enclosed.

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Student Regd. No.: **20MBPH08**

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School: **School of Management Studies**

Among 17 goals (https://sdgs.un.org/goals), under which SDG the work incorporated in the thesis will be addressed:

SDG 8 – Decent Work and Economic Growth; SDG 16 – Peace, Justice and Strong Institutions.

How the work incorporated in the thesis addressed the above SDG (in 250 words):

This thesis aligns with key United Nations Sustainable Development Goals by analysing how government capital infusion of state-owned banks influences financial resilience, institutional integrity, and inclusive growth. It identifies conditions under which capital infusions should mitigate systemic risk, while also highlighting potential unintended consequences. The study then proposes policy implications to ensure that capital infusion supports sustainable development.

SDG 8 - Decent Work and Economic Growth. By examining the link between capital infusions and banks' risk-taking behaviour, the thesis shows that stability in the financial sector is a prerequisite for sustained, inclusive economic growth. It demonstrates that moral hazard can fuel zombie lending, which crowds out credit to productive firms and slows job creation. It is recommended that capital infusion be supplemented by market-based funding, and robust post-infusion oversight helps safeguard credit quality, supporting resilient economic expansion.

SDG 16 - Peace, Justice and Strong Institutions. The work documents how political connections distort lending, erode transparency, and weaken institutional integrity. By quantifying the extent to which state-owned banks channel new capital to politically connected, and sometimes defaulting, borrowers it underscores the need for stricter disclosure rules, better governance of public banks, and clear criteria for capital injections. These measures promote accountability, reduce opportunities for rent-seeking, and strengthen the rule of law in financial oversight.

By aligning its empirical findings and policy implications with these SDGs, the thesis not only advances academic understanding of bank moral hazard but also provides a roadmap for policymakers seeking to harness financial interventions in support of sustainable, equitable development.

Dedicated to my late mother, Nasreen, and to my sister, Amreen, who became like a mother to me thereafter.

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Abstract

Despite theoretical predictions on the ill effects associated with capital infusions, the Global Financial Crisis (GFC) brought them into mainstream banking around the world. Empirical evidence on capital infusions during GFC supports the existence of moral hazard problem. However, what is not clear is whether the increase in bank risk post-capital infusions is due to an increase in bank risk-taking behaviour (moral hazard) or simply reflects an increase in the average firm-level risk due to poor economic conditions. Furthermore, existing literature on politically connected firms and bank lending mainly focuses on demand-side issues (undue benefits received by politically connected firms). Supply-side issues (adverse impact on banks that facilitate such favours) are underexplored. We try to disentangle these issues by using capital infusion data in the Indian banking industry, where government capital infusions in public sector banks happen in all economic conditions and hence allow us to control for a non-crisis environment. Our results strongly support the moral hazard problem in banks, surrounded by no apparent economic crisis. The results are also independent of the bank's propensity to take risks and its financial health. We also find that, post-capital infusion, banks favour politically connected risky firms. Further, capital infusions increase zombie lending practices by lending more to politically connected firms that are insolvent. Our study thus explains why, contrary to conventional wisdom, moral hazard can increase due to capital infusions in government-controlled banks, due to borrower-level political connections. One major implication of our findings is that repeated capital infusions to protect banks can be detrimental as it increases the fiscal risk of the country.

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CHAPTER 1

INTRODUCTION

Banks underpin modern economies not only by safeguarding deposits and extending credit, but by mobilising the flow of funds across diverse sectors, allocating capital to its most productive uses, absorbing and pooling risk, and transmitting monetary policy. Beyond their day-to-day lending and payment roles, banks are also gatekeepers of financial stability. Because they're deeply interconnected, a problem at one institution can quickly spread, creating a chain reaction that threatens the entire system. Individual bank failures can cascade into broader crises, disrupting credit flows, freezing payment networks, and undermining public confidence. Regulators, therefore, focus not just on each bank's health but on system-wide resilience, setting capital requirements, conducting stress tests, and providing safety nets to dampen shocks.

In particular, government interventions in the form of capital infusions, whether through direct equity injections, recapitalisation schemes, or contingent guarantees, are often deployed to restore confidence, shore up bank solvency, and mitigate systemic stress. While these interventions can be effective in stabilising institutions during crisis episodes, they also carry the risk of creating a latent moral hazard. Once banks anticipate that losses will be socialised, they may optimally shift toward riskier loan portfolios and asset holdings, secure in the knowledge that the state will partly bear downside costs. Furthermore, when banks are government-controlled, political economy considerations can compound this moral hazard, as politically connected firms may receive preferential credit at the expense of overall financial stability.

Globally, the average government ownership in commercial banks is around 15%, with some economies having more than 50% (Panizza, 2024). Higher government ownership is justified as a mechanism to avoid market failures and as a welfare measure where the government channels loans to priority sectors (Gerschenkron, 1962; Stiglitz, 1994). However, it is also criticised on the grounds that politicians may use state-owned banks for their own interests and to finance projects that are expected to be repaid with votes from supporters (Krueger, 1974; Shleifer & Vishny, 1994). Several studies supported the latter conjecture that, on the demand side, firm-level political connections facilitate politically connected firms exploiting banks for their private benefits (Chavaz & Rose, 2018; Chen et al., 2017; Firth et al., 2009; Khwaja & Mian, 2005; Liu et al., 2018; Zhou, 2009).

What is not clear is, on the supply side, how banks survive these exploitations. This issue merits investigation, especially when government-controlled banks are propped up by new capital infusions from taxpayers' funds. In that case, contrary to the conventional wisdom, government ownership in banks can lead to market failure if capital infusions are aimed at covering losses due to increased risk associated with politically connected lending. In this thesis, we attempt to explore the potential for these interlinkages between political connections, bad loans, capital infusions and moral hazard.

Theoretically, the effect of capital infusions on banks' risk-taking behaviour is contested. One view suggests that infusions restore charter value and thereby reduce risk-taking (Demsetz et al., 1996; Hakenes & Schnabel, 2010; Keeley, 1990). An opposing perspective argues that because the costs of these infusions are externalised, they induce moral hazard, banks take on more risk in anticipation of future bailouts (Flannery, 1998; Gropp et al., 2006; Sironi, 2003). Empirically, much of the evidence, especially from crisis episodes, supports the moral hazard hypothesis (Black & Hazelwood, 2013; Duchin & Sosyura, 2014; Hryckiewicz, 2014; Poczter, 2016).

However, a key limitation in the existing literature is its focus on crisis periods, during which it is difficult to isolate whether increased risk-taking reflects a deliberate shift in banks' behaviour (moral hazard) or simply a response to deteriorating economic fundamentals. In such contexts, banks are often mandated to expand lending to support economic recovery (Black & Hazelwood, 2013), and capital infusions serve not only as a survival mechanism but as a policy tool to stabilise the financial system amidst heightened systemic risk. Consequently, distinguishing between risk arising from bank behaviour due to an exogenous shock, capital infusion, and macroeconomic shocks remains challenging.

To understand how an economic crisis and borrower-level political connection affect bank moral hazard behaviour, we use the Indian market for this thesis, where the government periodically infuses capital into government-controlled banks due to their poor performance. During the period from 2008-09 to 2022-23, the Indian Government infused ₹ 4004.61 billion (roughly 60 billion USD[1]) taxpayers' funds into government-controlled banks. These infusions are mainly to mitigate the losses contributed by non-performing assets (NPAs). Thus, capital infusions are primarily a lifeline for banks' survival. Without this new capital, there will be bank failures, leading to economic and financial crises. Hence, banks that are infused with new capital should be more vigilant in their fund utilisation to avoid future crises. From this perspective, capital infusions are beneficial for economic stability. However, if there are periodic and repeated infusions, then banks are acting against the conventional wisdom.

1.2. Capital Infusions: Global Overview

Government-led capital infusions into the banking sector have historically served as a critical policy instrument during episodes of systemic financial distress. These interventions, often in the form of direct equity injections or the purchase of preferred shares, are typically aimed at

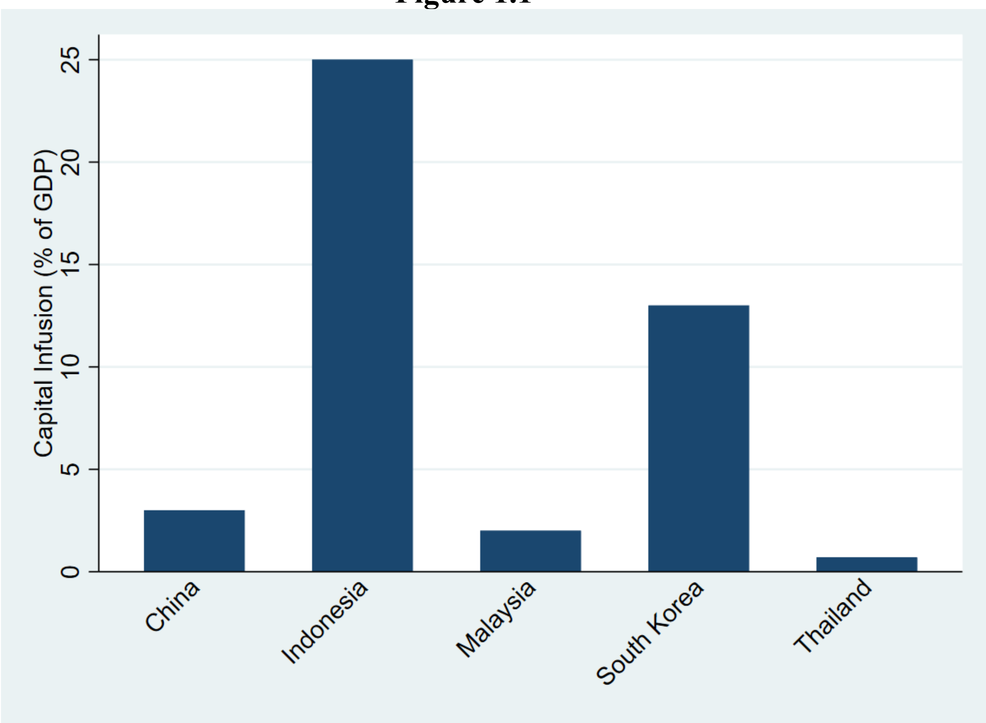
[1] Calculation based on yearly exchange rates.

restoring solvency, reviving credit intermediation, and preserving financial stability. This section provides a comparative overview of such support measures implemented during major global banking crises.

1.2.1. The Asian Financial Crisis (1997–1999)

In March 1999, Indonesia estimated that about 550 trillion rupiah in public funds were needed to revive its financial sector. By March 2000, around 300 trillion rupiah, roughly 25% of GDP, had been injected. In South Korea, a total of ₩ 64 trillion (about 13% of GDP) was provided in public funds, with ₩ 18.6 trillion (approximately 4% of GDP) coming specifically from the Korea Deposit Insurance Corporation. Malaysia had infused 6.2 billion ringgit (roughly 2% of GDP) into ten banks by the end of June 1999. China issued special government bonds worth 270 billion RMB (around 3% of GDP) in August 1998 to bolster the capitalisation of its four major state-owned commercial banks. In Thailand, public fund injections were resisted due to concerns over management accountability; ultimately, only one commercial bank accepted support totalling 32.5 billion baht (about 0.7% of GDP).

Figure 1.1



Note: This figure shows the government recapitalisation of banks as a percentage of the country's GDP during the Asian Financial Crisis. Source: Ministry of Finance, Japan[2]

1.2.2. The Japanese Banking Crisis (1998–2000)

In the wake of the November 1997 failures of Sanyo Securities, Hokkaido Takushoku Bank, Yamaichi Securities and Tokuyo City Bank, the government overcame its reluctance to deploy taxpayer funds and, in February 1998, enacted the Financial Function Stabilization Act (FFSA). One month later, under the FFSA, the authorities injected ¥1,815.6 billion into 21 banks. By October 1998, however, the FFSA was supplanted by the more expansive Prompt Recapitalisation Act (PRA), which raised the ceiling for public support from ¥13 trillion to ¥25 trillion. Under this new framework, a second round of capital injections was approved in March 1999, channelling a total of ¥7,459.25 billion into 15 banks, thereby strengthening the balance sheets of Japan's most vulnerable financial institutions and shoring up systemic confidence (Nakashima, 2016).

1.2.3. The Global Financial Crisis (2008–2009)

The Global Financial Crisis (GFC) of 2008–2009 prompted one of the largest waves of government recapitalisations in modern history. Facing a sudden collapse in interbank lending and acute solvency concerns at systemically important institutions, economies started infusing these institutions to restore confidence and stabilise the economic system.

In United States, under the Troubled Asset Relief Program (TARP), the first round of funding was disbursed on October 28 2008, when $125 billion in preferred stock was injected into nine major institutions (Citigroup, Bank of America, J.P. Morgan Chase, Wells Fargo, Goldman Sachs, Morgan Stanley, State Street, Bank of New York, and Merrill Lynch) without any formal

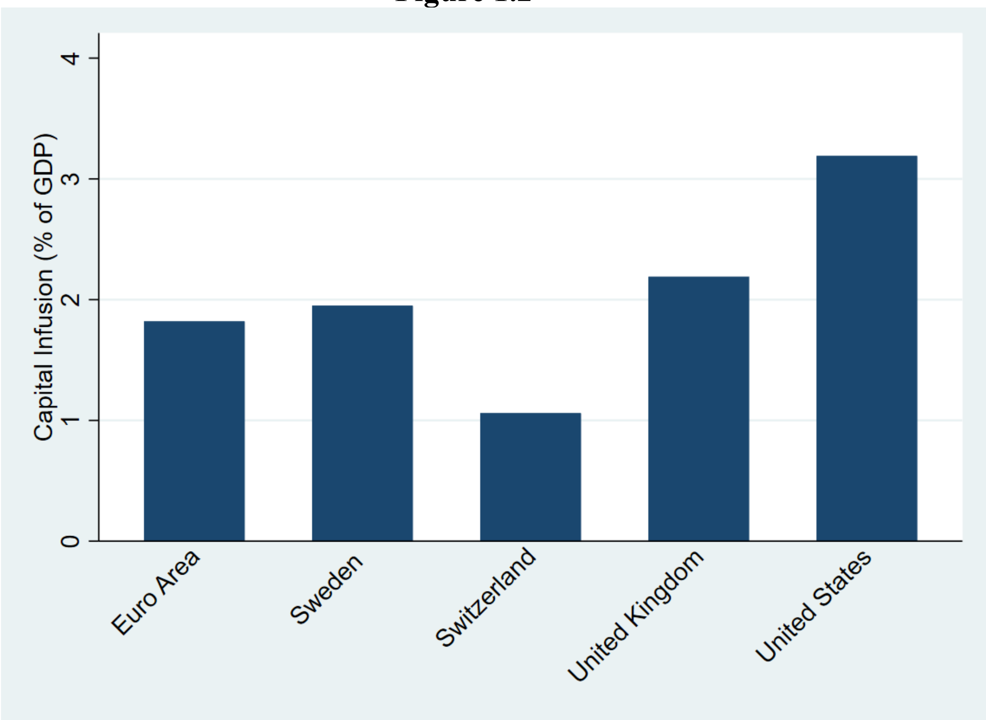
[2] https://www.mof.go.jp/english/about_mof/councils/customs_foreign_exchange/if022d.htm

application. Subsequent tranches required banks to apply for support and undergo a formal review process, with healthier, more viable institutions receiving priority. By the program's conclusion, a total of $204.9 billion had been deployed across 709 banking organisations, both public and private, as the Treasury assessed each applicant's financial health to determine eligibility and the size of its capital infusion (Berger et al., 2020)

In the United Kingdom, the recapitalisation program reached 2.19 % of GDP. Countries in the Euro Area (Austria, France, Germany, Greece, Ireland, Italy, the Netherlands, and Spain) injected 1.82 % of the composite GDP into troubled banks. Sweden injected 1.95 % of its GDP. In Switzerland, 1.06 % of the GDP was infused. While in Japan, only 0.02 % of the GDP was injected.

While the immediate goal was to shore up capital ratios and restore market confidence, the programs also raised complex questions about exit strategies, state ownership, and long-term competitive dynamics within the domestic banking industry.

Figure 1.2



Note: This figure shows the government recapitalisation of banks as a percentage of the country's GDP during the Global Financial Crisis. Source: International Monetary Fund[3]

1.3. Contextual Significance

1.3.1. Banks' Non-Performing Assets issue in India

NPA issue among the Indian banks became more transparent following the Asset Quality Review (AQR) in the financial year 2016, though a majority of the bad loans originated in 2006-08, when economic growth was strong[4]. In the aftermath of the Global Financial Crisis, the RBI removed the requirement to classify restructured loans as non-performing loans. This gave rise to zombie lending in the Indian banking sector (Flanagan & Purnanandam, 2019). RBI restored this requirement in 2015, but suspected that banks were still hiding bad loans. In August of 2015, the RBI introduced AQR, an audit conducted to bring out more transparency in the Indian banking sector.

Consequently, the NPA of Indian banks shot up significantly in the post-AQR years. Figure 1.3 reports the gross non-performing assets ratio (*GNPA*) of Indian banks over the sample period. We observe that *GNPA* is high even in the initial years before AQR and increases significantly after 2015, the year of AQR. We also observe that both the GOBs and the private sector banks were affected by AQR, but the effect is more pronounced for GOBs.

The Indian banking sector has also been plagued with defaults of very high magnitudes[5]. These defaults have usually been attributed to poor management by the banks and sometimes even to political meddling[6].

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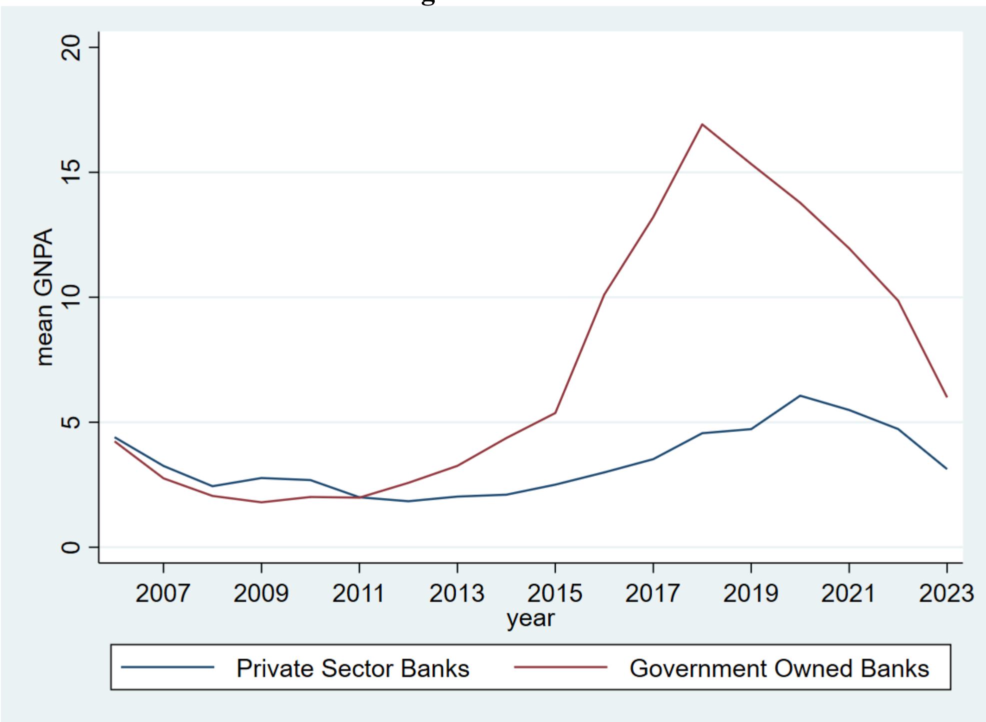
[3] https://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/~/media/Websites/IMF/imported-flagship-issues/external/pubs/ft/GFSR/2009/02/pdf/_chap3pdf.ashx
[4] https://www.moneycontrol.com/news/business/economy/raghuram-rajans-note-to-parliamentary-estimates-committee-on-bank-npas-2941201.html
[5] https://www.businesstoday.in/magazine/cover-story/story/indias-fallen-billionaires-301989-2021-07-22
[6] https://www.moneycontrol.com/news/business/analysis-urjit-patels-scathing-attack-on-rbi-upa-for-the-npa-mess-3-critical-insights-5570241.html

Figure 1.3



Mean GNPA of government-owned banks and private sector banks during the sample period. Source: CMIE Prowess Database.

1.3.2. Capital Infusion in India

The Indian government implemented a policy of capital infusions into government-owned banks (GOBs) as early as 1986[7]. These infusions, unlike those in many other economies, were not solely crisis-driven but were institutionalised to ensure GOBs maintained adequate regulatory capital. As highlighted in the 2017 audit report by the CAG, annual capital requirement projections by GOBs are submitted to the Department of Financial Services (DFS). The DFS, after careful scrutiny, determines the actual capital needs and allocates funds accordingly, following discussions with GOB senior management.

During the period 2008-09 to 2022-23, ₹ 4004.61 billion was injected into GOBs by the Government of India. The capital infusions became much more frequent during this period.

[7] https://www.thehindu.com/business/Economy/what-is-the-stimulus-to-public-sector-banks-all-about/article19982419.ece

The government's rationale for capital infusions includes maintaining GOBs' capital adequacy, promoting credit growth, and preserving its controlling interest in these banks. While in the early years of the sample period, infusions were ad hoc, the Indradhanush Plan introduced a more structured approach with planned capital injections contingent on bank performance. However, the Asset Quality Review necessitated additional infusions. Capital infusions during the sample period are reported in Table 1.1.

Table 1.1: Distribution of Capital Infusion

Name of Government-Owned Banks	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Total**
Allahabad Bank	0	0	670	0	0	400	320	973	451	1,500	6,896	0	0	0	**11210**
Andhra Bank	0	0	1,173	0	0	200	120	378	1,100	1,890	5,275	0	0	0	**10136**
Bank of Baroda	0	0	2,461	0	850	550	1,260	1,786	0	5,375	5042	7000	0	0	**24324**
Bank of India	0	0	1,010	0	809	1,000	0	3,605	2,838	9,232	14724	0	3000	0	**36218**
Bank of Maharashtra	0	0	940	470	406	800	0	394	300	3,173	4703	831	0	0	**12017**
Canara Bank	0	0	0	0	0	500	570	947	748	4,865	0	6571	0	0	**14201**
Central Bank of India	700	450	2,253	676	2,406	1,800	0	535	1,397	5,158	6,592	3353	4800	0	**30120**
Corporation Bank	0	0	309	0	204	450	0	857	508	2,187	11,641	0	0	0	**16156**
Dena Bank	0	0	539	0	0	700	140	407	1,046	3,045	0	0	0	0	**5877**
IDBI Bank Ltd.	0	0	3,119	810	555	1,800	0	2,229	1,900	12,471	0	4557	0	0	**27441**
Indian Bank	0	0	0	0	0	0	280	0	0	0	0	2534	0	0	**2814**
Indian Overseas Bank	0	0	1,054	1,441	1,000	1,200	0	2,009	2,651	4,694	5963	8217	4100	0	**32329**
Oriental Bank of Commerce	0	0	1,740	0	0	150	0	300	0	3,571	6686	0	0	0	**12447**
Punjab & Sind Bank	0	0	0	0	140	100	0	0	0	785	0	787	5500	4600	**11912**
Punjab National Bank	0	0	184	655	1,248	500	870	1,732	2,112	5,473	14155	16091	0	0	**43020**
State Bank of India	0	0	0	7,900	3,004	2,000	2,970	5,393	5,681	8,800	0	0	0	0	**35748**
Syndicate Bank	0	0	633	0	0	200	460	740	776	2,839	3963	0	0	0	**9611**
UCO Bank	450	450	1,613	48	681	200	0	935	1,925	6,507	6406	4272	2600	0	**26087**
Union Bank of India	0	0	793	0	1,114	500	0	1,080	541	4,524	4112	11768	0	0	**24432**
United Bank of India	250	300	558	0	100	700	0	480	1,026	2,634	4998	0	0	0	**11046**
Vijaya Bank	500	0	1,068	0	0	250	0	220	0	1,277	0	0	0	0	**3315**
Total	**1,900**	**1,200**	**20117**	**12000**	**12517**	**14000**	**6990**	**25000**	**25000**	**90000**	**101156**	**65981**	**20000**	**4600**	**400461**

Note: This table shows the distribution of capital infusions (in Crore ₹) from 2008-09 to 2021-22 to GOBs. Source: Report No.28 of 2017 - Recapitalisation of Public Sector Banks, and banks' annual reports.

