Behavioral Impact of IBC

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Executive Summary

Our study uses the NeSL dataset spanning 2018–2024 on corporate loan accounts which captures periodic filings by creditors on key metrics of loans issued to corporate debtors.[5] We also incorporate data on corporate insolvency resolution proceedings (CIRPs) from the IBBI dataset for the period 2017–2023, firm-level financial data from CMIE Prowess for the period 2010–2024 and data on non performing assets (NPAs) for banks from RBI for the period 2010–2024.

A major finding of our study is that the volume of accounts deemed 'Overdue' has reduced significantly, both in terms of the Rupee amount as well as in terms of the number of accounts.[6] Our interpretation is that the passage of the IBC has injected discipline in the credit allocation process and has prompted borrowers to adhere to stipulated payment schedules. However, we do not observe a comparable reduction in the volume of accounts labeled as 'Default', proportions of which have remained broadly stable in our sample period. We show that the proportion of 'Default' accounts has declined steadily after spiking in 2020 but the outstanding default amount as a share of total debt has increased slightly. Interestingly, the proportion of aggregate default amount in the system to the proportion of aggregate overdue amount has steadily increased over the years from 27% in 2018 to 80%

[5]We analyze loans for which the outstanding amount exceeds ₹1 Cr (Amendment 2020). We further validate our results after the inclusion of the full sample of loans.

[6]Amount overdue on overdue accounts as a percentage of total amount outstanding on all accounts reduced from 18% in 2018 to 9%. Number of overdue accounts has reduced from 22% of all accounts to 15% of all accounts.

in 2024, indicating, in our opinion, that there is greater confidence among creditors to take errant borrowers to task, even in the case of large overdue amounts. Our findings reveal a significant reduction of around 1% in the ratio of net NPAs to net advances during the period 2010 to 2024.[7]

We evaluate a loan account's transitions across four categories—'Normal' (N), 'Overdue' (O), 'Default' (D) and 'Suit Filed' (S)—over its life cycle. The yearly proportion of transitions from the Overdue category to the Normal category have increased over 2018–2024, supporting the view of an improvement in the credit culture of corporates. Transitions into the Default status do not show any such decreasing trend. We also show that mean transition times have reduced for all inter-category transitions and their variability across accounts has also fallen significantly. For example, it took on average 248–344 days for a loan account to transition from Overdue to Normal in 2019–2020, which has lessened to 30–87 days in 2023–2024. Similarly, in 2019–2020 an account spent, on average, 169–194 days in the Overdue category before it got classified as Default by the creditor, which subsequently reduced to 33–81 days in 2023–2024. Overall, such findings point towards a the success of IBC in reducing the time taken to resolve the delinquencies on behalf of creditors and debtors in one way or another, indicative of an efficient credit environment.

Merging NeSL data with firm-level data from Prowess, we offer evidence that firms that default show the following main characteristics (on average): i) higher leverage,[8] ii) higher short-term debt, iii) lower unsecured debt. Further, such firms hold more fixed assets, are smaller in size, suffer from poorer profitability and are more likely to be listed, and funded by PSU banks. On the other hand, firms that withdraw from CIRP tend to show, on average, lower leverage and higher profitability.[9] Interestingly, business group-affiliated

[7] 0.96% to be exact.

[8] Firms that recover from default display an average leverage of 56% and those that stay in default have an average leverage of 86%.

[9] On a related note, firms which transition away from default and do not fall into CIRP proceedings tend to show lower leverage, lower short term and unsecured debt levels.

firms are significantly less likely to withdraw once they enter the CIRP process, suggesting institutional or structural differences in how resolution strategies are pursued. Further, firms that successfully resolve defaults tend to experience subsequent improvements in profitability.

We also analyze changes in firm-level metrics on credit availability, cost of credit, and governance from pre-IBC period to post-IBC period. During our sample period 2010–2024, we show that for an average firm, leverage declined by 0.4% with long-term debt reducing by 0.7%. On the other hand, short-term leverage and unsecured leverage show an increasing trend in the same period. These patterns point to a strong demand-side response, where firms appear more cautious about taking on excessive debt in light of the IBC's disciplining mechanisms. However, for the pool of distressed firms, we show that leverage has significantly increased post-IBC in comparison to non-distressed firms, primarily driven by an increase in short-term debt.[10]

We find no significant impact on firms' cost of debt but show that for distressed firms there is around 3% reduction in their cost of debt post IBC (vs. non-distressed firms) indicating an improved credit environment for distressed firms. In terms of governance, we show that the average proportion of independent directors has increased by around 2.8% post-IBC, with the increase being more significant for distressed firms.

To summarize, our study offers evidence—based on data shared by the information utility NeSL—that the implementation of the IBC by the regulator IBBI has brought about significant behavioral changes in the credit ecosystem comprising corporates and banks. Credit monitoring has improved, overdue accounts have fallen in number and there is a systematic reduction in firms' use of debt, especially long term. We also find that there is an increasing tendency to settle debts to avoid the CIRP proceedings, which we interpret as a positive sign. Finally, banks have also shown to efficiently use the new legal apparatus for debt

[10] Firms having an interest coverage ratio below 1 and financial leverage in the highest quartile are classified as distressed firms.

recovery—either by resolution or by liquidation. We find these changes in the firm and bank behavior heartening and suggestive of the positive impact of IBC on the lender-borrower ecosystem in India.

Chapter 1

Introduction

The Insolvency and Bankruptcy Code (IBC) of 2016 was a transformative institutional reform in India that overhauled the country's insolvency and bankruptcy framework. Shifting control from debtors to creditors, the IBC introduced a time-bound resolution mechanism to streamline bankruptcy proceedings, reduce judicial delays, and improve creditor recoveries. The reform aimed to enhance corporate credit discipline and saw a moderate yet meaningful reduction in Non-Performing Assets (NPAs), especially where resolution timelines were adhered to. Private and public sector banks responded differently, with improved asset quality. The IBC sought to provide creditors with greater powers in recovering loans from defaulting debtors. Key features that set the IBC apart from extant bankruptcy regulations were the creditor-in-control model, rights of operational creditors to initiate bankruptcy proceedings, a relatively independent judicial architecture to guide the implementation, time-bound resolution process and stringent penalties, creation of professional agencies like the information utility and insolvency professionals to facilitate the insolvency process and a clear outline of offences with stringent penalties for any breaches.

On a broader level, the IBC appears to have catalysed structural shifts in firm behaviour.

Post-reform, firms have become more conservative in their use of leverage, especially those with tangible assets, likely responding to the threat of enforced liquidation.

The Insolvency and Bankruptcy Board of India (IBBI) has sought independent validation of the behavioral impact of IBC on the ecosystem of lenders and borrowers in the Indian economy. To facilitate the study, IBBI and NeSL have shared requisite datasets which can shed light on this important matter.

1.1 Objectives of the study

The broad objectives of the study are;

1. Comparison of NPA levels and NPA recovery pre- and post-IBC, and to quantify the impact of IBC in NPA reduction
2. Analysis of withdrawals due to threat of IBC: Number of cases withdrawn after filing under IBC, and the cases which were not even filed and were settled to avoid IBC filing and performance analysis of firms.
3. Analysis of loan/advances repayment and delinquency culture pre and post IBC and debt repayment behaviour of group companies.
4. Analysis of the impact of IBC on variables such as cost of credit, availability of credit, Governance, R&D, Innovation and Asset Specificity.

1.2 Review of Literature

This section reviews the research work followed by enactment of landmark institutional reform IBC in 2016. Two main arguments have been proposed: the demand-side and the supply-side. The demand-side argument emphasizes that strong creditor protection does not encourage managers and shareholders from using large amounts of debt because they want to avoid losing control in the case of financial distress [Acharya et al., 2011, Vig, 2013]. Thus, firms may reduce leverage which in turn, may negatively affect the loan growth of banks. Studies by Acharya and Subramanian [2009] and Acharya et al. [2011] show that as creditors get stronger, firms reduce risk-taking and investment into innovation. This view has been developed both through cross country studies [Cho et al., 2014] as well as through the impact of change in the bankruptcy legislation of a country on the leverage levels in that country [Lilienfeld-Toal et al., 2012]. On the other hand, the supply side view espouses that stronger creditor rights enhances the motivation of creditors to lend, leading to an increase in the level of credit in the economy. This result has largely been established through cross-country studies that found evidence of higher levels of credit in economies with greater creditor protection [Djankov et al., 2007, Qian and Strahan, 2007b, Houston et al., 2010]. Consequently, whether creditor-friendly bankruptcy reforms increase corporate leverage using lower cost of debt, or decrease it via creditors' increased liquidation bias, remains an empirical matter to be settled via detailed studies.

Research has also sought to identify the effects of creditor rights on various aspects of corporate behaviour. Some studies find positive effects of stronger bankruptcy protection on firm productivity and investment levels [Ponticelli and Alencar, 2016, Ersahin, 2020]. On the other hand, other studies shows that strong creditor rights leads to a reduction in innovation and risky investment [Acharya and Subramanian, 2009, Acharya et al., 2011].

In the Indian context, a number of studies have looked at the impact of the IBC in a variety of contexts. Initial studies sought to provide a succinct representation of the IBC, outlined mechanisms through which it could change the bankruptcy regime within the country and highlighted potential implementation challenges [Datta, 2018, Gupta, 2018, Tandon and Tandon, 2019, Rajsekhar, 2022, Bansal, 2022]. Recent papers have sought to examine the impact of the IBC on key economic parameters: corporate leverage levels [Bose et al., 2021, Jayadev and Krishna, 2022], firms' choice between debt and equity [Chakraborty and Sarkar, 2021] and the impact on bank lending stress [Gupta et al., 2020]. These studies have primarily relied on data on publicly listed firms to draw their inferences.

More vigorous enforcement of creditors' rights encourages firms to mitigate bankruptcy risk [Araujo et al., 2012]. In line with this argument Singh et al. [2021] observed that in India, the enhancement of creditors' rights following the implementation of the Insolvency and Bankruptcy Code (IBC) in 2016 led to significant changes in both the quantitative and qualitative aspects of firms' financial policies. Specifically, in the post-IBC period, firms not only reduced their overall debt levels but also shifted towards long-term borrowing from a limited pool of sources to manage bankruptcy risk. This indicates that firms adjust their financial strategies in response to strengthened creditor protections, aiming to lower their exposure to financial distress [Bose et al., 2021, Jiang et al., 2021, Singh et al., 2021]. These behavioral adjustments could be classified into leverage, cost behavior, cost of debt, innovation, agency costs, entrepreneurship, and others.

Jose et al. [2020] provides evidence that a decline in corporate borrowings in the post-IBC period, essentially depicts a new equilibrium scenario brought about by the countervailing factors of the income effect and substitution effect. The result that bank borrowings have declined after the introduction of the IBC is suggestive that the substitution effect dominates not only the income effect but also the supply-side factors, both of which would have pushed up borrowings. The IBC, in fact, has had a significantly negative impact on the interest expenses incurred by the firms after controlling for firm-specific (profits, total assets and total borrowings) and macroeconomic (GDP, GNPA and repo rate) variables. Bose et al. [2021] provide early evidence on impact of IBC on the access to credit and the performance of financially distressed firms. As firms closer to the point of distress are most likely to be influenced by the bankruptcy procedures, the empirical analysis is conducted by exploiting firm heterogeneity based on firms' status of being in financial distress. This paper uses a causal identification approach to investigate the impact of the IBC policy on the "credit channels" of distressed firms. This paper also studies the differential effects of the IBC policy on firm performance by accounting for firm heterogeneity based on the size, age and collateral of financially distressed firms. This paper finds a significant impact of the policy on long versus short-term debt financing, and firm's pricing of borrowing for the distressed firms. The economic magnitude of the interacted coefficients suggests that after the introduction of the policy reform, the access to long-term debt increased by 6.3%, short-term debt increased by 1.4%, while the cost of borrowing declined by 0.8% for distressed firms as compared to non-distressed firms. This paper further states that improvement in the performance of distressed firms with a greater collateral value as compared to their counterparts. The economic magnitude of this effect shows one standard deviation increase in long-term debt improves performance by 10.4%, and a one standard deviation reduction in cost of borrowing improves firm performance by 4.8% for more collateralized distressed firms. This paper uses financial distress of firms measured using accounting data that define a dummy for distressed firms, 'Distress', which takes value 1 if a firm in a year has accumulated losses equal to or exceeding 50% of its average net worth in the immediately preceding four financial years and 0 otherwise. This approach has serious limitation as the since 1993 the distress is more defined as Non-Performing Asset rather based on stock variables. Second is why do banks provide loans to distressed firms? As per the extant guidelines Banks do not provide any additional loan to distressed firms. Especially post IBC such finance is deeply discouraged, thus the results of this paper are contradicting with the policy recognising NPAs and extending additional finance to NPAs.

Singh et al. [2021] observed that firms responded to the strengthening of the bankruptcy law by decreasing their dependence on debt financing, especially short-term financing, which resulted in the concentration of debt in a few debt sources. Overall, this paper shows that strengthening of creditors' rights had a negative impact on debt ratio and debt heterogeneity and a positive impact on long-term debt maturity structure. These results were observed mainly in those firms that had a high probability of bankruptcy in the pre-implementation period. Singh et al. [2022] argues that effective bankruptcy reform not only improves credit supply, but also encourages distressed firms to take risky, but profitable projects. This study suggests that the bankruptcy law that rapidly resolves insolvency and favors restructuring over liquidation encourages distressed firms to invest in risky, but profitable projects, which in turn increases the probability of their survival. Thus, the paper concludes that IBC law boosts corporate risk-taking of distressed firms compared with non-distressed firms. The study sample is limited to public listed firms operating in the Indian market and covers the period from 2012 through 2020. This paper follows the definition of Bose etc. a firm as a distressed firm (treatment firms) if its accumulated losses are equal to or exceeding 50% of its average net worth of the previous four years, and the rest firms are assigned as non-distressed firms (control firms). Agarwal and Singhvi [2023] shows that despite an increase in the supply of credit, IBC led to a higher reduction in the secured debt of the high tangibility firms compared to the low tangibility firms. The paper finds that secured debt was substituted with other sources like equity, retained earnings, and accounts payable; more cash was held back. This paper findings suggest that managers' expected cost of bankruptcy obstructed the expected increase in supply of credit after IBC.

Rawal et al. [2024] investigate the impact of the Insolvency and Bankruptcy Code (IBC) on the capital structure speed of adjustment (SOA) of Indian firms. Utilizing a panel data methodology and propensity score matching-based difference-in-differences (PSM-DID) regression; this paper categorise firms into over-leveraged (treatment) and under-leveraged (control) groups. The findings reveal that the IBC significantly increased the SOA for over-leveraged firms, compelling them to reduce debt levels swiftly to avoid financial distress and bankruptcy. Conversely, under-leveraged firms exhibited a decreased SOA, reflecting a strategic shift towards financial stability over leveraging benefits. These results underscore the critical role of regulatory frameworks in shaping corporate financial strategies and align with the dynamic trade-off theory, highlighting firms' active adjustment towards optimal capital structures. The other related evidences are coming from Ghosh [2022] find that the law lowered overall debt and, especially, bank debt and reduced borrowing costs. The impact was pronounced for firms that maintain multiple banking relationships. In real terms, firms with single banking relationships experienced much higher cutbacks in investment. The results, therefore, demonstrate how improvements in creditor rights can have positive financial but negative real effects across firms with single versus multiple banking relationships. Jadiyappa and Kakani [2023] Strengthening of creditors' rights decrease the need for holding more cash. The value of excess cash has decreased following the implementation of bankruptcy law. Khan and Chakraborty [2022] highlight that after the implementation of IBC-2016, financing constraint of manufacturing firms has been reduced which has some important policy implications. It suggests that the implementation of IBC-2016 helped to ease out the credit constraints of the exporting firms to reorganize their business. Through the reform of the bankruptcy law, bargaining position of creditors has been strengthened which in turn helped the manufacturing firms to get rid of credit constraints and consequently it helped to improve their exports. However, the methodological framework of this paper is weak.

Another way looking interest cost is Corporate Bond spreads, (Sengupta and Vardhan [2023]) hypothesize that IBC would lower the credit spreads of the non-finance, non-PSU firms compared to the finance firms owned by the government. Bond investors in low rated bonds would see relatively greater benefit from IBC that those in highly rated bonds, given that ratings assigned to bonds by credit rating agencies capture the default probability of a bond. With the enactment of the IBC, bond investors are placed on an equal footing along with banks, when it comes to initiating insolvency proceedings against a defaulting debtor or in the committee of creditors. Hence it may be expected that with the implementation of IBC, the cost of borrowing, as reflected in the credit spreads in the bond market has come down. The paper finds that the IBC lowered the credit spreads for bonds issued by non-financial firms in the period from 2016-17 to 2019-20 compared to the bonds issued by the finance-firms in the years 2014-15 and 2015-16 especially when other issue-level determinants of credit spreads are taken into account. This is in line with our hypothesis that ushering in of the new bankruptcy regime would lower the cost of borrowing in the bond market. However, the limitation is that account for firm-specific factors, the statistical significance of this effect disappears. In other words, investors in the bond market seem to pay more attention to firm balance sheet features (such as firm size and financial health) as opposed to access to the IBC led resolution, in assessing credit risk in bonds and hence determining credit spreads.

A well-articulated theory [Mohanty and Sundaresan, 2018] is when creditor rights are strong, agency conflicts are smaller, and the benefits of hedging will exceed the costs. By contrast, when creditor rights are weak, firms will leave their debt unhedged and offer higher spreads on foreign currency loans. In a weak bankruptcy environment and poor credit protection dollar debt is priced reflecting contract enforcement costs. Mohanty and Sundaresan [2018] find that countries that score high on World Bank's strength of creditors' legal rights tend to benefit from lower degrees of currency mismatches on their corporate balance sheets. They also find strong evidence in favour of the incomplete market hypothesis that FX exposures are negatively associated with the degree of depth of the hedging markets (lower depth implying higher costs of hedging), implying that deeper FX markets may encourage firms to hedge a larger fraction of their FX exposures. The evidence on the Indian market shows that employing a probit model and dividing firms according to their ratio of foreign currency debt in total debt, they find a robust positive association between the new bankruptcy code and the probability of currency hedging by firms with a high share of foreign currency debt. Relative to the pre-new bankruptcy regime, the probability of these firms issuing loans on a currency-hedged basis rises by about 13%. The paper finds a positive relationship between the new bankruptcy code and the probability of currency hedging by firms with a high share of foreign currency debt. The probability that firms with high foreign currency debt will hedge increased significantly after the new bankruptcy law came into effect in India.

Among the factors playing a role in hedging decisions, the most important is the availability of a natural hedge through export revenues. Firms with a larger fraction of their sales in foreign currencies are more likely to issue unhedged debt. By contrast, growth opportunities significantly increase the likelihood of hedging currency and interest rate risk.

These studies define the distress or default differently, often a subjective approach rather than observed default, and are largely confined to listed companies. Our study has access to granular data of loan contracts, the start of these contracts, and the transition from normal to suit filed cases. Thus, the default is exactly the observed default as per the bank's records. As the data coverage is extensive and granular it provides evidence on both listed and several of unlisted companies. Ours is the unique study that examines the characteristics of firms that have withdrawn from CIRP. Thus, the study identifies the characteristics of firms under stress conditions to suit-filed status.

