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Article

Bad loan build-up in India: A reflection of soft budget constraints

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Abstract: This paper analyses the non-performing assets (NPA) crisis in the Indian banking system from the perspective of soft budget constraints. Using a panel dataset of 105 publicly listed firms, it explores the relationship between NPAs and bank lending behaviour, particularly examining credit rationing regarding firm size and risk level. The findings indicate that Indian banks favour large firms over smaller ones, while credit rationing is not adequately aligned with borrower riskiness. However, the Asset Quality Review (AQR) by the Reserve Bank of India and the introduction of the Insolvency and Bankruptcy Code (IBC) seem to have enforced risk-based lending to some extent. These results shed light on the systemic issues that drive NPAs, linking them to governance weaknesses and the prevalence of soft budget constraints.

Keywords: credit rationing, non-performing assets, soft budget constraints, rationing bias, evergreening

1. Introduction

The recurring build-up of non-performing assets (NPAs) in Indian public sector banks has become a critical concern for policymakers. The Indian economy presents a unique case for studying soft budget constraints due to extensive government ownership in financial and non-financial sectors. Public sector banks control over 70% of the market share (RBI, 2013) and serve as the primary conduit for household savings to industry. With a relatively underdeveloped bond market, the banking system is a vital source of credit for the Indian corporate sector.

The surge in NPAs starting around 2013 and lasting till 2020 highlights systemic inefficiencies. As of December 2017, NPAs comprised 10.2% of total banking assets, with stressed assets reaching 12.8%. Public sector banks, which account for 87% of these bad loans, reported massive losses exceeding ₹1.7 trillion from 2015 to 2018 (Bandyopadhyay, 2018). This crisis reflects broader economic issues, including governance failures, inefficient credit practices, and cyclical economic challenges (Reinhart & Rogoff, 2011). Structural challenges such as the weak corporate bond market also exacerbate the reliance on banking systems for credit.

The concept of soft budget constraints—first introduced by Kornai (1979, 1980)—is relevant in explaining this phenomenon. These constraints arise when firms or banks expect financial rescues during crises, leading to moral hazard and inefficiencies. In the Indian context, public sector bank managers often operate under the assumption of government bailouts, fostering risky lending behaviour. Evidence suggests that NPAs are concentrated in infrastructure, steel, and telecom sectors, reflecting governance lapses rather than economic sectoral risks. This is unlike the previous episodes where NPA was

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mainly contributed by politically directed lending to priority sectors like agriculture (Ruiz, Spiegel, & Takáts, 2016).

This study empirically examines the role of soft budget constraints in driving NPAs and bank lending behaviours. Using a panel dataset of 105 firms over 17 years (2002–2018), it evaluates the extent of credit rationing based on borrower risk levels and firm size.

The findings reveal that large firms disproportionately benefit from credit, even when their risk profiles suggest otherwise. We observed from the results that large firms enjoyed easier access to credit than medium and small firms. Small firms' cash flow sensitivities were much higher at a given risk level than large firms. This shows that large firms enjoy easier access to credit than small firms. Also, credit rationing seems to work perfectly within small firms, with low-risk firms enjoying better credit access than higher-risk small firms.

Two reasons can explain the rationing bias in favor of large firms. First, the existence of a public-private partnership (PPP) model for financing long-term and strategic projects in sectors like infrastructure (Sengupta & Vardhan, 2017). Large firms mostly take up these projects. Due to long gestation periods, most infrastructure projects defaulted. In a PPP model, the government acts as a lender and borrower simultaneously because the government owns public sector banks and is a part of PPP projects. This situation creates the right conditions for soft budget constraints. Banks feel more than safe to lend to PPP projects and do not care about due diligence as much as they should, and project promoters in PPP projects expect the government to keep the project afloat during difficult circumstances.