1.3.3. Contribution to Political Parties in India.

Section 29C of the Representation of the People Act, 1951, stipulates that political parties in India must disclose to the Election Commission all contributions exceeding twenty thousand rupees received from any source, including individuals, corporations, and other entities. The report should include the name, address, and Permanent Account Number (PAN) of the contributor, the mode of payment and the amount contributed.

Companies making donations to political parties are governed by the Companies Act, 2013. Government companies and relatively new companies which were incorporated within the last three years are prohibited from making contributions to political parties. Moreover, permissible contributions to political parties are subject to a cap of 7.5% of the average net profits earned over the preceding three fiscal years. This regulatory measure aims to prevent undue influence on political outcomes and ensure that contributions remain within reasonable limits. Companies are required to disclose the aggregate amount contributed to political parties in their profit and loss accounts. Companies that violate these provisions may be fined up to five times the contributed amount. Officers responsible for the violation may face imprisonment of up to six months and/or a fine up to five times the contributed amount.

1.4. Research Gap

Based on the extensive literature review, several gaps were identified. First, most existing empirical evidence documents moral hazard associated with capital infusions during crisis periods, when excessive risk-taking could be rationalised as a response to adverse economic conditions. However, as Berger et al. (2020) argue, the moral hazard problem may be more salient during non-crisis periods, when infusions are less likely to be viewed as responses to bad luck and more as enabling risky behaviour under a safety net. Second, little to no evidence exists that explores how targeted infusion (the government does not reveal which banks will be infused or the criteria for infusion) affects moral hazard behaviour. Third, the literature has extensively explored the moral hazard behaviour post capital infusion and how banks are exploited by politicians, but the role of borrower-level political connection in moral hazard behaviour post capital infusion has been largely overlooked.

1.5. Research Questions

Based on the research gaps identified, we ask the following research question:

- Does bank moral hazard behaviour differ during economic crises and normal periods?
- Does targeted infusion impact bank moral hazard?
- Does borrower-level political connection impact bank moral hazard?

1.6. Research Objectives

The primary objective of this thesis is to explore the channels of moral hazard behaviour. We formulate the following sub-objectives accordingly:

- To examine the impact of capital infusion on bank moral hazard.
    - To compare moral hazard behaviour during an economic crisis and normal periods.
    - To examine the role of targeted infusion on bank moral hazard.
- To examine the role of borrower-level political connections on bank moral hazard.

1.7. Main Findings

1.7.1. Bank-level analysis

We draw on bank-level data from the Centre for Monitoring Indian Economy (CMIE) Prowess database, the Credit Research Initiative at the National University of Singapore, and a Comptroller and Auditor General of India (CAG) audit report on capital infusions to compare the risk-taking behaviour of government-owned banks[8] (GOBs) that received capital injections (treatment group) with private sector banks that did not (control group). Within the treatment group, we further classify[9] banks by financial health using propensity scores as High Propensity (High PS), banks that are more distressed, and Low Propensity (Low PS), banks that are relatively healthier. This stratification allows us to test whether the government's capital allocation reflects banks' *ex-ante* distress levels. Drawing on Merton (1977), we hypothesise that only High PS banks, being closer to insolvency, would have strong incentives for moral hazard, while Low PS banks, facing lower default risk, would be less prone to such behaviour. Alternatively, if the intended disciplinary effect of targeted infusions is outweighed by moral hazard incentives, both High PS and Low PS banks would exhibit increased risk-taking, indicating that targeting does not mitigate moral hazard.

Our findings reveal that capital infusions lead to heightened risk-taking in non-crisis periods, but have no statistically significant impact during crisis years. In other words, moral hazard emerges mainly when economic conditions are improving, not when the average firm is under greater distress during a downturn. Once the economy begins to recover and average firm risk decreases, infused banks ramp up their risk appetite. This pattern suggests that opportunistic behaviour, rather than adverse economic conditions, drives the increase in bank risk-taking. Moreover, both High PS and Low PS banks demonstrate greater risk-taking following infusion, compared to private sector banks. This indicates that the targeting of capital infusions does not affect post-infusion risk behaviour, as even less-distressed institutions (Low PS) increase their risk exposure. These results hold across multiple risk metrics and alternative methods of classifying banks. Finally, we show that the observed increase in risk is directly attributable to the capital injections themselves, rather than to recognition of pre-existing bad loans under

[8] Only GOBs in India obtain capital infusions from the government.
[9] A comprehensive description of the bank classification is provided in Chapter 3.

tighter regulations, thereby ruling out the possibility that our findings merely reflect enhanced risk reporting.

1.7.2. Loan-Level Analysis

For our loan level analysis, we use hand-collected loan-level data of 8424 firm-bank year observations of 155 politically connected and 325 politically non-connected firms, from the Ministry of Corporate Affairs (MCA), Government of India website and bank and firm-level data from CMIE Prowess database, and other supporting data from the CAG and firm-level loan default data from CIBIL[10] website. More specifically, we investigate whether capital infusion leads to preferential lending to politically connected firms and whether this preferential lending turns out to be a risky one.

Employing a generalised difference-in-differences approach, we find that banks, post-capital infusions, increase their lending to politically connected firms. This increase in lending is even stronger for politically connected firms that have defaulted on their loans, indicating that capital infusion not only leads to preferential lending but also to risky preferential lending. We also find evidence of zombie lending to politically connected firms post-capital infusions. Our placebo tests confirm that these findings are not random.

Our findings remain robust across a variety of model specifications and after mitigating potential endogeneity concerns. Our results are also robust to alternative definitions of politically connected firms, risky firms, and zombie firms, as well as a battery of other robustness checks. Additionally, we find that politically connected firms, before the default, contributed more money to political parties compared to their non-defaulting counterparts. Our results suggest that post-capital infusions, political influence can play a significant role in bank

[10]CIBIL is India's largest credit information company.

risk-taking behaviour. In other words, higher risk-taking by the banks is driven by external forces that are beyond the banks' control.

1.8. Contribution to existing literature

Several studies evaluate the effect of political connections on bank lending behaviour and provide evidence of preferential treatment of politically connected firms (Cole, 2009; Dinc, 2005; Houston et al., 2014; Infante & Piazza, 2014; Khwaja & Mian, 2005; Liu et al., 2018; Sapienza, 2004; Zhou, 2023). These studies, however, only capture one side of the coin. The other side that has been overlooked in the literature is that banks can be bailed out using taxpayers' money even if they lend without proper due diligence. This, in turn, can give rise to politically motivated lending as banks will have an implicit guarantee from the government in case of losses occurring from politically motivated lending. We contribute to this body of literature by providing evidence on how capital infusion leads to preferential treatment of politically connected firms that are risky.

A separate strand of literature finds the prevalence of moral hazard behaviour among banks following government recapitalisation programs in crisis periods (Behr & Wang, 2020; Black & Hazelwood, 2013; Duchin & Sosyura, 2014; Elyasiani et al., 2014; Harris et al., 2013; Hryckiewicz, 2014; Poczter, 2016). These evidences of moral hazard do not, however, give any insights into how this risk-taking occurs. Through this thesis, we bridge these two streams of literature to draw new insights into why banks take more risk post-capital infusions due to political pressure. Furthermore, our evidence also shows that risk-taking mainly occurs during normal periods, thus providing a clean evidence of moral hazard behaviour.

1.9. Significance of the Study

Our evidence highlights a channel behind India's NPA surge. First, in the wake of the Global Financial Crisis, the RBI adopted regulatory forbearance, allowing banks to restructure loans without downgrading them to NPAs, which fostered widespread zombie lending (Flanagan & Purnanandam, 2019). Second, capital infusions created moral-hazard incentives, leading banks to extend credit to politically connected firms, even those that were high-risk and met the definition of zombie firms. Together, these mechanisms significantly contributed to the subsequent buildup of NPAs.

While it is well-established that government-owned banks tend to favour politically connected firms, this thesis provides novel evidence that the increase in risk-taking behaviour following capital infusions is driven by lending to politically connected borrowers, particularly those with prior defaults and zombie status. This borrower-level political channel offers a new explanation for moral hazard in recapitalised banks, bridging the gap between the literature on political connections and that on post-infusion risk-taking. Additionally, this thesis provides novel evidence of moral hazard in normal periods and of targeted infusion.

1.10. Thesis Structure

The current study comprises five chapters and is organised as follows:

Chapter 1 (Introduction): This chapter offers a concise overview of the key components of the thesis. The chapter opens by outlining the thesis's background, motivation, contextual setting, research gap, questions, and objectives, and concludes with an outline of its overall structure.

Chapter 2 (Literature Review): This chapter offers a survey of the existing literature on capital infusion and moral hazard behaviour, capital infusion and bank lending, risk-taking in stressed banks, political connection and bank lending, and bank zombie lending behaviour. The chapter first describes the theoretical background, followed by the empirical evidence on the extant literature. Based on the theory and existing empirical evidence, the chapter ends with the formulation of the main hypotheses.

Chapter 3 (Research Methodology): This chapter focuses on the data used and the research methods employed. First data and research methods are discussed at the bank-level and then at the loan-level.

Chapter 4 (Analysis and Findings): This chapter provides the data analysis and findings. In the first subsection, the analysis and findings are presented at the bank level. The second subsection provided the analysis and findings at the loan-level analysis.

Chapter 5 (Conclusion): This chapter focuses on the conclusion of the thesis, along with policy implications. The chapter ends with a discussion on future scope for research.

CHAPTER 2

LITERATURE REVIEW

Chapter Overview

This chapter offers a survey of the existing literature on capital infusion and bank moral hazard. This chapter introduces the relevant theories on capital infusion and risk-taking, followed by empirical evidence on risk-taking in stressed banks, capital infusion and lending, politically motivated bank lending, moral hazard behaviour through capital infusion and bank zombie lending behaviour. The chapter provides a discussion on how these streams of literature are related and thus formulates the hypotheses accordingly.

2.1. Theoretical Background

There is no clear consensus in the theoretical literature regarding how capital infusions affect bank risk-taking. Advocates argue that such interventions are crucial during financial crises to restore trust in the banking system. A prominent example is the collapse of Lehman Brothers during the Global Financial Crisis, which led to a freeze in credit markets (Benmelech & Bergman, 2018; Domanski & Turner, 2011). Additionally, proponents contend that infusions help recapitalise distressed banks, thereby restoring their charter value, and reducing incentives to take excessive risks, as the potential cost of failure increases with higher charter value (Cordella & Yeyati, 2003; Demsetz et al., 1996; Hakenes & Schnabel, 2010; Keeley, 1990).

Conversely, critics argue that capital infusions may induce moral hazard by diminishing the disciplining role of creditors, who anticipate future government support and therefore have less incentive to monitor risk-taking (Flannery, 1998; Gropp et al., 2006; Sironi, 2003). In this view, capital support may embolden banks to increase risk, knowing they may be bailed out. Cordella and Yeyati (2003) suggest that both risk-mitigating and risk-inducing channels coexist, and the net effect of capital infusion depends on the relative strength of these mechanisms.

Merton (1977), in the context of deposit insurance, argued that banks close to insolvency face heightened incentives to increase risk-taking, treating the insurance as a put option. The same conceptual framework can be extended to capital infusions, which act as contingent guarantees, encouraging banks to take more risk in distress since they expect government support in the event of failure. In contrast, Froot and Stein (1998) posit that banks nearing distress may become more risk-averse due to heightened funding constraints.

The impact of capital infusions is not necessarily confined to recipient banks. Theoretical work by Hakenes and Schnabel (2010) suggests that bailouts can distort competition, as refinanced banks receive subsidised funds and adopt aggressive strategies, prompting competitor banks, those not bailed out, to also increase risk-taking in order to remain competitive.

Additionally, moral hazard can emerge due to the size or number of distressed banks. Goodhart and Huang (2005) argue that systemically important (too-big-to-fail) banks may assume more risk *ex-ante*, knowing that their size compels regulators to intervene in crises. Similarly, Acharya and Yorulmazer (2007) propose the too-many-to-fail hypothesis, where widespread distress among banks increases the likelihood of government support, leading to herding behaviour in risk-taking, such as concentrated exposure to certain sectors or assets.

2.2. Risk-taking in Stressed Banks

Existing studies reveal a somewhat ambiguous relationship between financial stress and subsequent bank risk-taking. Banks have been shown to increase risk-taking after experiencing a decline in share prices (Koudstaal & van Wijnbergen, 2012). Several studies contend that financially troubled banks ramp up their risk exposure, often by issuing hefty shareholder payouts that erode their equity buffers (Acharya et al., 2011; Baldursson & Portes, 2013; Drechsler et al., 2016). In contrast, banks that faced significant losses and are more distressed have been shown to cut down lending to risky borrowers (Ben-David et al., 2020; Bidder et al., 2021; di Patti & Kashyap, 2017; Peydró et al., 2023).

In summary, the evidence on risk-taking behaviour by troubled banks is mixed. However, this evidence does not consider government-led capital infusion. Dam and Koetter (2012) argue that capital infusions targeted at specific institutions can impose discipline on banks. However, this disciplining effect may be undermined by the moral hazard created through expectations of future support. In line with this logic, we consider banks with less distress as those banks that should reduce risk-taking if targeted infusion has an effect on risk-taking, because these banks cannot anticipate future infusions.

2.3. Capital Infusion and Bank Lending

Much of the evidence on the effect of capital infusion on bank lending comes from the TARP. The effect of TARP on bank lending remains fiercely debated. On one hand, several studies report large credit-supply boosts. One analysis instruments for TARP participation using political and regulatory variables and estimates an additional $404 billion in loans (Li, 2013). States with a higher share of TARP-funded banks saw faster employment growth and fewer bankruptcies in the post-TARP period (Berger & Roman, 2017). By focusing on firms borrowing simultaneously from multiple banks, thereby holding credit demand constant, other work finds that individual banks extended significantly more business loans after TARP injections (Berger et al., 2019; Chu et al., 2019). Even within the same holding companies, undercapitalised banks that received TARP funds expanded small-business lending far more than their better-capitalised siblings (Puddu & Walchli, 2014). Similar to TARP literature, Poczter (2016) find that recapitalised banks extended more loans in Indonesia, and Brei et al. (2013) found similar evidence in a cross-country setup.

Yet a parallel literature uncovers a much more muted or even negligible lending response. One study shows that TARP recipients primarily used their injections to shore up capital ratios, resulting in only about $1.04 of new lending for every dollar injected (Taliaferro, 2021). Using a congressional-oversight instrument similar to Li (2013), another analysis detects no statistically significant increase in lending following TARP participation (Duchin & Sosyura, 2012).

In summary, banks may extend more credit after a capital infusion during a crisis scenario to help the economy recover. However, the same credit growth could be driven by borrowing firms' political ties, discussed in the next section, which may become detrimental to the banks.

2.4. Political connections and bank lending

Firm-level political connection impacting bank lending is one of the well-researched topics in banking literature. Given that banks play an important role in economic development, they generally work with the governments to fulfil the governments' mandate. For instance, government-owned banks (GOBs) engage more in priority sector lending, where the welfare motive is more important than the profit motive. Politicians can use this welfare motive during election years to gain an advantage in winning elections. Accordingly, GOBs have been shown to charge lower interest rates in economically struggling areas depending on the political affiliation of banks (Sapienza, 2004) and allocate credit to politically significant regions and sectors (Carvalho, 2014; Cole, 2009).

Contrary to the welfare angle, banks can be exploited by powerful politicians for their private benefits. In other words, firms can help politicians with funding and in return politicians influence banks to give these firms more loans (Chavaz & Rose, 2018; Chen et al., 2017; Firth et al., 2009; Khwaja & Mian, 2005; Liu et al., 2018; Zhou, 2009), charge lower interest rates (Arifin et al., 2020; Houston et al., 2014; Infante & Piazza, 2014), and these firms even enjoy superior financial performance (Akey, 2015; Claessens et al., 2008; Yeh et al., 2013). Banks are also more likely to restructure loans instead of filing bankruptcy proceedings against politically connected firms (Halford & Li, 2020).

Government-controlled banks tend to increase lending around election years (Bircan & Saka, 2021; Chen et al., 2013; Dinc, 2005), which indicates the influence of elected politicians on the lending behaviour of these banks. Contrary to these findings, Baum et al. (2010) and Fungáčová et al. (2023) found that both government-controlled and privately owned banks were more likely to expand their lending operations during the elections.

Some evidence also shows the negative economic consequences post the increase in lending in the election years, such as a deterioration in credit quality (Bian et al., 2021; Chu & Zhang, 2022; Huang & Thakor, 2024), a decrease in bank profitability (Huang & Thakor, 2024; Shen & Lin, 2012), increased loan defaults (Englmaier & Stowasser, 2017), and a reduction in credit to the manufacturing sector (Kumar, 2020). While banks favouring politically connected borrowers has been shown as a result of political pressure, Zhou (2023) demonstrated that banks that lend to these borrowers enjoy regulatory reliefs indicating an incentive for banks as well to carry out politically motivated lending.

In summary, there is strong evidence that shows firms reaping benefits from banks because of their affiliation with politicians. More specifically, government-controlled banks are more prone to exploitation by politicians through compromising lending practices.

2.5. Capital infusion and bank risk-taking

There is an independent stream of literature on the supply-side issues in banking capital markets. We focus on how banks cope to avoid possible bank failures due to higher risk-taking behaviour. As banks play an important role in the economy, bank failure can lead to an economic crisis, as evidenced by the Global Financial Crisis (GFC). There is growing literature on how governments involve capital infusions in reducing bank failures and whether such capital infusions help banks to reduce risk-taking behaviour.

As a response to the GFC, the US government introduced the Troubled Asset Relief Program (TARP), which infused a significant amount of capital into the banks. Most of the empirical evidence points to an increase in the risk-taking of banks post-TARP infusions (Behr & Wang, 2020; Black & Hazelwood, 2013; Duchin & Sosyura, 2014; Elyasiani et al., 2014; Harris et al., 2013).

Similar evidences of moral hazard behaviour were found in economies other than the US (Dam & Koetter, 2012; Hryckiewicz, 2014; Poczter, 2016). As opposed to the findings presented above, Berger et al. (2016) found a reduction in bank risk-taking in Germany following government interventions.

In summary, the growing literature on capital infusions does not support the conventional wisdom that capital infusions are meant for banks to survive and manage risk better. On the contrary, they engage in higher-risk lending practices. We posit that the supply-side issues may be driven by several other factors that are beyond banks' control. For instance, the previous stream of literature that we discussed on political connections clearly shows that banks favour politically connected firms even though they are riskier. Such external pressure has the potential for banks to experience higher moral hazard problems. Given that the government can always come back and infuse capital allows them to lax their strict lending guidelines. Thus, we hypothesise that capital infusions can lead to higher risk-taking behaviour when banks have liquidity channels from the government through capital infusions. Such behaviour should be more in government-controlled banks than private banks as taxpayers' funds allocation is controlled by the government.

Furthermore, the body of existing research documents moral hazard following capital infusions solely in crisis periods, an outcome more likely driven by adverse external shocks than by deliberate risk-taking under normal economic conditions, and, as Berger et al. (2020) argue, moral hazard is in fact more prone to emerge during non-crisis periods.

2.6. Zombie Lending

A growing body of literature provides empirical evidence on zombie lending, where banks continue to lend to unviable firms, particularly in contexts of undercapitalisation (Chopra et al., 2021; Giannetti & Simonov, 2013). Banks continue to lend to these zombie firms even after a capital infusion if the bank remains undercapitalised (Acharya et al., 2019).

While undercapitalisation has been shown as the main cause of zombie lending, measures by regulators, such as regulatory inspections, have been shown to curb zombie lending (Bonfim et al., 2023). Banks have been shown to lend relatively less to zombie firms in industries where they have sectoral expertise (De Jonghe et al., 2025). Bankruptcy reforms have also been shown to reduce zombie lending, though the banks that remain severely undercapitalised continue to lend to zombie firms even with reforms (Kulkarni et al., 2025).

Although the prevailing literature links zombie lending chiefly to banks' under-capitalisation, Qu (2018) finds that political pressure on government-owned banks can also fuel this practice. If political ties indeed outweigh capital adequacy in determining credit allocation, then capital infusions alone may prove insufficient to eliminate zombie lending. After receiving fresh equity, a bank might have both the capacity and the regulatory mandate to expand credit, but if the banks remain subject to political directives, they will continue to prop up politically connected zombie firms. In effect, the infusion restores lending power without altering the incentive structure that drives misallocation.

Based on the discussions in the above sections, we formulate four testable hypotheses, as follows:

Hypothesis 1: *Capital infusions during non-crisis periods induce moral hazard problem.*

Hypothesis 2: *The extent of a bank's risk-taking behaviour is dependent on its pre-existing level of financial distress.*

Hypothesis 3*: Capital-infused government-controlled banks, post-infusion, lend more to politically connected firms.*

Hypothesis 4*: The increase in post-infusion risk-taking behaviour of the government-controlled banks can be explained by the political connection of the borrowing firm.*

CHAPTER 3

RESEARCH METHODOLOGY

Chapter Overview

This chapter describes the data used from different sources in the analysis at both the bank and loan levels, and the research methods. First, the data and sample construction used in the bank-level analysis are described. In the next section, the research methods used for bank-level analysis are presented. Then the chapter focuses on data used for loan-level analysis, the sample construction, variables used and their definition. The last section of this chapter presents the research methods employed for the loan-level analysis.

3.1. Type of Study

This is a causal study that employs a quasi-natural experiment design that exploits the Indian government's staggered capital infusions into government-owned banks between 2006 and 2023 as exogenous shocks. In the subsequent sections, we describe the data and methodology at the bank-level and loan-level.

3.2. Bank-Level

3.2.1. Sources of Data

For testing our first and second hypotheses, we use data at the bank level. Our capital infusion information is drawn primarily from the Comptroller and Auditor General of India's audit report, which covers the period 2009-2017; we supplemented this with manually collected data for 2006-2008 and extended the series through 2020 using banks' annual reports. To obtain financial variables, we rely on the Centre for Monitoring Indian Economy's Prowess database, selecting all GOBs and private sector banks that are listed on either the Bombay Stock Exchange or the National Stock Exchange. In addition, we incorporate credit-risk measures from the Credit Research Initiative (CRI) of the National University of Singapore (accessed June 23, 2023).

3.2.2. Period of the Study

In our bank-level analysis, we use data from 2006 to 2020. The capital infusion started from 2009, so we use data from 2006 to incorporate the pre-treatment period for banks that first received the infusion in 2009. We do not consider data beyond 2020, so that the results are not distorted by the COVID-19 crisis, as it was not a typical economic crisis.

3.2.3. Sample

For our empirical analysis, GOBs[11] constitute the treatment group, while private sector banks serve as the control group; within the GOB cohort, we further distinguish between less distressed and more distressed institutions. We exclude any bank subsidiaries operating as commercial banks, and we also omit banks that have been publicly traded for fewer than 125 days (six calendar months) during our sample period. Our final panel spans 2006 through 2020 and comprises 40 distinct banks (21 GOBs and 19 private sector banks), resulting in 600 bank-year observations.