1.3 Data Description

In this study, we combine data from multiple sources for our analysis. Our primary dataset is on the details of corporate loan accounts from the National E-Governance Services Limited (NeSL), India's first information utility, set up under the aegis of the IBC. We also utilize data from the Insolvency and Bankruptcy Board of India (IBBI) on firms undergoing the corporate insolvency resolution process (CIRP) under the IBC. Finally, we also incorporate data on the financials of public and private firms in India from the Prowess CMIE.

The NesL dataset consists of data on corporate loans extended by various credit providers (banks and non-banking finance companies) in the country. Credit providers report details of these loans on a periodic basis, including details on the borrower, the creditor, the amount outstanding, the status of the loan, amounts overdue/default (if any) and date of any action initiated. In addition, the dataset also provides details of collateral posted (if any) for a particular loan. The loan dataset consists details 6, 03, 77, 975 filings made across 58, 40, 324 debt contracts, implying an average of 10.3 filings per debt contract. After cleaning duplicated filings and filings that had negative values for amounts overdue or default amount, our final loan accounts dataset had 4, 41, 99, 032 filings.[1] These final set of filings pertained to 58, 39, 936 unique loan contracts across 5, 58, 567 unique corporate debtors and 9, 51, 787 unique creditor-debtor pairs.

Given that the application of the IBC to corporate loans has been restricted to loans having an outstanding amount greater than ₹1.0 crore, we restrict the primary focus of this analysis to loan contracts which have had an outstanding amount of ₹1.0 crore or more at some point in its life-cycle (henceforth, referred to as 'large loans'). However, we test the general validity of all major findings of our study in the general case by replicating the analysis in the full loan contract dataset. Restricting the sample to large loans, we obtain a dataset consisting of 1, 14, 07, 462 filings across 9, 87, 892 loan contracts pertaining to 1, 77, 101 corporate debtors.[2] Table (1.1) presents the details of the large loan contracts in the NeSL dataset by year.

The IBBI dataset consists of details of the CIRPs that have been initiated in India under the aegis of the IBC. It provides details of the firm undergoing CIRP, the type of initiator of the CIRP, claim details, division bench of the NCLT and the outcome of the CIRP. We use the dataset for the period December 2016 to December 2023, wherein we have details of 7, 325 CIRPs initiated over this period.

[1] 1, 61, 61, 098 filings were discarded as duplicated filings due to them having identical time stamp for submission date as other filings in the data set. 12, 937 filings were discarded due to negative overdue amounts and 4, 908 filings were discarded due to negative default amounts. The dataset also contains 10, 25, 067 filings with negative outstanding amounts. However, these filings have been retained in our sample as negative outstanding amounts can be interpreted as keeping a positive balance with the creditor.

[2] The dataset has 85, 45, 364 filings that have an outstanding amount greater than ₹1.0 crore pertaining to 9, 87, 892 loan contracts. However, for completeness, we include all filings for these 9, 87, 892 loan contracts taking the size of the total dataset of large loans to 1, 14, 07, 462 filings.

Table 1.1: Summary of NeSL Loan Dataset - Large Loans

The table presents the yearwise aggregation of the number of large loan accounts and amount outstanding associated with these large loan accounts based on the complete NeSL loan dataset. Large loan accounts are defined as loan accounts in which the amount outstanding has exceeded ₹1 crore at least at one point in time in its life-cycle.

Year	No. of Loan Contracts	No. of Filings	Mean Outstanding Amount (₹lakhs)	Median Outstanding Amount (₹lakhs)	Max. Outstanding Amount (₹lakhs)
2018	1,530	1,530	3,390	452	6,86,610
2019	1,56,827	5,30,538	2,383	328	29,10,000
2020	2,92,587	11,54,557	2,063	292	51,51,215
2021	3,51,394	14,86,772	4,132	294	90,00,000
2022	3,92,528	18,59,015	2,570	254	41,40,864
2023	4,82,305	25,04,948	2,407	258	70,00,000
2024	5,99,152	38,70,102	2,357	257	29,10,000

1.4 Scope and Limitations of the study

The study primarily utilizes the data on loan contracts of corporates reported by creditors over the period 2018-24 to NeSL. In addition, we combine the NeSL data with data from the IBBI on CIRPs and data from Prowess CMIE on financial characteristics of firms. The conclusions drawn are based on the analysis of these datasets.

We faced two key challenges in the conduct of this study. First was the availability of a unique identifier for merging these datasets. While the NeSL dataset identifies firms using their PAN number, the Prowess CMIE dataset has CIN number of firms as their primary identifier. As Prowess CMIE also gives the PAN of a firm as a secondary identifier for a subset of firms, we are able to match only a subset of the observations. In addition, data on Prowess CMIE, especially for unlisted firms, is limited in comparison to the MCA database.[3] Consequently, there is a considerable drop in observations when we match the NeSL dataset

[3] Prowess CMIE has data for around $58,000$ firms while the MCA database has data on close $1,000,000$ firms.

with the Prowess dataset.[4]

Therefore, the inferences drawn are limited to the data available.

1.5 Organization of the study

This report is divided into four chapters. The first chapter presents the objectives, data and methodology and structure of the study.

The second chapter analyses the NeSL data of loan accounts and transitions of loan accounts across categories during the period 2018-24. We also analyse the change in borrower behavior in the post-IBC period financially. We examine whether they have become better at managing their risk and financial prudence. We also present our analysis on the non-performing loans in the economy in this chapter.

The third chapter looks at three dimensions. We analyse how some firms are able to withdraw from CIRP and some are not. We examine the characteristics of these firms and bring forth the discriminating factors between the firms that withdraw from CIRP and firms that default in CIRP. The next category of interest is the firms that default but for which no CIRP is filed against them. We look at the distinguishing characteristics of such firms and recognize the main features that help them escape bankruptcy proceedings. Finally, we observe firms that remain default-free despite having loan accounts in overdue status. They are of particular interest to us as these firms manage their risk such that there is no default registered for them.

The fourth chapter brings forth the behavioral changes in the firms since the implementation of IBC. We study a longer time period of 2010-24, wherein we analyze firms on five parameters

[4] For example, of the 27,299 unique firms with default filings as per the NESL dataset, after merging with the Prowess dataset, our sample drops to 3,521.

– leverage, cost of debt, governance, innovation, and asset tangibility.

Chapter 2

Analysis of NPAs and Loan Account Transitions

This Chapter presents analysis of NPAs at Indian banks at macro level and transition of loan accounts of corporate debtors at a micro level to develop a composite picture of the evolution of the corporate credit landscape in India.

Section (2.1) presents the results of our analysis of NPAs. We seek to understand key trends and drivers that impact the NPAs at banks over our sample period of 2010–2024. We further augment these results through a detailed analysis of loan account transitions based on the NeSL dataset for the post IBC period (2018–2024). Filings at NeSL by creditors allow us to classify a loan account as a standard asset (Normal), overdue loan (Overdue), loan in default (Default) or a loan with suit filed (Suit Filed) at a given point in time. In Section (2.2), we evaluate trends in aggregate amounts associated with each of the four categories as well as trends in transition times across categories over the sample period. In Section (2.3) we combine the loan account transition data with firm-level financial data from CMIE Prowess to draw conclusions about drivers of these transitions.

2.1 NPAs of Indian banks

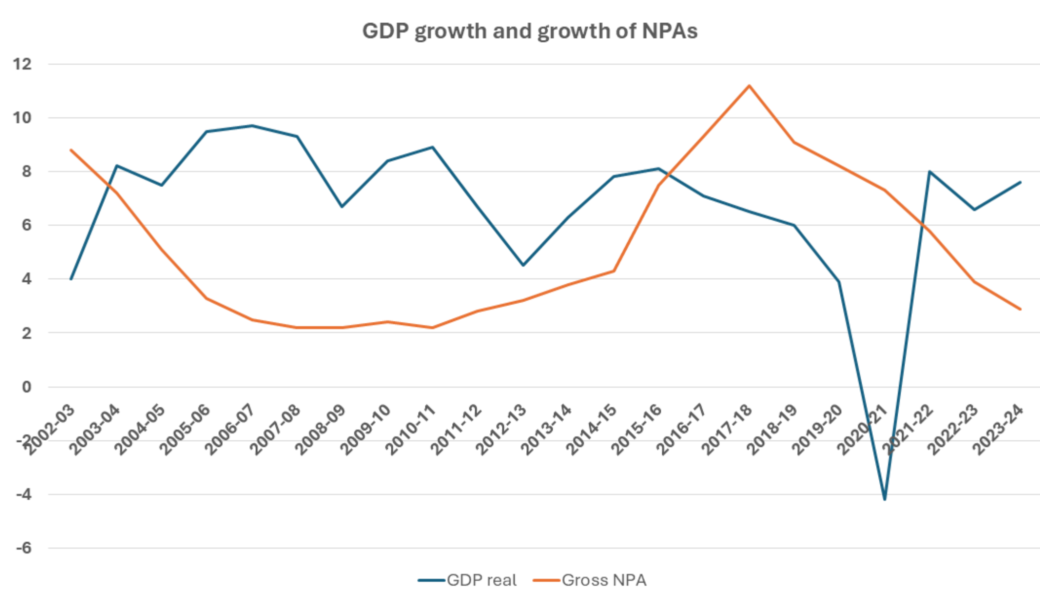
The banking sector in India has gone through sharp swings in performance and asset quality in the last two decades. In 2011, the share of NPAs in gross loans of the consolidated banking sector in India was 2.4 percent. The period 2004-09 of Indian economy witnessed growth as the larger part of economic growth is government thrust on infrastructure development and growth bank credit is due to bank's financing infrastructure. Further weak credit standards of banks turned this large credit to infrastructure as NPAs. At the end of March 2016, the Gross NPAs of Indian banks are at peak. Thanks to RBI's stringent review of Asset Quality and imposing the strict conditions on banks with huge NPAs, the gross NPAs of the scheduled commercial banks have declined from the peak of 11.2% in March 2018 to 2.8% in March 2024. A good part of that reduction is attributable to resolution processes enabled under IBC. The resolution mechanism of IBC found to be effective in addressing the bad loan recovery of bank NPAs.

As of September 2024, 8,002 cases have been admitted into the Corporate Insolvency Resolution Process (CIRP) and approximately 75% of these cases were closed through resolution, withdrawal, review, settlement, or liquidation. Of the closed cases, 56% were either resolved, settled, or withdrawn. In a positive trend, the ratio of resolutions to liquidations has risen from 21% in 2017-18 to 61% in 2023-24. In addition to facilitating resolution outcomes, the IBC has also been effectively used by both financial and operational creditors to encourage borrowers to repay their debts. By March 2024, 28,818 cases involving an outstanding default amount of ₹10.22 lakh crore were withdrawn prior to admission.

In terms of the powers vested under newly inserted Section 35AA of the Banking Regulation Act, RBI had issued directions to banks in 2017 in respect of 41 entities, which accounted for more than 35% of the banking system NPAs at that point, for filing CIRP applications. So far, resolution plan has been approved in the case of 17 borrowers[1], orders of liquidation have been issued in the case of 12 borrowers, settlement was reached by lenders with 2 borrowers; and in 4 cases the lenders have assigned their exposures to ARCs. The aggregate realisation for financial creditors from the 17 resolved cases has been around 50% of admitted claims and 190% of liquidation value.

Financial creditors are now actively leveraging the Code for resolution of stressed assets. As of September 2024, around 633 corporate debtors, where insolvency application was initiated by financial creditors, have been successfully resolved under IBC, yielding an average realization of 30.09% of admitted claims. Further, CIRP applications filed by financial creditors in 702 corporate debtor accounts have been either resolved through appeal/review/settlement or withdrawn under section 12A. Similarly, liquidation orders have been passed in respect of 1224 corporate debtors.

Figure 2.1: NPA growth vs. GDP growth



Source: RBI

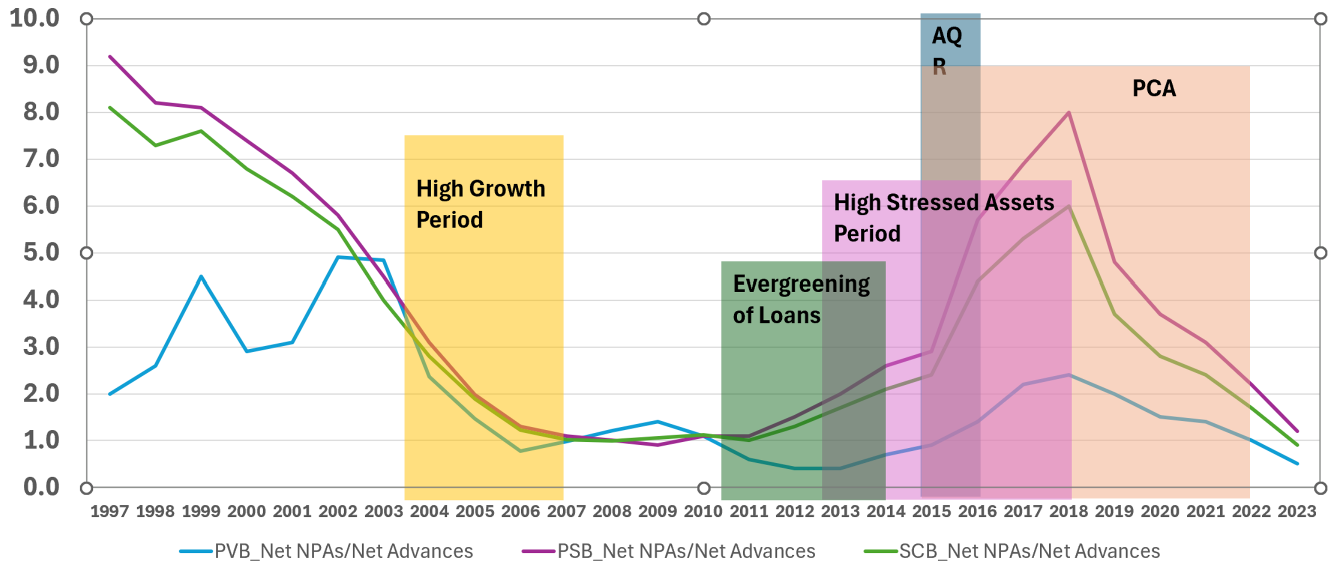
[1]https://www.rbi.org.in/Scripts/BS_SpeechesView.aspx?Id=1491#FN4

Figure 2.1 shows the broad trends of NPAs of Indian banks over the period 1997 to 2023. It is evident that post 2016, the NPA levels of banks have reduced; this may be attributed to banks' quick action.

Figure 2.2 gives the NPA trends along with policy changes.

While analysing credit aspects of Indian banks, we must understand that government-owned banks or public sector banks account for more than two-thirds of overall lending in India. All these banks are listed in the stock exchanges and their government ownership ranges from 55% to 80%. Private sector banks cater to the rest of the market. Within the large private sector banks, the ownership is widely dispersed with substantial stakes held by institutional investors. Foreign institutions own more than 50% of stake in most of these banks. Additionally, some small private-sector banks have concentrated ownership, mainly catering to small geographical areas. Finally, foreign banks have a minimal presence in India. The above distinctions between the various categories of banks are essential for our study, as it has been shown in the Indian context that different types of banks engage with systematically different types of borrowers [Bhue et al., 2015, Bhaumik et al., 2011, Berger et al., 2008].

Figure 2.2: Gross and Net Non-Performing Assets Ratio



We next identify the major factors responsible for NPAs of PSBs in India based on 51 selected banks with 14 years' data of each of the selected banks from RBI website. Thus, we have a panel dataset of 521 observations with respect to each of the selected bank-specific variables, which are summarized in the table.

Table 2.1: Summary Statistics for bank-level variables

We present the summary statistics of bank-level variables in this table. The $NetNPAtoNetAdv$ is the ratio of Net NPAs to Net Advances. CAR Tier1 is the Capital Adequacy ratio for Tier 1 capital. CdR is credit to deposit ratio. GrowthAdvances is the rate of growth of advances and log of assets is the natural logarithm of total assets of the banks. We have 51 banks in total with bank-years of 575.

Variable	Obs	Mean	Std. dev.	Min	Max
Net NPA / Net Adv.	575	2.708	2.802	0.010	16.690
CAR Tier1	575	13.093	15.503	0.880	270.420
Cost of Funds	575	5.943	1.178	3.187	8.889
Return on Assets	575	1.016	0.748	0.010	5.490
CDR	575	75.424	23.529	45.881	556.019
Growth Advances	540	0.143	0.196	-0.312	2.974
Ln (Assets)	575	11.859	1.459	7.019	15.637

We conduct a multivariate panel data fixed effects regression as described in equation 2.1.

$$
\begin{aligned}
NetNPA/NetAdv_{it} = \beta_0 + \beta_1 Post\_IBC + \beta_2 CdR_{i(t-1)} + \beta_3 ROA_{i(t-1)} + \beta_4 GrowAdv_{i(t-1)} \\
+ \beta_5 CAR_{i(t-1)} + \gamma_i + \rho_t + \epsilon_{it}
\end{aligned}
\tag{2.1}
$$

The $NetNPAtoNetAdv$ or ratio of Net NPAs to Net Advances is the dependent variable. The main variable of interest is $Post\_IBC$ on the right-hand side. It is a binary variable that takes the value of 1 if the year is more than 2016 and 0 if the year is less than 2017. γ_i represents bank fixed effects and ρ_t represents year fixed effects. The control variables are $CdR_{i(t-1)}$ or Credit Deposit Ratio, $ROA_{i(t-1)}$ is the return on assets, $GrowAdv_{i(t-1)}$ is the growth rate in advances and $CAR_{i(t-1)}$ is the capital adequacy ratio. These control variables are identified from Rahaman and Sur [2025]. The results of this regression is tabulated in Table 2.2. The univariate regression in the first column shows that IBC was not significant in reducing the NPAs. However, when we add the control variables, we find that the IBC decreased the ratio of Net NPAs to Net Advances by 0.96.

Table 2.2: Effect of IBC on NPAs at Bank-level

This table evaluates the determinants of Non-Performing Assets of Public Sector Banks in India and Effect of IBC on NPAs. The Dependent variable is Net NPAs to Net Advances. Credit-deposit ratio (CdR)is the ratio of the total advances given by a bank and the total deposits mobilized by it. Capital Adequacy Ratio (Tier-I) is the ratio of Tier-I capital to the bank's risk-weighted assets. Tier-I capital of a bank refers to the share capital and the disclosed reserves minus goodwill, if any. Growth in Advances is the annual growth in a bank's total loans and advances. We have considered the lagged values of the Credit-deposit ratio, return on assets, and capital adequacy ratio.

	Net NPA / Net Adv.	Net NPA / Net Adv.
Post IBC	0.32	-0.96***
	0.74	-2.35
Lagged Credit / Deposits		0.01
		0.55
Lagged RoA		-0.07
		-0.55
Growth in Advances		-8.47***
		-11.98
Lagged Tier I CAR		0.05**
		2.02
Observations	575	521
R-squared	35%	59.88%
Bank fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

2.2 Analysis of Characteristics of Transitions of Loan Accounts

In this section, we analyze trends in transition of loan accounts across various categories as per the filing by creditors with the NeSL. We analyze trends in outstanding, overdue and default amounts associated with loan accounts in each category. Further, we evaluate trends in time spent by a loan account in a specific category.