Second, in the absence of strong credit appraisal and due diligence, the size of a firm may be taken as a signal of its creditworthiness by banks, as large companies have comparatively a lot to lose if they default (Hoshi, Kashyap, & Scharfstein, 1993; Davis, 1994). Market discipline becomes weak in an economy with soft budget constraints, and bankers are not forced to adopt rigorous credit appraisal and due diligence. The lack of strict credit rationing in an economy can encourage more and more borrowers to undertake risky projects, leading to moral hazard-type lending. Such lending will benefit managers and stockholders at the cost of the government if the government keeps taking the burden of NPAs on its shoulders.

With massive stress in the banking system, recapitalization of PSBs alone will not solve the problem. Our study reveals that AQR and IBC have induced some discipline in the market. Credit rationing seems to have taken hold after the introduction of AQR and IBC.

The rest of this paper is organised as follows: Section 2 discusses select literature on NPAs and soft budget constraints. Section 3 presents the theoretical framework and model. Section 4 describes the methodology. Sections 5 and 6 provide empirical analyses, and section 6 presents discussions and conclusions.

2. Literature review

The literature on non-performing assets (NPAs) and soft budget constraints (SBCs) provides a robust foundation for analysing systemic inefficiencies in the Indian banking sector. Kornai's seminal work (1979) introduced the concept of SBCs, describing scenarios where firms or financial institutions operate beyond their financial limits, expecting external bailouts. This phenomenon is particularly prevalent in economies with significant state ownership, such as India and China, where government intervention weakens market discipline (Maskin & Xu, 2001; Kornai, Maskin, & Roland, 2003). Soft Budget Constraints (SBCs) in the banking sector have been linked to the accumulation of bad loans due to lax lending practices and inadequate governance. Studies on China's state-owned banks highlight how government ownership exacerbates SBC-related inefficiencies, leading to chronic NPAs (Lu, Thangavelu, & Hu, 2005; Du & Li, 2007). Similar dynamics are observed in India, where public sector banks dominate the credit market, serving both state-owned enterprises and politically influential private firms (Das & Rawat, 2018a; Sengupta & Vardhan, 2017).

The theory of credit rationing, as developed in imperfect capital market literature, underscores the role of information asymmetry in lending decisions (Myers & Majluf, 1984). Banks operating under SBCs often prioritise lending to large firms over small and medium enterprises despite similar risk profiles (Hoshi, Kashyap, & Scharfstein, 1993; Davis, 1994). Public-private partnerships (PPPs) further reinforce this size bias, where banks feel assured of government intervention to sustain large projects (Sengupta & Vardhan, 2017).

Empirical Studies on NPAs identify both internal and external factors contributing to NPAs. Internal factors primarily include managerial inefficiencies in credit risk appraisal and fund monitoring, while external factors involve macroeconomic downturns and rising corporate leverage (Ghosh, 2005; Bawa et al., 2019). The "twin balance sheet problem," characterised by weakened corporate and bank balance sheets, has further compounded the NPA crisis in India (Chandrasekhar & Ghosh, 2017).

Reforms such as Asset Quality Review (AQR) and Insolvency and Bankruptcy Code (IBC) have been pivotal in addressing NPAs. The AQR exposed hidden bad loans, while the IBC aimed to expedite loan resolution processes. However, delays in implementation and low recovery rates have limited their effectiveness (Rebello & Ray, 2019; Roy, 2019)

While much research has been done regarding the factors responsible for NPA accumulation in the Indian banking system (Misra & Dhal, 2010; Lokare, 2014; Chandrasekhar & Gosh, 2017; Sengupta & Vardhan, 2017; Das and Rawat, 2018a; Bawa et al., 2019), there are no studies which have viewed NPAs as a systemic problem. The link between the existence of soft budget constraints in the Indian economy in general and public sector banks in particular and the accumulation of NPAs has not been thoroughly examined. We suspect soft budget constraints syndrome encourages public sector bank managers to show laxity towards the credit risk of borrowers because they expect the government to come to their rescue in the event of an impending bankruptcy. Budget constraints are softened when a business firm expects some other economic entity to cover its expenses wholly or in part. Softening of budget constraints may be the direct result of ownership structure and the resultant governance emerging from such ownership structure, or it may also emerge due to interference in the working of an entity (firm or bank) by some other economic agent (firm, govt., bank etc.)