3.2.4. Sample Justification

We have used a sample of all the GOBs and private sector banks, which is a good representation of commercial banks in India, as these two categories of commercial banks dominate the industry. According to the *Report on Trend and Progress of Banking in India 2023-24*, the GOBs and private sector banks hold 92.64% of the total assets of all the scheduled commercial banks (SCBs) in India as of March 2024. Furthermore, GOBs and private sector banks account for 94.13% of the total SCB deposits and 95.48% of the total loans extended by SCBs.

3.2.5. Tools and Techniques used for the Analysis of Data

Our empirical strategy unfolds in two stages. First, to gauge whether targeted capital infusions reflect differential moral hazard behaviour, we classify GOBs by distress using propensity scores derived from a random-effects probit model. Specifically, we estimate:

[11] Effective January 21, 2019, the RBI reclassified IDBI as a private sector bank; prior to that date, it had been categorised among the "other GOB" group. However, because Life Insurance Corporation (a public sector undertaking) remains its largest shareholder, followed by the Government of India, and because IDBI continued to receive capital infusions even after being classified as a private bank, we maintain its designation as a public sector bank in our analysis.

$$y_{it} = \beta_1 CRAR_{it} + \beta_2 GNPA_{it} + \beta_3 ROE_{it} + \beta_4 cost\ to\ income_{it} + \beta_5 liquidity_{it} + \beta_6 senstivity_{it} + u_i + \epsilon_{it} \quad (1)$$

where $y = 1$ if bank i receives a capital infusion in year t, and zero otherwise. The CAMELS proxies serve as regressors, u_i captures bank-specific error term, and ϵ_{it} is the idiosyncratic error term. The estimated propensity score[12] for each bank-year, interpreted as its probability of receiving a capital infusion, serves as a proxy for distress.

We classify banks into high and low propensity groups based on a cut-off score of 0.5. Specifically, banks with a propensity score of 0.5 or higher are categorized as high propensity (more distressed), while those with scores below 0.5 are considered low propensity (less distressed). For each bank, we assess how frequently it falls into each category across time. If a bank is more often classified as high propensity, it is designated as a high propensity (more distressed) bank; otherwise, it is identified as a low propensity (less distressed) bank.

Second, to identify the causal impact of capital infusion on banks' risk-taking behaviour, we employ an enhanced Difference-in-Differences (DiD) approach designed for settings with multiple time periods, as proposed by Callaway and Sant'Anna (2021). While the generalised DiD framework has been widely used in empirical research, recent advancements in the econometrics literature have highlighted several limitations of this method. Notably, studies by de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021), and Sun and Abraham (2021) reveal that the DiD estimator in the generalised framework can be biased. This bias arises primarily because the method treats groups that receive the intervention earlier as controls for those treated later. Such a practice often results in the assignment of negative weights to earlier-treated groups, despite the fact that, logically, these weights should be positive. This undermines the validity of the estimated treatment effects.

[12] We do not include private sector banks in this regression as they do not receive infusion.

To overcome this issue, newer and more robust methodologies have been developed, including the one by Callaway and Sant'Anna (2021). Their approach addresses the problem of negative weighting by using either the never-treated or the not-yet-treated units as the control group. This avoids contamination from previously treated units and ensures more credible identification of treatment effects. By relying on this improved setup, the method estimates a weighted average of all valid Average Treatment Effects on Treated (ATTs) from multiple conventional DiD comparisons, thus avoiding the bias associated with inappropriate control group specification.

An added advantage of the Callaway and Sant'Anna (2021) method is that it provides ATT estimates disaggregated by calendar periods, which is particularly valuable for our analysis, given the staggered nature of capital infusions. The key estimating equation under this framework is as follows:

$$ATT(g,t) = [EY(g)_t - EY(NT)_t] - \left[EY(g)_{g-1} - EY(NT)_{g-1}\right] \tag{2}$$

In this equation, ATT denotes the average treatment effect on the treated banks, where *g* represents the year, a bank first receives capital infusion (i.e., the treatment), and *t* refers to the time. *NT* denotes the group of banks that have not yet been treated (or never treated). The first component captures the difference in outcomes at time *t* between the treated and control groups, and the second component adjusts for pre-treatment differences at time *g*-1, the period before the treatment begins. Once all ATT estimates are obtained, the method aggregates as the Aggregate ATT (AGGTT), using the following formula:

$$AGGTT = \frac{\Sigma(w_{g,t} * ATT(g,t))}{\Sigma(w_{g,t})} \tag{3}$$

Here, AGGTT represents the overall average treatment effect across all treated groups and time periods. The weights reflect the relative contribution of each ATT(g,t) estimate to the overall calculation, with more reliable estimates (i.e., those based on a larger number of observations) receiving greater weight. This weighting mechanism ensures that the final aggregated estimate gives prominence to treatment effects with higher precision while minimising the influence of potentially noisy estimates based on limited data.

3.2.6. Main Dependent Variables

Our primary outcome measures are the natural logarithm of the *z-score* and the *actuarial spread*[13]. The *z-score*, introduced by Roy (1952), serves as a proxy for a bank's insolvency risk and is computed as [Mean (ROA) + Mean (Equity/Assets)]/Stdv. ROA. Following Hryckiewicz (2014), we calculate *z-scores* by taking four-year moving averages, which show how many standard deviations profits must decline before equity is depleted (Boyd & De Nicolò, 2005). Because the *z-score* distribution is highly skewed, we follow Laeven and Levine (2009) and transform *z-scores* in logarithm form. Although the *z-score* captures insolvency risk, to assess credit risk explicitly, we also employ the *actuarial spread* as an outcome variable to examine how capital injections influence lending risk.

3.2.7. Control Variables

To account for heterogeneity in bank characteristics, our control variables encompass both CAMELS (Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk) proxies and additional bank-specific measures. Specifically, for capital adequacy, we include the capital-to-risk-weighted-assets ratio (*CRAR*), since undercapitalised banks may pursue greater risk (Acharya et al., 2019; Giannetti & Simonov, 2013). Asset quality is proxied by the gross non-performing assets ratio (*GNPA*), as banks with elevated NPAs might engage in riskier lending to recover losses. Management efficiency is

[13] The actuarial spread is a measure of credit risk that combines the term structure of default probabilities with the risk-free discount rate, effectively translating those "actuarial" default likelihoods into a credit default swap spread. For a comprehensive discussion, refer to the NUS CRI Technical Reports 2023.

measured by the *cost to income* ratio, reflecting the tendency of less efficient banks to gamble on high-risk opportunities to boost performance (Williams, 2004). Profitability and liquidity are captured by return on equity (*ROE*) and the ratio of current assets to total assets (*liquidity*), respectively, variables that, if strong, might discourage excessive risk-taking (Laeven & Levine, 2009). Sensitivity to market risk (*sensitivity*) is operationalised as the absolute difference between short-term assets and short-term liabilities, scaled by total assets. Beyond CAMELS, we control for *credit activity* (total loans to total assets) to ensure our findings on risk are not merely driven by lending volume, and we include bank size (*ln assets*) because larger institutions may diversify and reduce risk-taking (Saunders et al., 1990). We also incorporate the ratio of interest income to total income (*interest income*) and the deposit-to-asset ratio (*deposit to asset*) to distinguish traditional funding and income sources. Banks relying more on non-traditional activities may exhibit higher risk appetites. Finally, we include mergers and acquisitions dummy (*M A Dummy*) to capture the consolidation wave among GOBs during our sample period. When *ln z-score* is the dependent variable, we omit *CRAR* and *ROE* from the controls, since they overlap conceptually with equity/asset and profitability measures used to construct *z-score*.

Table 3.1: Descriptions of Variables at the Bank-Level

Variable	Description
Z-Score	Computed as [Mean(ROA) + Mean(Equity/Assets)]/Stdv. ROA]. This metric captures a bank's distance from insolvency, combining its average profitability and average equity-to-asset ratio, normalised by profit volatility.
Ln z-score	The natural logarithm of the z-score, used to reduce the skewness of the z-score distribution when modelling insolvency risk.
Actuarial spread	A forward-looking credit-risk indicator derived from the term structure of default probabilities and the risk-free rate. It represents the credit default swap spread calculated using actuarial inputs based on modelled probabilities of default.

DTD	The Merton (1974) distance to default model, adapted for banking firms.
Infusion	A binary indicator equal to 1 if bank *i* receives a capital infusion in year *t* and 0 otherwise.
Infusion Amount	The total value (in ₹ millions) of capital injected into bank *i* in year *t*.
GVAR	The calendar year in which bank *i* receives its first capital infusion.
CAMELS Proxies:	
Capital Adequacy- CRAR	The ratio of a bank's capital to its risk-weighted assets (expressed in per cent). A higher CRAR indicates stronger capitalization.
Asset Quality- GNPA	Gross Non-Performing Asset ratio (in percent), measuring the share of loans classified as nonperforming relative to gross advances.
Management Efficiency- cost to income	Operating expenses divided by the sum of net interest revenue plus other operating income (expressed in percent). This ratio reflects how much a bank spends to generate a rupee of operating income.
Earning Quality- ROE	Return on equity (in percent), calculated as net income divided by shareholders' equity. Higher ROE suggests better profitability
Liquidity- liquidity	The ratio of current assets to total assets (in percent). It indicates how much of a bank's asset base remains in liquid form.
Sensitivity to Market Risk- sensitivity	Defined as the absolute difference between current asset and current liabilities divided by total assets (in percent). This measures a bank's exposure to maturity mismatches and short-term interest rate changes.
Credit Activity	Total loans divided by total assets (in percent). This ratio serves as a proxy for the bank's overall lending volume relative to its balance sheet size.
Interest Income	Interest income as a percentage of total operating income. It captures the bank's reliance on traditional interest-earning activities.
Deposit to asset	Total customer deposits divided by total assets (in percent). This ratio indicates how heavily a bank depends on deposit funding.
LN_asset	The natural logarithm of a bank's total assets, used as a bank size proxy.

M_A_dummy	A binary indicator that equals 1 if bank *i* was part of a merger or acquisition in year *t* and 0 otherwise.
PD (Probability of Default)	The one-year estimated probability of default for each bank, calculated by an external credit-risk model.
Δloans	The natural log of the year-over-year change in total loans. This measures new lending activity.
AQR	A dummy variable that equals 1 for years 2016 through 2020, reflecting the period immediately after the RBI's Asset Quality Review, and 0 for all earlier years. This captures a regime shift toward stricter NPA recognition standards.

Note: This table provides detailed descriptions of all variables employed in the analysis.

3.3. Loan-Level

3.3.1. Sources of Data

For testing hypotheses 3 and 4, we use loan-level data from various sources. We obtain data regarding contributions made to political parties from the Election Commission of India (ECI). This data is maintained on the ECI website and is publicly available[14]. We obtain capital infusions data from an audit report by the CAG, which covers the years 2009 to 2017, and we manually collect data on capital infusions from annual reports of the banks for 2006-2008 and 2018-2023.

We collect loan-level data manually from the MCA website following Chopra et al. (2021). To obtain bank and firm-level financial variables, we use the Prowess database maintained by the CMIE. Additionally, we collect loan default data from CIBIL. CIBIL maintains data on suits filed by banks against defaulters on loan defaults above ₹10 million. We use this data to identify the year of defaults from firms' annual reports.

[14] https://www.eci.gov.in/contribution-reports

3.3.2 Period of the Study

Similar to our bank-level analysis, we collect data from 2006 to account for the pre-treatment period. We then extend this data till 2023, which was the latest available data at the time of data collection[15].

3.3.3. Sample Construction

Our data on political contributions contains 36428 observations, and we drop observations that are below the 90th percentile of the yearly total contribution[16], which leaves us with 3303 observations. We then drop observations containing donations from individuals and companies that are unlisted. Our final sample of politically connected firms includes 163 firms. We then include 404 non-connected firms from the BSE 500 index as the control firms in our sample. Of these BSE 500 firms, 96 are politically connected and are already included in our sample. Our data on banks includes GOBs and private-sector banks and we use them as the treatment group and the control group, respectively. We exclude banks that are not listed on a stock exchange and banks which are subsidiaries of another bank in the sample. Our final sample of banks includes 40 banks of which private sector banks are 19 and GOBs are 21.

We further exclude firms that do not borrow from GOBs or private sector banks during the sample period. Our final sample contains 480 firms of which 155 are politically connected and 325[17] are non-connected firms. Our loan-level data includes 8424 firm-bank-year observations after making the aforementioned exclusions.

[15] Data collection was done in 2024, and the prowess database was not updated with the financial year 2024 data at the time.
[16] We drop these observations because we cannot consider all the companies to be politically connected, as observations include contributions as low as ₹ 20000.
[17] We also exclude banks from BSE 500 firms.

3.3.4. Sample Justification

As argued in Section 3.2.4 of the bank-level sample, we consider only GOBs and private sector banks for the study, as they represent the bulk of commercial banking in India. Our sample of politically connected firms includes firms that have made high contributions to political parties, contributions greater than 90 percentile of the total contribution, and we include BSE firms for comparability. Furthermore, these companies borrow huge amounts of loans from banks due to their size. The average loan amount in our sample is ₹ 2.95 billion, which makes these companies a good sample for studying the role of political connection on bank moral hazard behaviour.

3.3.5. Tools and Techniques used for the Analysis of Data

In our empirical setup, a firm is considered politically connected if it has made a financial contribution to a political party that is a member of the ruling coalition of the central (federal) government or is the largest opposition party. Our econometric framework focuses on banks that have received capital infusions during the sample period and how these banks favour politically connected firms after the treatment. More specifically, we use a generalised difference-in-differences approach in our setup to identify the causal effects of capital infusion on politically motivated risky lending. Banks, in this case, do not know whether they will be infused in the future as the government does not disclose the banks that will receive infusion or the criteria for infusion, before the actual infusion, making the treatment exogenous.

To investigate the effect of capital infusions on politically motivated lending by banks, we employ the following difference-in-differences regressions along with interactions:

$$ln\ loans_{ijt} = \beta_1 infusion_{jt} + \beta_2 political_{it-1} + \beta_3 infusion_{jt} * political_{it-1} + \beta_4 bank\ controls_{jt-1} + \beta_5 firm\ controls_{it-1} + \beta_6 loan\ controls_{ijt} + \gamma_i + \theta_j + \pi_t + \epsilon_{ijt} \quad (4)$$

$$ln\ loans_{ijt} = \beta_1 infusion_{jt} + \beta_2 political_{it-1} + \beta_3 infusion_{jt} * political_{it-1} + \beta_4 bank\ controls_{jt-1} + \beta_5 loan\ controls_{ijt} + \gamma_i + \theta_j * \pi_t + \epsilon_{ijt} \quad (5)$$

Our main dependent variable is *ln loans,* the natural logarithm of total loans lent to firm *i* to bank *j* at time *t*. The independent variables include *infusion* (the difference-in-differences term) which is a dummy variable indicating capital infusion for bank *j* at time *t*, *political* which is a dummy variable indicating firm *i* donating to political parties at time *t-1* and the interaction effect of *infusion* and *political*. Our set control variables vary at bank, firm and loan level. Our first set of control variables *bank controls* includes *ROA* (banks' return on assets), *GNPA* (gross non-performing loans to total loans), *CRAR* (capital to risk-weighted assets) and *ln assets* (the natural logarithm of total assets). Our second set of control variables *firm controls* includes *leverage* (firms' debt-equity ratio), *liquidity* (current assets to current liabilities ratio), *ROA* (firms' return on assets) and *ln asset* (the natural logarithm of total assets). Our third set of control variables *loan controls* includes *loans completed*, *loan tenure* and *relationship* following Chopra et al. (2021). *Loans completed* is the number of loans completed by firm *i* with bank *j* in the last 5 years at time *t*. *Loan tenure* is the maximum loan tenure of completed loans between firm *i* and bank *j* at time *t*. *Relationship* is the number of years in a firm-bank pair with a loan outstanding in the past 5 years at time *t*. γ, θ and π are bank, firm and time-fixed effects, respectively. ϵ is the error term. Table 3.2 reports the definition of all the variables used in the analysis. In our second specification, we include borrower*year fixed effects to isolate bank supply-side effects from firm-specific demand-side effects.

Table 3.2: Descriptions of Variables at the Loan-Level

Variable	Description
Ln loans	The natural logarithm of total loans lent to firm *i* by bank *j*.
Infusion	Dummy variable taking the value 1 if bank *j* receives capital infusion from the government at time *t*.
GOB	Dummy variable taking the value 1 if bank *j* is a government-owned bank.

Political	Dummy variable taking the value 1 if firm *i* makes a donation (top 10 percentile of all the donations) at time *t* to a political party from the ruling alliance of the Central (Federal) Government or to the biggest opposition party.
Default	Dummy variable taking the value 1 if firm *i* defaults on its loan at time *t*.
Zombie	Dummy variable taking the value 1 for firms with an interest coverage ratio < 1 at time *t*.
CRAR	Capital to risk-weighted assets ratio.
GNPA	Gross non-performing assets to total loans ratio.
ROA	Return on assets.
Ln assets	The natural logarithm of total assets.
Leverage	Debt-to-equity ratio.
Liquidity	Current assets to current liabilities ratio.
Loans completed	The number of loans completed by firm *i* with bank *j* in the last 5 years at time *t*.
Loan tenure	The maximum loan tenure of completed loans between firm *i* and bank *j* at time *t*.
Relationship	The number of years in a firm-bank pair with a loan outstanding in the past 5 years at time *t*.
ICR	Interest coverage ratio.
Low dtd	Dummy variable taking the value 1 for firms if their distance to default (dtd) is less than the 25^{th} percentile in the sample.
Zombie2	Dummy variable taking the value 1 if a firm, over a three-year period, its accumulated recurring cash flows fail to cover accumulated interest expenses, fails to cover interest in at least two of those individual years, and is at least ten years old.
Zombie3	Dummy variable taking the value 1 if a firm has an interest coverage ratio less than 1 and is at least 10 years old.
Undercap	Dummy variable taking the value 1 if a bank is within 3% of the minimum regulatory capital requirement.
AQR	Banks' exposure to the Asset Quality Review.
Ln contributions	The natural logarithm of the total contribution made by firms to political parties.

Note: This table shows the description of all the variables used in the loan-level analysis.

To estimate the impact of capital infusion on politically motivated risky lending, we employ a difference-in-differences (DiD) framework with a triple interaction term:

$$ln\ loans_{ijt} = \beta_1 infusion_{jt} + \beta_2 political_{it-1} + \beta_3 default_{it-1} + \beta_4 infusion_{jt} * political_{it-1} + \beta_5 infusion_{jt} * default_{it-1} + \beta_6 political_{it-1} * default_{it-1} + \beta_7 infusion_{jt} * political_{it-1} * default_{it-1} + \beta_8 bank\ controls_{jt-1} + \beta_9 loan\ controls_{ijt} + \gamma_i + \theta_j * \pi_t + \epsilon_{ijt} \quad (6)$$

where *default* is a dummy variable indicating the firm has defaulted on its loan to a lender, 0 otherwise. The remaining variables follow the same definitions as in Equation 4. Our main variable of interest is the triple interaction term *infusion* * *political* * *default*.

CHAPTER 4

ANALYSIS AND FINDINGS

Chapter overview

This chapter presents the analysis and findings at both the bank-level and loan-level. At both levels, the summary statistics, univariate analysis, and regression analysis are reported. Furthermore, additional analysis and robustness analysis are also reported. Finally, the analysis to address endogeneity concerns at the loan level is presented.

4.1. Results at the Bank-Level Analysis.

4.1.1. Summary Statistics

Upon examining the summary statistics presented in Table 4.1, we find that the average value of *ln z-score* across all banks is 3.4, indicating the overall level of insolvency risk in the sample. The mean *actuarial spread* for all banks stands at 1.69. With respect to the CAMELS proxies, the average *CRAR* is 13.538, suggesting that the banks in the sample were generally well-capitalised, as the measure is well above the regulatory minimum of 9%. The *GNPA* ratio averages 4.955, while the *ROE* has a mean of 6.634. The average values for *cost-to-income* ratio, *liquidity*, and *sensitivity* are 52.738, 11.08, and 16.369, respectively. These statistics collectively suggest that, while the banks maintained adequate capital and maintained profitability, the relatively elevated *GNPA* indicates some deterioration in asset quality over the sample period. Further, the mean values of other bank characteristics show that the average *ln assets* is 13.797, *credit activity* is 60.04, *interest income* is 86.097, and the *deposit to asset* ratio is 80.822.

Table 4.1: Summary Statistics of All Banks.

	N	Mean	SD	Median
Ln z-score	551	3.4	1.064	3.454
Actuarial spread	527	1.69	1.669	1.143
Dtd	518	.941	1.508	.659
Gnpa (%)	567	4.955	5.091	2.99
Crar (%)	571	13.538	4.025	12.88
Roe (%)	571	6.634	17.979	11.49
Cost to income (%)	568	52.738	12.849	49.645
Liquidity (%)	573	11.08	5.745	10.313
Sensitivity (%)	573	16.369	211.115	6.952
LN assets	573	13.797	1.553	13.945
Credit activity (%)	571	60.04	5.439	60.565
Interest income (%)	564	86.097	8.102	88.155
Deposit to asset (%)	570	80.822	11.241	84.85
Rwa (%)	560	62.329	9.602	61.341
Δloans	506	11.31	1.434	11.457
Infusion amount (in ₹ Million)	153	24566.08	30809.86	10540

Note: This table presents descriptive statistics for the full sample of banks. N indicates the count of observations; Mean denotes the average; SD refers to the standard deviation; and Median refers to the median value.

Next, we report summary statistics of GOBs and private sector banks in Tables 4.2 and 4.3, respectively. The summary statistics reveal that private sector banks exhibit lower average risk-taking behaviour compared to all treatment groups. Moreover, their higher average values on financial indicators suggest relatively better financial health.

Table 4.2: Summary Statistics of GOBs.

	N	Mean	SD	Median
Ln zscore	306	3.203	0.941	3.332
Actuarial spread	295	2.474	1.786	2.14
Dtd	286	.142	0.914	.106
Gnpa (%)	305	6.438	6.011	3.71
Crar (%)	306	12.233	1.292	12.285
Roe (%)	306	4.495	20.051	10.745
Cost to income (%)	305	50.111	8.291	48.7
Liquidity (%)	306	10.82	3.252	10.409
Sensitivity (%)	306	7.639	3.311	7.039
LN assets	306	14.483	0.939	14.445
Credit activity (%)	306	60.128	4.941	60.752
Interest income (%)	304	88.316	3.810	88.875
Deposit to asset (%)	306	84.277	6.055	85.565
Rwa (%)	306	59.423	7.332	59.067
Δloans	263	11.817	1.014	11.77
Infusion amount (in ₹ Million)	153	24566.08	30809.86	10540

Note: This table presents descriptive statistics for government-owned banks. N indicates the count of observations; Mean denotes the average; SD refers to the standard deviation; and Median refers to the median value.

Table 4.3: Summary Statistics of Private Sector Banks

	N	Mean	SD	Median
Ln zscore	245	3.647	1.154	3.697
Actuarial spread	232	.692	0.702	.48
Dtd	232	1.927	1.513	1.871
Gnpa (%)	262	3.229	2.924	2.45
Crar (%)	265	15.045	5.366	14
Roe (%)	265	9.103	14.900	12.15
Cost to income (%)	263	55.786	16.130	51.18
Liquidity (%)	267	11.378	7.660	10.266
Sensitivity (%)	267	26.373	309.258	6.95

LN assets	267	13.012	1.737	12.986
Credit activity (%)	265	59.938	5.971	60.247
Interest income (%)	260	83.503	10.638	86.815
Deposit to asset (%)	264	76.818	14.174	82.18
Rwa (%)	254	65.83	10.787	65.297
Δloans	243	10.762	1.612	10.612

Note: This table presents descriptive statistics for private sector banks. N indicates the count of observations; Mean denotes the average; SD refers to the standard deviation; and Median refers to the median value.