2.2.1 Data Description

A key aspect of the NeSL dataset is the ability to classify each loan contract into standard or delinquent status at a given point in time based on the latest filing made by the creditor. Loans that are being regularly serviced by the corporate debtor are considered to be standard assets and we tag it as a Normal ('N') loan contract in our study. When the corporate debtor fails to meet obligations on the contract for over a period of over 90 days, the loan contract gets tagged as Overdue ('O') by the creditor. Subsequent to a loan being tagged as Overdue, the creditor can change its classification to Default ('D') based on the internal classification policies of the creditor. Typically, the factors considered by the creditor in classifying an account as Default include the nature of relationship with the borrower, internal assessment of the borrower's financial condition, macroeconomic environment, guidelines from the Reserve Bank of India and the protection available to the creditor under the bankruptcy legislation. By classifying a loan contract as Default a creditor could potentially impose considerable pressure on the corporate debtor. Communication of the Default status of a contract by the creditor to the NeSL would lead to onward communication of the default to other creditors of the corporate debtor, leading to the risk of all lines of credit being frozen for the borrower. Therefore, the Default classification of a loan contract would typically lead to negotiations between the creditor and the debtor towards the resolution of the default. If these negotiations do not bear fruit, the creditor could initiate legal proceedings against the corporate debtor. In our dataset, we classify a filing of a loan contract as Normal ('N') unless it meets one of the three delinquency criteria: a) filings which have a 'Date of Filing of Suit' populated are classified as Suit Filed category ('S'), b) filings which have a "Date of Default" populated but no 'Date of Filing of Suit' are classified as Default ('D'), and c) filings which have an 'Overdue Amount' greater than 0 but neither 'Date of Default' or 'Date of Filing of Suit' populated are classified as Overdue ('O'). Table (2.3) presents details of the percentage of filings tagged under each category and some key metrics regarding each category. 83.9% of the filings correspond to loan contracts that are in the Normal category corresponding to the loan being a performing standard asset at that point in time.

Table 2.3: Summary of Categorization of Loan Contract Filings

The table presents the category wise aggregation of loan contract filings for large loans. Source: NeSL data

Category Category Identifier	Normal N	Overdue O	Default D	Suit Initiated S
Percentage of Filings	83.9%	10.2%	5.4%	0.5%
Mean Outstanding Amount (₹lakhs)	2,128	1,497	3,719	2,746
Median Outstanding Amount (₹lakhs)	212	243	527	651
Mean Overdue Amount (₹lakhs)	-	676	2,794	2,498
Median Overdue Amount (₹lakhs)	-	6	350	557
Mean Default Amount (₹lakhs)	-	-	2,791	2,498
Median Default Amount (₹lakhs)	-	-	349	557
Mean Days Past Due	-	-	1,220	2,346
Median Days Past Due	-	-	944	2,273

In our analysis of this primary NeSL dataset, we look at how overdue and default accounts have trended over the sample period to evaluate if there are signs of change in creditor/debtor behaviour. We shall also seek to exploit the richness of the data in terms of multiple filings on a loan contract to evaluate the transitions made by a loan contract over its life-cycle.

2.2.2 Delinquent Behaviour post IBC Implementation

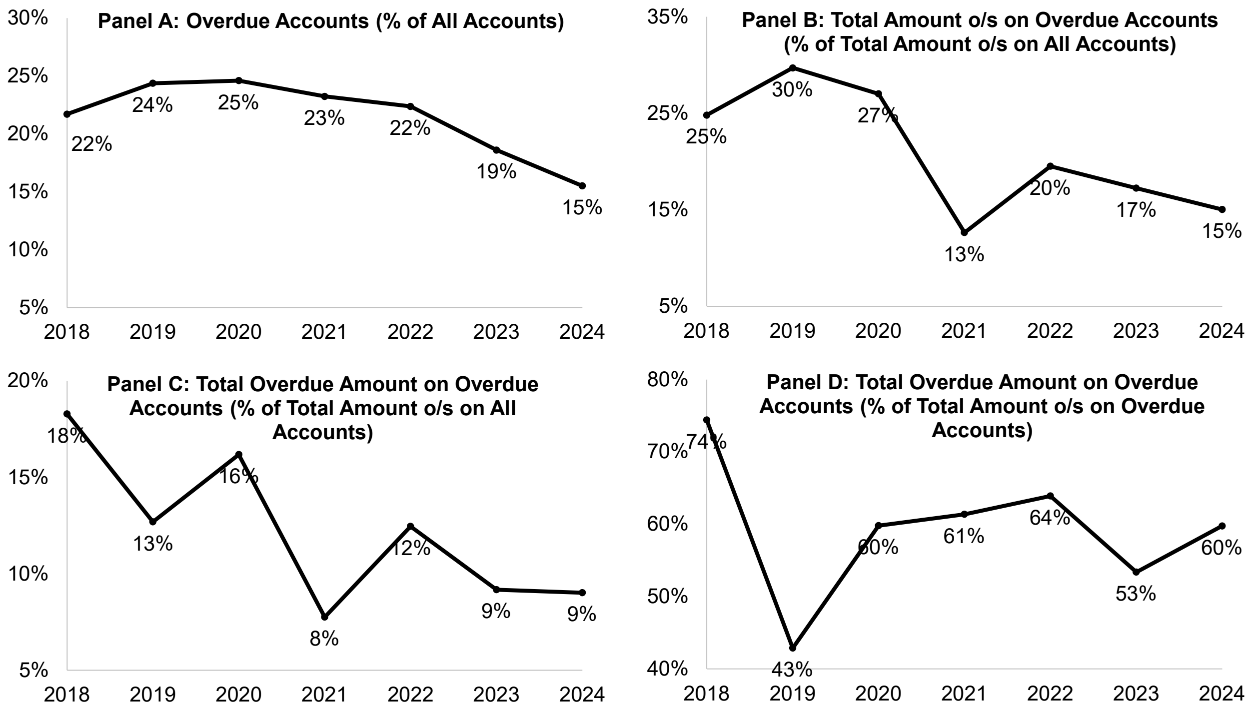
In this subsection, we present our analysis of how delinquent behaviour by corporate debtors has evolved over the sample period. The broad idea is to evaluate if there has been an improvement in the credit environment from the early days of IBC implementation in 2018-2020 to the later period in 2022-2024.[2] Our primary sample set is the filings on large loans that have had an amount outstanding over ₹1 crore in at least one filing in the sample period of 2018 to 2024. As the NeSL was set up under the IBC and it started collecting data on loan contracts from 2018 onwards, we are unable to compare the credit environment pre and post-IBC in this part of the study.

We present the Trend of loan contracts in Overdue status in Figure (2.3). In Panel A, we observe that the percentage of loan contracts in Overdue status has reduced over the sample period, especially post-COVID in 2020. In Panel B, we observe that the total amount outstanding on these overdue loan contracts as a percentage of the aggregate amount outstanding on corporate loans has also decreased considerably in the latter part of the sample period from 25%–30% in 2018-2020 to 15%–20% in 2022-2024. Panel C shows that the amount overdue on corporate loan accounts as a percentage of the aggregate amount outstanding on corporate loans has almost halved during the sample period. These three results point towards greater borrower prudence over time in the post-IBC period possibly driven by an increased motivation to maintain loan contracts in standard state towards the later part of the sample period. Finally, Panel D displays that the percentage of outstanding amount that is classified as overdue (in the case of Overdue loan contracts) has remained relatively constant over this period.

[2] One broad caveat with respect to the analysis in this subsection is that as the NeSL dataset does not provide an exhaustive listing of all active corporate debt contracts at any point in time. As the dataset is a function of loan contracts reported by creditors, the dataset suffers from sample selection bias at any point in time due to the varying motivations of creditors to report data to NeSL. However, over time, this bias is likely to reduce as the reporting culture of creditors improves, as evidenced by the increase in filings over the latter part of the sample period.

Figure 2.3: Trend of Overdue Loans vs. All Loans

The figure presents key statistics regarding the Trend of Overdue loan contracts in the sample. Panel A presents the percentage of accounts in Overdue status vis-à-vis aggregate number of accounts. Panel B presents the total amount outstanding on Overdue accounts vis-à-vis aggregate amounts outstanding across all loans in the sample. Panel C presents the total overdue amount on Overdue accounts as a percentage of the aggregate amounts outstanding across all loans in the sample. Panel D presents the total overdue amount on Overdue accounts as a percentage of the aggregate amounts outstanding across all Overdue loans in the sample. Source: NeSL



Next we turn our attention to the Trend of Default accounts in the sample set. The classification of a loan contract as a Default account is largely based on the discretion of the creditor, therefore, both the motivation of the debtor to rectify a delinquency as well as the ability of the creditor to take an errant debtor to task have an impact on this classification decision. A stronger creditor rights environment would, on one hand, lead to stronger motivation on behalf of the corporate debtor to prevent Overdue accounts from getting classified as Default, on the other hand, it would also witness creditors seeking to put pressure on debtors by classifying Overdue accounts as Default at a much earlier stage. Consequently, it would be challenging to make clear predictions regarding the impact of increasing creditor rights on the percentage of Default accounts in the economy. In Figure (2.4) we present similar metrics for Default accounts as we did for Overdue accounts in Figure (2.3).[3] We observe in Panel A of Figure (2.4) that while there was a spike in the percentage of accounts classified as Default accounts in 2020, subsequently, there has been a gradual decline in this percentage. At the same time, the total amount outstanding on Default accounts (as a percentage of total amount outstanding on all accounts) in Panel B and the total default amount on default accounts (as a percentage of total amount outstanding on all accounts) in Panel C are fairly constant over the sample period, barring a spike in 2020.[4] Finally, Panel D shows that the total default amount on default accounts (as a percentage of total amount outstanding on default accounts) has been steadily increasing over this period. We see this trend more clearly in Panel B of Figure (2.5) wherein we observe that aggregate default amounts form an increasing percentage of aggregate overdue amount in the economy in recent years. In our view, these results broadly point towards greater keenness among creditors to put pressure on large defaulters by classifying these loan accounts as Default.

Overall, the results in this subsection point towards a shift in the corporate credit culture with corporate debtors showing greater keenness to prevent loan accounts moving into Overdue status while there also seems to be greater willingness among creditors to penalize errant debtors through classification of Overdue accounts as Default (especially the large corporate debt accounts).

2.2.3 Transition Analysis of Loan Contracts

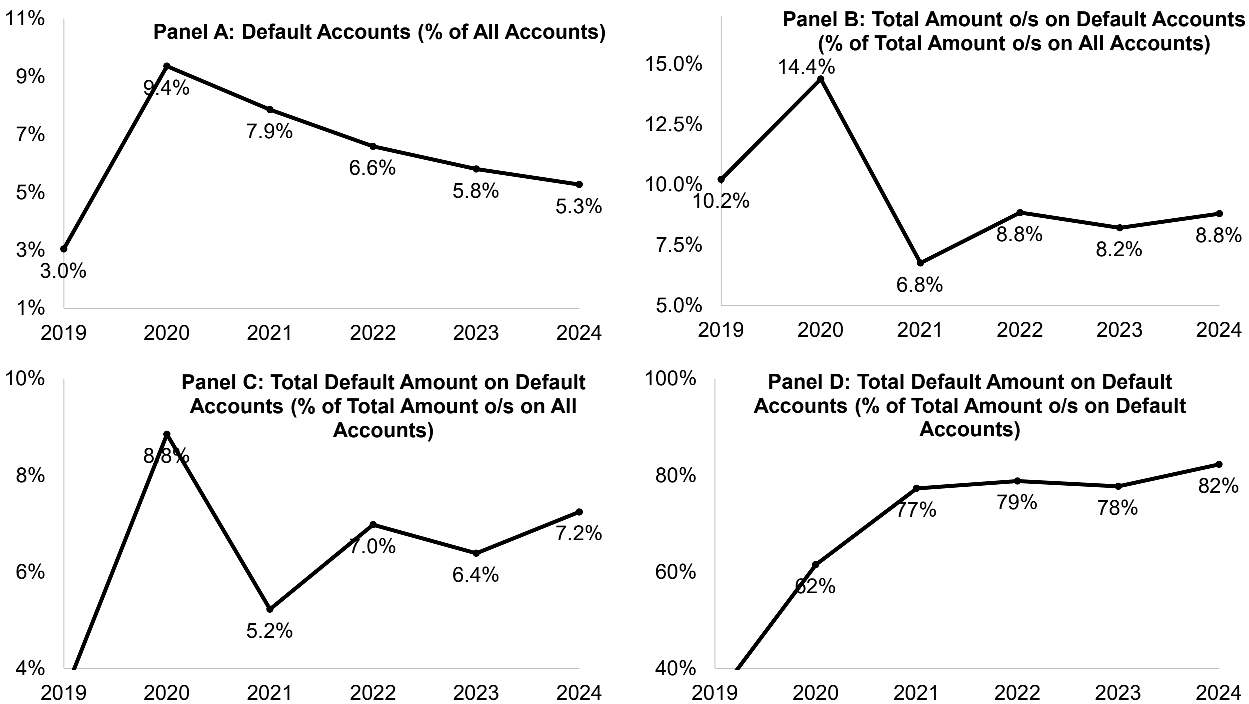
In this sub-section, we evaluate the transitions made by a loan contract over its life cycle through the analysis of multiple filings made on the contract. A filing is classified into

[3]The first instance of a filing in Default status is observed in 2019 in our sample of large loans, therefore, we do not have any observations for 2018 in Figure (2.4).

[4]The spike in 2020 could possibly be related to stress on corporate debtors due to the advent of COVID resulting in increased Default classifications.

Figure 2.4: Trend of Loans in Default vs. All Loans

The figure presents key statistics regarding the Trend of loan contracts marked as Default in the sample. Panel A presents the percentage of accounts in Default status vis-à-vis aggregate number of accounts. Panel B presents the total amount outstanding on Default accounts vis-à-vis aggregate loan amounts outstanding(o/s) across all loans in the sample. Panel C presents the total default amount on Default accounts as a percentage of the aggregate amounts outstanding across all loans in the sample. Panel D presents the total default amount on Default accounts as a percentage of the aggregate amounts outstanding across all default accounts in the sample.

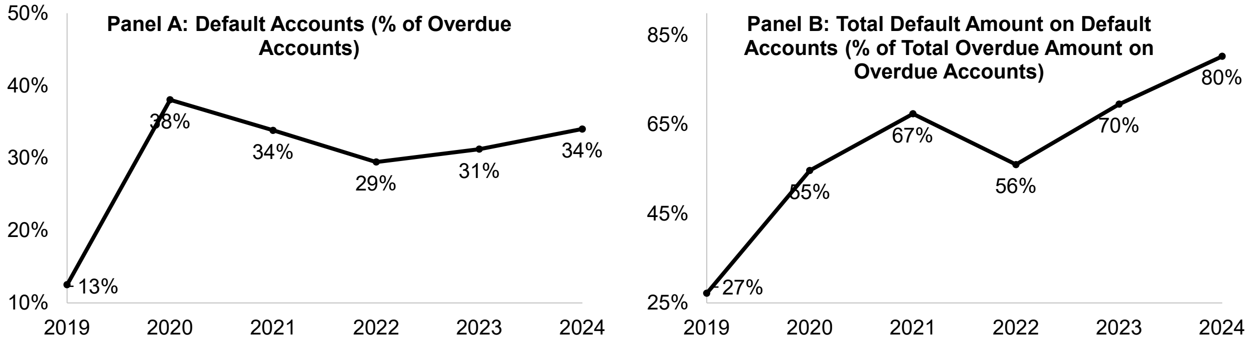


one of four possible categories depending on whether the loan contract is reported to be a standard asset (Normal or 'N' category) or if some delinquency is associated with it. The three delinquent categories are: Overdue or 'O', Default or 'D', and Suit Filed or 'S'. Section 2.2.1 presents details of the approach used for this classification and Table (2.3) presents the distribution of filings across these four categories. Our focus is on analyzing the nature of transitions made by a loan contract across categories and the time spent by a loan contract in a particular category before it transitions into a different category (e.g., from Normal category to Overdue category or from Default category to Normal category).

Of the 9, 87, 892 large loan contracts that we consider in our analysis, we observe that

Figure 2.5: Trend of Loans in Default vs. Overdue Loans

The figure presents additional statistics regarding the Trend of loan contracts marked as Default in the sample. Panel A presents the percentage of accounts in Default status vis-à-vis aggregate number of accounts in Overdue status. Panel B presents the total default amount on Default accounts as a percentage of the total overdue amounts on Overdue accounts in the sample.



7, 59, 621 loan contracts (76.9%) continue to remain classified as Normal for their entire life-cycle. Similarly, 17, 462 loan contracts (1.8%) continue to remain in Overdue category, 12, 009 loan contracts (1.2%) continue to remain in Default category, and 836 loan contracts (0.08%) continue to remain in Suit Filed category, for their entire life-cycle. Therefore, the primary focus of this analysis are the remaining 197, 964 (26.1%) loan contracts that transition across two or more categories over the course of their life-cycle.

Our first step is to obtain a category transition matrix that captures the number of transitions made by loan contracts, which we present in Table (2.4). A transition is defined as a change in the category of a loan contract across two consecutive filings. For example, if a loan contract is reported is classified as being in Normal category based on a filing made on 20 June 2021 and the next filing on 29 October 2021 classifies it as an Overdue account, then this is captured as a transition from 'N' to 'O' state in our matrix. Panel A of Table (2.4) presents the number of transitions that occur out the category specified in the first column to one of the categories specified in the four columns on the right. For example, Row 1 of Panel A implies that for loan contracts that have a filing in Normal category, there are 83, 76, 757 instances of the contract continuing to be in Normal category in the subsequent filing for the contract, 2, 74, 211 instances of the contract transitioning into Overdue category in the subsequent filing, 34, 453 instances of the contract transitioning into Default category in the subsequent filing and 183 instances of the contract transitioning into Suit Filed category in the subsequent filing. The following rows present metrics for transitions out of Overdue, Default and Suit Filed categories respectively. Panel B of Table (2.4) presents the corresponding row-wise percentages for a given transition. For example, Row 3 of Panel B implies that of all the loan contracts that had a filing in Default status, the subsequent filing continued to be in Default status for 89.6% cases, while it transitioned into Normal, Overdue and Suit Filed Categories in 6.3%, 3.8% and 0.2% cases respectively.

Table 2.4: Transitions of Loan Contracts across Categories - Number and Percentage of Transitions

Panel A of the table presents the number of transitions made by a loan contract across categories over its life-cycle in the sample. For each transition, the first column specifies the starting category of the loan contract based on a given filing, while the next four columns specify the ending category of that loan contract for that transition obtained from the subsequent filing on the loan contract. Panel B of the table presents the percentage of transitions made by loan contracts originating in the starting category to each of the ending categories using a similar structure as Panel A. The percentages add up to 100% row-wise.