This study empirically examines the Indian Banks' lending behaviour under soft budget constraints and its linkage with an accumulation of NPAs. The underlying idea is that a bank operating under hard budget constraints will lend according to the riskiness of a borrower, while a bank facing soft budget constraints will not. The data for the current study was collected from 105 non-financial sector firms for 17 years from March 2002 to March 2018, based on the availability of the CMIE Prowess database. The research strategy laid out in the paper tries to infer banks' lending behaviour from the borrowing firms because, in India, the primary source of debt financing for the corporate sector is bank borrowing rather than bonds and debentures.

3. Theoretical framework

3.1. Soft budget constraints and NPAs

Soft budget constraints (SBCs) have been extensively used to explain inefficiencies in economies dominated by state ownership. Kornai (1979) introduced SBCs to describe firms that exceed their budget constraints and expect external financial support during crises. In the banking sector, SBCs emerge when banks or borrowers expect bailouts or leniency from governments, leading to risky lending behaviour and governance failures.

In India, public sector banks are heavily influenced by government policies. Directed lending, political interference, and periodic recapitalisation of banks have softened budget constraints. Managers of public sector banks often prioritise politically connected firms or large-scale projects without adequate risk assessment. Consequently, systemic inefficiencies arise, resulting in an accumulation of bad loans. The literature on SBCs highlights similar issues in economies like China, where state-owned banks have exhibited biased lending practices due to government ownership and interference (Maskin & Xu, 2001; Tian & Estrin, 2007). Studies emphasise that government interventions, such as frequent bailouts, exacerbate moral hazard in state-owned banks, perpetuating NPAs (Alnabulsi et al., 2023; Robinson & Torvik, 2023). Research highlights the role of SBCs in fostering financial fragility, as banks tend to refinance riskier loans during crises instead of facing bad debt write-offs (Thakor & Yu, 2023; Kornai et al., 2003). The dynamics of endogenous money creation within banks reveal their inclination to accommodate speculative credit demands during booms, a precursor to lousy loan crises under SBC frameworks (Minsky, 2008; Thakor & Yu, 2023).

3.2. Credit rationing under SBCs

Credit rationing occurs when banks limit credit supply to borrowers based on asymmetric information and risk-return considerations. Under SBCs, credit rationing becomes distorted. Banks fail to differentiate between high-risk and low-risk borrowers effectively, leading to resource misallocation. Moreover, large firms may exploit their political and economic influence to secure credit despite weak financial profiles. This study tests two hypotheses rooted in the theory of SBCs:

1. **H1:** Banks do not ration credit according to borrower riskiness.
2. **H2:** Credit rationing is biased in favour of large firms.

3.3. Model

In an imperfect capital market with asymmetric information, a firm should go for internal finance before going for external sources of capital. If a firm has to raise external capital, low-risk debt should be preferred over equity (Myers & Majluf, 1984). Thus, in an imperfect capital market, a firm's investments will be constrained by the availability of internal finance. The asymmetric information will be more severe for more risky firms, and such firms are more likely to get credit rationed. This means that in the case of a high-risk firm, internal capital will have a more significant effect on investment decisions than a low-risk firm. To test the credit rationing hypothesis, we test the sensitivity of investments to the internal cashflows.

The study employs a panel dataset of 105 non-financial firms to assess bank lending behaviour. The relationship between firm investments and internal cash flows is used as a proxy for credit rationing. Firms are categorised into risk classes based on their probability of default, derived from logistic regression models. The sensitivity of investments to internal cash flows across these risk classes serves as the primary metric for assessing credit rationing.

We develop the following testable model in line with Fazzari, Hubbard, Petersen, Blinder, & Poterba (1988).