Summary statistics for High PS and Low PS banks are reported in Tables 4.4 and 4.5, respectively. When comparing High PS and Low PS banks, we find that, on average, Low PS banks face higher insolvency risk, whereas High PS banks are more exposed to credit risk. As for bank fundamentals, Low PS banks tend to be in better financial condition as indicated by higher *CRAR* and *ROE* and lower *GNPA*, which aligns with expectations. Additionally, the mean capital infusion amount appears to be slightly greater for Low PS banks compared to High PS banks.

Table 4.4: Summary Statistics of High PS Banks

	N	Mean	SD	Median
Ln z-score	115	3.094	0.994	3.238
Actuarial spread	108	2.582	1.715	2.421
Dtd	104	-.102	0.835	-.14
Gnpa (%)	114	7.279	7.145	3.93
Crar (%)	115	12.043	1.277	11.95
Roe (%)	115	.651	23.232	9.28
Cost to income (%)	115	50.265	8.494	49.16
Liquidity (%)	115	10.364	2.911	9.803
Sensitivity (%)	115	7.747	2.870	7.353
LN assets	115	14.098	0.652	14.136
Credit activity (%)	115	58.918	5.341	60.428
Interest income (%)	115	89.167	3.706	89.66
Deposit to asset (%)	115	83.902	8.913	86.75
Rwa (%)	115	60.154	9.427	58.663
Δloans	92	11.341	0.750	11.474
Infusion amount (in ₹ Million)	58	20515	25027.92	10130

Note: This table presents descriptive statistics for High PS banks. N indicates the count of observations; Mean denotes the average; SD refers to the standard deviation; and Median refers to the median value.

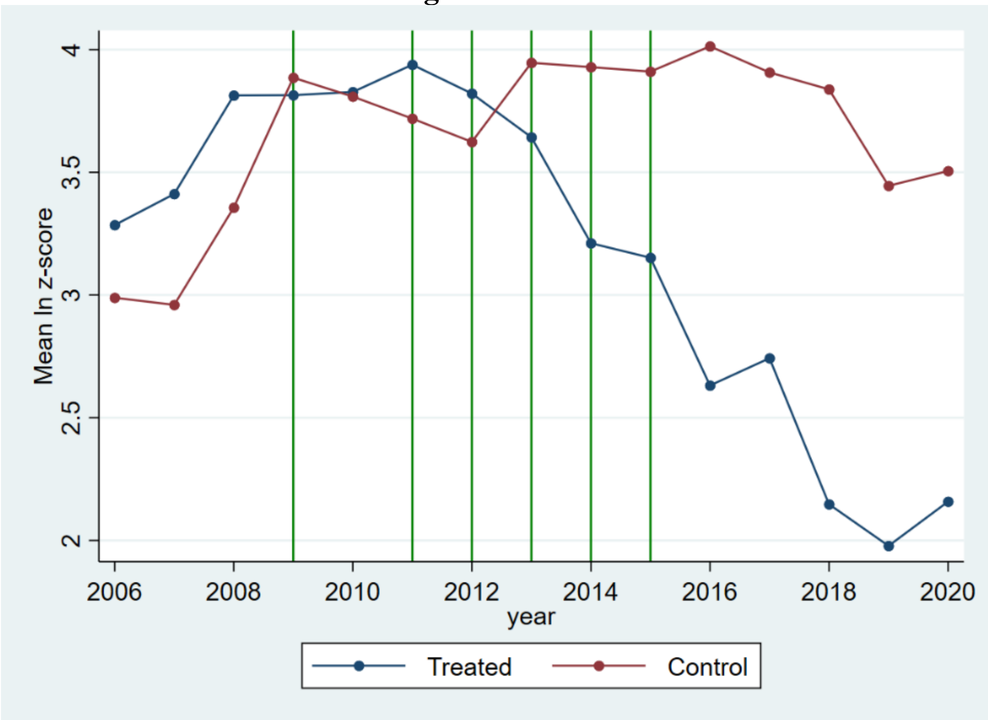
Table 4.5: Summary Statistics of Low PS Banks

	N	Mean	SD	Median
Ln z-score	191	3.268	0.904	3.367
Actuarial spread	187	2.412	1.828	2.001
Dtd	182	.281	0.930	.297
Gnpa (%)	191	5.937	5.174	3.67
Crar (%)	191	12.348	1.291	12.43
Roe (%)	191	6.81	17.528	12.57
Cost to income (%)	190	50.017	8.188	48.575
Liquidity (%)	191	11.095	3.419	10.774
Sensitivity (%)	191	7.574	3.556	6.843
LN assets	191	14.714	1.008	14.633
Credit activity (%)	191	60.856	4.545	61.246
Interest income (%)	189	87.797	3.789	88.27
Deposit to asset (%)	191	84.502	3.326	84.75
Rwa (%)	191	58.983	5.697	59.171
Δloans	171	12.073	1.045	12.053
Infusion amount (in ₹ Million)	95	27039.36	33746.24	11000

Note: This table presents descriptive statistics for Low PS banks. N indicates the count of observations; Mean denotes the average; SD refers to the standard deviation; and Median refers to the median value.

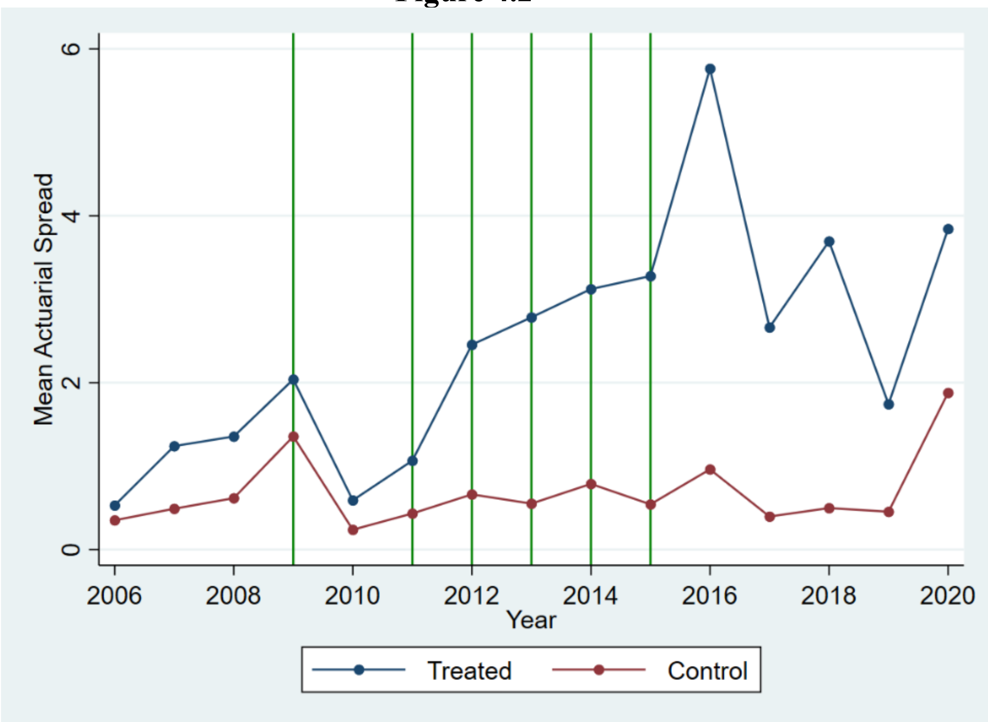
To gain an initial understanding of how risk-taking behaviour evolved over time for our treatment group (GOBs) and control group (private banks), we visualise the temporal trends in our risk measures in Figures 4.1 and 4.2. In Figure 4.1, before capital infusions began in 2009, private banks exhibit, on average, lower *ln z-score* values compared to GOBs, indicating higher risk-taking. This pattern persists through 2012, after which, beginning in 2013, private banks' average *ln z-score* surpasses that of GOBs, signalling relatively lower risk-taking among private institutions from that point onward. Turning to Figure 4.2, we see that the average *actuarial spread* remains consistently higher for GOBs than for private banks across all years in our sample, reflecting that GOBs generally undertake more credit risk. It is noteworthy that, outside of crisis periods, GOBs tend to display elevated risk-taking relative to private banks.

Figure 4.1



Note: Mean value of *ln z-score* for both treatment and control banks throughout the sample period; vertical markers indicate each bank's first year of receiving a capital infusion.

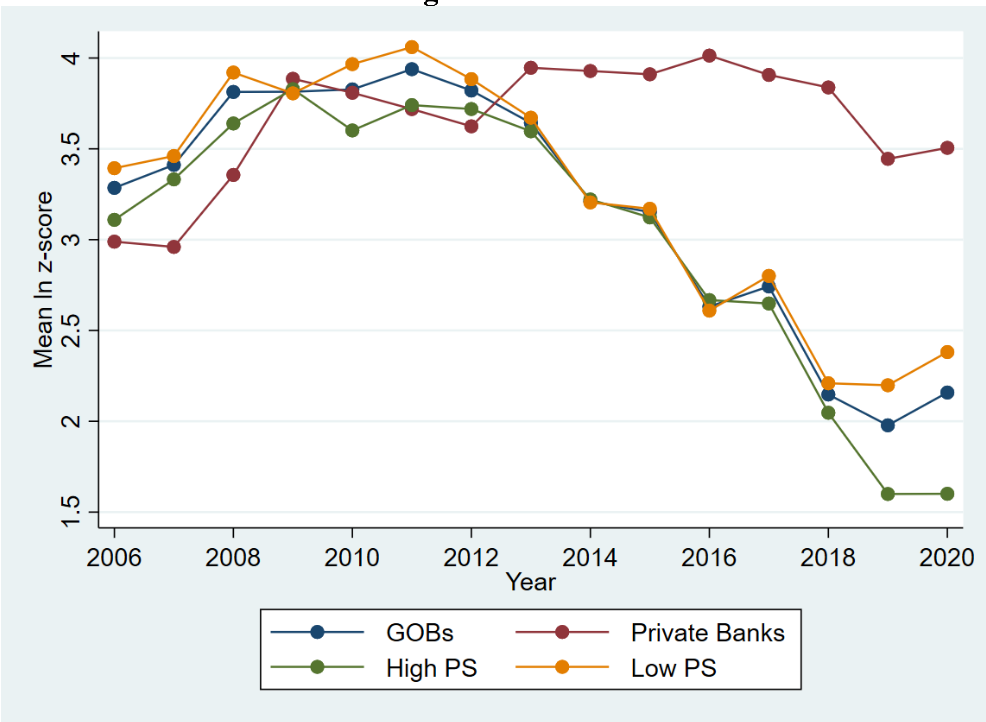
Figure 4.2



Note: Mean value of *actuarial spread* for both treatment and control banks throughout the sample period; vertical markers indicate each bank's first year of receiving a capital infusion.

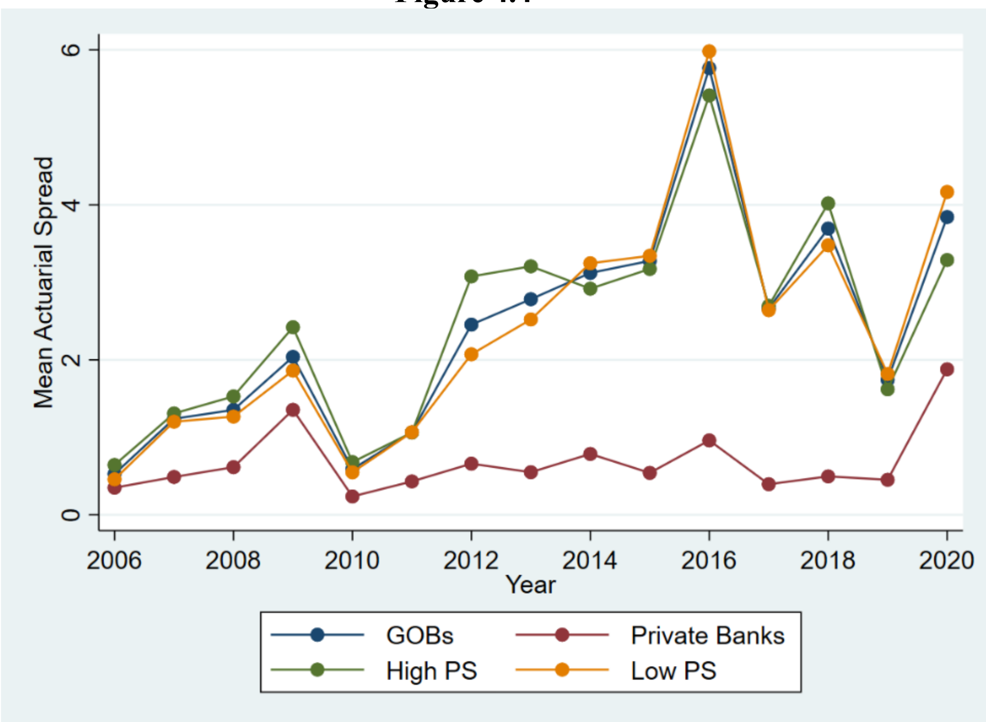
Next, we extend these visual comparisons by including High PS and Low PS subgroups alongside GOBs and private banks in Figures 4.3 and 4.4.

Figure 4.3



Note: Mean *ln z-score* of GOBs, Private Banks, High PS and Low PS throughout the sample period.

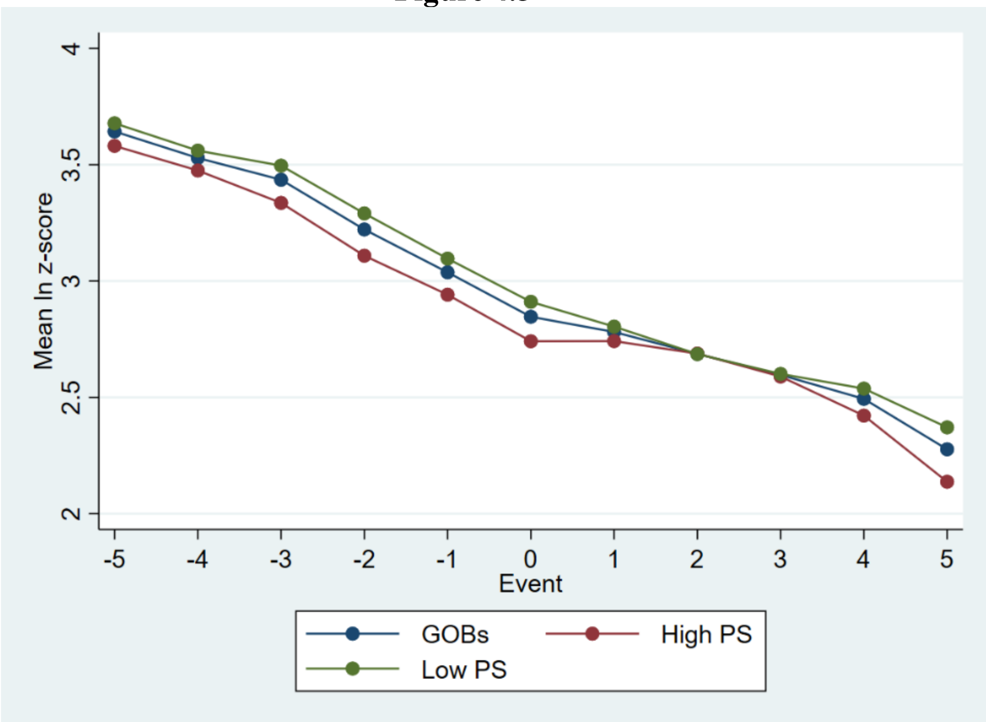
Figure 4.4



Note: Mean *actuarial spread* of GOBs, Private Banks, High PS and Low PS throughout the sample period.

In Figure 4.3, the average *ln z-score* for Low PS banks exceeds that for High PS banks, indicating that Low-PS banks are, on average, less risky in terms of insolvency than their High PS counterparts. Figure 4.4 shows that High PS banks generally register larger average *actuarial spreads* than Low PS banks, suggesting that High PS banks take on more credit risk over time.

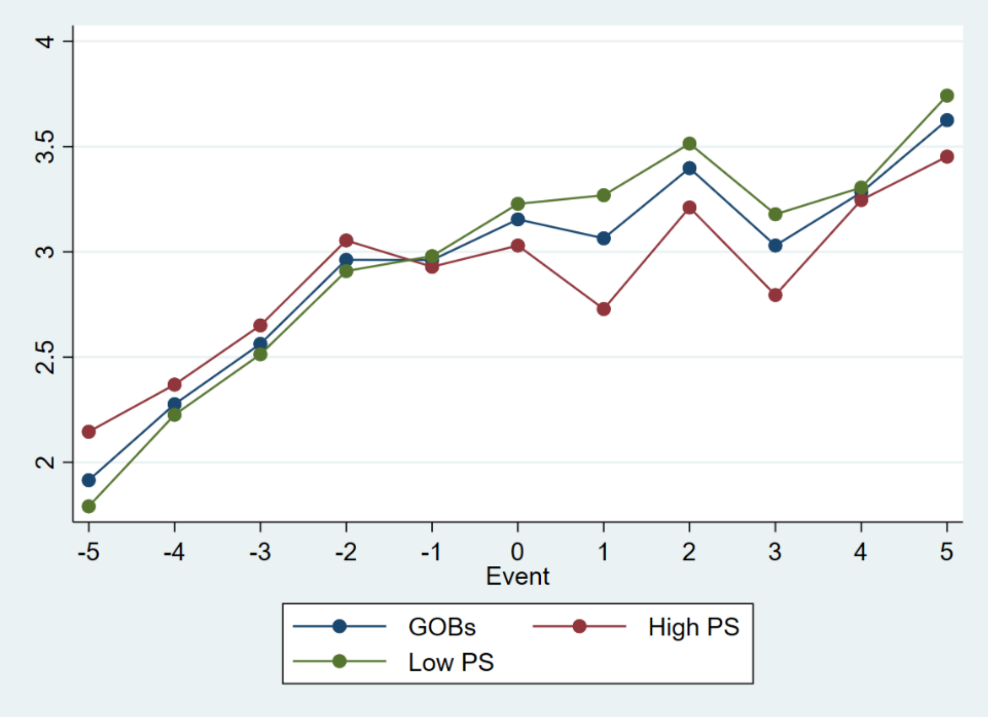
Figure 4.5



Note: Average *ln z-score* plotted across the event-time window surrounding each bank's infusion year.

Subsequently, we chart the temporal evolution of our risk indicators using event windows in which *t* denotes the year of capital infusion for each bank *i*. As shown in Figure 4.5, before the treatment occurs, Low-PS banks exhibit lower insolvency risk compared to the other groups. Yet, all three cohorts experience a drop in *ln z-score* once they move from the pre-treatment to the post-treatment interval, signifying that insolvency risk increases following infusion. Turning to credit risk, shown by the actuarial spread in Figure 4.6, we find that in the years after infusion, spreads sometimes rise and sometimes fall, indicating that credit risk both increases and decreases across different post-treatment periods.

Figure 4.6



Note: Average *actuarial spread* plotted across the event-time window surrounding each bank's infusion year.

4.1.2. Univariate Analysis

Table 4.6 presents the results of our mean-difference tests. We begin by comparing the average *ln z-score* and *actuarial spread* between GOBs and private sector banks in Panel A of the table. The findings indicate that private sector banks have a significantly higher *ln z-score* with a difference of .444, which implies that GOBs exhibit greater insolvency risk. Conversely, the *actuarial spread* is significantly lower for private sector banks with a difference of -1.782, again signalling that GOBs carry higher credit risk.

Next, we examine the difference in *ln z-score* and *actuarial spread* between High PS banks and Low PS banks, in Panel B. Interestingly, neither *ln z-score* nor *actuarial spread* differs significantly between these two subgroups, suggesting comparable levels of both insolvency and credit risk over the sample period.

We then compare our primary outcome variables, *ln z-score* and *actuarial spread*, between High PS banks and private sector banks, in Panel C. Here, private sector banks again show a significantly higher *ln z-score*, and a significantly lower *actuarial spread* than High PS banks, with the difference being .553 and -1.89, respectively, indicating that private banks have lower insolvency and credit risk compared to High PS banks.

Finally, we compare Low PS banks with private sector banks, in Panel D. The results mirror the previous comparison as private sector banks maintain a significantly higher *ln z-score* and a significantly lower *actuarial spread* relative to Low-PS banks, with the difference being .379 and -1.72, respectively, reaffirming that private banks are less risky than the Low PS treatment group.

In summary, our univariate analysis reveals that both insolvency risk and credit risk are consistently higher for GOBs (including both High PS and Low PS subgroups) compared to private sector banks throughout the sample period. Moreover, there is no statistically significant difference in either insolvency risk or credit risk between the High PS and Low PS groups over the same timeframe.

Table 4.6: Mean Difference Test

Panel A			
Variables	**Private Sector Banks**	**GOBs**	**Mean Difference**
Ln z-score	3.647	3.203	.444***
			(4.85)
Actuarial spread	.693	2.474	-1.782***
			(-15.65)

Panel B			
Variables	**Low PS**	**High PS**	**Mean Difference**
Ln z-score	3.268	3.094	.175
			(1.55)
Actuarial spread	2.412	2.583	-.171
			(-.8)

Panel C			
Variables	**Private Sector Banks**	**High PS**	**Mean Difference**
Ln z-score	3.647	3.094	.553*** (4.65)
Actuarial spread	.693	2.583	-1.89*** (-11.05)

Panel D			
Variables	**Private Sector Banks**	**Low PS**	**Mean Difference**
Ln z-score	3.647	3.268	.379*** (3.85)
Actuarial spread	.693	2.412	-1.72*** (-12.5)

Note: This table presents the results of mean-difference tests for *ln z-score* and *actuarial spread* across various bank group comparisons. Panel A compares private sector banks with government-owned banks. Panel B compares Low-PS banks to High-PS banks. Panel C examines private sector banks versus High-PS banks, and Panel D compares private sector banks to Low-PS banks. The t-statistics are shown in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.1.3. Regression Results

In this section, we present our regression analysis using the Callaway and Sant'Anna (2021) Difference-in-Differences framework. Table 4.7 contains the key regression results. For the *ln z-score*, the estimated ATT coefficients are negative and statistically significant at the 5% level (or less) across all three treatment cohorts, indicating that insolvency risk increases following capital infusion. These findings point to moral hazard behaviour in GOBs, although these ATT estimates pool together both crisis and non-crisis periods. In particular, the High PS group exhibits the most pronounced effect as its ATT for *ln z-score* is -1.484, the lowest among all treatment groups, implying the greatest post-infusion rise in risk-taking.

When we switch to *actuarial spread* as the dependent variable, all three treatment groups have positive ATT coefficients that are significant at the 10% level (or lower), demonstrating an increase in credit risk after infusion. Here, the Low PS group stands out by showing the largest jump in credit risk.

Table 4.7: Impact of Capital Infusion on Bank Risk-Taking Behaviour.

VARIABLES	(1) Ln z-score (All GOBs)	(2) Actuarial spread (All GOBs)	(3) Ln z-score (High PS)	(4) Actuarial spread (High PS)	(5) Ln z-score (Low PS)	(6) Actuarial spread (Low PS)
ATT	-1.45***	1.893***	-1.478**	1.508*	-1.432**	2.14***
	(.539)	(.475)	(.703)	(.91)	(.634)	(.481)
Observations	539	484	350	314	425	390

Note: This table reports the results of difference-in-differences regressions. The dependent variables are ln z-score and actuarial spread. The treatment group for model 1 and 2 is all PSBs. The treatment group for model 3 and 4 is High PS banks. The treatment group for model 5 and 6 is Low PS banks. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy. CRAR and ROE are excluded in model 1,3 and 5. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

To disentangle how risk-taking behaviour varies across crisis versus non-crisis episodes, we examine the ATT coefficients by calendar year. Table 4.8 reports these year-specific estimates. For the *ln z-score*, the ATT coefficients for 2009, 2010, and 2011 are not statistically significant, indicating no detectable moral hazard during those crisis years. The ATT for *ln z-score* reaches its most negative and statistically significant level in 2013.