Panel A: Number of Transitions

Starting Category	Ending Category N	O	D	S
N	8,376,757	2,74,211	34,453	183
O	2,88,231	7,68,147	41,851	2,100
D	36,286	21,800	5,14,420	1,389
S	565	788	867	55,935

Panel B: Percentage of Transitions

Starting Category	Ending Category N	O	D	S
N	96.4%	3.2%	0.4%	0.0%
O	26.2%	69.8%	3.8%	0.2%
D	6.3%	3.8%	89.6%	0.2%
S	1.0%	1.4%	1.5%	96.2%

Next, we obtain the category transition matrix on a year-wise basis for our sample set to examine if there are any notable trends in the frequency of specific transitions over the six years in our sample. First, we focus on transitions of contracts from Overdue category to Normal category in Panel A of Figure (2.6) and transitions of contracts from Normal category to Overdue Category in Panel B of Figure (2.6). We observe that while the trend of transitions from Overdue to Normal category is broadly increasing, the reverse trend is fairly constant (except for a spike in 2020, possibly related to COVID period stress) overall indicative of greater desire on part of corporate debtors to resolve Overdue accounts. However, when we look at transitions out of and in to Default category in Panel C and Panel D of Figure (2.6), respectively, we do not see any such trend indicating changes in debtor behaviour (ignoring the spikes in 2020 related to the COVID period). Detailed transition matrix for each year is given in Table (4.16) in the Appendix.

We now turn our attention to the time spent by a loan contract in a particular category before it transitions into the next category. To obtain this measure, we exclude filings where the loan contract continues to remain in the same category as in its previous filing and only consider filings where the category is different from the category in the immediately preceding filing for the contract. Then we obtain the time spent in a particular category prior to transition as the difference in the submission dates of these two consecutive filings.[5] Our final sample consists of $6,45,099$ transitions across categories. Table (2.5) presents summary statistics of the time taken by loan contracts to transition across categories. We observe that the two most common types of transition in the dataset are transition from Normal category to Overdue category and vice-versa. We analyze how the average time taken for specific transitions have varied over the sample period to draw inferences regarding changes in the corporate credit environment.

[5]While doing the analysis, we observed that there were a few cases where a loan contract transitioned in to and out of a particular category within a day or a two. Given that such transitions are likely to be spurious in nature arising out of an erroneous filing, we ignore any filings where the time spent within a category is less than 7 days and the loan contract is assumed to continue in the previous category in that period.

Figure 2.6: Yearwise Transitions of Loan Contracts

The figure presents the percentage of specific category transitions on a yearwise basis. Panel A presents the percentage of Overdue accounts that transition into Normal accounts across the years in the sample. Panel B presents the percentage of Default accounts that transition into either Normal or Overdue accounts across the years in the sample. Panel C presents the percentage of transitions of Default accounts into Normal or Overdue accounts. Panel D presents the percentage of transitions of Normal and Overdue accounts into Default accounts

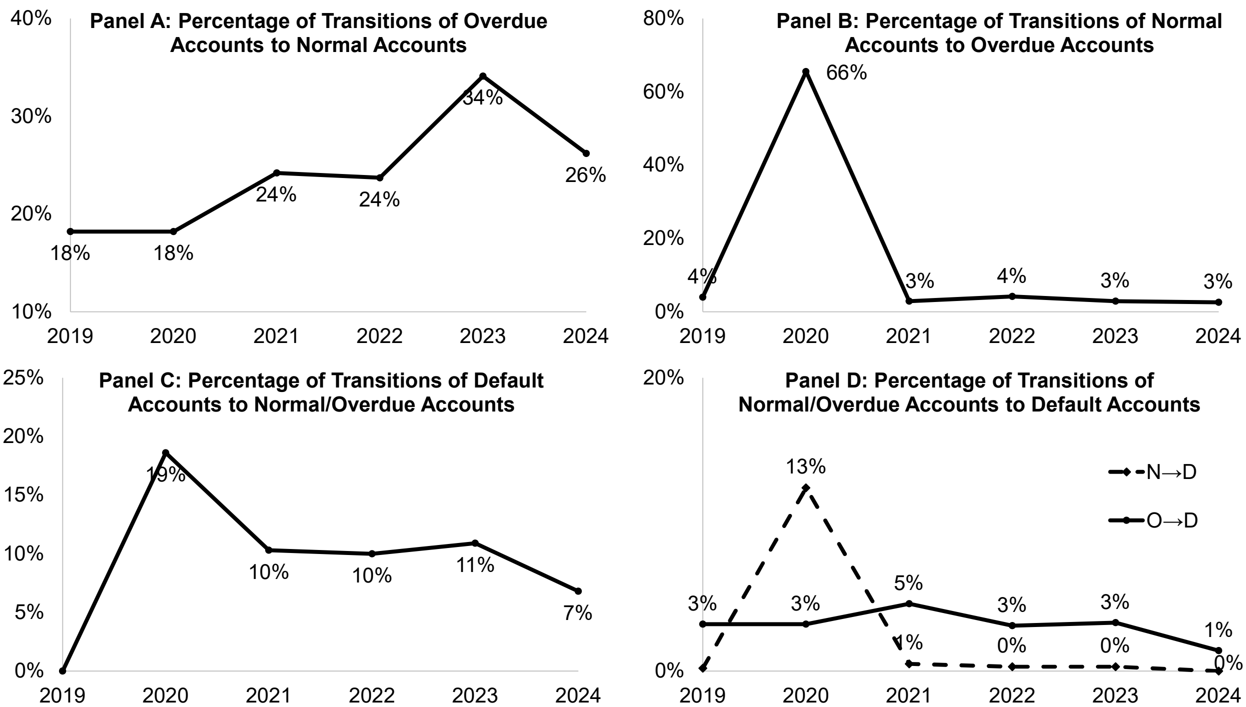


Table 2.5: Summary of Transition Time across Categories

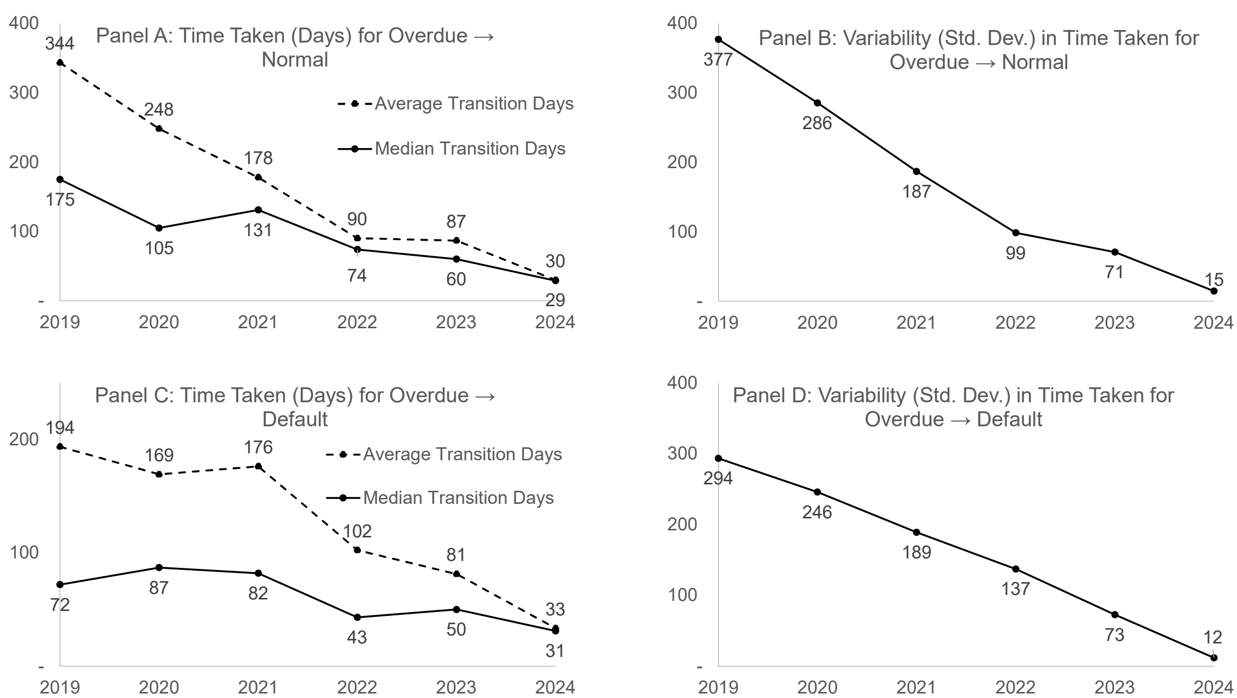
The table presents summary statistics of the time taken by loan contracts to transition across categories.

Transition Type	Number	Mean Transition Time (Days)	Median Transition Time (Days)	Min Transition Time (Days)	Max Transition Time (Days)	Std. Dev. Transition Time (Days)
N → O	254,840	209	93	7	2,142	275
N → D	29,428	310	181	7	2,118	344
N → S	112	504	309	7	2,118	481
O → N	269,092	178	83	7	2,090	242
O → D	39,106	195	89	7	2,091	258
O → S	663	189	7	7	1,860	314
D → N	31,409	226	95	7	1,816	323
D → S	960	547	380	7	1,631	433

In Figure (2.7), we look at how the time taken by a contract to transition out of Overdue status has varied over time. We observe in Panels A and C that there has been a steady decline in the average (and median) time taken for an Overdue account to get reclassified either as Normal account or as a Default account. Further, we observe in Panel B and Panel D that the variability of time taken by different loan contracts to make that transition has also reduced over time. The faster transition from Overdue status to Default status is indicative of creditors getting more aggressive to put pressure on errant borrowers to behave. At the same time, the faster transition from Overdue status to Normal status could be seen as evidence of improved debtor behaviour in light of the credible threat of creditor action highlighted above.

Figure 2.7: Trend of Transition Time - Overdue Accounts

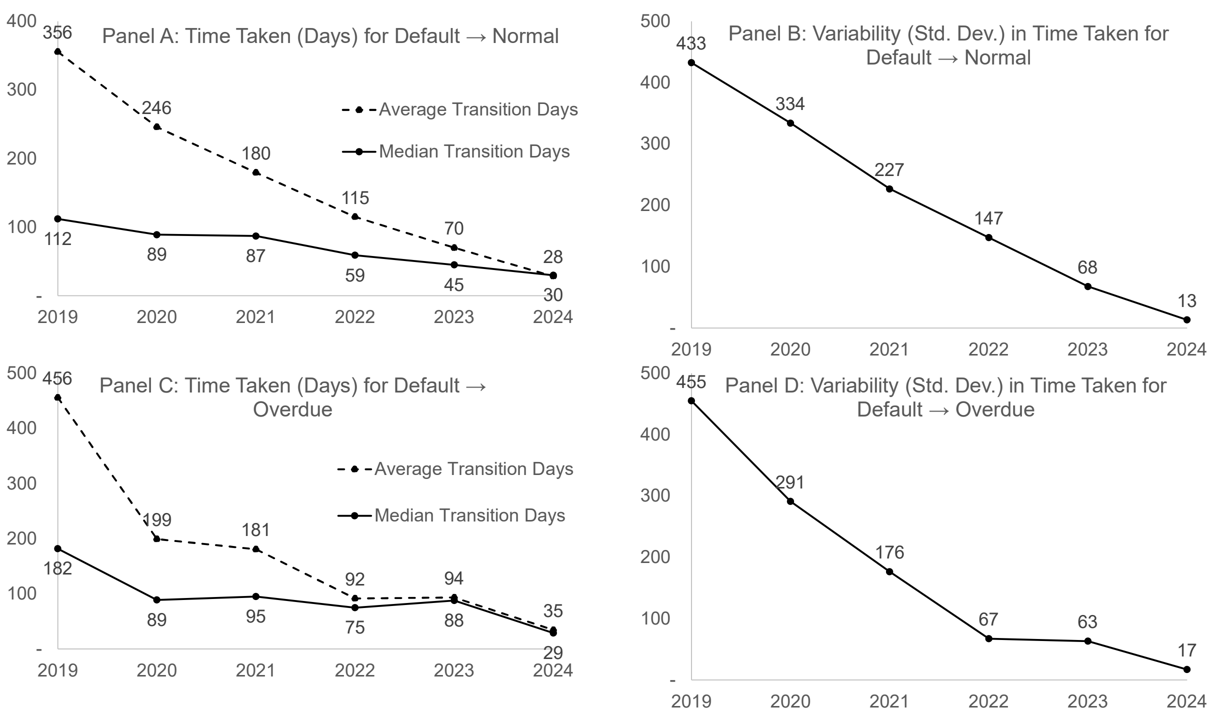
The figure presents details of the time taken for specific transitions out of the Overdue category. Panel A presents the average and median time taken for an account to transition from an Overdue to Normal category. Panel B presents the standard deviation of the time taken for the Overdue to Normal transitions. Panel C presents the average and median time taken for an account to transition from an Overdue to Default category. Panel D presents the standard deviation of the time taken for the Overdue to Default transitions.



Next, we look at the time taken for transitions from Default category to Normal and Overdue categories over the sample period in Figure (2.8). Once again, we observe that average transition times and variation in these transition times have decreased considerably for both these transitions. The faster transition times towards the later part of the sample period are, once again, indicative of greater alacrity shown by corporate borrowers in resolution of defaults.

Figure 2.8: Trend of Transition Time - Default Accounts

The figure presents details of the time taken for specific transitions out of the Default category. Panel A presents the average and median time taken for an account to transition from a Default to Normal category. Panel B presents the standard deviation of the time taken for the Default to Normal transitions. Panel C presents the average and median time taken for an account to transition from an Default to Overdue category. Panel D presents the standard deviation of the time taken for the Default to Overdue transitions.



Overall, the analysis of transition times of loan contracts indicates that the corporate credit environment has become more responsive in the later years of the IBC, possibly driven by a greater willingness by both parties: the creditor and the debtor to engage and resolve delinquencies or take them to their logical conclusion. We conduct a similar analysis for all the loans in the dataset and find similar conclusions for the larger set too (see Table (4.17) in the Appendix).

2.2.4 Trends in Debtor Behaviour Post-IBC

The analyses in Sections (2.2.2) and (2.2.3) were focused on analysing the trends and transitions at the level of loan contracts. In this section we aggregate the loan accounts at the level of the corporate debtor and analyze key trends in debtor behaviour. The large loans dataset has $1,77,101$ debtors and $9,87,892$ loan contracts implying 5.6 loans on average per debtor. We obtain loan details at the debtor level on a quarterly basis starting from June 2018 and ending at March 2024. For every quarter, we consider loan accounts that have a filing on either side of the quarter end date and aggregate the details of these loans at the debtor level. As each of these loans could be in one of the four categories, there are 16 possible category aggregations that a debtor could have at a given point in time, which we refer to as debtor category.[6] Table (2.6) presents the definition of each of these debtor categories and the percentage of observations in this aggregated dataset belonging to each debtor category.[7]

74% of the observations are in the debtor category N implying that, in general, most debtors have all their loan accounts in the Normal category. In slightly over 9% of cases, all loan accounts of the debtor are in Overdue category, while for a similar percentage of cases, debtors have a mix of Normal and Overdue loan accounts in parallel. In close to 5% of cases, all loan accounts of the debtor are in Default. Figure (2.9) shows the trend of debtors having loans only in one category over the sample period. In Panel A, we see that the percentage of debtors who have all loans in the Normal category has been relatively constant throughout

[6] Debtor category is different from loan category. Loan category refers to the state of the loan account at the time of a filing. Debtor category refers to the categorization of the debtor based on the loan categories of the loan accounts that the debtor has active at that point in time.

[7] Each observation in this aggregated dataset captures the aggregate status of a debtors' loans at the end of each quarter.

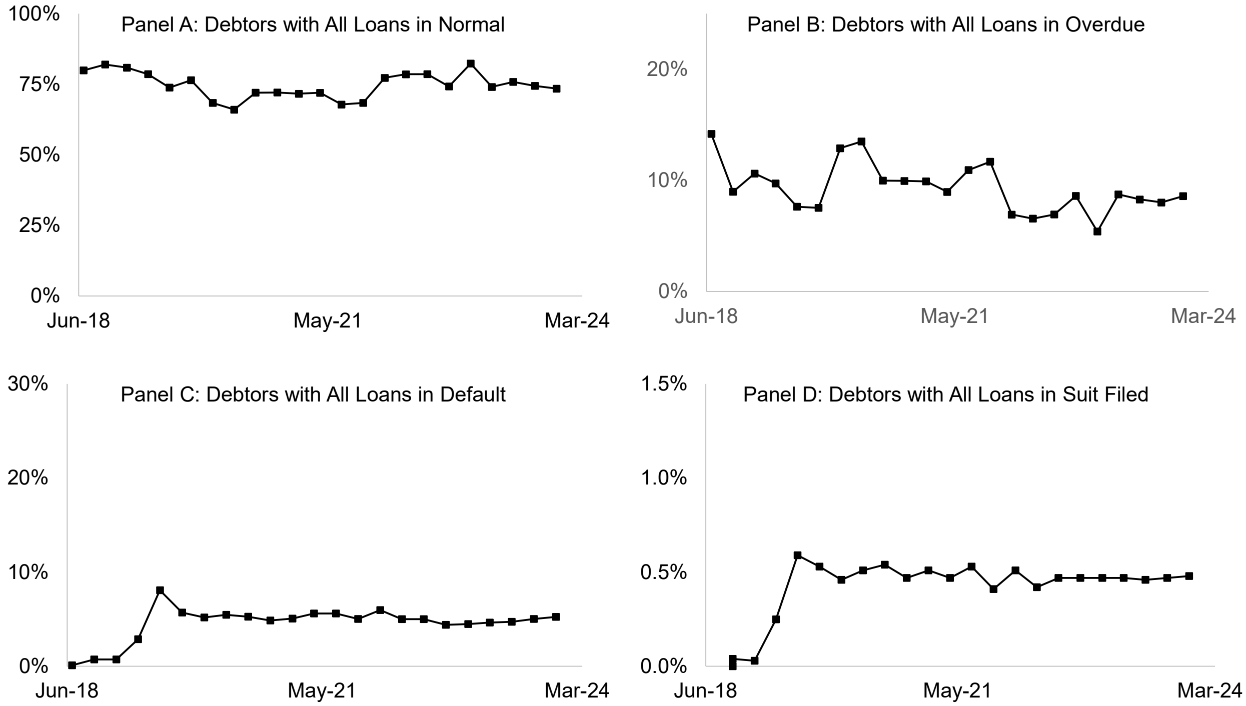
Table 2.6: Debtor Classification Summary

The table presents the debtor classification obtained by aggregating loan accounts at the debtor level.