A random-effects model is employed to estimate the following equation:

$$INC_{it} = \beta_0 + \beta_1 Q + \beta_2 Q_{i,t-1} + \beta_{31} CFC_{it} * RC1 + \beta_{32} CFC_{it} * RC2 + \beta_{33} CFC_{it} * RC3 + \beta_{34} CFC_{it} * RC4 + \beta_4 CFC_{i,t-1} + \beta_5 SC_{it} + \beta_6 SC_{i,t-1} + \alpha_{re,i} + \pi_{it}, \quad (1)$$

where:

- INC: Investment to capital stock ratio;
- Q: Tobin's Q (market value to book value ratio);
- CFC: Cash flow to capital stock;
- RC: Risk class dummies (1-4, with RC4 being the riskiest);
- $\alpha_{re,i}$ the time-invariant random effect and;
- $\pi_{i,t}$ is the residual error

The detailed description of variables is given in Table 1.

The interaction terms (RCj × CFC) capture differential credit rationing across risk classes. For effective rationing, cash flow sensitivities should decline as firm risk increases. The interaction of risk dummies and cashflows gives us a measure of investment cash flow sensitivities of firms in different risk classes. For credit rationing to hold, $\beta_{31}<\beta_{32}<\beta_{33}<\beta_{34}$, which leads us to the hypothesis: $\beta_{31}=\beta_{32}=\beta_{33}=\beta_{34}$ that implies that the differences in the coefficients of interaction terms of cash flow with different risk levels are insignificant.

Table 1. Variable description

Variable name	Description
INC	Investments/ capital stock. Investments include expenditures on fixed assets and long—and short-term investments. Capital stock is the book value of intangible assets, fixed assets, and long-term investments.
D	Default. If profit for t-1 and t-2 is negative, D = 1, otherwise 0
RC1, RC2, RC3, RC4	Dummy variables for risk classes 1, 2, 3 and 4 based on the probability of default derived from the logistic regression model. Firms belonging to Risk Level 1 are the least risky, and those belonging to Risk Level 4 are the worst risk firms.
SIZE	The sample was divided into three groups based on the range of Firm size (Log of Total Assets): Small, Medium, and large.
CFC	Cash flow from operations/ capital stock
Q	Tobin's q = Market value of equity/book value of equity. This ratio indicates the market valuation of investment opportunities.
L_E	Log of equity
SC	Sales to capital stock
L_S	Log of Sales
OIS	Operating income to Sales
WCTA	Working Capital to total assets
ROC	Return on capital employed
DMKT	Debt to Market Capitalization

4. Methodology

4.1. Data collection and variables

The dataset comprises financial information for 105 firms from 2002 to 2018, sourced from the CMIE Prowess database. Firms are categorised into six sectors: manufacturing, mining, infrastructure, construction, electricity, and non-financial services. The analysis period of 2002–2018 was chosen to capture a complete economic cycle, including the global financial crisis of 2008 and its aftermath, which profoundly impacted credit markets in India. The selection of 105 firms was based on their availability in the CMIE Prowess database, ensuring a consistent panel across the study period. These firms represent publicly listed companies from key sectors, providing a diverse dataset for analysing lending behaviour. The study period from 2002 to 2018 was a perfect time to capture pre and post-crisis lending behaviour. After 2019, there was a new crisis episode (COVID-19), which was not a financial crisis per se and thus would not be ideal for evaluating SBC-based lending. Key variables in the study include:

- *Dependent Variable*: Investment to the capital stock ratio (INC).
- *Independent Variables*: Cash flow to capital stock (CFC), Tobin's Q, and Sales to Capital stock.
- *Risk Classes*: Firms are classified into four risk categories (RC1 to RC4) based on the probability of default, which is derived using logistic regression, as explained below.