Turning to *actuarial spread*, the ATT estimates are insignificant in 2009, 2010, 2019, and 2020, again suggesting that credit risk does not rise during crisis periods. For all other sample years, the ATT coefficients on *actuarial spread* are positive and statistically significant, with the largest effect observed in 2016.

Table 4.8: ATT by Calendar Periods with Ln Z-Score and Actuarial Spread as the Dependent Variables.

ATT	(1) Ln z-score	(2) Actuarial spread
2009	-0.423	0.302
	(0.436)	(0.287)
2010	-0.673	-0.165

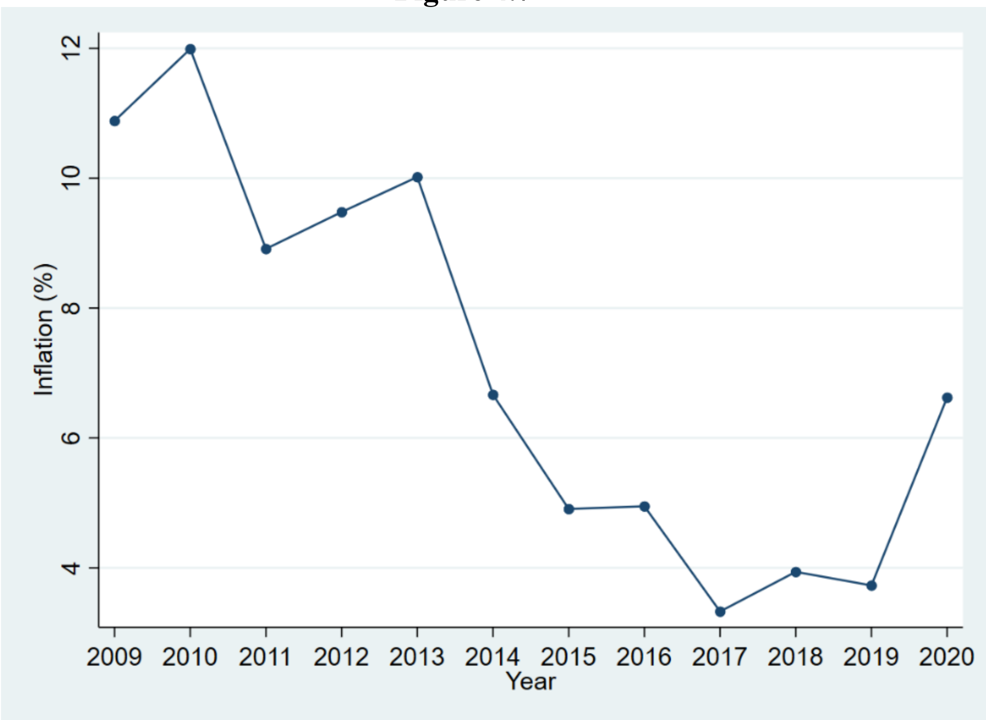
	(0.699)	(0.246)
2011	-0.520	0.639**
	(0.454)	(0.276)
2012	-1.325***	1.339***
	(0.425)	(0.249)
2013	-2.478***	1.606***
	(0.665)	(0.290)
2014	-1.906***	1.455***
	(0.706)	(0.538)
2015	-1.690*	2.512***
	(0.888)	(0.571)
2016	-2.114**	4.531***
	(1.038)	(0.964)
2017	-0.178	1.718***
	(0.809)	(0.612)
2018	-1.138	2.809***
	(0.854)	(0.568)
2019	-1.560	0.923
	(0.976)	(0.573)
2020	-2.138*	0.994
	(1.099)	(1.748)
Observations	539	484

Note: This table reports the results of difference-in-differences regressions showing average treatment effect on treated by calendar periods. The dependent variables are ln z-score and actuarial spread. The treatment group for model 1 and 2 is all PSBs. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy. CRAR and ROE are excluded in model 1. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

We next plot the ATT estimates for each calendar year along India's annual retail inflation rate and the prevailing lending interest rate, displaying these relationships in Figures 4.7, 4.8, 4.9, and 4.10. Economic theory suggests that a higher inflation environment may squeeze corporate liquidity, elevating the likelihood of firm-level defaults (Wadhwani, 1986), while elevated lending rates tend to depress credit demand. In our sample, retail inflation peaks in 2009 and 2010, and the average lending rate is at its highest in 2008 and 2009. Yet, during these years of heightened macroeconomic stress, the ATT coefficients for both insolvency and credit-risk outcomes remain statistically insignificant. In other words, despite adverse macro conditions, banks do not exhibit an uptick in post-infusion risk-taking during the crisis years.

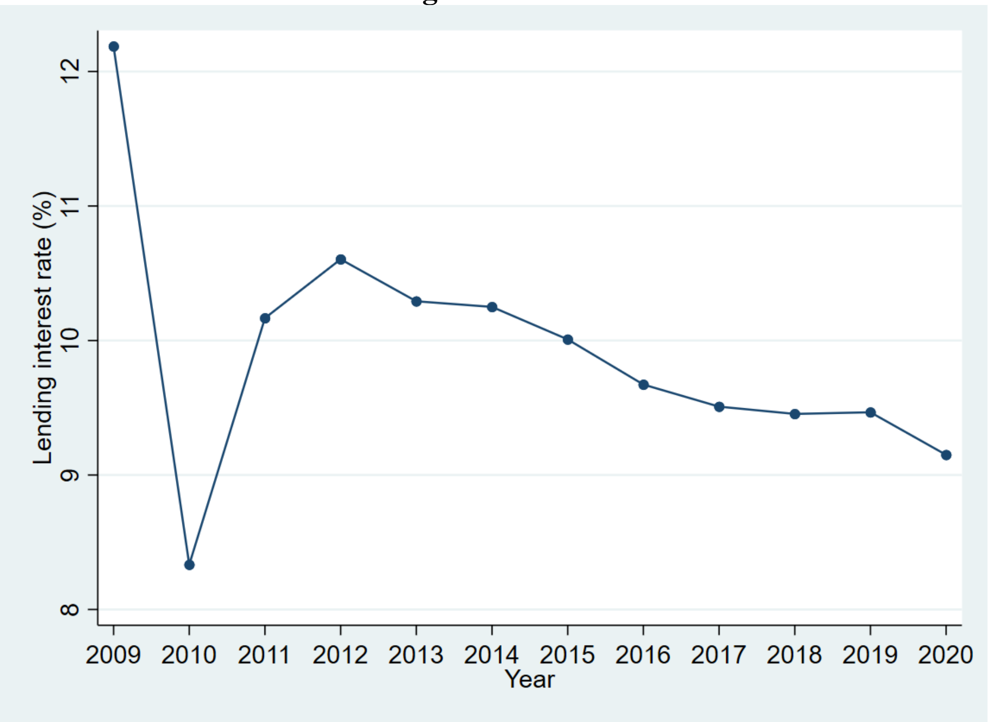
By contrast, we find that the most pronounced (and statistically significant) increases in insolvency risk occur in 2013 and again in 2016. Likewise, credit-risk ATTs reach their largest significant values in 2016 and 2018. It is notable that inflation is relatively low in 2017 and 2019, while lending rates have rebounded from their crisis-era troughs, creating a more favourable borrowing environment and likely boosting loan demand. Taken together, these patterns indicate that capital infusions disbursed during the crisis peak do not immediately spur moral hazard. Rather, the behavioural shift toward riskier bank lending and lower insolvency buffers becomes evident only after the worst macro-financial stress has abated, suggesting moral hazard emerges in the post-crisis recovery period.

Figure 4.7



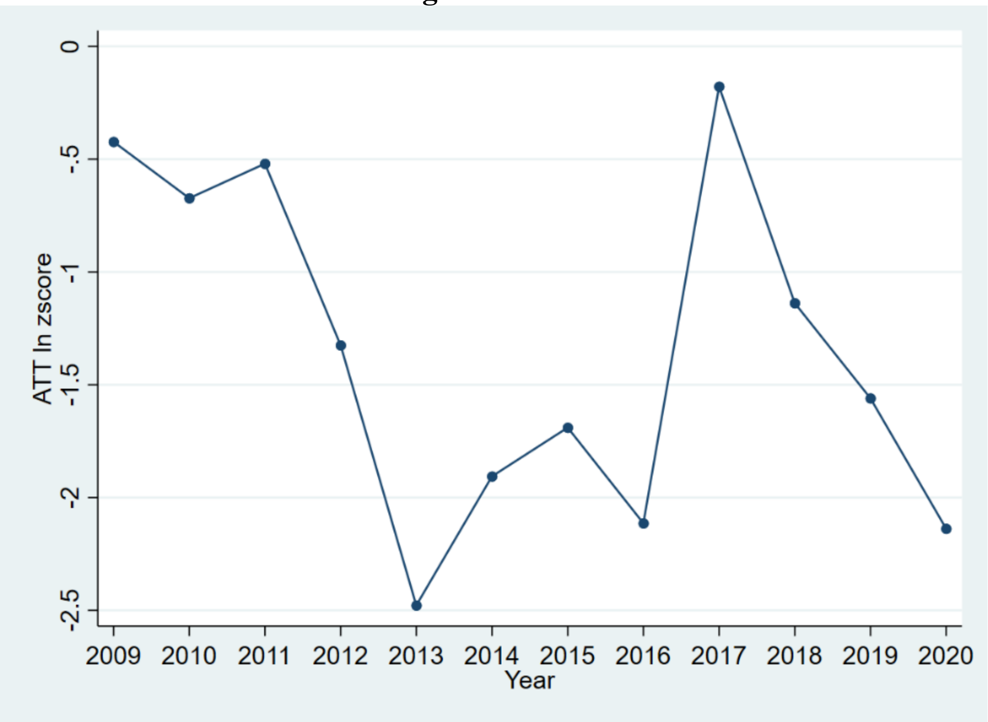
Note: Retail inflation trends in India across the Average Treatment Effect on the Treated (ATT) periods, segmented by calendar years, are presented in this figure. The data is sourced from the World Bank Open Data.

Figure 4.8



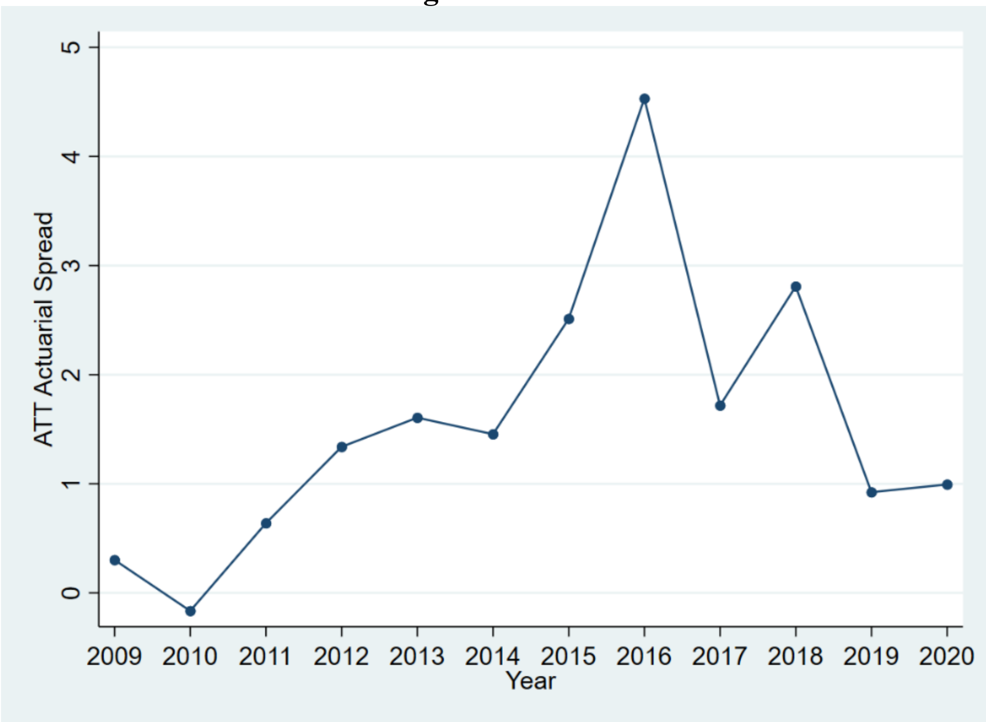
Note: Lending interest rate trends in India across the Average Treatment Effect on the Treated (ATT) periods, segmented by calendar years, are presented in this figure. The data is sourced from the World Bank Open Data portal.

Figure 4.9



Note: This figure presents the Average Treatment Effect on the Treated (ATT) coefficients for *ln z-score* across calendar years.

Figure 4.10



Note: This figure presents the Average Treatment Effect on the Treated (ATT) coefficients for *actuarial spread* across calendar years.

Collectively, our baseline findings indicate that banks do not alter their risk-taking behaviour following a capital infusion if the infusion occurs during periods of financial distress (i.e., crisis years). In contrast, we document clear evidence of moral hazard once we move into non-crisis intervals. This pattern aligns with our first hypothesis and corroborates the contention of Berger et al. (2020) that moral hazard incentives tend to materialise during normal economic conditions rather than during a crisis.

Moreover, the policy of allocating capital infusions selectively, i.e., targeting certain banks as directed by the Department of Financial Services, Government of India, appears to have no significant impact on *ex post* risk-taking. According to Merton (1977) framework, banks with higher propensity scores (the High PS group) should theoretically face stronger incentives to gamble on riskier assets once they receive fresh capital. Our results confirm this expectation in terms of insolvency risk as High PS banks exhibit a larger post-infusion decline in *ln z-score*.

However, no analogous uptick in credit risk emerges for these High PS banks. Crucially, though, both the High PS and the Low PS cohorts display moral hazard behaviour in our estimates. The fact that even the less distressed banks (Low PS group) increase risk after receiving capital suggests that the incentive to take on additional risk is not confined to banks already in poor financial health; rather, it appears to be a more general response to obtaining new capital.

Since banks across both distress levels behave as if they are unconstrained after an infusion, we find no support for our second hypothesis. If targeted infusions affected their risk appetite, we would expect the Low PS banks to exhibit no significant moral hazard effects. Instead, the observed increase in risk among Low PS banks implies that any potential stabilising influence of a targeted capital injection is completely offset by the banks' *ex post* incentives to exploit the safety net, i.e., the moral hazard effect dominates. Consequently, regardless of a bank's initial distress level, the infusion of new capital induces an increase in both insolvency and credit risk, reflecting the overarching predominance of moral hazard incentives.

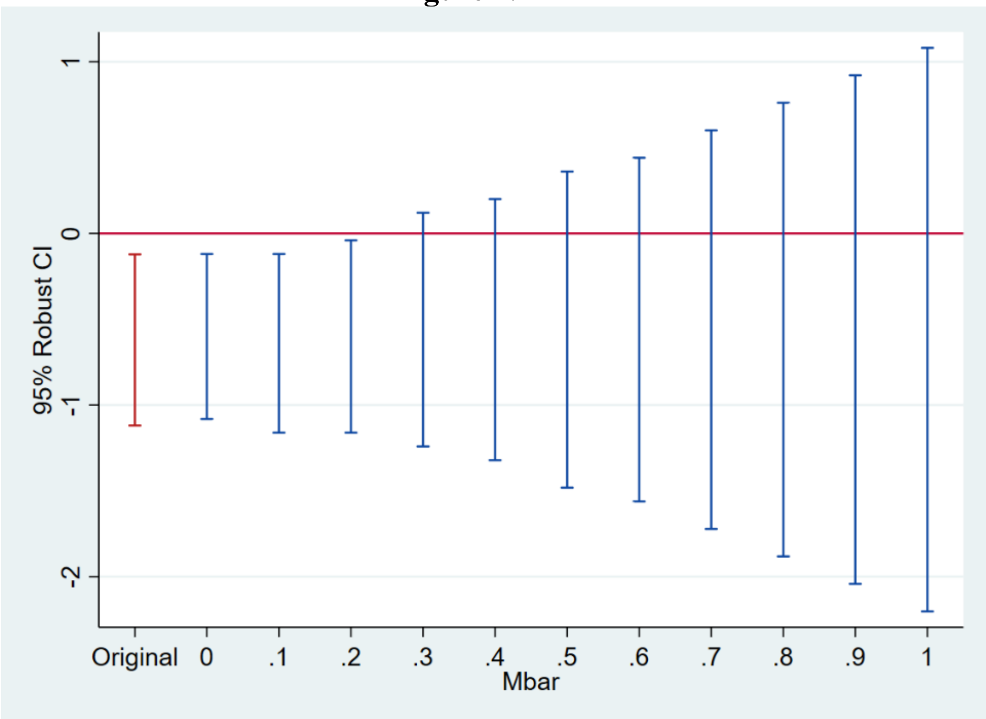
4.1.4. Parallel Trend Assumption

The validity of the DiD approach hinges on the assumption that, in the absence of treatment, the treated and control units would have exhibited identical outcome trajectories. A standard way to assess the parallel trend assumption is to test for differences in pre-treatment trends. Our test reveals that the parallel trends assumption is violated, so we implement the Rambachan and Roth (2023) sensitivity analysis to allow partial identification.

Rambachan and Roth (2023) formalise the idea that information from the pre-treatment period constrains how far post-treatment trends can deviate. Specifically, they show that the size of any deviation from parallel trends after treatment cannot exceed the maximum deviation observed before treatment by more than a constant, $\bar{M}$. In other words, setting $\bar{M} = 1$ requires that any post-treatment departure from parallel trends be no larger than the worst pre-treatment departure.

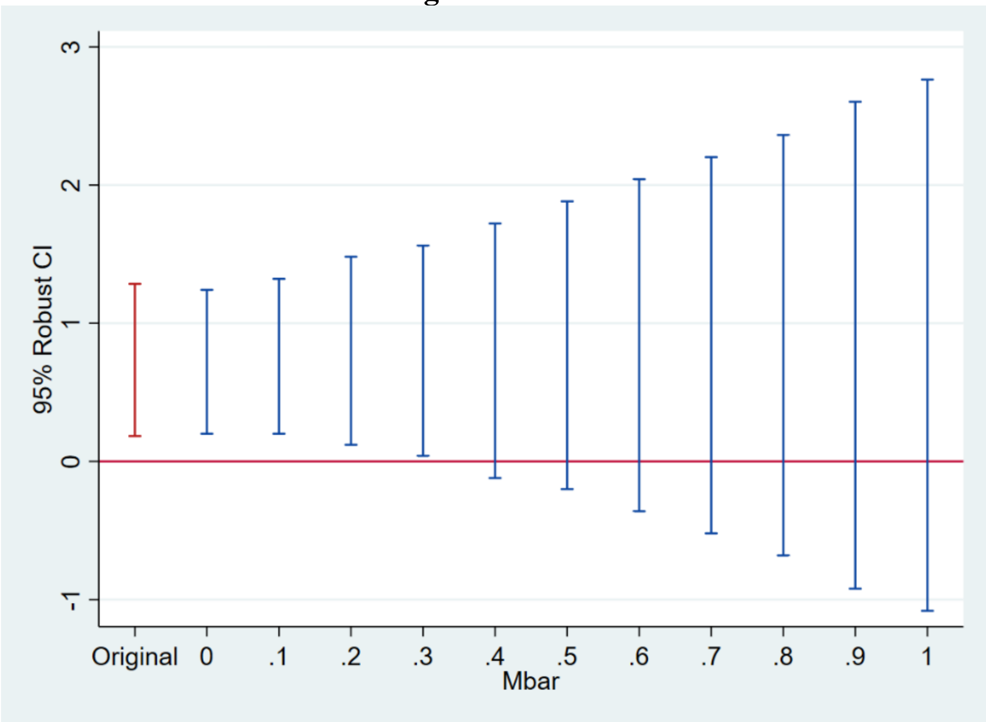
Figures 4.11 and 4.12 display the resulting sensitivity regions for our two main outcomes, indicating that the parallel trends condition is indeed satisfied, but only up to a certain allowance for deviations. When $\bar{M}$ is between 0 and 0.25, the parallel trend assumption holds. Put differently, our sensitivity analysis implies that post-treatment deviations remain within 30% of the largest pre-treatment deviation, which keeps the parallel trends assumption intact under reasonable bounds.

Figure 4.11



Note: This figure presents the results of a sensitivity analysis using the framework proposed by Rambachan and Roth (2023), with *ln z-score* as the outcome variable.

Figure 4.12



Note: This figure presents the results of a sensitivity analysis using the framework proposed by Rambachan and Roth (2023), with *actuarial spread* as the outcome variable.

4.1.5. Robustness Checks

To assess the robustness of our baseline findings, we re-estimate the regressions using alternative proxies for insolvency and credit risk. Specifically, we employ Merton's Distance to Default[18] (*DTD*) as a proxy for insolvency risk, and the ratio of gross non-performing assets (*GNPA*) to total assets as a proxy for credit risk. The results, reported in Table 4.9, are consistent with our earlier findings as the ATT coefficient for *DTD* is negative and statistically significant across all three treatment groups, indicating heightened insolvency risk post-capital infusion.

[18] We employ the Distance to Default (DTD) model sourced from the CRI (Credit Research Initiative) database, which incorporates specific adjustments tailored for financial firms. A negative DTD value signifies a heightened risk of insolvency. For a comprehensive methodological explanation, refer to the NUS CRI Technical Reports 2023.

Similarly, the ATT coefficient for the *GNPA* ratio is positive and significant for all groups, suggesting a rise in credit risk.

Table 4.9: Impact of Capital Infusion on Bank Risk-Taking Behaviour with Alternate Variables.

VARIABLES	(1) DTD (All GOBs)	(2) DTD (High PS)	(3) DTD (Low PS)	(4) GNPA (All GOBs)	(5) GNPA (High PS)	(6) GNPA (Low PS)
ATT	-2.2***	-2.645*	-1.89**	6.668***	8.653***	5.35***
	(.827)	(1.501)	(.825)	(1.375)	(2.636)	(1.12)
Observations	473	314	379	550	361	436

Note: This table reports the results of difference-in-differences regressions. The dependent variables are DTD and GNPA ratio. The treatment group for model 1, 2 and 3 is all PSBs, High PS banks and Low PS banks respectively. The treatment group for model 4, 5 and 6 is all PSBs, High PS banks and Low PS banks respectively. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy for model 1,2 and 3. GNPA is excluded as control variable in model 4,5 and 6 as it is the dependent variable. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

When we examine the ATT estimates by calendar year in Table 4.10, we find that both *DTD* and *GNPA* are statistically insignificant in 2009. However, by 2010, still within the crisis period, *DTD* becomes significantly negative and *GNPA* significantly positive, suggesting an earlier onset of moral hazard behaviour than in the baseline specification. Notably, the most pronounced increase in insolvency risk appears in 2018, while credit risk peaks in 2020.

Despite some variation in the timing of risk-taking, these robustness checks reinforce the main conclusion from our baseline analysis that banks are more prone to engage in moral hazard behaviour in non-crisis periods.

Table 4.10: ATT by Calendar Periods with DTD and GNPA as the Dependent Variables.