Debtor Category	Definition	Percentage
N	All loans are in Normal	74.16%
O	All loans are in Overdue	9.01%
D	All loans are in Default	4.95%
S	All loans are in Suit Filed	0.46%
NO	Normal and Overdue Loans	9.06%
ND	Normal and Default Loans	1.16%
NS	Normal and Suit Filed Loans	0.05%
OD	Overdue and Default Loans	0.37%
OS	Overdue and Suit Filed Loans	0.01%
SD	Suit Filed and Default Loans	0.12%
NOD	Normal, Overdue and Default Loans	0.51%
NOS	Normal, Overdue and Suit Filed Loans	0.01%
NDS	Normal, Default and Suit Filed Loans	0.07%
ODS	Overdue, Default and Suit Filed Loans	0.02%
NODS	Loans in all four categories	0.04%

the sample period. At the same time, the percentage of debtors who have all loans in Overdue category has reduced marginally from above 10% in the early part of the sample set to below 10% in the later part of the sample set. In parallel, we see in Panel A and Panel B of Figure (2.10) that the percentage of debtors who have kept a mix of Normal and Overdue loans has trended upward from 6% to around 10%. Percentage of debtors having all loan accounts in Default or all loan accounts in Suit Filed status have been relatively constant over the sample period. Overall, it appears that there is an increasing effort by debtors to maintain loan accounts in Normal status.

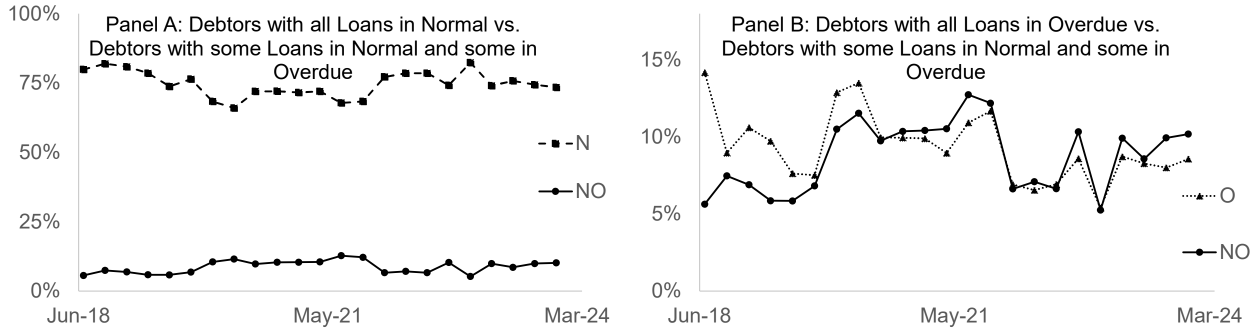
Figure 2.9: Trend of Debtors with Loans only in one Category



2.3 Analysis of Drivers of Transitions of Loan Accounts

In this section, we analyze the drivers of these transitions of loan accounts across various categories. Our focus is on identifying firm level characteristics that lead to transition of a loan account either in or out of Default category and in or out of Overdue category. To do so, we combine the NeSL dataset with firm-level data from CMIE Prowess.

Figure 2.10: Evolution of Debtors with Loans across Categories



2.3.1 Determinants of Transitions of Normal / Overdue Loan Accounts To Default

We evaluate transition of loan accounts from Normal / Overdue category to Default category. To do so, we define loan accounts making the following transitions – $N \rightarrow D$ and $O \rightarrow D$ as the treated category and loan accounts making the following transitions $N \rightarrow N$, $N \rightarrow O$, $O \rightarrow O$, and $O \rightarrow N$ as the control category. We first conduct univariate tests of firm characteristics between the treatment and control group. The results of the univariate tests are presented in Table (2.7). We find that both in the case of listed firms and in the case of unlisted firms, accounts transitioning into default are associated with significantly higher leverage, higher levels of short-term debt, lower levels of profitability, and smaller size.

To test the validity of these results in a multivariate setting, we define a binary variable $Default\ Transition$ which takes a value of 1 for a transition belonging to the treated category (i.e., N→D, N→D) and a value of 0 for a transition belonging to the control category (i.e., N→N, N→O, O→N, O→O). We conduct logistic regression using the specification given in Equation (2.2). We focus on the impact of leverage (Lev), short-term debt percentage (ST_Debt_Pct), return on assets ($NITA$) and of the lender being a PSU bank ($PSU\ ID$). Further, we also use additional set of controls for unsecured debt percentage, asset tangibility,

Figure 2.11: Summary of Transitions in firms

The table presents category transitions in the loan accounts held by listed (public) and Unlisted (private) firms in India. D represents the Default, N represents a normal account, and O represents Overdue account.

Listed firms

From \ To	N	O	D
N	2,70,905	12,622	2,534
O	15,794	16,239	3,155
D	2,998	1,581	7,948

Unlisted firms

From \ To	N	O	D
N	4,61,877	34,387	4,674
O	38,897	39,282	5,787
D	5,357	3,067	14,319

size ($ln(sales)$) and interest coverage ratio, represented by the vector χ in the specification. We also control for year-fixed effects (γ) and industry-fixed effects (ρ). Given the COVID period was a key event in our sample window, we also run an alternate specification wherein we interact all the explanatory and control variables with a binary variable PC which takes a value of 1 for years greater than 2021.

$$\begin{aligned} Default\ Transition_{i,t} = \beta_0 + \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pcti,t + \beta_3 NITA_{i,t} \\ + \beta_4 PSU\ ID_{i,t} + \beta\chi_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \end{aligned} \tag{2.2}$$

The results of our regression are presented in Table (2.8). Consistent with the univariate results, we observe that transition into default has a strong and significant association with high leverage levels and high reliance on short-term debt. This association is partially reversed in the post-COVID period. On the other hand, the strong negative association with return on assets gets further intensified in the post-COVID period. Finally, we also observe

Table 2.7: univariate Tests of Transitions into Default

The table presents univariate tests of key firm characteristics between firms that have loan accounts transition from normal or overdue category to default category (N→D, O→D) vs. firms that have loan accounts that do not make such a transition (N→N, N→O, O→N, O→O). Panel A presents the tests for Listed Firms while panel B presents the tests for unlisted firms.

Panel A: Listed Firms						
	N→N, N→O, O→N, O→O		N→D, O→D			
Metric	Observations	Value	Observations	Value	Difference	T-Stat
Leverage	3,12,738	31%	5,679	62%	-31%***	-93.2
Short Term Leverage (%)	2,73,834	59%	4,854	67%	-8%***	-20.2
Unsecured Leverage (%)	3,06,296	25%	5,385	24%	2%***	3.7
NI / TA	3,15,551	3.60%	5,688	-5.90%	9.5%***	98.3
Log (Sales)	3,00,443	9.7	5,454	8.1	1.5***	43.1

Panel B: Unlisted Firms						
	N→N, N→O, O→N, O→O		N→D, O→D			
Metric	Observations	Value	Observations	Value	Difference	T-Stat
Leverage	5,63,240	42%	10,345	75%	-33%***	-110
Short Term Leverage (%)	4,84,457	56%	8,686	56%	0%	-0.9
Unsecured Leverage (%)	5,43,426	23%	9,813	26%	-3%***	-11.1
NI / TA	5,74,160	2.20%	10,387	-5.30%	7.5%***	89.1
Log (Sales)	5,30,331	8.3	9,109	7.2	1.1***	49.4

that transitions into default are more strongly associated with PSU banks, though this association has reduced considerably in the post-COVID period. The variation of estimated probability of default over time based on the regression is showcased in Figure (2.12). We can see that the likelihood of transition into default has reduced fairly consistently for both listed and unlisted firms.

Our estimated probability from Figure 2.12 is consistent with that of loss rates from BiS MiDAS credit Loss Measure as shown in Figure 2.13.

In Figure 2.13, we plotted the estimated credit loss rate according to the BiS MiDAS website. (https://amro-asia.org/credit-loss-rates/dashboards/). BIS MiDAS Credit Loss Database was introduced by Ong, Schmieder, and Wei (2023), and use 1 minus this ratio as the imputed recovery rate. Loss rates (in percent) are computed as issuer-weighted corporate default rate

Table 2.8: Determinants of Transition into Default

The table presents logistic regression of Default Transition on firm characteristics for firms having loan accounts in normal/overdue categories. Default Transition is a binary variable that takes a value of 1 for loan accounts that make N→D or O→D transitions and a value of 0 for loan accounts that make N→N, N→O, O→N, or O→O transitions. PC is a binary variable that takes a value of 1 for years that are post covid (year > 2021). Other controls include unsecured debt percentage, interest coverage ratio, asset tangibility, and ln (sales).

	Listed Firms		Unlisted Firms	
	Default Transition	Default Transition	Default Transition	Default Transition
Leverage	1.479***	1.573***	1.383***	1.560***
	22.35	18.07	32.21	26.94
PC * Leverage		-0.167		-0.441***
		(1.257)		(5.088)
ST Debt Pct.	0.307***	0.205**	0.430***	0.508***
	4.027	2.003	-8.735	8.034
PC * ST Debt Pct.		0.338**		-0.200**
		-2.253		(-2.078)
NI/TA	-4.585***	-3.914***	-2.779***	-2.262***
	(-21.18)	(-13.67)	(-20.93)	(-12.32)
PC * NI/TA		-1.594***		-1.089***
		(3.721)		(4.134)
PSU ID	0.838***	0.896***	0.726***	0.945***
	24.61	19.33	28.8	26.84
PC * PSU ID		-0.121*		-0.490***
		(1.774)		(9.385)
Other Controls	Yes	Yes	Yes	Yes
Time-Fixed Effects	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,75,146	2,75,146	4,60,076	4,60,076

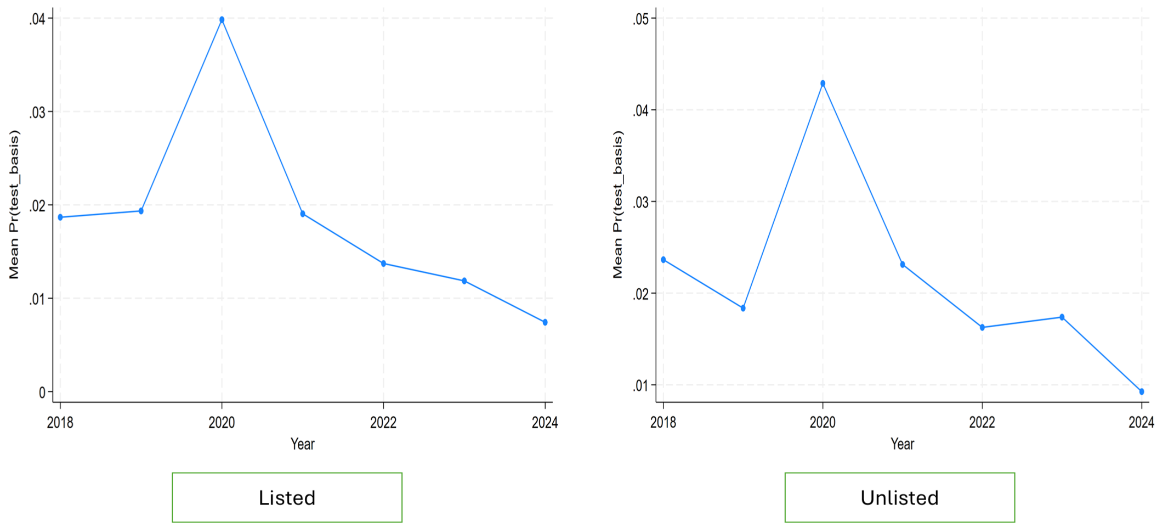
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

series multiplied by LGDs based on historical relationships (Hardy and Schmieder [2020]).

The plot in figure 2.13 has NPL ratios reported by banks and national authorities to compute the corresponding flow of loss rates. This rate is estimated using the time-to-resolution of

Figure 2.12: Estimated Probability of Default over Time

The figure plots the probability of going into default status over the sample time period using the number of loan accounts in the NeSL dataset.



losses in the country and the corresponding economy-level LGDs for a particular year.

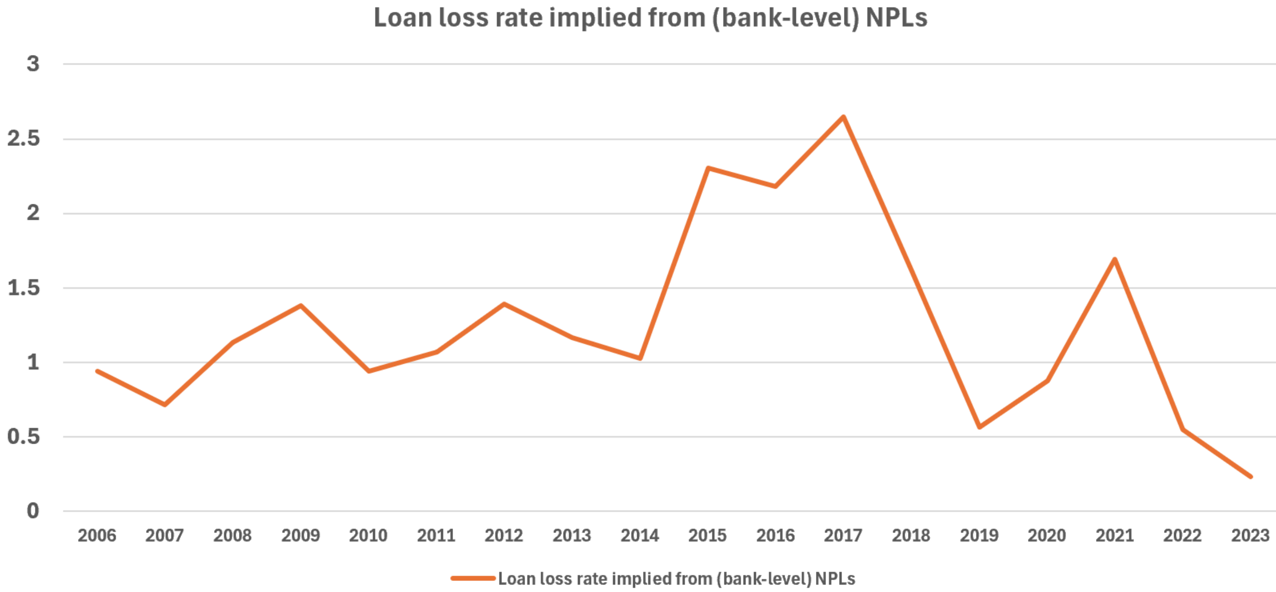
Determinants of Transitions out of Default (To N / O)

Next, we evaluate the characteristics of firms that have loan accounts transitioning out of default. In this case, loan accounts making the D→N or D→O form our treated group referred to as Default Resolution, while the control group is firms whose loan accounts do not make such a transition (i.e., D→D accounts). The results of the univariate comparison of firm characteristics across these two groups are presented in Table (2.9).

Table 2.9 shows that firms with loans that transition from default status back to normal tend to exhibit certain financial strengths. These firms generally have lower leverage, indicating a more sustainable capital structure, and demonstrate better profitability, reflecting stronger operational performance. Additionally, they rely less on short-term debt, reducing liquidity

Figure 2.13: BIS MiDAS Credit Loss Measure

BIS uses NPL ratios reported by banks and national authorities to compute the corresponding flow of loss rates. These rates are estimated using the time-to-resolution of losses in the respective jurisdictions and the corresponding economy-level LGDs for a particular year.



risk. Another notable trait is that these firms are typically larger in size, which may provide them with greater financial resilience and access to resources that facilitate revival. Firms that recover from default have 56% leverage and firms that stay in default have a leverage of 82%.

Next we analyze the significance of these results using a multi-variate setting using the specification given in Equation (2.3).[8] The only difference is in the explained variable being $Default\ Resolution$, a binary variable which takes a value of 1 for all transitions in the treated group (D→N, D→O) and 0 for all transitions in the control group (D→D).

$$\begin{aligned} Default\ Resolution_{i,t} &= \beta_0 + \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pcti,t + \beta_3 NITA_{i,t} \\ &\quad + \beta_4 PSU\ ID_{i,t} + \beta\chi_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \end{aligned} \tag{2.3}$$

[8] The variables have the same definition as in Equation (2.2).

Table 2.9: univariate Tests of Transitions out of Default

The table presents univariate tests of key firm characteristics between firms that have loan accounts transition from default category to normal / overdue category (D→N, D→O) vs. firms that have loan accounts that do not make such a transition (D→D). Panel A presents the tests for Listed Firms while panel B presents the tests for unlisted firms.

Panel A: Listed Firms						
	D→D		D→N, D→O			
Metric	Observations	Value	Observations	Value	Difference	T-Stat
Leverage	7,918	82%	4,566	56%	26%	29.3
Short Term Leverage (%)	6,555	69%	3,958	62%	7%	11
Unsecured Leverage (%)	7,249	28%	4,223	24%	4%	5.9
NI / TA	7,947	-8%	4,579	-3%	-5%	-21.6
Log (Sales)	7,370	7.7	4,380	8.3	-0.6	-14.2

Panel B: Unlisted Firms						
	D→D		D→N, D→O			
Metric	Observations	Value	Observations	Value	Difference	T-Stat
Leverage	14,080	91%	8,334	68%	22%	32.3
Short Term Leverage (%)	11,406	56%	7,232	54%	1%	2.8
Unsecured Leverage (%)	12,837	28%	7,817	28%	0%	1.1
NI / TA	14,178	-7%	8,355	-3%	-4%	12.9
Log (Sales)	11,995	6.9	7,448	7.4	-0.5	-12.3

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

From the table 2.10 we show that firms that successfully come out of default typically exhibit certain financial characteristics: they tend to have lower leverage, lower short-term debt and higher return on assets.

The source of debt also plays a role in normalcy outcomes. If the debt is from a Public Sector Undertaking (PSU) bank, the probability of default to normal is generally lower. However, post-COVID, the likelihood of default to normal from PSU-backed debt has improved.

Table 2.10: Determinants of Transitions out of Default

The table presents logistic regression of Default Resolution on firm characteristics for firms having loan accounts in default category. Default Resolution is a binary variable that takes a value of 1 for loan accounts that make D→N or D→O transitions and a value of 0 for loan accounts that remain in default category (i.e., D→D) . PC is a binary variable that takes a value of 1 for years that are post covid (year > 2021). Other controls include unsecured debt percentage, interest coverage ratio, asset tangibility, and ln (sales).

	Listed Firms		Unlisted Firms	
	Default Resolution	Default Resolution	Default Resolution	Default Resolution
Leverage	-1.227***	-1.363***	-0.926***	-0.932***
	(-15.20)	(-11.35)	(-17.80)	(-12.21)
PC * Leverage		0.186		0.0168
		(1.185)		(0.162)
ST Debt Pct.	-0.208**	-0.0577	-0.349***	-0.480***
	(-2.506)	(-0.421)	(-5.852)	(-5.364)
PC * ST Debt Pct.		-0.294*		0.219*
		(-1.684)		(1.822)
NI/TA	2.429***	2.138***	0.871***	1.100***
	(9.642)	(5.556)	(4.739)	(3.895)
PC * NI/TA		1.005**		-0.264
		(.986)		(-0.705)
PSU ID	-1.302***	-1.951***	-1.299***	-1.900***
	(-24.18)	(-21.68)	(-30.78)	(-26.30)
PC * PSU ID		1.078***		0.975***
		(9.492)		(11.23)
Other Controls	Yes	Yes	Yes	Yes
Time-Fixed Effects	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,413	9,413	14,548	14,548

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Determinants of Transitions into Overdue

In this section, we evaluate the determinants of transitions of loan accounts into Overdue status. We use the multi-variate specification given by Equation (2.4). The results are presented in Table (2.11).

$$Overdue\ Transition_{i,t} = \beta_0 + \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pcti, t + \beta_3 NITA_{i,t} + \beta_4 PSU\ ID_{i,t} + \beta\chi_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \tag{2.4}$$

Firms with high leverage and low return on assets, are seen to have a greater propensity to enter the overdue state. The effect of short-term debt on likelihood of transitioning into overdue is positive for loan accounts of listed firms and negative for loan accounts of unlisted firms. PSU banks have a higher probability of having loans entering overdue state for both listed and unlisted firms. The relationship is partially weakened post-COVID in case of return on assets, while its enhanced in case of the impact of PSU banks. The variation of estimated probability of overdue over time based on the regression is showcased in Figure (2.14). We can see that the likelihood of transition into overdue has reduced fairly consistently for both listed and unlisted firms.