4.2. Probability of default estimation

Logistic regression is used to estimate one-year default probabilities for each firm. Default is defined as two consecutive years of negative profitability. Coats & Fant (1993) and Lu et al. (2005) follow a similar notion. Logit models have been extensively applied in the literature to find the probability of bankruptcy (Martin, 1977; Ohlson, 1980; West, 1985; Heyliger & Holdren, 1991; Vilén, 2010; Zeineb & Rania, 2016; Jing & Fang, 2018). Logistic regression demonstrates robustness in bankruptcy prediction, with its accuracy reaching up to 98% in comparative studies involving machine learning methods (Altman et al., 2020; Máté et al., 2023).

The logistic function is:

$$\mathrm{PD}_{it} = \frac{1}{1+e^{-(\beta_0+\beta_1 X_{it})}} \tag{2}$$

where:

PD: Probability of default

Xi : is the vector of predictors of default for the ith observation, and b, an unknown parameter, is estimated by the logarithm of the following maximum likelihood function:

$$l(b) = \sum_{i\epsilon DF} logP(X_i, b) + \sum_{i\epsilon NDF} \log\{1 - P(X_i, b)\} \tag{3}$$

where DF is the default firm set, and NDF is the non-default firm set in the sample.

Firms are assigned to risk classes as follows:

- RC1: Low-risk (PD ≤ 0.11);
- RC2: Moderate risk (0.11 < PD ≤ 0.22);
- RC3: High risk (0.22 < PD ≤ 0.33);
- RC4: Extreme risk (0.11 < PD > 0.33).

4.3. Estimation techniques

The study employs the Random Effects Generalized Least Squares (GLS) model to analyse investment cash flow sensitivities across various risk classes, as it allows for efficient estimation in panel data settings where individual-specific effects are uncorrelated with explanatory variables. Unlike the Generalized Method of Moments (GMM), which is often used for addressing endogeneity issues in dynamic panel data models, GLS is more appropriate here as the study primarily focuses on cross-sectional heterogeneity rather than dynamic relationships. GLS provides reliable and unbiased estimates in cases where the data does not strongly exhibit issues of endogeneity or serial correlation, making it a robust choice for examining risk-sensitive investment patterns without overcomplicating the model specification. Moreover, random-effects GLS captures variations across entities more effectively in this context, where firm-level data across risk categories and cash flow sensitivities are analysed over a relatively long panel.

5. Empirical results

The one-year Probability of default (PD) for each firm in the sample was calculated for the entire period using the binary logistic model. For the default (D) prediction, we chose the six most frequently used accounting ratios in our logistic regression model from a set of ten variables based on their predictive power in a stepwise regression model. These ratios, along with their coefficients in the binary logistic regression model, are given in Table 2.

Table 2 shows the results of the logit model run on a panel of 105 firms. The constant term is suppressed, and the Newton-Raphson method is used for estimation. Our model correctly classified 75 out of 94 default events and 1666 out of 1691 non-default observations. With a cut-off value of 0.33, the classification accuracy for default cases (actual positive rate or sensitivity) is 79.8 per cent, and the classification accuracy for non-default cases (actual negative rate or specificity) is 98.5 cent. The overall model prediction accuracy is 97.5 per cent. Using the probability of default (PD) obtained from the logit model, we divided the firms into the following risk categories: (1) RC1 =1 if PD ≤ 0.11, or 0 otherwise; (2) RC2 = 1 if 0.11 < PD ≤ 0.22, 0 otherwise; (3) RC3 = 1 if 0.22 < PD ≤ 0.33, 0 otherwise; (4) RC4 = 1 if PD > 0.33. From 2002 to 2018, out of a total of 1785 cases, 1104 are grouped as risk level 1 (61.85per cent), 309 cases as risk level 2 (17.31per cent), 140 cases as risk level 3 (7.84per cent) and 232 cases as risk level 4 (13per cent). This discrete classification is according to the common banking practice and makes it possible to analyse the relationship between firm risk and investment sensitivity.