ATT	(1) DTD	(2) GNPA
2009	.012	2.216

	(.335)	(1.531)
2010	-1.957***	3.699***
	(.362)	(1.174)
2011	-.993	0.303
	(.769)	(0.679)
2012	-1.043	0.470
	(.704)	(0.668)
2013	-1.766**	1.238
	(.853)	(0.960)
2014	-.564	2.472**
	(.712)	(1.147)
2015	-3.162***	4.877***
	(.876)	(1.597)
2016	-2.173**	9.365***
	(.983)	(1.949)
2017	-3.806***	11.66***
	(1.407)	(2.224)
2018	-5.334**	13.56***
	(1.389)	(2.705)
2019	-2.426*	10.98***
	(1.284)	(2.906)
2020	.366	13.30**
	(1.173)	(5.219)
Observations	473	550

Note: This table reports the results of difference-in-differences regressions showing average treatment effect on treated by calendar periods. The dependent variables are DTD and GNPA. The treatment group for model 1 and 2 is all PSBs. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy for model 1. GNPA is excluded as control variable in model 2 as it is the dependent variable. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

We recognise that dividing the treatment group based on propensity scores may have influenced our finding that targeted capital injections do not alter banks' moral hazard behaviour. As an alternative distress metric, we therefore employ each bank's one-year Probability of Default[19] (*PD*). To stratify the treatment banks into "high" versus "low" distress categories, we use the annual median *PD* as our cutoff. Specifically, for each calendar year, a bank with a *PD* at or above that year's median is classified in the High PD cohort, while a bank with *PD* below the

[19] The Probability of Default (PD) is derived using a forward-looking model developed by Duan et al. (2012). For a comprehensive explanation of the methodology and its application, refer to the NUS CRI Technical Reports 2023.

median is assigned to the Low PD cohort. We then tally how often each bank falls into the High PD category versus the Low PD category over the full sample period. If a bank is more frequently classified as High PD, we label it a High PD bank; if it is more often in the Low PD category, we designate it a Low PD bank.

With this alternative distress classification in hand, we re-estimate our baseline Difference-in-Differences specifications using *ln z-score* and *actuarial spread* as the dependent variables. The results, presented in Table 4.11, remain consistent with our baseline analysis: both High PD and Low PD banks exhibit significant moral hazard behaviour following capital infusion. Notably, when relying on *PD* to define distress, the less distressed (Low PD) group now registers marginally larger increases in both insolvency risk and credit risk compared to the High PD group. Despite this reclassification, the overarching conclusion remains unchanged that targeted infusions fail to curb *ex-post* risk-taking, regardless of whether banks are deemed relatively more or less distressed under the *PD* metric.

Table 4.11: Impact of Capital Infusion on Bank Risk-Taking Behaviour when Treatment Group is Divided Using PD.

VARIABLES	(1) Ln z-score (High PD)	(2) Ln z-score (Low PD)	(3) Actuarial Spread (High PD)	(4) Actuarial Spread (Low PD)
ATT	-1.127** (.444)	-1.992** (.886)	1.592** (.681)	2.3*** (.528)
Observations	421	354	368	336

Note: This table reports the results of difference in differences regressions. The dependent variable is ln z-score for model 1 and 2 and Actuarial Spread is the dependent variable for model 5 and 6. The treatment group for model 1 and 3 is high PD banks. The treatment group for model 2 and 4 is low PD banks. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy. Model 1 and 2 excludes CRAR and ROE as controls. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.1.6. Regulation and treatment of risk

It is plausible that the apparent rise in risk-taking following capital injections, highlighted in our baseline results, actually reflects a shift toward tighter regulatory scrutiny, whereby banks are compelled to recognise latent bad loans rather than truly expanding their risk exposures. Put differently, in periods of stricter oversight, what may look like heightened risk-taking could instead be an outcome of banks formally acknowledging problem assets that were masked under more lenient rules. At the same time, however, it is also possible that even under tighter regulations, banks continue to originate riskier loans while simultaneously recognising previously hidden loss provisions. To disentangle these two forces, genuine expansion of risk versus recognition of bad loans, we introduce two additional measures into our empirical setup, the annual change in total loans which captures the net increase (or decrease) in a bank's lending portfolio and the Asset Quality Review (AQR), marking the period when the RBI enforced more stringent guidelines on loan classification and provisioning.

Before August 27, 2008, Indian banks were required to classify restructured exposures as nonperforming assets (NPAs) and to set aside provisions accordingly. However, in response to the Global Financial Crisis, the RBI issued a circular on that date allowing banks to treat restructured loans as standard loans rather than NPAs (Chopra et al., 2021). This regulatory forbearance enabled banks to mask underlying credit deterioration by rolling delinquent accounts into restructured packages, thus keeping them off the NPA registers (Flanagan & Purnanandam, 2019). Although the RBI withdrew this forbearance on April 1, 2015, it remained dissatisfied with the depth and accuracy of banks' disclosures. Consequently, between August and December 2015, the RBI conducted an Asset Quality Review (AQR) that required banks to undertake detailed, loan-by-loan assessments, exposing any ever-greened exposures and forcing full recognition of impaired assets that may have been buried in earlier years (Chopra et al., 2021). In the years following the AQR, regulatory scrutiny remained elevated, further tightening the classification and provisioning standards across the banking sector.

To separate the actual increase in risk-taking from increased risk recognition driven by these policy changes, we estimate a panel regression of the form:

$$Risk_{it} = \beta_1 \Delta Loans_{it} + \beta_2 AQR_{it} + \beta_3 \Delta Loans_{it} * AQR_{it} + \beta_4 Infusion + \gamma Controls_{it} + \theta_i + \omega_t + \varepsilon_{it} \quad (7)$$

where Risk denotes one of our four main risk metrics, namely *ln z-score*, *actuarial spread*, *DTD*, and *GNPA*. Here, Δ*Loans* is the natural logarithm of the year-to-year change in total loans, capturing new lending, *AQR* equals 1 for 2016 and subsequent years (when AQR-induced recognition tightened) and 0 for 2006–2015; the interaction term (Δ*Loans* * *AQR*) tests whether the link between new lending and risk changes under stricter AQR rules, *Infusion* is a dummy that equals 1 in any year bank *i* receives a capital infusion, *Controls* includes the full set of covariates outlined in Chapter 3, Section 3.2.7., θ and ω are bank and year fixed effects, respectively; and ε is the error term.

Table 4.12 reports the estimation results for each risk measure. In Model 1, where *ln z-score* is the dependent variable, we find no significant standalone effect of Δ*Loans* or the *AQR* dummy on insolvency risk; however, the interaction term (Δ*Loans***AQR*) is negative and significant, implying that once tighter recognition rules are in place, banks that expand their loan books further drive down their z-scores (i.e., increase insolvency risk). The *infusion* dummy itself is negative and significant, with a larger magnitude than the interaction term, reinforcing the moral hazard result that infusions increase insolvency risk. In Model 2, where *actuarial spread* serves as the risk metric, neither *AQR* nor Δ*Loans***AQR* is significant, suggesting that new-loan growth does not drive credit risk directly during the *AQR* period, whereas the *AQR* indicator is negative and significant. *Infusion* is likewise positive and significant, confirming that capital injections lead to higher risk-taking. In Model 3, using *DTD* as the outcome, we observe a negative and significant coefficient on the *AQR* variable, indicating that banks' *DTD* decreases post-AQR, while Δ*Loans* and Δ*Loans***AQR* remain insignificant. The infusion dummy is negative and significant, showing that capital injections reduce *DTD* (raise insolvency risk). Finally, in Model 4, with *GNPA* as the risk measure, the coefficient on Δ*Loans* is negative and significant, implying that banks growing their loan books more aggressively tend to report lower *GNPA* ratios, while the *AQR* dummy and Δ*Loans***AQR* are insignificant, and the *infusion* dummy is positive and significant.

Table 4.12: The Effect of Infusion and Tighter Regulations on Bank Risk-Taking.

VARIABLES	(1) Ln z-score	(2) Actuarial spread	(3) DTD	(4) GNPA
AQR	1.212	1.705	-2.865**	1.600
	(0.827)	(1.060)	(1.395)	(3.159)
Δloans	0.0511	-0.291**	0.145	-0.775***
	(0.0679)	(0.123)	(0.101)	(0.264)
AQR*Δloans	-0.109*	-0.0842	0.0749	0.431
	(0.0632)	(0.0823)	(0.0945)	(0.256)
Infusion	-0.157*	0.856***	-0.525***	0.551**
	(0.0833)	(0.198)	(0.131)	(0.263)
ROE		-0.00621	0.0100	-0.138***
		(0.00898)	(0.00892)	(0.0139)
CRAR		-0.0752*	0.0859*	-0.0789*
		(0.0384)	(0.0436)	(0.0390)
GNPA	-0.149***	0.0987**	-0.0960**	
	(0.0241)	(0.0445)	(0.0448)	
Cost to income	-0.0249***	0.0156	-0.0163*	-0.0409**
	(0.00754)	(0.0107)	(0.00905)	(0.0176)
Liquidity	0.0108	-0.0397	-0.0192	-0.0489
	(0.0318)	(0.0360)	(0.0365)	(0.0721)
Ln_assets	0.347**	0.303	0.530	-1.601**
	(0.149)	(0.270)	(0.420)	(0.679)
M_a_dummy	0.110	0.00185	-0.0977	0.910***
	(0.210)	(0.203)	(0.245)	(0.224)
Sensitivity	-0.0277	0.00949	0.0409	0.0805
	(0.0245)	(0.0286)	(0.0484)	(0.0578)
Credit_activity	-0.0216	0.0814***	-0.0589***	-0.106***
	(0.0137)	(0.0194)	(0.0182)	(0.0375)
Interest income	0.0263	0.0109	-0.0422**	-0.0591*
	(0.0162)	(0.0167)	(0.0188)	(0.0313)

Deposit to asset	-0.0209*	0.00290	-0.0132	0.0387*
	(0.0111)	(0.0104)	(0.0118)	(0.0216)
Constant	0.994	-5.799	1.111	45.06***
	(2.206)	(4.263)	(5.030)	(7.799)
Observations	483	456	455	495
R-squared	0.464	0.552	0.532	0.868
Number of Banks	40	39	39	40
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Note: This table reports the results of fixed effects regressions. The dependent variables are ln z-score, loan loss provisions, DTD and GNPA for model 1, 2, 3 and 4, respectively. The independent variables are AQR, ΔLoans,the interaction effect of AQR and ΔLoans and Infusion. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy. Model 1 excludes CRAR and ROE as control. Model 4 excludes GNPA as control. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Across all four specifications, the coefficient on the *Infusion* dummy consistently indicates a rise in risk-taking, whereas the interaction term between *AQR* and Δ*Loans* is only statistically significant in Model 1. Moreover, in every model, the *Infusion* coefficient exceeds the magnitude of the *AQR**Δ*Loans* coefficient. Taken together, these findings imply that the observed increase in risk-taking following capital infusion is driven primarily by moral hazard incentives, rather than by heightened recognition of existing bad loans.

4.1.7. Ex-ante measure of credit risk

So far, our credit-risk metrics have been *ex-post*. Here, we examine whether our findings persist when using a forward-looking proxy, the ratio of risk-weighted assets to total assets (*RWA*), which has been employed as an *ex-ante* credit-risk measure by Berger and Bouwman (2009) and Horvath et al. (2016). The results in Table 4.13 show that the ATT coefficients on *RWA* are positive and statistically significant for both GOBs and the Low PS subgroup, indicating increased risk-taking following capital injections. In contrast, the ATT estimate for the High-PS banks is not significant.

Table 4.13: Impact of Capital Infusions on an Ex-Ante Measure of Credit Risk.

VARIABLES	(1) RWA (All GOBs)	(2) RWA (High PS)	(3) RWA (Low PS)
ATT	2.582*	-.366	4.539***
	(1.473)	(2.452)	(1.407)
Observations	539	342	425

Note: This table reports the results of difference-in-differences regressions. The dependent variable is RWA. The treatment group for model 1, 2 and 3 is all PSBs, High PS banks and Low PS banks respectively. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy for model 1,2 and 3. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

When we break out the ATT coefficients by calendar year in Table 4.14, we again observe the largest upticks in risk-taking in 2013 and 2016, closely mirroring our baseline findings. The only exception is that the High-PS group no longer exhibits a significant post-infusion increase in *RWA*. Overall, however, our main conclusion is unchanged: targeted infusions do not mitigate *ex-ante* credit-risk behaviour, since the Low PS banks continue to display moral hazard even under this forward-looking measure.

Table 4.14: ATT by Calendar Periods with RWA as the Dependent Variable.

ATT	(1) RWA
2009	.277
	(2.965)
2010	4.982*
	(2.888)
2011	.316
	(1.72)
2012	2.62

	(2.324)
2013	5.135**
	(1.887)
2014	4.318
	(2.583)
2015	4.846*
	(2.256)
2016	5.631*
	(2.727)
2017	2.212
	(2.800)
2018	0.249
	(3.283)
2019	-1.628
	(3.057)
2020	1.004
	(5.959)

Note: This table reports the results of difference-in-differences regressions showing average treatment effect on treated by calendar periods. The dependent variable is RWA. The treatment group is all PSBs. Control variables include CRAR, ROE, GNPA, cost_to_income, liquidity, sensitivity, credit activity, interest income, deposit to asset, LN_assets and M_A_dummy. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2. Results on Loan-Level Analysis

4.2.1. Summary Statistics

Table 4.15 reports the summary statistics in Panel A and the univariate analysis in Panel B. While looking at bank-level summary statistics, we observe mean values of .559, 5.034, 13.83 and 14.12 for *ROA*, *GNPA*, *CRAR* and *ln assets,* respectively. These statistics indicate that banks are adequately capitalised and experience slightly high non-performing assets issues along with lower profitability. Coming to firm-level characteristics, we observe mean values of 3.605, 1.587, 4.747, 10.177, and 24.279 for *leverage*, *liquidity*, *ROA*, *ln assets*, and *ICR,* respectively. Firm-level statistics reveal that the firms have high leverage, are liquid, are profitable, and are well equipped to cover their interests on debt. The average values, for loan-level characteristics, are 20.293, 1.582, 8.491, and .658 for *ln loans*, *loans completed*, *loan tenure* and *relationship.*

Loans completed has an average value of 1.582, indicating that on average a firm has more than one loan with a lender in the last five years. For *loan tenure*, the average value is 8.491, indicating that the average maximum tenure of the loans is at least 8 years. *Relationship* has an average value of .658, which shows that on average, the number of years is 0.658 in a bank-firm pair with a loan outstanding in the last 5 years.

Panel B reports the univariate analysis between infused and non-infused banks and between politically connected and non-connected firms. We observe that non-infused banks have higher *ROA* and *CRAR* while significantly lower *GNPA* and *ln assets* compared to infused banks. This result indicates that non-infused banks are more profitable and adequately capitalised compared to their infused counterparts. The asset quality of non-infused banks is significantly better. In terms of size, infused banks are bigger on average. Coming to the comparison between politically connected and non-connected firms, we observe that there is no significant difference in firms in terms of *liquidity* and *ROA*. Connected firms have significantly lower *leverage* and *ln assets* and higher *ICR,* indicating that non-connected firms are more leveraged, are bigger in size, and are more equipped to cover their interest. Lower *leverage* does point to connected firms not being relatively risky. However, *ICR* is also lower for connected firms, indicating higher riskiness.

Table 4.15: Summary Statistics and Univariate Analysis.

A. Summary Statistics

Banks					
Variables	Observation Level	N	Mean	Median	SD
ROA	Bank-Year	611	.559	0.680	1.024
GNPA	Bank-Year	607	5.034	3.180	4.846
CRAR	Bank-Year	611	13.83	13.190	3.012
Ln assets	Bank-Year	612	14.125	14.166	1.455
Firms					
Variables	Observation Level	N	Mean	Median	SD
Leverage	Firm-Year	3334	3.603	1.100	62.492
Liquidity	Firm-Year	3446	1.587	1.085	15.263
ROA	Firm-Year	3402	4.748	4.130	9.46

Ln Assets	Firm-Year	3450	10.182	10.182	1.816
ICR	Firm-Year	3235	24.243	2.890	213.635

Loan Characteristics

Variables	Observation Level	N	Mean	Median	SD
Ln loans	Firm-Bank-Year	8424	20.294	20.512	1.991
Loans completed	Firm-Bank-Year	8424	1.582	0.000	5.294
Maximum loan tenure	Firm-Bank-Year	8424	8.49	6.000	8.119
Relationship	Firm-Bank-Year	8424	.657	0.000	2.249

B. Univariate Analysis

Banks

Variables	Observation Level	Non-Infused Banks	Infused Banks	Mean Difference
ROA	Bank-Year	0.812	-.205	1.016***
GNPA	Bank-Year	3.729	8.941	-5.213***
CRAR	Bank-Year	14.381	12.165	2.216***
Ln Assets	Bank-Year	13.880	14.866	-.985***

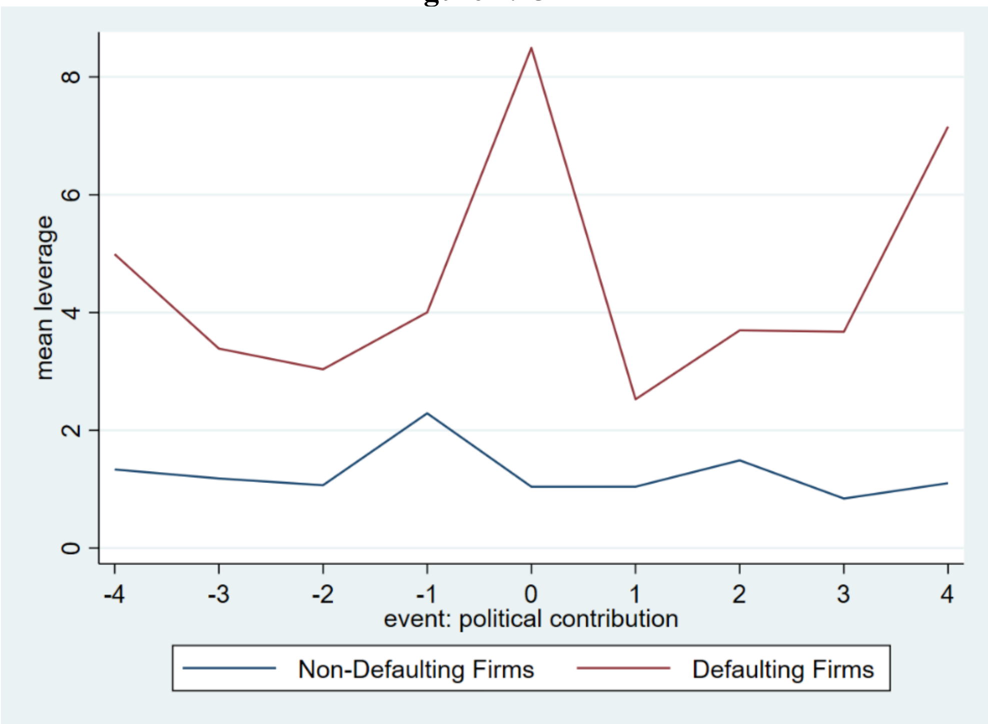
Firms

Variables	Observation Level	Non-Connected Firms	Connected Firms	Mean Difference
Leverage	Firm-Year	3.691	1.468	2.224*
Liquidity	Firm-Year	1.598	1.312	.285
ROA	Firm-Year	4.705	5.814	-1.109
Ln Assets	Firm-Year	10.159	10.649	-.49***
ICR	Firm-Year	24.840	10.114	14.725***

Note: This table reports summary statistics in Panel A and univariate analysis in Panel B.

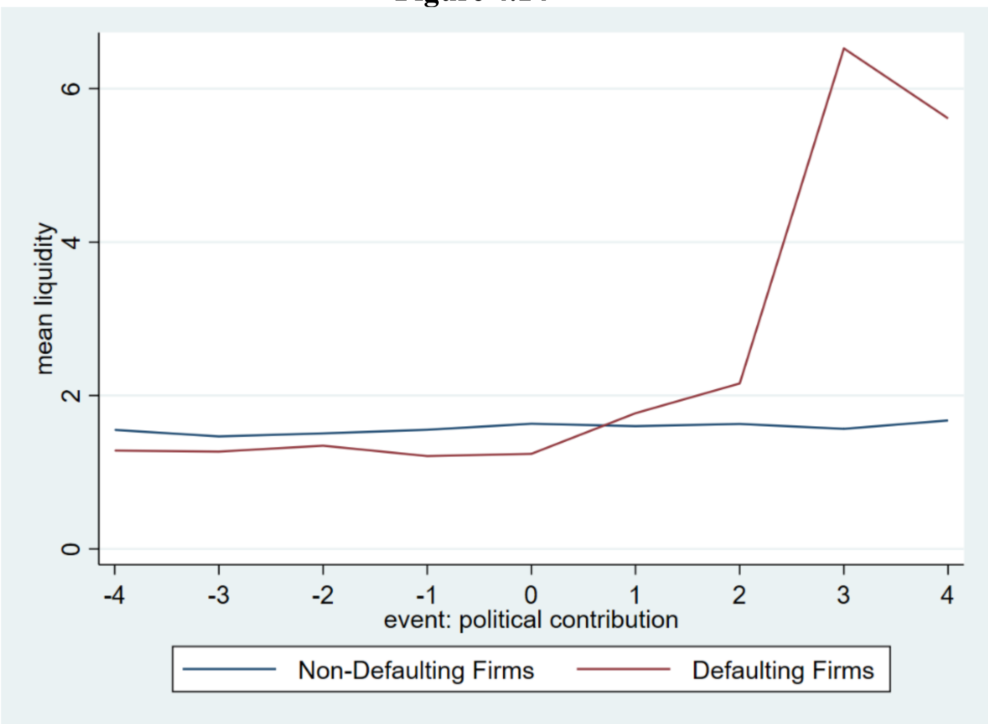
We now plot *leverage*, *liquidity* and *ROA* of politically connected non-defaulting and defaulting firms, taking the year the firm makes a political contribution as the event year. In Figure 4.13, we observe that the *leverage* of defaulting firms increases in the year of contribution, while the *leverage* decreases for non-defaulting firms in the year of contribution. In the years after the contribution, the *leverage* reaches back to the level of pre-contribution years for defaulting firms with an increasing trend and for non-defaulting firms, the *leverage* remains somewhat similar to pre-contribution years. The leverage for defaulting firms increases in the year of contribution, indicating that these firms have a greater appetite for risk after they make contributions.

Figure 4.13



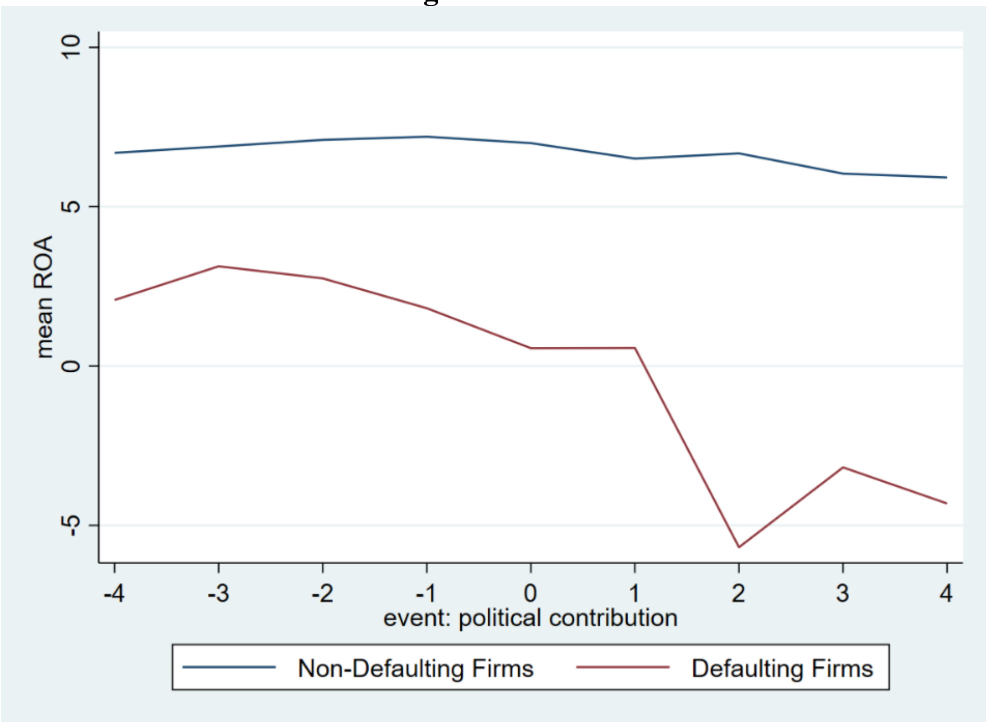
Note: Mean leverage of politically connected firms over the event windows.