Determinants of Transitions out of Overdue

In this section, we evaluate the determinants of transitions of loan accounts from Overdue back to Normal status. We use the multi-variate specification given by Equation (2.5). The results are presented in Table (2.12).

$$Overdue\ Resolution_{i,t} = \beta_0 + \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pcti, t + \beta_3 NITA_{i,t} + \beta_4 PSU\ ID_{i,t} + \beta\chi_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \tag{2.5}$$

Firms with low leverage, low short-term debt and high return on assets, are seen to have a greater propensity to enter the overdue state. PSU banks have a lower probability of having loans entering overdue state for both listed and unlisted firms. This could be a reflection of

Table 2.11: Determinants of Transitions into Overdue

The table presents logistic regression of Overdue Transition on firm characteristics for firms having loan accounts in normal/overdue category. Overdue Transition is a binary variable that takes a value of 1 for loan accounts that make N→O transitions and a value of 0 for loan accounts that either remain in normal category (i.e., N→N) . PC is a binary variable that takes a value of 1 for years that are post covid (year > 2021). Other controls include unsecured debt percentage, interest coverage ratio, asset tangibility, and ln (sales).

	Listed Firms		Unlisted Firms	
	Overdue Transition	Overdue Transition	Overdue Transition	Overdue Transition
Leverage	0.994***	0.909***	0.635***	0.604***
	(20.15)	(11.95)	(23.76)	(14.67)
PC * Leverage		0.108		0.0404
		(1.072)		(0.747)
PC * Leverage				0.108
				(1.072)
Short-term Debt Pct.	0.174***	0.0712	-0.0447*	-0.144***
	(3.954)	(1.006)	(-1.840)	(-3.838)
PC * Short-term Debt Pct.		0.190**		0.177***
		(2.127)		(3.692)
NI/TA	-0.716***	-1.589***	-0.0770	-1.051***
	(-4.194)	(-6.066)	(-0.869)	(-7.796)
PC * NI/TA		1.772***		1.682***
		(5.108)		(9.400)
PSU ID	0.762***	0.563***	0.658***	0.454***
	(35.15)	(16.35)	(50.00)	(22.06)
PC * PSU ID		0.314***		0.333***
		(7.112)		(12.65)
Other Controls	Yes	Yes	Yes	Yes
Time-Fixed Effects	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Observations	242,886	242,886	388,735	388,735

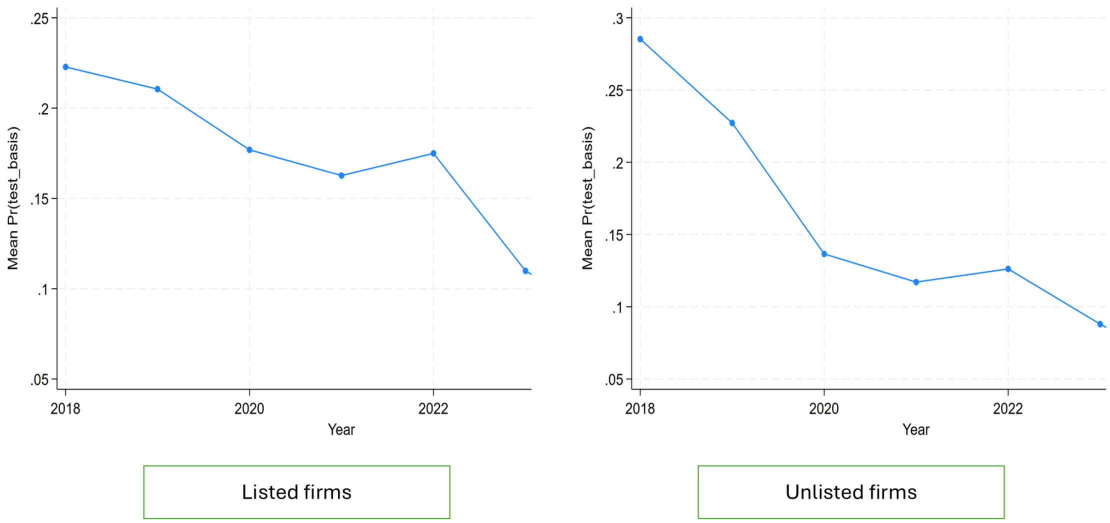
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the greater caution exercised by PSU banks in settling with the borrowers to resolve distress.

The relationship is partially weakened post-COVID in case of leverage, return on assets and

Figure 2.14: Estimated Probability of Overdue over Time

The figure plots the probability of going into overdue status over the sample time period using the number of loan accounts in the NeSL dataset.



the impact of PSU banks.

Table 2.12: Determinants of Transitions out of Overdue

The table presents logistic regression of Overdue Resolution on firm characteristics for firms having loan accounts in overdue category. Overdue Resolution is a binary variable that takes a value of 1 for loan accounts that make O→N transitions and a value of 0 for loan accounts that remain in overdue category (i.e., O→O) . PC is a binary variable that takes a value of 1 for years that are post covid (year > 2021). Other controls include unsecured debt percentage, interest coverage ratio, asset tangibility, and ln (sales).

	Listed Firms		Unlisted Firms	
	Overdue Resolution	Overdue Resolution	Overdue Resolution	Overdue Resolution
Leverage	-0.720***	-0.927***	-0.564***	-0.765***
	(-10.80)	(-9.452)	(-16.31)	(-14.72)
PC * Leverage		0.541***		0.420***
		(3.951)		(6.003)
ST Debt Pct.	-0.152***	-0.057	-0.144***	-0.149***
	(-2.788)	(-0.698)	(-4.422)	(-3.105)
PC * ST Debt Pct.		-0.114		0.0539
		(-1.038)		(0.837)
NI/TA	1.641***	2.286***	0.975***	1.504***
	8.554	8.049	8.5	8.453
PC * NI/TA		-1.362***		-1.125***
		(-3.528)		(-4.775)
PSU ID	-0.304***	-0.606***	-0.371***	-0.486***
	(-11.06)	(-13.37)	(-21.36)	(-17.18)
PC * PSU ID		0.470***		0.196***
		(8.325)		(5.52)
Other Controls	Yes	Yes	Yes	Yes
Time-Fixed Effects	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Observations	27,646	27,646	64,042	64,042

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.4 Conclusions

We find that the IBC decreased the ratio of Net NPAs to Net Advances by 0.96. The amount of 'Overdue' corporate loans in the economy has reduced significantly over the duration of the study (2018–2024). We do not find such reduction for accounts flagged as 'Default'. We find strong evidence that this result is driven by creditors who use such categorization to put pressure on delinquent loan accounts. For example, in 2019-2020, an account spent, on average, 169–194 days in Overdue category before it got classified as Default by the creditor, which has reduced to 33–81 days in 2023–2024. The usage of short-term leverage is strongly associated with a higher probability of a loan account transitioning into Default status, indicating heightened credit risk for firms relying heavily on short-term debt. This suggests that the shock of default may induce more prudent financial behavior. When it comes to Public Sector Undertaking (PSU) banks, the likelihood of default is higher for loans issued by them, while the chances of resolving default cases are comparatively lower. However, PSU banks demonstrate a greater likelihood of resolving overdue accounts, and when a loan transitions back to normal status, the reduction in the outstanding amount tends to be more substantial in PSU-originated loans. Transition back to normal from default is characterized by reduced leverage and increased profitability. There is a lower likelihood for loans coming back to normal from default in the case of loans given out by PSU banks, though effect is ameliorated post-COVID. We find very similar characteristics of firms moving back to normal from overdue. These firms are are less reliant on short-term debt and unsecured debt and are larger in size.

We can see that the likelihood of transition into default and the probability of overdue have reduced fairly consistently for both listed and unlisted firms.

Chapter 3

Analysis of Resolution of Financial Distress

In this chapter, we evaluate the drivers and consequences of a financially distressed firm being able to resolve the distress without letting it escalate into the next stage. We analyze firms at three stages of financial distress:

1. Firms that are already undergoing CIRPs.

2. Firms that have Defaults generated on at least one loan account.

3. Firms that have an overdue amount on at least one loan account.

In Section (3.1), we consider firms that are undergoing CIRPs and evaluate firm-level characteristics that determine whether the CIRP is withdrawn or not. We also compare the performance of these two groups of firms in the year following the CIRP initiation. Next, in Section (3.2), we conduct a similar analysis for firms that have Defaults generated against one of their loan accounts but never enter the CIRP process vis-à-vis firms that enter the CIRP process. Finally, in Section (3.3) we analyze firms that have overdue loan accounts that never translate into Defaults vis-à-vis firms that get Defaults generated against one of their loan accounts.

3.1 Analysis of Withdrawal of CIRPs

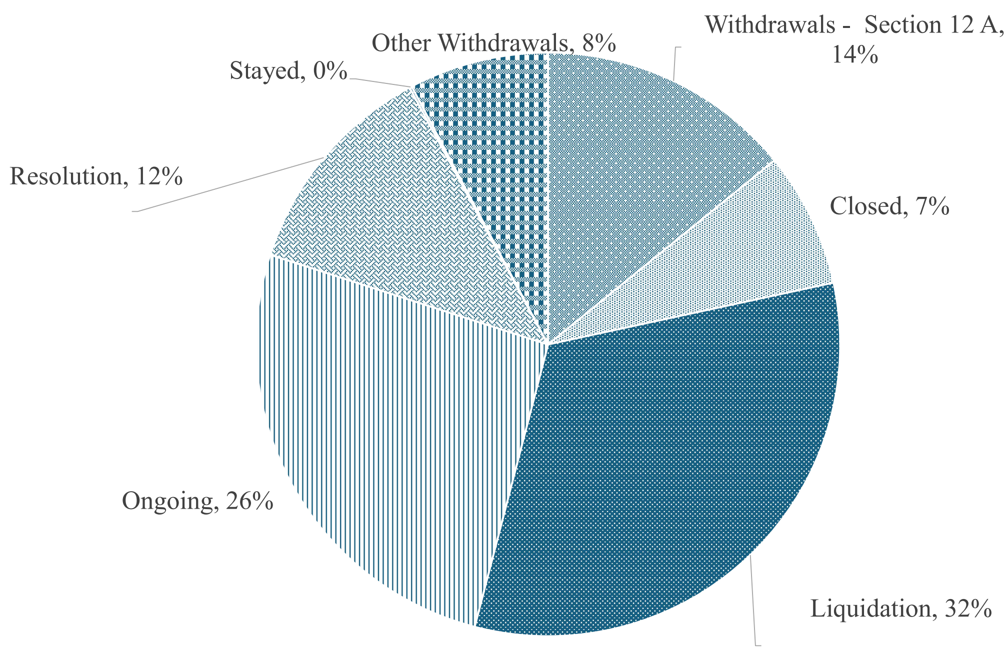
Under the IBC, once a CIRP is initiated against a firm and the Committee of Creditors ("CoC") is formed, then it can be withdrawn under Section 12A of the IBC if a mutual settlement is arrived at between the creditors and the firm. In certain cases where a settlement is achieved before the formation of the CoC, the CIRP can be withdrawn with the approval of the NCLAT. However, if a settlement is not achieved, then the CIRP proceeds to its logical conclusion of either a resolution being achieved or a liquidation being ordered. In this section, we analyze systematic differences between cases where the CIRPs against firms were withdrawn and where the CIRPs were not withdrawn. We also evaluate whether there are differences in the performance of firms based on the category they belong to.

We obtain from the IBBI, data on firms that have faced corporate insolvency resolution proceedings (CIRPs) under the IBC since its inception. There have been $7,325$ CIRPs initiated since the inception of the IBC in December 2016 till December 2023, pertaining to $7,032$ unique firms.[1] 45% of these CIRPs had been initiated by financial creditors, 49% by operational creditors and 6% by the corporated debtors. Of the total CIRPs initiated till December 2023, $1,899$ were ongoing as of 31 December 2023, while the remaining have either reached a resolution/liquidation outcome or were withdrawn/settled. Figure (3.1) presents the percentage distribution of CIRPs by outcomes achieved. It can be seen that while 45% of the CIRPs reached a conclusion of a resolution or a liquidation, 22% of CIRPs were withdrawn either under Section 12 A of the IBC or for other reasons based on the direction of NCLT, NCLAT or the Supreme Court of India.

[1]259 firms have had two CIRPs initiated against them, 14 firms have had 3 CIRPs against them and 2

Figure 3.1: Summary of CIRP Outcomes

The figure presents the distribution of CIRPs by outcomes achieved.



We match the CIRP dataset with the data from Prowess on firm level details. Of the 7,032 unique firms which have been admitted into the CIRP process, we are able to match 2,001 firms. However, only for 818 of these firms, we have data in the year in which the CIRP is initiated against them.[2] This forms our final sample of analysis, details of which are also presented in Table (3.1). Of these 818 firms that underwent CIRPs, 213 were withdrawn.

We first conduct univariate tests of firm characteristics between firms that have CIRPs withdrawn and firms that do not have CIRPs withdrawn. Table 3.2 presents the results of this analysis. We observe that for the group that has CIRPs withdrawn, leverage levels are significantly lower at 56% in comparison to 120% for firms where CIRPs are not withdrawn.

firms have had 4 CIRPs initiated against them over this period.

[2]There are 10 instance of CIRPs being stayed by either the NCLT, the NCLAT, the High Court or the Supreme Court. In addition, there are 2 instances of the CIRP being settled on the guidance of the NCLT. We consider both these cases to be part of the withdrawn group. In our final sample after matching with Prowess data, there are 2 instances of stayed CIRPs and 1 instance of a settled CIRP.

Table 3.1: Sample Construction for CIRP Withdrawal Analysis

The table presents the details of sample construction for the CIRP withdrawal analysis by merging the IBBI data on CIRPs with Prowess data on firm level characteristics. Period is 2018-2023

Criteria	No.of Firms
Total CIRPs	7,325
Unique firms with CIRPs	7,032
Unique CIRP Firms that match with Prowess dataset	2,001
Firms with data available for the year of the CIRP	818

Interestingly, asset tangibility levels are significantly higher for firms where CIRPs were not withdrawn, indicating that firms with low asset tangibility are more likely to have the CIRPs withdrawn. This result is in line with the findings of Hotchkiss [1995] and Altman and Hotchkiss [2010] who show that firms with low asset tangibility have higher rates of bankruptcy withdrawal in the US. We also observe that firms that have CIRPs withdrawn have significantly better return on assets (NI/TA) and PBITDA margins and are larger in size than their counterparts.

Next, we assess the robustness of our results in a multivariate setting. We perform a logistic regression where the dependent variable $CIRP\_Withdrawn$ is a binary variable that takes the value of 1 if there is a withdrawal from CIRP and 0 if there is no withdrawal. The regression specification is given by equation 3.1. Apart from the variables used in Table (3.2), we also use to additional explanatory variables of Age and $Group\_Ind$. $Group\_Ind$ is a binary variable that takes a value of 1 if the firm is part of a business group and 0 if it is a standalone firm. γ_t represents year fixed effects and rho_n represents industry fixed effects.

$$\begin{aligned} CIRP\_Wthdrawn_{i,t} = {} & \beta_0 + \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pct_{i,t} + \beta_3 Unsec\_Debt\_Pct_{i,t} \\ & + \beta_4 Tangibility_{i,t} + \beta_5 NITA_{i,t} + \beta_6 Ln(Sales)_{i,t} + \beta_7 Age_{i,t} \\ & + \beta_8 Group\_Ind_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \end{aligned} \tag{3.1}$$

Table 3.2: T-tests: CIRPs Withdrawn vs. Non-Withdrawn

The table presents the t-tests of key financial variables between two groups of firms within the subset that have entered the CIRP process. The first group has CIRPs that do not get withdrawn (i.e., Ongoing / Resolution / Liquidation) while the second group has CIRPs that get withdrawn. We compare the firms based on Leverage which is Total Debt to Total Assets, Short Term Leverage or short-term debt to total debt, Unsecured Debt percentage or Unsecured Debt to total debt. We have two measures of profitability, and they are NITA or Net Income to Total Assets and PBITDA Margin or Profit Before Interest, Tax, Depreciation and Amortization Margin. Period is 2018-2023

	CIRP Not Withdrawn		CIRP Withdrawn			
Metric	Obs	Value	Obs	Value	Difference	T-Stat
Leverage	577	120%	213	56%	64%***	7.7
ST Debt (%)	466	61%	196	56%	4%	1.4
Unsec. Debt (%)	505	27%	194	30%	-3%	(1.2)
Tangibility	568	34%	215	26%	8%***	3.6
NI/TA	586	-19.3%	220	-3.8%	-16%***	(9.0)
PBITDA Margin	463	-34.7%	192	-7.0%	-27%***	(4.6)
Ln(Sales)	486	6.1	202	6.6	-0.5***	(2.5)

Table (3.3) presents the results of this logistic regression. In column (1) we include year fixed effects, and in column (2) we add year and industry fixed effects. We observe that low leverage and high NI/TA are significant determinants of the likelihood of CIRP withdrawal. We also use the coefficients from the logistic regression to plot the probability of withdrawal over time in Figure (3.2). We observe that the probability of CIRP withdrawal has increased over time peaking in 2022 at 71% and coming down to 50% in 2023.