Table 2. Logit model estimation results for predicted default probability

Variable D	Coeff.	Standard Error
DMKT	1.0806***	0.0168
L_S	-0.3156***	0.0815
L_E	-3.6730***	1.4475
WCTA	-0.1227***	0.0670
OIS	0.9080**	0.0361
ROC	-0.8629***	0.0169

*, **, *** represent 10%, 5% and 1% significance level

5.1. Investment patterns across risk classes

Table 3 shows the investment pattern of our sample firms classified by risk categories. The mean and median investments decrease with the risk level. The variability of investments is lowest in default firms. This can be due to their indifference to the riskiness of investment opportunities.

Table 3. Investment of firms by risk category

Risk Level	RC1	RC2	RC3	RC4	All Firms
			Investments (INC)		
Mean	1.9086	1.2906	0.7170	0.5304	1.5290
Med	1.7223	0.7741	0.3278	0.2297	1.1145
Max	6.2929	5.0405	5.1493	3.8373	6.2929
Min	0.0005	0.0005	0.0005	0.0006	0.0005
Sd	1.5059	1.3728	1.1022	.7543	1.4752

5.2. Investment patterns across firm sizes

Table 4 shows the investment pattern of small, medium and large firms. Based on the range of Firm size (Log of Total assets), we divided the sample firms into small, medium and large groups. The capital growth of large firms is much more significant than the sample average. The variability of investments is lesser in the case of small firms, possibly due to a lack of access to capital for expansion. In the absence of strong credit appraisal and due diligence, the size of a firm may be taken as a signal of its creditworthiness by banks, as large companies have comparatively a lot to lose if they default (Hoshi, Kashyap and Scharfstein, 1993; Davis, 1994). In an economy with soft budget constraints, market discipline becomes weak, which does not force bankers to adopt rigorous credit appraisal and due diligence

5.3. Credit rationing and risk sensitivity

Regression results (Table 5) highlight the effectiveness of credit rationing across risk classes. Cash flow sensitivities decline marginally from **RC1 to RC3**, suggesting partial alignment with risk-based rationing. However, **RC4 firms** display a counterintuitive negative relationship, where investments increase despite declining cash flows. This suggests banks' speculative lending practices, likely driven by the expectation of eventual government bailouts. The lack of strict credit rationing in an economy can encourage more and more borrowers to undertake risky projects, leading to moral hazard-type lending. Such lending will benefit managers and stockholders at the cost of the government if the government keeps taking the burden of NPAs on its shoulders. With considerable stress in the banking system, recapitalisation of PSBs alone will not solve the problem.

Table 4. Investment of firms by firm size

Size	Small	Medium	Large	All Firms
		Investments (INC)		
Mean	0.2702	1.0926	3.1635	1.5290
Med	0.0829	0.6697	3.2198	1.1145
Max	1.2315	4.6710	6.2929	6.2929
Min	0.0080	0.0005	0.0073	0.0005
Sd	0.2942	1.1215	1.4123	1.4752

Table 5. Estimation results of investments-to-cashflow sensitivity model

Variable	Coeff.	Std. Err.
Q	0.0035***	0.0002
Q (-1)	0.0043***	0.0003
RC1*CFC	0.1531***	0.0340
RC2*CFC	0.1191**	0.0477
RC3*CFC	0.0134**	0.0006
RC4*CFC	-0.1560*	0.0758
CFC (-1)	0.0622**	0.0230
SC	0.3114***	0.0372
SC (-1)	-0.0576*	0.0264

*, **, *** represent 10%, 5% and 1% significance level. Dependent Variable: INC; Number of firms: 105; Number of observations = 1785
GLS random-effects regression

5.4. Credit rationing bias by firm size

Table 6 examines credit rationing across firm sizes within risk classes. Investments of large firms are less responsive to internal cash flows than small and medium firms, even at the same risk level. This indicates a systemic size bias favouring large firms. Small firms face stricter credit constraints, with cash flow sensitivities increasing significantly across risk classes.