Figure 4.14



Note: Mean liquidity of politically connected firms over the event windows.

Figure 4.15

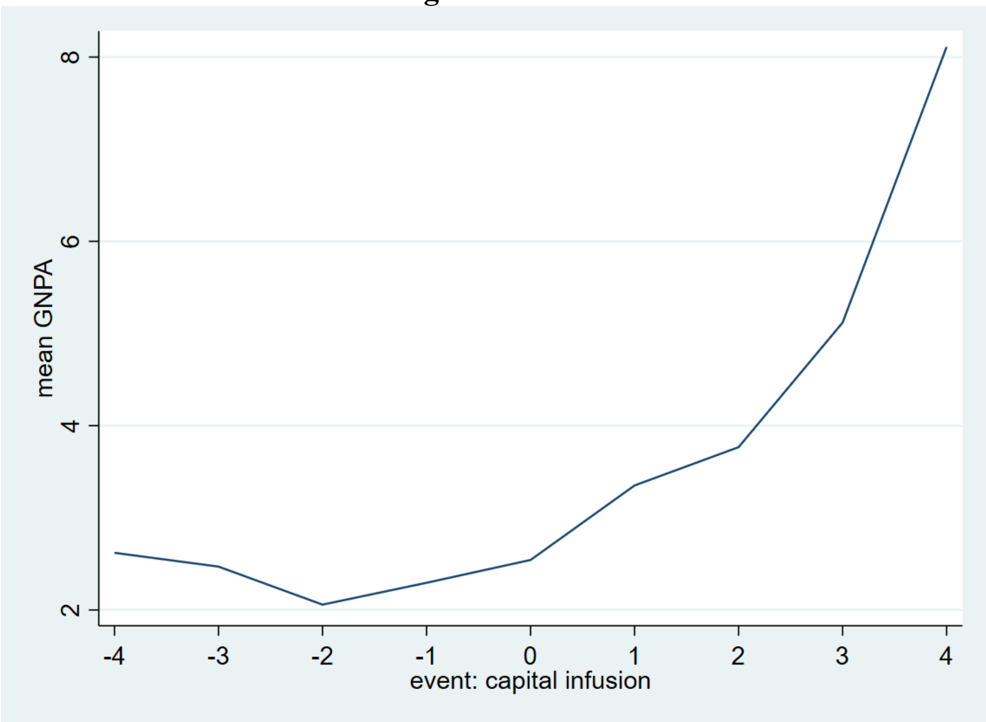


Note: Mean ROA of politically connected firms over the event windows.

In Figure 4.14, we observe that the *liquidity* does not change much for non-defaulting firms before and after they contribute. On the contrary, defaulting firms' *liquidity* shows an upward trend post-contribution and shoots up really high 3 years after the contribution. The increase in liquidity suggests that these firms may have been able to better manage liquidity post-contribution with better credit facilities. In Figure 4.15, we observe that *ROA* does not change much for non-defaulting firms, similar to *liquidity*. For defaulting firms, *ROA* follows a downward trend in post-contribution years. After making the contribution, defaulting firms' *ROA* becomes and remains negative, indicating that even with political favours, these firms fail to turn around their fortune.

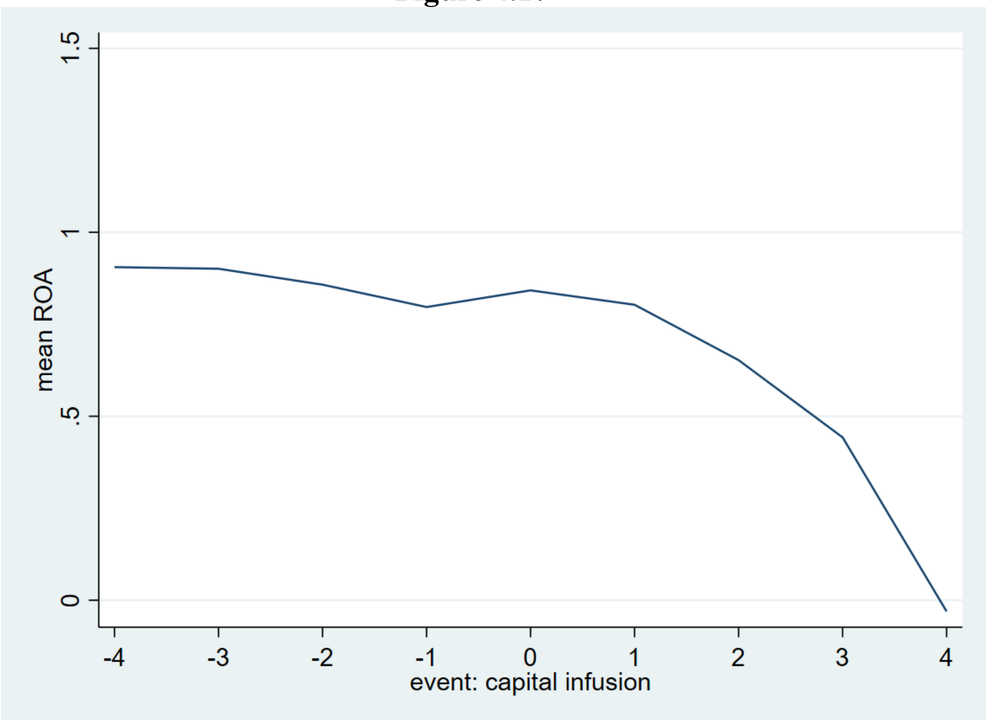
Next, we plot banks' *GNPA* and *ROA,* taking the year of capital infusion as the event year. In Figure 4.16, we observe that banks' *GNPA* keeps rising after capital infusion in line with the moral hazard evidence presented in the bank-level analysis. Similarly, in Figure 4.17, we observe declining profitability after capital infusion.

Figure 4.16



Note: Mean GNPA of infused banks over the event windows.

Figure 4.17



Note: Mean ROA of infused banks over the event windows.

4.2.2. Regression Results

We now turn our attention to our main specification in Equation 4. The results are reported in models 1 to 4 in Table 4.16. The coefficient for *political* is negative and significant in Models 1 and 2, while the coefficient for *infusion* is positive and significant in all four models. The coefficient for *political* * *infusion* is positive and significant. We find that all the banks in our sample decrease their lending to politically connected firms when Borrower*Year fixed effects are excluded, while infusion leads to an increase in lending to all the firms in our sample. We also find that infused banks indeed lend more to politically connected firms, as the interaction effect is positive and significant. We use different specifications in terms of clustering of standard errors and different combinations of fixed effects, and our results are qualitatively similar across these specifications[20]. More importantly, Models 3 and 4 include Borrower*Year fixed effects that account for loan demand.

Table 4.16: Infused Bank Lending to Politically Connected Firms.

	(1)	(2)	(3)	(4)
VARIABLES	Ln loans	Ln loans	Ln loans	Ln loans
Political	-0.392***	-0.392**	0.932	0.932
	(0.144)	(0.165)	(1.242)	(0.749)
Infusion	0.180**	0.180**	0.150*	0.150***
	(0.0772)	(0.0728)	(0.0846)	(0.0570)
Political*infusion	1.072***	1.072***	1.799***	1.799***
	(0.213)	(0.300)	(0.397)	(0.557)
Constant	15.42***	15.42***	17.45***	17.45***
	(1.964)	(1.776)	(2.461)	(1.508)
Observations	7,136	7,136	7,614	7,614
R-squared	0.482	0.482	0.763	0.763
Lender Controls	✓	✓	✓	✓
Borrower Controls	✓	✓	✗	✗
Loan Controls	✓	✓	✓	✓

[20] Going forward, we cluster the standard errors at lender-level for all our loan-level regressions.

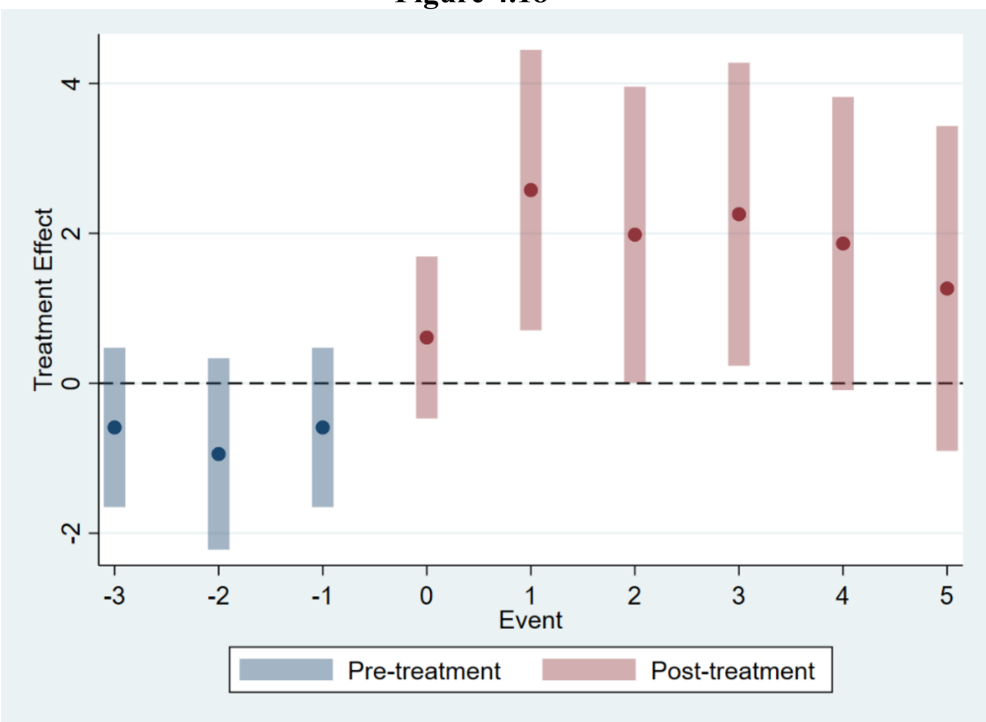
Lender FE	✓	✓	✓	✓
Borrower FE	✓	✓	✗	✗
Year FE	✓	✓	✗	✗
Borrower*Year FE	✗	✗	✓	✓
Clustering	Lender	Borrower	Lender	Borrower
Oster (2019) Beta Bounds	1.072-1.195	1.072-1.195	1.799-2.057	1.799-2.057

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The key independent variable is the interaction effect political*infusion. Control variables vary at bank-firm-loan levels. See Chapter 3 Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.3. Parallel Trend Assumption

One potential concern in our analysis is that banks might have been lending to politically connected firms even before the capital infusions, which would directly lead to violation of the parallel trend assumption. To address this concern, we now plot event study estimates of the treatment effect (*infusion*) interacted with *political* in Figure 4.18. All the pre-treatment coefficients are statistically insignificant at 95% confidence interval. The event study estimates corroborate the causal interpretation that capital infusion leads to politically motivated lending.

Figure 4.18



Note: Event study estimate of the interaction between event (infusion) and political.

4.2.4. Negative weights of Generalised Difference-in-Differences

Even though we have used advanced Callaway & Sant'Anna (2021) DiD in our bank-level analysis, we use generalised DiD in our loan-level setup, despite the problems of negative weight associated with it (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021), for interacting *political* variable with *infusion* (DiD term). In our setting, the capital infusion happens at different points in time for different banks, making the treatment timing heterogeneous, which may increase the number of negative weights when they should be positive. This problem of negative weights gives biased estimates as the earlier-treated group is used as the control group.

We formally test whether this issue exists in our analysis following de Chaisemartin and D'Haultfœuille (2020) methodology. de Chaisemartin and D'Haultfœuille (2020) developed a method to identify the number of negative weights in a generalised difference-in-differences setting to assess the magnitude of the bias. Table 4.17 reports the results showing that the percentage of negative weight is 0.0066%. This result shows that our difference-in-differences[21] model produces unbiased estimates as the percentage of negative weights is very low.

Table 4.17: Difference-in-Differences Weights

Treatment variable: infusion	ATTs	Σ weights
Positive weights	151	1.0009
Negative weights	1	-0.0009

[21] We do not use newer estimators (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021) which do not have the problem of negative weights, even as a robustness test because these estimators do not support interaction effect with the difference-in-differences term which is essential for our analysis.

Total		152	1

Note: This table reports generalised difference-in-differences estimate weights based on de Chaisemartin and D'Haultfœuille (2020). The dependent variable is ln loans. The treatment variable is infusion.

4.2.5. Risky lending to politically connected firms

We now ask the question of whether the infused banks increase their lending to politically connected firms that have defaulted. We expect banks to increase their lending to defaulting firms if they are politically connected because infused banks will be more willing to lend to these firms because of the political influence. Table 4.18 reports the results. The coefficients are similar to those of Table 4.16. The triple interaction term *infusion*political*default* is positive and significant at 1%.

Table 4.18: Infused Bank Lending to Politically Connected Defaulting and Zombie Firms.

VARIABLES	(1) Ln loans	(2) Ln loans
Political	0.933	0.927
	(1.239)	(1.259)
Infusion	0.146*	0.137
	(0.0851)	(0.0840)
Political*infusion	1.573***	0.536
	(0.448)	(0.475)
Infusion*default	0.227	
	(0.398)	
Political*infusion*default	4.048***	
	(0.722)	
Infusion*zombie		0.0986
		(0.170)
Political*infusion*zombie		3.588***
		(1.014)
Constant	17.47***	16.92***
	(2.475)	(2.785)
Observations	7,614	7,036
R-squared	0.764	0.761
Lender Controls	✓	✓
Borrower Controls	✗	✗

Loan Controls	✓	✓
Lender FE	✓	✓
Borrower FE	✗	✗
Year FE	✗	✗
Borrower*Year FE	✓	✓
Clustering	Lender	Lender
Oster (2019) Beta Bounds	4.048-4.195	3.588-4.086

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The main independent variables are the interaction effect political*infusion*default and political*infusion*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Overall, the results suggest that politically connected firms receive higher loans post-default from infused banks, even more so compared to politically connected firms that have not defaulted. These results indicate that political connection helps firms get preferential treatment even when it would be detrimental for banks to lend to these firms. These results also suggest that bank risk-taking post-capital infusion can also be driven by borrowing firms' political connections.

4.2.6. Zombie Lending

While the broader literature attributes zombie lending primarily to under-capitalisation, Qu (2018) demonstrates that political pressure on GOBs can also induce such lending. In our setting, capital infusions should, in theory, alleviate under-capitalisation and thus curb zombie lending irrespective of firms' political ties. However, if political connections themselves sustain zombie lending, we should observe banks, despite their improved capital buffers, continuing to extend credit to politically connected zombie firms.

We test this conjecture by replacing *default* in Equation 6 with *zombie*. We consider firms to be zombie firms if their interest coverage ratio is less than 1 at time t[22]. The results are reported

[22] In robustness analysis, we use more stringent definitions of zombie firms as our baseline definition might falsely include young start-ups as zombie firms.

in Model 2 of Table 4.18. The interaction term *zombie**infusion* is statistically insignificant. The triple interaction term *political*infusion*zombie* is positive and significant, indicating that infused banks lend more to politically connected zombie firms. In summary, our results indicate that the role of bank undercapitalisation becomes less important once firm-level political connection is accounted for.

4.2.7. Placebo Test

Our analysis in the previous sections has been based on the identification approach we have adopted, where only the contributors are considered politically connected. It can be argued that firms that are not contributing to political parties might also be politically connected in an indirect way, which cannot be identified. Following this logic, BSE 500 firms that have not contributed to political parties might still be politically connected. To address this issue, we restrict our sample to BSE 500 firms that have not contributed to the political parties and estimate the regression again from Equation 2. We randomly assign a *placebo political* dummy, replacing *political* dummy, to BSE 500 firms for this purpose.

Table 4.19 reports the results. The coefficient for *placebo political* * *infusion* is insignificant. Although we cannot rule out the possibility that other firms might also be politically connected, our results indicate that it is only the firms that contribute to political parties that receive preferential treatment in terms of increased lending from infused banks. As a further test of robustness, we randomly assign a dummy variable *placebo default* to non-defaulting firms and *placebo zombie* to non-zombie firms in our sample and run the regressions again. The interaction effects *infusion* * *political* * *placebo default* and *infusion* * *political* * *placebo* zombie are statistically insignificant.

Table 4.19: Placebo Analysis Using Randomly Assigned Placebo Effects.

VARIABLES	(1) Ln loans	(2) Ln loans	(3) Ln loans
Political		-0.0457	0.875
		(0.424)	(1.264)
Infusion	0.164	0.191*	0.0781
	(0.102)	(0.103)	(0.0915)
Political*infusion		1.919***	-0.108
		(0.455)	(0.820)
Political*placebo default		2.067	
		(1.983)	
Infusion*placebo default		-0.0925	
		(0.114)	
Political*infusion*placebo default		-1.100	
		(0.680)	
Placebo political*infusion	-0.0403		
	(0.107)		
Infusion*placebo zombie			0.122
			(0.0881)
Political*infusion*placebo zombie			0.816
			(0.897)
Constant	17.01***	17.66***	17.27***
	(2.388)	(2.498)	(2.776)
Observations	5,385	7,564	6,487
R-squared	0.778	0.764	0.759
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The main independent variables are placebo political*infusion, political*infusion*placebo default and political*infusion*placebo zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

We also extend our placebo analysis by replacing *infusion* with a 1-year lead of *infusion*. The interaction effects *infusion lead*poltical*, *infusion lead*poltical*default,* and *infusion lead*poltical*zombie* are statistically insignificant, reported in Table 4.20.

Table 4.20: Placebo Analysis Using Infusion Lead.

	(1)	(2)	(3)
VARIABLES	Ln loans	Ln loans	Ln loans
Political	0.637	0.637	0.851
	(1.368)	(1.368)	(1.343)
Infusion lead	0.0774	0.0774	0.0615
	(0.0634)	(0.0634)	(0.0655)
Political*infusion lead	0.522	0.522	0.0998
	(0.541)	(0.541)	(0.400)
Infusion lead*zombie			0.0815
			(0.158)
Political*infusion lead*zombie			1.157
			(1.327)
Constant	17.41***	17.41***	16.76***
	(2.560)	(2.560)	(2.889)
Observations	7,614	7,614	7,036
R-squared	0.761	0.761	0.758
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The main independent variables are political*infusion lead, political*infusion lead*default and political*infusion lead*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.8. Robustness Checks

4.2.8.1. Alternative Definition of Political Connection

So far, we have identified firms to be politically connected if they contribute to either the political parties in the ruling alliance or to the political party that is the biggest opposition at the central (federal) level. Since the capital is infused into the GOBs only by the federal government, it can be argued that only firms that contribute to political parties that are part of the ruling alliance will be given preferential treatment by the infused banks. The logic behind this argument is that only the ruling parties will actually be able to influence the capital infusion process. Although we do not believe that is the case[23], we only consider firms to be politically connected if they contribute to parties in the ruling alliance of the federal government for the sake of argument. We report the results with this definition of *political* (excluding firms that contribute to the opposition party only) in Table 4.21. Our results still hold that infused banks lend more to firms that are politically connected, and the effect is higher in magnitude when the politically connected firms turn out to be defaulting ones or a zombie firm.

Table 4.21: Infused Bank Lending to Firms that Contribute to Political Parties in the Ruling Alliance at the Federal Government.

	(1)	(2)	(3)
VARIABLES	Ln loans	Ln loans	Ln loans
Infusion	0.174*	0.171*	0.155*
	(0.0864)	(0.0878)	(0.0861)
Political*infusion	1.941***	1.609***	0.570
	(0.487)	(0.585)	(0.678)
Infusion*default		0.103	
		(0.438)	
Political*infusion*default		4.136***	
		(0.820)	
Infusion*zombie			0.00975
			(0.163)
Political*infusion*zombie			3.646***
			(1.144)
Constant	17.58***	17.62***	17.20***
	(2.429)	(2.447)	(2.717)
Observations	7,262	7,262	6,697
R-squared	0.765	0.765	0.763
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender

[23] Even though the opposition party cannot influence the process of capital infusion, it can still influence infused GOBs to lend to politically connected firms.

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The key independent variables are the interaction effects political*infusion, political*infusion*default, political*infusion*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.8.2. Alternative Variables for Borrower-Level Risk

To test the robustness of our results on risky lending, we use alternative measures of firm riskiness. More specifically, we use *low dtd* (firms with distance to default less than the 25th percentile in the sample) and *ICR* (interest coverage ratio) in place of *default* in Equation 6. Table 4.22 reports the results. Regardless of the variable used, we consistently find evidence of increased lending to risky, politically connected firms by infused banks.

Table 4.22: Infused Bank Lending to Politically Connected Firms with Alternative Variables on Risk and Zombie.

VARIABLES	(1) Ln loans	(2) Ln loans	(3) Ln loans	(4) Ln loans
Political	-4.020	2.217	0.951	0.815
	(3.549)	(1.944)	(1.246)	(1.301)
Infusion	0.147*	0.0434	0.137*	0.138
	(0.0850)	(0.0960)	(0.0801)	(0.0847)
Political*infusion	1.860***	1.155**	1.568***	1.127**
	(0.446)	(0.554)	(0.441)	(0.555)
Political*ICR	1.550			
	(1.376)			
Infusion*ICR	-0.000225			
	(0.000242)			
Political*infusion*ICR	-0.0528***			
	(0.0191)			
Political*low dtd		-2.317		
		(1.985)		
Infusion*low dtd		0.185		
		(0.150)		
Political*infusion*low dtd		1.996**		
		(0.947)		
Infusion*zombie2			-0.00730	
			(0.941)	
Political*infusion*zombie2			4.253***	
			(1.135)	
Infusion*zombie3				-0.580

				(0.400)
Political*infusion*zombie3				2.424**
				(1.080)
Constant	16.65***	17.83***	16.90***	17.00***
	(2.767)	(2.798)	(2.124)	(2.407)
Observations	7,036	5,210	6,741	6,489
R-squared	0.760	0.750	0.756	0.758
Lender Controls	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓
Borrower FE	✗	✗	✗	✗
Year FE	✗	✗	✗	✗
Borrower*Year FE	✓	✓	✓	✓
Clustering	Lender	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The main independent variables are the interaction effect political*infusion*ICR, political*infusion*low dtd, political*infusion*zombie2 and political*infusion*zombie2. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.8.3. Alternative definitions of Zombie Firms

Our baseline definition classifies firms as zombie if their ICR falls below 1. However, this rule can inadvertently label start-ups, which typically operate at a loss in their early years but are not financially distressed, as zombies. To address this issue, we use two alternative, and more stringent definitions following De Jonghe et al. (2025) and Andrews and Petroulakis (2017). Table 4.22 reports the results. Our results still hold using these alternative definitions. This robustness check demonstrates that our results are not an outcome of misidentifying young loss-making start-ups as zombies; rather, they reflect genuine distortions from long-lived, financially impaired firms.

4.2.8.4. Sector-Specific Demand Shocks

To guard against the possibility that our estimated policy effects are simply picking up sector-level demand booms, we augment our baseline specification with industry*year fixed effects.

Specifically, we classify each borrower by its two-digit National Industrial Classification (NIC) and interact it with the time variable as a fixed effect in the model. This absorbs any time-varying, industry-wide shocks that could otherwise bias our treatment estimates.

Because these fixed effects soak up all variation in lending growth that is common to firms within the same sector in a given year, identification of the treatment's impact now comes purely from within-industry, cross-bank differences in exposure to the treatment.

As shown in Table 4.23, the inclusion of industry*year fixed effects leaves our key coefficients virtually unchanged in sign and statistical significance. The robustness of our results to controlling directly for sector-level demand dynamics provides further confidence that the estimated credit responses indeed reflect the causal effect of the treatment, rather than coincident industry cycles.

Table 4.23: Baseline Regressions with Industry*Year Fixed Effects.