Lastly, we intend to understand the impact of the withdrawal of the CIRP on the return on assets of firms ($NITA$) in the year following the CIRP. We conduct the panel data fixed effects regression as specified by Equation (3.2). The main variable of interest is $CIRP\_Withdrawn$. We control for leverage, size ($Ln(Sales)$), tangibility, and age of the firm. γ_t represents year fixed effects and ρ_n represents industry fixed effects.

$$NITA_{i,t+1} = \beta_0 + \beta_1 CIRP\_Withdrawn_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Ln(Sales)_{i,t} + \beta_4 Tangibility_{i,t} + \beta_5 Age_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \tag{3.2}$$

Table 3.3: Drivers of CIRP Withdrawal

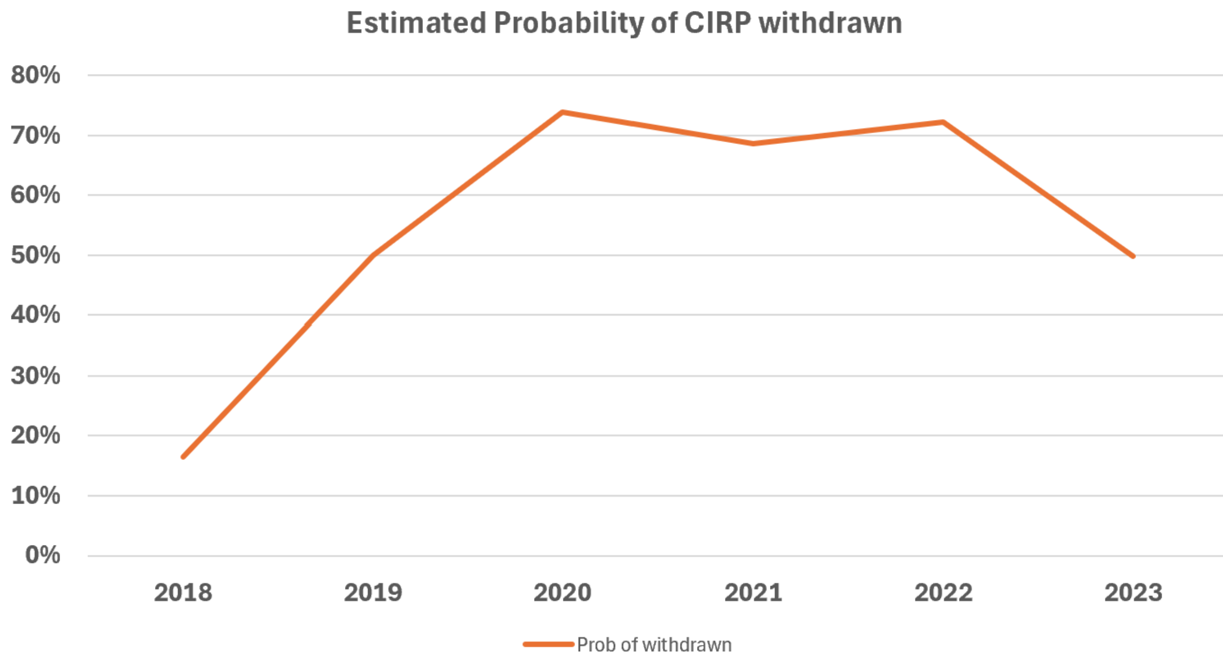
The table presents the logistic regression of CIRP withdrawal indicator on firm level financial variables.Period is 2018-2023

	(1) CIRP Withdrawal	(2) CIRP Withdrawal
Leverage	-0.859***	-0.869***
	(-3.467)	(-3.471)
ST Debt (%)	-0.00480	-0.183
	(-0.0128)	(-0.475)
Unsecured Debt (%)	0.436	0.473
	(1.121)	(1.159)
Tangibility	-0.492	-0.520
	(-1.056)	(-1.021)
NI/TA	3.335***	3.068***
	(3.906)	(3.644)
PBITDA Margin	-0.0559	-0.0533
	(-0.535)	(-0.511)
Ln(Sales)	0.0801	0.0698
	(1.435)	(1.183)
Age	0.00407	-0.000625
	(0.485)	(-0.0701)
Group Ind.	-0.522*	-0.345
	(-1.937)	(-1.215)
Constant	-3.216***	-2.963***
	(-3.621)	(-3.134)
Observations	547	547
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The regression results are tabulated in Table 3.4. We observe in column (1) that the coefficient of $CIRP\_Withdrawn$ is both positive and significant, indicating that firms that are able to settle with their creditors and withdraw from the CIRP have a significantly higher return on assets in the year following the CIRP compared to firms that continue in the CIRP. We perform sub-sample regressions for group and standalone firms in columns (2)

Figure 3.2: Probability of Withdrawal from CIRP across Time



and (3), where we see that the improvement in profitability is significant only in the case of standalone firms. One possible explanation for the results is that the withdrawal from CIRP leads to stronger financial performance in the following year. Alternatively, firms that expect to have a stronger performance in the following year are more likely to settle with their creditors.

Table 3.4: Impact of CIRP Withdrawal on Future Returns

The table shows the regression of the one-year-forward returns of a firm undergoing CIRP on CIRP Withdrawn Ind., a binary variable that takes a value of 1 if a firm is withdrawn from the CIRP and 0 if it is not withdrawn. Returns are measured as the ratio of net income to the firm's total assets. Column (1) shows the results of the full-sample regression, while columns (2) and columns (3) show the sub-sample results for group firms and standalone firms. Period is 2018-2023

	(1) Full Sample NI/TA	(2) Group Firms NI/TA	(3) Standalone Firms NI/TA
CIRP Withdrawn Ind.	0.0572***	0.0295	0.0722***
	(3.079)	(0.799)	(3.119)
Lagged Leverage ,	-0.0425***	-0.104***	-0.0304*
	(-2.769)	(-3.665)	(-1.814)
Lagged Ln (Sales) ,	-0.00429	-0.00859	-0.00170
	(-1.059)	(-1.059)	(-0.349)
Lagged Tangibility ,	-0.00569	0.0375	-0.0290
	(-0.167)	(0.666)	(-0.620)
Age	0.000319	0.000602	0.000689
	(0.651)	(0.708)	(1.160)
Constant	-0.102**	-0.209**	-0.0741
	(-2.390)	(-2.259)	(-1.482)
Observations	484	145	339
R-squared	0.150	0.309	0.160
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.2 Analysis of Resolution of Defaults (Default)

In this section, we analyze the drivers and consequences of resolution of Defaults, i.e., Defaults that do not translate into CIRPs. Based on the NeSL dataset, we have 652,341 instances of defaults on 66,055 unique contracts for 27,299 unique firms (debtors).[3] We match this dataset with the Prowess dataset to obtain 4,009 firms for which firm level data exists in Prowess dataset. Further, filtering firms for which we have financial data for the year in which they record their first Default, we obtain a short list of 3,521 firms of which 513 subsequently end up in the CIRP process. The details of the sample creation are presented in Table (3.5)

Table 3.5: Sample Construction for Default Resolution Analysis

The table presents the details of sample construction for the Default resolution analysis by merging the NeSL data on Defaults with Prowess data on firm level characteristics. It is subsequently combined with IBBI data on CIRPs. Period is 2018-2023

Criteria	No.of Firms
Unique firms with Defaults	27,299
Matched with Prowess	4,009
Firms with data available for the year of the first Default	3,521
Firms that go into CIRP	513

We first conduct univariate tests of firm characteristics between firms that have Defaults resolved (i.e., do not translate into CIRPs) and firms that have CIRPs initiated against them. Table 3.6 presents the results of this analysis. We observe that for the group with resolved Defaults, leverage is significantly lower at 60% compared to 102% for firms that enter CIRP. Furthermore, their usage of short-term debt is also significantly lower than firms that enter CIRP. We see similar results on tangibility as we had seen in the case of CIRP withdrawal in Section (3.1). Firms that go into CIRP have higher asset tangibility than firms that have Defaults resolved (34% vs. 29%). Lastly, we also observe that firms that have Defaults resolved have higher return on assets (NI/TA), profitability (PBIDTA margin) and size (Ln (Sales)) than firms that enter CIRP.

Next, we assess the robustness of our results in a multi-variate setting. We conduct a logistic

[3]For large loan contracts where amount outstanding exceeds ₹10 million.

Table 3.6: T-tests: Defaults resolved vs. CIRPs

The table presents the t-tests of key financial variables between two groups of firms within the subset that have had a default generated on at least one loan account. The first group has Defaults that lead to CIRPs while the second group has Defaults that get resolved.
We compare the firms based on Leverage which is Total Debt to Total Assets, Short Term Leverage or short-term debt to total debt, Unsecured Debt percentage or Unsecured Debt to total debt. We have two measures of profitability, and they are NITA or Net Income to Total Assets and PBITDA Margin or Profit Before Interest, Tax, Depreciation and Amortization Margin. Period is 2018-2023

	CIRP		Default Resolved			
Metric	Obs	Value	Obs	Value	Difference	Tstat
Leverage	507	102%	2,985	60%	41%***	12.1
Short Term Leverage Percentage	426	61%	2,614	55%	5%***	3.2
Unsecured Debt Percentage	455	25%	2,834	24%	1%	0.7
Tangibility	502	34%	2,937	29%	5%***	4.1
NITA	504	-11.6%	2,993	-1.9%	-10%***	(13.9)
PBITDA Margin	415	-28.5%	2,540	6.8%	-35%***	(14.1)
Ln (Sales)	440	6.3	2,706	7.1	-0.8***	(6.4)

regression as specified in Equation 3.3 where $DefaultResolved$ takes the value 1 if the firm has its Default resolved and 0 if it enters CIRP.

$$\begin{aligned} Default\_Resolved_{i,t} = \beta_0 + \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pct_{i,t} + \beta_3 Unsec\_Debt\_Pct_{i,t} \\ + \beta_4 Tangibility_{i,t} + \beta_5 NITA_{i,t} + \beta_6 Ln(Sales)_{i,t} + \beta_7 Age_{i,t} \\ + \beta_8 Group\_Ind_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \end{aligned} \tag{3.3}$$

Table 3.7 shows that low leverage and low short-term debt are significant predictors of Default resolution. In fact, for a 1 percent increase in leverage, the probability of Default resolution decreases by 3.18%. Similarly, high return on assets (NI/TA), profitability (PBIDTA Margin) and size also have a positive and significant relation with Default resolution. For a 1 percent increase in NI/TA the probability of Default resolution increases by 11%. We predict the probabilities from the logistic regression results in Table 3.7 and show that default resolutions are steadily rising due to the disciplining effect of IBC on firms.

Table 3.7: Drivers of Default Resolution

The table presents the logistic regression of Default resolution indicator on firm level financial variables. Firms that Default but do not go into CIRP are called DefaultResolution and take the value 1 and firms that go into CIRP after default take the value DefaultResolution =0. Period is 2018-2023

	(1) Default Resolution	(2) Default Resolution
Leverage	-0.386***	-0.443***
	(-3.492)	(-3.760)
ST Debt %	-0.586**	-0.701***
	(-2.525)	(-2.973)
Unsecured Debt %	0.443*	0.424
	(1.726)	(1.637)
Tangibility	0.200	0.0704
	(0.754)	(0.235)
NI/TA	1.949***	1.922***
	(4.298)	(4.120)
PBITDA Margin	0.102**	0.112**
	(2.038)	(2.156)
Ln(Sales)	0.107***	0.0891***
	(3.656)	(2.839)
Age	-0.000681	-0.000106
	(-0.171)	(-0.0258)
Group Ind.	-0.270*	-0.180
	(-1.833)	(-1.215)
Constant	0.777**	0.618*
	(2.366)	(1.780)
Observations	2,731	2,731
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	No	Yes

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Lastly, we study the impact of the Default resolution on the return on assets of firms ($NITA$) in the year following the first Default. We conduct the panel data fixed effects regression as specified by Equation (3.4). The main variable of interest is $Default\_Resolved$. We control for leverage, size ($Ln(Sales)$), tangibility, and age of the firm. γ_t represents year fixed effects and ρ_n represents industry fixed effects.

$$NITA_{i,t+1} = \beta_0 + \beta_1 Default\_Resolved_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Ln(Sales)_{i,t} + \beta_4 Tangibility_{i,t} + \beta_5 Age_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \quad (3.4)$$

The regression results are tabulated in Table 3.8. We observe in column (1) that the coefficient of $Default\_Resolved$ is both positive and significant, indicating that firms that are able to negotiate with their creditors and prevent Defaults from escalating into CIRPs have a significantly higher return on assets in the year following the first Default compared to firms that subsequently enter CIRPs. We perform sub-sample regressions for group and standalone firms in columns (2) and (3), where we see that the improvement in profitability is significant only in the case of standalone firms. Similar to the case with CIRP withdrawal, the causal inference can work both ways. The higher returns in subsequent years could be a function of Default resolution or Default resolution can be in anticipation of higher returns in subsequent years.

Table 3.8: Impact of Default Resolution on Future Returns

The table shows the regression of the one-year-forward returns of a firm with at least one loan account in default on Default Resolution Ind., a binary variable that takes a value of 1 if a firm resolves the Default without a CIRP being generated and 0 if the firm becomes part of a CIRP subsequently. Returns are measured as the ratio of net income to total assets of the firm. Column (1) shows the results of the full-sample regression, while columns (2) and columns (3) show the sub-sample results for group firms and standalone firms. Period is 2018-2023

	(1)	(2)	(3)
	Full Sample	Group Firms	Standalone Firms
	NI/TA	NI/TA	NI/TA
Default Resolved	0.0618***	0.0541***	0.0634***
	(5.410)	(3.135)	(4.242)
Lagged Leverage	-0.0437***	-0.0529***	-0.0389***
	(-4.708)	(-3.472)	(-3.339)
Lagged Ln(Sales)	0.00604***	0.00404*	0.00771***
	(4.513)	(1.777)	(4.633)
Lagged Tangibility	-0.0150	-0.0479*	-0.00533
	(-1.054)	(-1.840)	(-0.309)
Age	0.000163	0.000259	0.000209
	(1.075)	(1.283)	(0.846)
Constant	-0.127***	-0.145***	-0.122***
	(-6.809)	(-4.553)	(-5.178)
Observations	2,502	779	1,723
R-squared	0.142	0.214	0.125
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.3 Analysis of Default-Free firms

In this section, we understand the drivers and consequences of firms preventing overdue accounts from going to default status. Based on NeSL dataset, we have $1,810,194$ instances of overdue accounts on 227, 297 unique contracts for 96, 171 unique debtors.[4] We match this dataset with the Prowess dataset to obtain 11, 653 firms for which firm level data exists in Prowess dataset. Further, filtering firms for which we have financial data for the year in which they have their first overdue filing, we obtain a short list of 11, 054 firms of which 3, 378 subsequently end up having at least one Default. The details of the sample creation are presented in Table (3.9)

Table 3.9: Sample Construction for Analysis of Default-Free Firms

The table presents the details of sample construction for the analysis of default-free by merging the NeSL data on Overdue Accounts with Prowess data on firm level characteristics. Period is 2018-2023

Criteria	No.of Firms
Unique firms with Overdue Accounts	96, 171
Matched with Prowess	11, 653
Firms with data available for the year of the first Overdue Filing	11, 054
Firms that subsequently have Defaults	3, 378

We first conduct univariate tests of firm characteristics between firms that are default-free (i.e., they have atleast one Default account at some point but never have any default account) and firms that have Defaults generated against them. Table 3.10 presents the results of our analysis. We observe that firms that never go into default have significantly lower leverage, lower usage of short-term debt, higher usage of unsecured debt, lower tangibility of assets, higher return and profitability measures and larger size than firms that go into default.

Next, we assess the robustness of our results in a multivariate setting. We conduct a logistic regression as specified in Equation 3.5 where $Default\_Free$ takes the value 1 if the firm has never had a Default generated against it and 0 if it has had a Default generated at some

[4] For large loan contracts where amount outstanding exceeds ₹10 million.

Table 3.10: T-tests: Overdue vs. Defaults

The table presents the t-tests of key financial variables between two groups of firms within the subset that have had an overdue filing on at least one loan account. The first group has at least one of the loan accounts transitioning into a default status while the second group has no loan accounts that transition into default status.
We compare the firms based on Leverage which is Total Debt to Total Assets, Short Term Leverage or short-term debt to total debt, Unsecured Debt percentage or Unsecured Debt to total debt. We have two measures of profitability, and they are NITA or Net Income to Total Assets and PBITDA Margin or Profit Before Interest, Tax, Depreciation and Amortization Margin.

	Default		Overdue			
Metric	Obs	Value	Obs	Value	Difference	Tstat
Leverage	3,368	62%	7,558	41%	21%	21.6
Short Term Leverage Percentage	3,007	57%	6,717	53%	4%	5.9
Unsecured Debt Percentage	3,240	23%	7,262	26%	-2%	(4.1)
Tangibility	3,330	30%	7,575	26%	4%	8.0
NITA	3,365	-3.4%	7,668	1.9%	-5.3%	(22.8)
PBITDA Margin	2,942	3.1%	7,044	11.4%	-8.3%	(11.4)
Ln(Sales)	3,101	7.2	7,311	6.9	0.3	5.9

point.

$$\begin{aligned} Default\_Free_{i,t} = \beta_0 &+ \beta_1 Lev_{i,t} + \beta_2 ST\_Debt\_Pct_{i,t} + \beta_3 Unsec\_Debt\_Pct_{i,t} \\ &+ \beta_4 Tangibility_{i,t} + \beta_5 NITA_{i,t} + \beta_6 Ln(Sales)_{i,t} + \beta_7 Age_{i,t} \\ &+ \beta_8 Group\_Ind_{i,t} + \gamma_t + \rho_n + \epsilon_{i,t} \end{aligned} \tag{3.5}$$

Table 3.11 shows that low leverage, low short-term debt percentage and high unsecured debt percentage are significant predictors of a firm being default-free. We further observe that return on assets has a positive relationship with a firm being default- free. Interestingly, size has a significant negative correlation indicating that larger firms are more likely to default. This result is thematically at variance with earlier results where we observed that larger firms were more likely to have Default resolved. Finally, the group indicator is negative and significant, indicating that group firms are more likely to transition from default to overdue status.

Table 3.11: Drivers of Default-Free Firms

The table presents the logistic regression of the Default-Free indicator on firm-level financial variables. Firms that have loan accounts in Overdue status but do not go into Default Status are called Default-Free with the Default-Free Indicator taking a value of 1 , whereas firms where at least one loan account transition into Default are called Default firms with Default-Free Indicator taking a value of 0.

	(1) Default Free	(2) Default Free
Leverage	-0.806***	-0.818***
	(-7.944)	(-7.967)
ST Debt %	-0.234**	-0.318***
	(-2.553)	(-3.347)
Unsecured Debt %	0.569***	0.579***
	(5.623)	(5.687)
Tangibility	-0.0621	-0.187
	(-0.520)	(-1.434)
NI/TA	2.671***	2.706***
	(8.801)	(8.883)
Ln(Sales)	-0.115***	-0.119***
	(-7.341)	(-7.438)
Age	-0.00220	-0.00246*
	(-1.504)	(-1.655)
Group Ind.	-0.328***	-0.305***
	(-5.375)	(-4.898)
Constant	0.0177	-0.337
	(0.0457)	(-0.866)
Observations	9,120	9,120
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	No	Yes

Robust z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Lastly, we study the impact of the being default-free on the return on assets of firms ($NITA$) in the year following the first account being overdue for the firm. We conduct the panel data fixed effects regression as specified by Equation (3.6). The main variable of interest is $Default\_Free$. We control for leverage, size ($Ln(Sales)$), tangibility, and age of the firm. γ_t represents year fixed effects and ρ_n represents industry fixed effects.

$$
\begin{aligned}
NITA_{i,t+1} = \beta_0 + \beta_1 Default\_Free_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Ln(Sales)_{i,t} \\
+ \beta_4 Tangibility_{i,t} + \beta_5 Age_{i,t} + \gamma_i + \rho_n + \epsilon_{i,t}
\end{aligned}
\tag{3.6}
$$

The regression results are tabulated in Table 3.12. We observe in column (1) that the coefficient of $Default\_Free$ is both positive and significant, indicating that firms that are able to resolve overdue accounts and prevent them from escalating to Defaults have a significantly higher return on assets in the year following the first overdue account, compared to firms that subsequently see accounts transitioning into default. We perform sub-sample regressions for group and standalone firms in columns (2) and (3), and the results are largely consistent with the full sample.