Table 6. Estimation results of investments-to-cashflow sensitivity model across firm size

Variable	Coeff.	Std. Err.
Q	0.0024***	0.0002
Q (-1)	0.0004**	0.0002
SF*CFC	0.6612***	0.1495
MF*CFC	0.3523**	0.1552
LF*CFC	0.2580*	0.1211
CFC (-1)	0.0546**	0.0217
SC	0.2765***	0.0352
SC (-1)	-0.0591**	0.0264

*, **, *** represent 10%, 5% and 1% significance level. Dependent Variable: INC; Number of firms: 105; Number of observations = 1785. GLS random-effects regression.

5.5. Post-AQR credit rationing

The model includes a post-AQR dummy variable to evaluate the impact of the Asset Quality Review (AQR) and Insolvency and Bankruptcy Code (IBC). Table 7 summarises the results. Post-AQR, credit rationing improves marginally for **RC1 to RC3**, with increased cash flow sensitivity aligning with risk profiles. However, **RC4 firms** continue to receive funding despite weak financial metrics, reflecting unresolved NPAs and systemic inefficiencies.

Table 7. Estimation results for Investment-to-cash flow sensitivity post-Asset Quality Review (AQR)

Variable	Coeff.	Std. Err.
Q	0.0035	0.0002
Q (-1)	0.0004	0.0001
RC1*CFC	0.1724	0.0348
RC1*CFC*post_AQR	0.0725	0.0331
RC2*CFC	0.0980	0.0488
RC2*CFC*post_AQR	0.3108	0.0918
RC3*CFC	0.0366	0.0174
RC3*CFC*post_AQR	0.3569	0.1155
RC4*CFC	-0.1544	0.0776
RC4*CFC*post_AQR	0.1593	0.0779
CFC (-1)	0.0580	0.0229
SC	0.3091	0.0371
SC (-1)	-0.0525	0.0263

*, **, *** represent 10%, 5% and 1% significance level. Dependent Variable: INC; Number of firms: 105; Number of observations = 1785. GLS random-effects regression.

6. Discussion and conclusion

The findings of this study underscore systemic inefficiencies in the Indian banking sector, particularly in the allocation of credit and the role of soft budget constraints (SBCs) in exacerbating the NPA crisis. Banks in India demonstrate a lack of effective risk-based credit rationing, as evidenced by their tendency to continue lending to high-risk firms (RC4) even during economic downturns. This practice reflects speculative evergreening, where banks extend credit to avoid declaring loans as NPAs, aligning with earlier observations that such behaviour perpetuates financial instability (Ghosh, 2017). Furthermore, the weak differentiation in credit access between low-risk (RC1) and moderate-risk (RC2) firms suggests inefficiencies in credit appraisal processes, contributing to suboptimal credit allocation.

A significant bias favouring large firms is evident from the results, where firm size appears to override risk profiles in determining credit access. Large firms, often perceived as more creditworthy due to their size and connections to public-private partnerships (PPPs), dominate lending portfolios despite contributing disproportionately to NPAs (RBI, 2018; Sengupta & Vardhan, 2017). This systemic bias undermines the efficiency of credit markets and poses greater risks to financial stability (IMF, 2023; OECD, 2023; Schüle, 2018; World Bank, 2023). Although reforms such as the Asset Quality Review (AQR) and the Insolvency and Bankruptcy Code (IBC) have introduced elements of credit discipline, their impact remains constrained by delays in NPA resolution and limited improvements in recovery rates (Rebello & Ray, 2019).

These findings highlight the need for structural reforms to address governance issues and reduce moral hazard stemming from repeated recapitalisations of public sector banks (PSBs). Strengthening risk-based lending frameworks, minimising political interference, and developing alternative financing channels, such as corporate bond markets, are critical to enhancing credit discipline. Limiting unconditional government bailouts through performance-based recapitalisation policies can mitigate SBC-induced inefficiencies and foster accountability among banks and borrowers. While recent regulatory measures have shown promise, addressing these underlying systemic issues is essential to preventing future NPA crises and ensuring sustainable financial stability.

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