VARIABLES	(1) Ln loans	(2) Ln loans	(3) Ln loans
Political	0.932	0.933	0.927
	(1.242)	(1.239)	(1.259)
Infusion	0.150*	0.146*	0.137
	(0.0846)	(0.0851)	(0.0840)
Political*infusion	1.799***	1.573***	0.536
	(0.397)	(0.448)	(0.475)
Infusion*default		0.227	
		(0.398)	
Political*infusion*default		4.048***	
		(0.722)	
Infusion*zombie			0.0986
			(0.170)
Political*infusion*zombie			3.588***
			(1.014)
Constant	17.45***	17.47***	16.92***
	(2.461)	(2.475)	(2.785)
Observations	7,614	7,614	7,036
R-squared	0.763	0.764	0.761
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓

Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Industry*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The key independent variables are the interaction effects political*infusion, political*infusion*default, political*infusion*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.8.5. Bank-specific supply shocks

To ensure that our core estimates are not inadvertently capturing idiosyncratic changes in individual banks' willingness or capacity to lend, we augment the baseline specification with lender*year fixed effects. By doing so, we effectively isolate and remove any time-varying, bank-level supply-side shifts that might otherwise confound our treatment variable. As a result, identification comes solely from cross-sectional variation in banks' exposure to the treatment, rather than from any within-bank lending dynamics. Table 4.24 presents these robustness checks. The coefficients on our key variables remain virtually unchanged in sign and statistical significance once lender*year fixed effects are included. In short, controlling directly for bank-specific supply shocks confirms the stability and reliability of our main results.

Table 4.24: Baseline Regressions with Lender*Year Fixed Effects.

	(1)	(2)	(3)
VARIABLES	Ln loans	Ln loans	Ln loans
Political	0.819	0.818	0.725
	(1.003)	(1.003)	(1.033)
Political*infusion	1.836***	1.653***	0.598
	(0.378)	(0.417)	(0.419)
Infusion*default		0.277	
		(0.455)	
Political*infusion*default		3.735***	
		(0.787)	
Infusion*zombie			0.0647

			(0.182)
Political*infusion*zombie			3.473***
			(0.930)
Constant	20.50**	20.13**	17.99**
	(8.281)	(8.209)	(7.332)
Observations	7,614	7,614	7,036
R-squared	0.792	0.793	0.793
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✗	✗	✗
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Lender*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The key independent variables are the interaction effects political*infusion, political*infusion*default, political*infusion*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.8.6. Highly Levered Sectors

To test the robustness of our results, we exclude sectors that are highly levered. Firms belonging to sectors that are more dependent on bank credit might make political contributions in order to access more credit from GOBs, which would bias our causal interpretation. We consider a sector to be highly levered if the mean value of sector leverage is above the 75th percentile in our sample. Table 4.25 reports the results. Our results remain qualitatively similar.

Table 4.25: Baseline Regressions with Highly Levered Sectors Excluded.

VARIABLES	(1) Ln loans	(2) Ln loans	(3) Ln loans
Political	0.901	0.903	0.895
	(1.240)	(1.237)	(1.264)
Infusion	0.138	0.134	0.118
	(0.0858)	(0.0864)	(0.0854)
Political*infusion	1.797***	1.570***	0.541
	(0.395)	(0.444)	(0.472)

Infusion*default		0.215	
		(0.389)	
Political*infusion*default		4.093***	
		(0.713)	
Infusion*zombie			0.127
			(0.172)
Political*infusion*zombie			3.567***
			(0.999)
Constant	17.10***	17.13***	16.60***
	(2.666)	(2.682)	(2.944)
Observations	7,064	7,064	6,530
R-squared	0.762	0.762	0.760
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The key independent variables are the interaction effects political*infusion, political*infusion*default, political*infusion*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.8.7. Undercapitalised banks

The baseline results show that firm-level political connection leads to zombie lending based on the assumption that capital infusion is sufficient enough to make the banks adequately capitalised. There is concern that banks might still be undercapitalised after a capital infusion, which would bias our results. To address this concern, we first define undercapitalised banks whose *CRAR* is within 3%[24] range of the regulatory minimum. We then interact this variable with our variables of interest[25]. Table 4.26 reports the results. The triple interaction term *infusion*political*zombie* remains positive and statistically significant, while

[24] We also use 2% and 4% thresholds in unreported results. The results remain qualitatively similar.
[25] Following Acharya et al. (2019), we utilise the four-way interaction.

*infusion*undercap*zombie* is statistically insignificant. The four-way interaction term *infusion*political*undercap*zombie* is statistically insignificant. This result corroborates our finding that firm-level political connection influences zombie lending more than bank-level undercapitalisation.

Table 4.26: Politically Motivated Zombie Lending in Undercapitalised Banks.

VARIABLES	(1) Ln loans
Political	0.979
	(1.362)
Infusion	0.107
	(0.0973)
Political*infusion	0.396
	(0.450)
Infusion*zombie	0.285
	(0.201)
Political*infusion*zombie	3.601***
	(1.081)
Undercap	0.0695
	(0.102)
Political*undercap	-0.0513
	(0.518)
Infusion*undercap	0.146
	(0.130)
Political*infusion*undercap	0.500
	(0.644)
Zombie*undercap	-0.228
	(0.211)
Political*zombie*undercap	1.902*
	(1.062)
Infusion*zombie*undercap	-0.627
	(0.403)
Political*infusion*zombie*undercap	-1.250
	(1.146)
Constant	16.78***
	(2.763)
Observations	7,030
R-squared	0.761
Lender Controls	✓
Borrower Controls	✗
Loan Controls	✓
Lender FE	✓
Borrower FE	✗

Year FE	✗
Borrower*Year FE	✓
Clustering	Lender

Note: This table reports the difference-in-differences regression. The dependent variable is ln loans. The main independent variables is the interaction effect political*infusion*zombie*undercap. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.9 Endogeneity Concerns

4.2.9.1. Self-Selection Bias

A concern in our identification strategy is that firms are choosing to borrow from a particular bank. Politically connected risky firms might be targeting banks that are infused, betting on the fact that lending criteria might be loosened post-capital infusions. This would lead to self-selection bias.

To address this bias, we match politically connected firms to non-connected firms that are similar in terms of balance sheet variables. We use the *PanelMatch* R package for matching, which allows for heterogeneous treatment timing for matching. More specifically, we use *infusion* as the treatment variable on our firm-level data, where *infusion* equals 1 if the firm borrows from an infused bank, 0 otherwise, and the covariates used are the firm-level controls in our analysis. We then extract this matched sample and run our baseline regressions on our loan-level data. Table 4.27 reports the results. We find that *infusion*political*, *infusion*political*default*, and *infusion*political*zombie* remain positive and significant.

Table 4.27: Regressions Based on Matched Politically Connected and Non-Connected Borrowers.

VARIABLES	(1) Ln loans	(2) Ln loans	(3) Ln loans
Political	2.457	2.458	2.569
	(2.182)	(2.189)	(2.213)
Infusion	0.142	0.133	0.161

	(0.246)	(0.246)	(0.272)
Political*infusion	2.809***	1.854	0.159
	(0.939)	(1.368)	(0.992)
Infusion*default		1.147***	
		(0.278)	
Political*infusion*default		2.580*	
		(1.517)	
Infusion*zombie			-0.0332
			(0.325)
Political*infusion*zombie			5.466***
			(1.225)
Constant	22.53***	22.37***	19.77***
	(5.277)	(5.311)	(5.696)
Observations	2,133	2,133	2,000
R-squared	0.775	0.776	0.780
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗
Borrower*Year FE	✓	✓	✓
Matched Pair FE	✓	✓	✓
Clustering	Lender	Lender	Lender

Note: This table reports the difference-in-differences regression which includes only matched politically connected and non-connected borrowers. The dependent variable is ln loans. The key independent variables are the interaction effects political*infusion, political*infusion*default, political*infusion*zombie. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.9.2. Selection Bias

Our causal inference based on the evidence presented in the previous section relies on the assumption that the capital infusions by the GOI are exogenous. There is a concern that the government might infuse banks with the aim of helping the companies that fund them, which would make the treatment effect endogenous. To address this concern, we adopt instrumental variable regression strategy. More specifically, we use the GOBs' exposure to the AQR as an instrument for predicting capital infusions. The exposure to AQR necessitated fresh capital infusions. Since AQR was conducted by the RBI independently, the GOBs' exposure to AQR serves as a good instrument.

Table 4.28 presents the results for the two-stage instrumental variable regression. Model 1 shows the first-stage regression when *AQR*GOB* is the independent variable and infusion is the dependent variable. Model 2 presents the first stage regression when *AQR*GOB*political* is the independent variable and *infusion*poltical* is the dependent variable. Likewise Models 4 and 5 present the results on the same specification, respectively, with the standard errors clustered at the borrower level. Models 3 and 6 present the second-stage regression. Our variable of interest *political*infusion* remains positive and significant in both models. Furthermore, Table 4.28 presents a few diagnostic tests results which confirm the validity of our instrument.

Table 4.28: Instrumental Variable Regressions.

VARIABLES	(1) 1st Stage (Infusion)	(2) 1st Stage (Infusion*Political)	(3) 2nd Stage (Ln loans)
AQR*GOB	0.715***	-0.0407***	
	(0.192)	(0.0143)	
AQR*GOB*political	-0.0877	1.523***	
	(0.229)	(0.415)	
Political	0.0194	0.190***	-0.660***
	(0.0154)	(0.0566)	(0.226)
Infusion			1.031***
			(0.375)
Infusion*political			2.275**
			(0.931)
Observations	7,136	7,136	7,136
Lender Controls	✓	✓	✓
Borrower Controls	✓	✓	✓
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✓	✓	✓
Year FE	✓	✓	✓
Borrower*Year FE	✗	✗	✗
Clustering	Lender	Lender	Lender

Kleibergen-Paap rk LM stat	10.26***
Cragg-Donald Wald F stat	68.32
Kleibergen-Paap rk Wald F stat	7.335
Stock-Yogo 10% crit. val.	7.030
Stock-Yogo 15% crit. val.	4.580
Stock-Yogo 20% crit. val.	3.950
Stock-Yogo 25% crit. val.	3.630

Note: This table reports the instrumental variable regressions. AQR*GOB is the instrument for infusion. The dependent variable (stage 2) is ln loans. The main independent variable is the interaction effect political*infusion. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

In Table 4.29, we report the instrumental variable analysis with Borrower*Year fixed effects included in the regressions. The results are qualitatively similar to the results in Table 4.28, thus showing that our results hold and instruments remain valid with Borrower*Year fixed effects.

Table 4.29: Instrumental Variable Regressions with Borrower*Year Fixed Effects.

VARIABLES	(1) 1st Stage (Infusion)	(2) 1st Stage (Infusion*Political)	(3) 2nd Stage (Ln loans)
AQR*GOB	0.738***	-0.0184**	
	(0.209)	(0.00791)	
AQR*GOB*political	-0.187	1.171***	
	(0.297)	(0.347)	
Political	-0.179*	-0.000208	1.025
	(0.102)	(0.00271)	(1.267)
Infusion			0.641
			(0.486)
Infusion*political			2.928**
			(1.303)
Observations	7,614	7,614	7,614
Lender Controls	✓	✓	✓
Borrower Controls	✗	✗	✗
Loan Controls	✓	✓	✓
Lender FE	✓	✓	✓
Borrower FE	✗	✗	✗
Year FE	✗	✗	✗

Borrower*Year FE	✓	✓	✓
Clustering	Lender	Lender	Lender
Kleibergen-Paap rk LM stat			13.03***
Cragg-Donald Wald F stat			47.84
Kleibergen-Paap rk Wald F stat			6.612
Stock-Yogo 10% crit. val.			7.030
Stock-Yogo 15% crit. val.			4.580
Stock-Yogo 20% crit. val.			3.950
Stock-Yogo 25% crit. val.			3.630

Note: This table reports the instrumental variable regressions. AQR*GOB is the instrument for infusion. The dependent variable (stage 2) is ln loans. The main independent variable is the interaction effect political*infusion. Control variables vary at bank and loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

While our instrument might be valid, there is still a concern that the assumption of exclusion restriction might be violated, as the AQR may have impacted bank lending negatively. To assess the robustness of our instrumental variable (IV) estimates, we employ the two-step approach proposed by van Kippersluis and Rietveld (2018), which combines a zero-first-stage (ZFS) test with the plausibly exogenous method developed by Conley et al. (2012).

We identify a subsample of GOBs where the instrument *AQR*GOB* has minimal predictive power for *infusion*. Specifically, we focus on observations where the instrument's value falls below the 90th percentile of its distribution among GOBs with positive instrument values. This selection ensures that within this subsample, the instrument exhibits negligible variation in the treatment variables (*infusion* and *infusion*political*), effectively creating a scenario where the instrument's influence on the treatment is minimal.

In the ZFS subsample, we regress the outcome variable, *ln loans*, on the instruments. The resulting coefficient on the instrument is statistically insignificant, suggesting that the instrument does not have a direct effect on the outcome variable in this subsample. This finding supports the validity of the exclusion restriction in the context of our analysis.

Building on the ZFS findings, we apply the Local-to-Zero (LTZ) method to the full sample to account for potential violations of the exclusion restriction. We estimate the direct effect of the instrument on the outcome using the ZFS subsample and treat this estimate as a prior in the LTZ analysis. By specifying a normal distribution for the direct effect with a mean and standard deviation derived from the ZFS estimate, we obtain adjusted confidence intervals for the treatment effect that account for plausible direct effects of the instrument on the outcome.

The LTZ analysis in Table 4.30 shows that *infusion* becomes statistically insignificant once we allow for a small direct effect of the instrument, confirming that *infusion* per se is sensitive to violation of the exclusion restriction. In contrast, *infusion*political* remains positive and statistically significant, indicating that the preferential lending to politically connected firms persists even under plausible exclusion-restriction violations. This two-step robustness check, first demonstrating a near-zero direct effect in the ZFS subsample and then applying LTZ bounds, reinforces the credibility of our IV estimates and the causal interpretation of the effect of capital infusion on politically motivated lending.

Table 4.30: Zero First-Stage and Instrumental Variable Regression Under Plausibly Exogenous Instruments.

VARIABLES	(1) Zero First Stage (Ln loans)	(2) Plausibly Exogenous (Ln loans)
AQR*GOB*political	-3.307	
	(2.570)	
AQR*GOB	1.222	
	(1.131)	
Political	1.464*	-1.209***
	(0.726)	(0.366)
Infusion		-0.584
		(2.161)
Infusion*political		3.860***
		(1.482)
Constant	23.62*	13.52***
	(12.47)	(0.869)
Observations	337	7136

Lender Controls	✓	✓
Borrower Controls	✓	✓
Loan Controls	✓	✓
Lender FE	✓	✓
Borrower FE	✓	✓
Year FE	✓	✓
Borrower*Year FE	✗	✗
Clustering	Lender	Lender

Note: This table presents zero first stage and instrumental variable regression under plausibly exogenous instruments. The dependent variable is ln loans. The main independent variable is the interaction effect political*infusion. Control variables vary at bank-firm-loan levels. See Chapter 3, Section 3.3.5 for a detailed explanation. Robust standard errors in parentheses, clustered at the lender level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.9.3. Omitted Variable Bias

To account for the omitted variable bias, we use Oster (2019) beta bounds. Specifically, Oster (2019) beta is estimated when R^2 is maximised. If the Oster (2019) beta bounds do not include 0, it can be interpreted that beta estimates from the main regressions would remain positive and significant even after accounting for unobserved omitted variables ($R^2 = 1$). In Tables 4.16 and 4.18, we see that Oster (2019) beta bounds[26] do not include 0 in all our main regression results. Thus, our results are robust to omitted variable bias.

4.2.10. Do defaulting politically connected firms contribute more?

We now ask the question of whether defaulting politically connected firms contribute more money to political parties in the years before the default, compared to their non-defaulting counterparts. We organise the data to the firm-year level for this analysis and restrict the sample to politically connected firms. We estimate the following specification:

[26] Beta bounds are the beta estimate from the main regressions and Oster (2019) beta.

$$ln\ contributions_{it} = \beta_1 default_{it+k} + \beta_2 firm\ controls_{t-1} + \gamma_i + \pi_t + \epsilon_{it} \quad (8)$$

where *ln contributions* is the natural logarithm of total contributions made by firm *i* at time *t*. *default* is a dummy variable that takes the value 1 for the years before the firm defaults. All other variables follow the same definition as in equation 1.

Table 4.31 reports the results. The coefficient for default is positive and significant. This result indicates that politically connected firms, before the default, contribute more money to political parties, suggesting that they make this contribution as insurance against future defaults.

Table 4.31: Political Contributions by Defaulting Firms.

VARIABLES	(1) Ln contributions
Default	1.674*
	(0.913)
Liquidity	0.0318
	(0.0407)
Ln assets	0.294
	(0.200)
ROA	0.0645***
	(0.0226)
Leverage	-0.000733
	(0.000975)
Constant	-3.004*
	(1.651)
Observations	2,398
R-squared	0.040
Borrower FE	✓
Year FE	✓

Note: This table reports the regression estimates at borrower-year level. The dependent variable is ln contributions. The main independent variable is default. Control variables include liquidity, ln assets, ROA and leverage. Robust standard errors in parentheses, clustered at the borrower level. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

CHAPTER 5

CONCLUSION

Chapter Overview

This chapter provides a summary of findings and conclusions, along with policy implications and scope for future research.

5.1. Summary and Discussion

Does the infusion of capital result in moral hazard behaviour? To date, empirical studies have examined this relationship almost exclusively in the context of a one-off capital infusion preceded by a systemic crisis event. In such crisis periods, however, multiple endogenous variables influence risk-taking decisions, making it difficult to disentangle the pure effect of the infusion from confounding factors. Moreover, there is a lack of evidence regarding the influence of strategically targeted capital infusions on subsequent risk-taking behaviour.

Government-owned banks providing preferential treatment to politically connected firms is well established in the literature, and so is bank moral hazard behaviour post-government capital infusions. However, there are no proper links established between these two streams of literature. Banks showing increased risk-taking post-capital infusion is usually attributed to the moral hazard incentives. There is a possibility that infused banks are influenced by external pressures, from politicians to lend to their connected risky borrowers who fund them. In such a scenario, risk-taking behaviour can be driven by political influence.

In this thesis, we try to fill this gap by studying the effect of regular capital infusions in India. Our results, at the bank-level analysis, indicate that capital infusions leave risk-taking behaviour largely unchanged during crisis periods but give rise to moral-hazard issues in non-crisis times. For GOBs outside of crisis episodes, both insolvency risk and credit risk increase following a capital injection. Moreover, banks at both higher and lower distress levels exhibit heightened risk-taking after receiving new capital. We also find that strategically targeted infusions have no measurable effect on subsequent risk-taking, a result we attribute to moral-hazard incentives offsetting any potential disciplinary impact of targeted support. Finally, the post-infusion rise in risk-taking cannot be explained by enhanced risk recognition under tighter regulation, suggesting that moral-hazard behaviour persists even when regulatory scrutiny intensifies.

Our results, at the loan-level analysis, show that capital infusion leads to increased lending to politically connected firms, and this increase in lending becomes stronger after the politically connected firms have defaulted on their loans and meet the definition of a zombie firm. Our results suggest that bank risk-taking post-capital infusions is linked to political connections along with bank moral hazard incentives.

Indian banks during this period were facing very high NPA issues. It is not a mere coincidence that some of the biggest defaulters were politically connected. The fact that these companies continued getting newer loans even after their initial defaults, which were of very high magnitude, suggests that it was political pressure rather than banks' poor judgment that led to these defaults. Our evidence suggests that political connectedness played a crucial role in the deteriorating health of Indian banks.

One potential reason infused banks engage in politically connected risky lending is their obligation to expand overall lending following capital infusions, as mandated by the government. Simultaneously, implicit bailout guarantees create a safety net for losses stemming from defaults on such connected loans. Faced with this mandate and safety net, bank managers are incentivised to allocate fresh loans to politically connected, higher-risk firms. This strategy can boost reported loan growth, while potential distress caused by losses could be mitigated through taxpayer-funded government capital infusions.

5.2. Implications

A key policy implication of our study is that repeatedly recapitalising banks to shield them from distress can backfire by heightening the nation's fiscal risk. Regulators should therefore implement robust post-infusion oversight mechanisms to curb excessive risk-taking. Even so, banks would likely be better served, outside of crisis periods, by tapping market funding to sidestep the adverse side effects of government injections.

From a practical standpoint, the GOBs' heavy dependence on government recapitalisations is ultimately counterproductive for both the institutions themselves and for taxpayers. This dependence is perpetuated by the government's majority ownership stake. To mitigate this unsustainable reliance, we propose reducing the government's equity holdings in public sector banks to encourage greater access to capital markets and consolidating weaker banks with stronger peers to lessen the fiscal burden on the state.

Another policy implication from our study is that regulators should be wary of the political connections and the corresponding pressure that influences banks to take more risks. However, if the moral hazard problem is mainly driven by a few politically connected firms, a carpet rule of restricting further credit to the defaulted firms can hamper economic growth, as genuine entrepreneurs will shy away from bank loans. In summary, a more granular approach is needed to address the problem associated with lending to politically connected firms.

Future studies could consider a cross-country analysis in other emerging or advanced economies with different institutional and regulatory frameworks. Future studies can also consider the inclusion of unlisted firms. Future studies can also compare outcomes of different recapitalisation instruments, direct equity injections, recapitalisation bonds, and back-stop guarantees to determine which tools optimise bank performance and fiscal efficiency.

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Capital infusions and Bank risk-taking behaviour

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ABSTRACT

Despite theoretical predictions on the ill effects associated with capital infusions, the Global Financial Crisis (GFC) brought them into mainstream banking around the world. Empirical evidence on capital infusions during GFC supports the existence of moral hazard problem. However, what is not clear is whether the increase in bank risk post-capital infusions is due to an increase in bank risk-taking behaviour (moral hazard) or simply reflects an increase in the average firm-level risk due to poor economic conditions. We try to disentangle this issue by using capital infusion data in the Indian banking industry, where government capital infusions in public sector banks happen in all economic conditions and hence allow us to control for a non-crisis environment. Our results strongly support the moral hazard problem in banks, surrounded by no apparent economic crisis. The results are also independent of the bank's propensity to take risks and its financial health. One major implication of our findings is that repeated capital infusions to protect banks can be detrimental as it increases the fiscal risk of the country.

1. Introduction

The theoretical literature is split on the effect of capital infusion on risk-taking behaviour. On the one hand, it is argued that capital infusions will reduce the overall risk-taking behaviour as the charter values of the banks are restored (Demsetz et al., 1996; Hakenes and Schnabel, 2010; Keeley, 1990). On the other hand, capital infusions can result in moral hazard behaviour as the cost of infusions is not borne by the banks (Flannery, 1998; Gropp et al., 2006; Sironi, 2003). However, existing empirical evidence, which is surrounded mainly during market-wide financial crisis periods, supports the argument that capital infusions lead to moral hazard behaviour (Black and Hazelwood, 2013; Duchin and Sosyura, 2014; Hryckiewicz, 2014; Poczter, 2016).

One drawback in the existing studies is that they were undertaken during financial crisis periods, where it is hard to distinguish whether the increase in the risk is attributed to bank managers' risk-taking behaviour (leading to moral hazard problem) or it is simply a reflection of the increase in the risk of the average firm in the economy. In other words, the increase in the risk in the banks' balance sheet can be driven by endogenous factors. Banks that receive capital infusions are also expected to increase their lending to help the economy recover from the crisis (Black and Hazelwood, 2013). In such situations, banks are expected to lend to risky borrowers due to governments' mandate. Furthermore, capital infusions become a necessity during a financial crisis to help banks maintain their eroding capital. The governments are forced to intervene as the collapse of these institutions can easily result in the collapse of the whole financial system because of the systemic risk they pose towards the financial system.

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