3.4 Conclusion

Firms that withdraw from the CIRP process have lower leverage and higher profitability when compared to the firms that stay in CIRP. Business group firms have a lower chance of CIRP withdrawal after entering the CIRP process.

Firms that have withdrawn have 5.72% higher profitability than firms that remain in CIRP. Standalone firms that have withdrawn have a higher profitability of 7.22% compared to those that continue to stay in CIRP mode. Firms that have withdrawn have a 48% higher PBITDA margin than those that remain in CIRP.

In this chapter, we analysed the determinants of defaulting firms that do not manage to

Table 3.12: Impact of being Default-Free on Future Returns

The table shows the regression of the one-year-forward returns of a firm with at least one loan account in overdue status on Default-Free Indicator, a binary variable that takes a value of 1 if a none of the loan accounts of the firm ever transition into default and 0 if at-least one of the loan accounts of the firm transitions into default. Returns are measured as the ratio of net income to total assets of the firm. Column (1) shows the results of the full-sample regression, while columns (2) and columns (3) show the sub-sample results for group firms and standalone firms.

	(1) Full Sample NI/TA	(2) Group Firms NI/TA	(3) Standalone Firms NI/TA
Default-Free	0.0279***	0.0221***	0.0285***
	(10.37)	(4.118)	(9.256)
Lagged Leverage	-0.0712***	-0.0960***	-0.0594***
	(-10.01)	(-6.786)	(-7.347)
Lagged Ln(Sales)	0.00573***	0.00398**	0.00694***
	(8.291)	(2.538)	(8.885)
Lagged Tangibility	-0.00250	-0.0118	0.00214
	(-0.411)	(-0.893)	(0.309)
Age	-5.09e-05	9.82e-05	-8.12e-05
	(-0.758)	(0.748)	(-1.003)
Constant	-0.138***	-0.0499	-0.192***
	(-5.043)	(-1.389)	(-5.071)
Observations	9,232	2,074	7,158
R-squared	0.156	0.222	0.139
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

go into CIRP. Impact of Default Resolution on Future Profitability On average, Default-resolved firms exhibit a leverage of 44%, whereas CIRP firms have a significantly higher average leverage of 89%. CIRP firms have higher short-term debt and unsecured debt when compared to Default resolved firms. The Profitability (NI/TA) of Default resolved firms is -0.5% and -13% for CIRP firms. For a 1 percent increase in leverage the probability of Default resolution decreases by 3.18%. For a one percent increase in NI/TA the probability of Default resolution increases by 11 %. For a one percent increase in ln(sales) the probability of Default resolution increases by 0.75%. Short Term Debt percentage, unsecured debt percentage, tangibility and Age are not significant in the logistic regression. Firms that have default resolution exhibit profitability increase by 7.27% in the full sample. Group firms increase their profitability by 7.98% and standalone firms increase their profitability by 6.21%. Default-free firms have an increase in NI/TA of 2.79% in the full sample. The standalone firms show an increase of NI/TA by 2.85%. A one unit increase in leverage would decrease the NI/TA by 7.12% for the full sample, 9.6% for group firms, and 5.94% for standalone firms.

Chapter 4

Effect of IBC on Firm Characteristics

4.1 Introduction

The impact of creditor rights on corporate characteristics and behaviour has been a subject of considerable academic debate over the years. The primary focus of such research has been to evaluate the impact of creditor rights on leverage levels in the economy. There are primarily two schools of thought on this front – the supply side view which espouses that an increase in creditor rights increases the willingness to lend for creditors resulting in an increase in leverage [Djankov et al., 2007, Qian and Strahan, 2007a] and the demand side which posits that an increase in creditor rights is followed by a reduction in borrowing by firms in an attempt to reduce the risk of a bankruptcy [Vig, 2013, Acharya et al., 2011].

In this context, the enactment of the IBC has provided fertile ground for multiple studies in this space. Early research on this area focused on the impact of IBC on leverage levels. Jose et al. [2020] and Singh et al. [2021] find evidence of a reduction in leverage post IBC, giving support to the demand side view of creditor rights. However, Bose et al. [2021] finds that while aggregate leverage has indeed reduced, in case of firms that are distressed, there is evidence of increase in leverage levels indicating both supply side and demand side effects working in parallel. Agarwal and Singhvi [2023] find evidence of firms substituting away from corporate debt in the post IBC world, despite an increase in the supply of credit. Exploring the impact of the IBC on sources of debt, Ghosh [2022] observe that firms have cut down on bank debt in the post IBC world despite a reduction in borrowing costs. Sengupta and Vardhan [2023] detect that the reduction in yield spreads to be significant for bonds issued by non financial firms in the post IBC world, suggesting that the increase in creditor rights is stronger for bond holders vis-a-vis bank debt.

Recent research has focused on analyzing the responses of firms to a stronger creditor rights environment. Singh et al. [2021] find evidence of risk-shifting behaviour in highly leveraged firms as they take up riskier projects in an attempt to stave off bankruptcy. Rawal et al. [2024] observes that over-leveraged firms have increased the speed of adjustment of capital structure in the post IBC world. Studies have also found that firms have responded to this increase in ease of financing by reducing their cash holding levels [Jadiyappa and Kakani, 2023] and increasing investments in exports [Khan and Chakraborty, 2022]. Mohanty and Sundaresan [2018] observe evidence of greater forex hedging by firms having higher exposure to foreign currency debt in the post IBC world.

Our analysis seeks to extend the work of these earlier studies by looking at the impact of the IBC on corporate characteristics in both panel data and difference-in-differences settings. We look at a larger time period post IBC (2017-2024) as well as a larger dataset that includes both public and private firms.

4.2 Data and Results

We obtain data from CMIE Prowess on both public and private firms for this analysis. We focus on large firms and exclude observations in which the total assets of a firm is below 100 crore in a given year. Our primary data set consists of $129,888$ firm-year observations over the period 2014 to 2024. Of these observations, $74,547$ observations pertain to public firms (i.e., listed firms) while $55,341$ pertain to private firms. Table (4.1) presents the summary statistics for our final sample.

Table 4.1: Summary Statistics

The table presents the summary statistics of the dataset used for analysis.

	Obs.	Median	Mean	Std. Dev.	Min	Max
Leverage	1,29,888	33%	38%	30%	0%	128%
Long-Term Leverage	1,04,800	12%	21%	24%	0%	96%
Short-Term Leverage	1,04,800	13%	18%	18%	0%	82%
Secured Leverage	1,13,647	23%	27%	23%	0%	88%
Unsecured Leverage	1,13,647	4%	11%	17%	0%	77%
Ln (Total Assets)	1,29,888	8.2	8.6	1.3	7.0	12.3
Tangibility	1,29,888	21%	26%	24%	0%	89%
Asset Specificity	1,29,340	18%	24%	23%	0%	84%
Ind. Director (%)	1,19,009	40%	34%	24%	0%	75%

4.2.1 IBC and Credit Availability

We first evaluate the impact of the IBC on corporate credit availability in the economy. We use Leverage level of firms as a proxy for credit availability in the economy. Figure 4.1 illustrates the trend in leverage levels of firms in the sample from 2010 to 2024. In Panel A, we see that Leverage shows a decreasing trend over this period, especially after the period of IBC implementation in 2016. In Panel B, we observe that both long-term leverage and short-term leverage mirror the decreasing trend in Leverage. Finally, in Panel C, we find that while leverage related to secured debt has reduced over this period, unsecured leverage has been relatively flat.

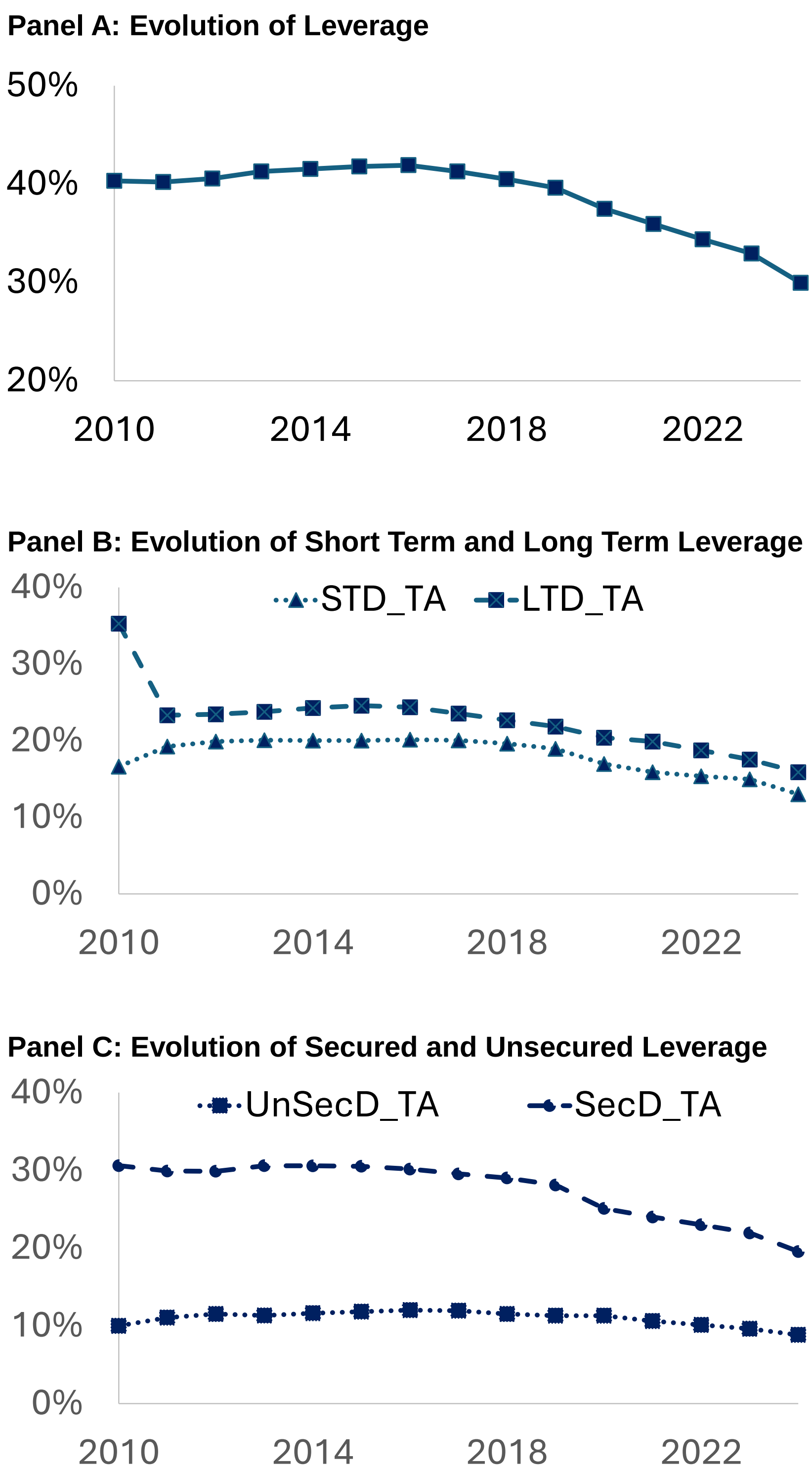
Next, we assess the significance of these results in a regression setting. The final regression specification that includes controls and fixed effects is given by Equation (4.1). $PostIBC_t$ is a binary variable that takes the value 1 for years 2017 to 2024, and 0 otherwise. γ_i represents firm fixed effects and ρ_n represents industry fixed effects.

$$\begin{aligned} Leverage_{i,t} = &\beta_0 + \beta_1 PostIBC_t + \beta_2 ln(TotalAssets)i,t + \beta_3 Tangibility_{i,t} \\ &+ \beta_5 Age_{i,t} + \gamma_i + \rho_n + \epsilon_{it} \end{aligned} \tag{4.1}$$

The results of our regression analysis are shown in Table (4.2). Column (1) presents the univariate results, while the regression in column (2) includes controls for size, tangibility, and age of the firm. In column (3), we include industry fixed effects, while in column (4) we add firm fixed effects. In the first three specifications, we observe that the coefficient of *Post IBC* is negative and significant. However, when firm fixed effects are also introduced in column (4), the coefficient is positive and significant. The results indicate that at once the average level of leverage for a firm is controlled for, incremental leverage change post IBC has been positive. The results lend support to the supply side theory of creditor rights (Djankov et al. [2007]) that indicates that stronger creditor rights incentivizes creditors to lend more as the expected value of recoveries in case of a default increase.

Next, we showcase the impact of IBC on long-term leverage and short-term leverage in the Table 4.3. The specifications in column (1) and column (3) include controls for firm specfic characteristics and industry fixed effects, while the specifications in column (2) and column (4) include firm fixed effects as well. From column (2), we observe that the long-term leverage has decreased by 0.68%, and from column (4), we observe that short-term leverage has increased by 1.29% for the aggregate economy.

Figure 4.1: Leverage Trends in the Economy
Panel A shows the trends in the mean value of Leverage in the economy. Panel B shows the trends in long-term and short-term leverage. Panel C shows the trends in secured and unsecured leverage.



Source: Prowess

Table 4.2: Impact of IBC on Leverage

The table presents the impact of IBC on Leverage of firms. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond. Leverage is calculated as the ratio of total debt of a firm to its total assets.

	(1) Total Leverage	(2) Total Leverage	(3) Total Leverage	(4) Total Leverage
Post IBC	-0.0436***	-0.0357***	-0.0323***	0.00401**
	(-17.85)	(-14.69)	(-13.36)	(2.051)
Ln (Total Assets)		0.00778***	0.000853	-0.0186***
		(4.538)	(0.502)	(-5.730)
Tangibility		0.248***	0.248***	0.185***
		(27.38)	(25.52)	(20.97)
Age		-0.00288***	-0.00253***	-0.00259***
		(-23.56)	(-20.52)	(-6.005)
Constant	0.412***	0.337***	0.385***	0.548***
	(152.3)	(23.95)	(27.26)	(25.37)
Observations	134,739	129,888	129,888	128,470
R-squared	0.005	0.082	0.126	0.795
Industry Fixed Effects	No	No	Yes	Yes
Firm Fixed Effects	No	No	No	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The observed increase in short-term leverage alongside a decrease in long-term leverage may reflect a shift in the firm's debt maturity structure, potentially due to constrained access to long-term capital markets or a strategic move to exploit more flexible, short-term borrowing. While this may temporarily improve liquidity, it also increases the firm's exposure to rollover risk and short-term financial pressures.

Next, we analyze the impact of the IBC on secured and unsecured leverage in Table 4.4.

Table 4.3: Impact of IBC on Long-Term and Short-Term Leverage

The table presents the impact of IBC on Long-Term and Short-Term leverage of firms. Long-term Leverage is calculated as the ratio of long-term debt to total assets of the firm. Short-term leverage is calculated as the ratio of short-term debt to total assets of the firm. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Long-Term Leverage	(2) Long-Term Leverage	(3) Short-term Leverage	(4) Short-term Leverage
Post IBC	-0.0227***	-0.00678***	-0.0295***	0.0129***
	(-11.00)	(-3.808)	(-16.39)	(7.643)
Ln (Total Assets)	0.00551***	0.0124***	-0.00934***	-0.0344***
	(4.365)	(4.576)	(-9.019)	(-13.16)
Tangibility	0.264***	0.123***	-0.0304***	0.0526***
	(33.76)	(15.10)	(-5.135)	(7.621)
Age	-0.00207***	-0.00446***	-0.000268***	-2.65e-05
	(-21.50)	(-12.31)	(-3.246)	(-0.0734)
Constant	0.148***	0.178***	0.295***	0.453***
	(13.87)	(9.516)	(33.28)	(26.13)
Observations	104,800	103,579	104,800	103,579
R-squared	0.228	0.799	0.036	0.698
Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Focusing on the specifications that include firm fixed effects – column (2) and column (4), we observe that while secured leverage has not displayed any significant change, unsecured leverage has increased marginally by 0.382%. Increase in unsecured leverage could possibly be a consequence of higher confidence of lenders to recover their dues in case a of default in the post IBC world, even in the absence of collateral. On the other hand, secured lenders who enjoyed protection under the SARFAESI act might not find much incremental protection under the IBC, reflecting in the insignificant impact on secured leverage.

Table 4.4: Impact of IBC on Secured and Unsecured Leverage

The table presents the impact of IBC on Secured and Unsecured leverage of firms. Secured Leverage is calculated as the ratio of secured debt to total assets of the firm. Unsecured leverage is calculated as the ratio of unsecured debt to total assets of the firm. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Secured Leverage	(2) Secured Leverage	(3) Unsecured Leverage	(4) Unsecured Leverage
Post IBC	-0.0413***	-0.00121	-0.00332**	0.00382**
	(-20.61)	(-0.684)	(-2.128)	(2.523)
Ln (Total Assets)	0.00148	0.0212***	0.00327***	-0.0317***
	(1.066)	(8.242)	(3.258)	(-14.73)
Tangibility	0.196***	0.121***	0.0496***	0.0552***
	(26.36)	(16.56)	(8.312)	(9.045)
Age	-0.00170***	-0.00646***	-0.000658***	0.00270***
	(-17.97)	(-18.34)	(-9.289)	(8.962)
Constant	0.269***	0.212***	0.0849***	0.296***
	(23.79)	(12.25)	(10.07)	(20.58)
Observations	113,654	112,182	113,647	112,175
R-squared	0.125	0.769	0.034	0.692
Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To further delineate causal impact of IBC on credit availability, we use a difference-in-differences (DID) setup by classifying firms into two groups. In the first instance, we use tangibility of assets as the classifying variable based on the approach of Vig [2013]. It is expected that the impact of increased creditor rights would be felt more strongly by firms having high tangibility of assets as the value that creditors can recover in case of bankruptcy would be higher for such firms. Therefore, we define our treated group as firms having high tangibility of assets (that lie in the top quartile of asset tangibility in a given year) while the control group is defined as firms that have low tangibility of assets (that lie in the bottom quartile of asset tangibility in a given year). The $HighTangInd_i$ is a binary variable that takes a value of 1 for firms in the treatment group and 0 for firms in the control group. $PostIBC_t$ is a binary variable that takes the value of 1 for years – 2017 and beyond. We have γ_j as an indicator for industry fixed effects and ρ_i as an indicator of firm fixed effects. Our main variable of interest is $PostIBC_t \times HighTangInd_i$ that captures the impact of the IBC policy on the debt structure of high-tangible firms, compared to low-tangibility firms. Equation 4.2 presents the regression specification.

$$\begin{aligned} Leverage_{i,t} = &\beta_0 + \beta_1 PostIBC_t \times HighTangInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighTangInd_{i,t} \\ &+ \beta_4 ln(TotalAssets)_{i,t} + +\beta_5 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \end{aligned} \tag{4.2}$$

Table 4.5 presents the results of this DID estimation. The coefficient on the DiD variable is significantly negative for Leverage (Column 1), long-term leverage (Column 2), short-term leverage (Column 3), and secured leverage (Column 4). However, the coefficient is not significant in the case of unsecured leverage (Column 5). Differential reduction in leverage is seen to be 4% in case of Leverage, 3.6% in case of long-term leverage, 1.5% in case of short-term leverage and 4.6% in case of secured leverage. The results point towards the demand side effect dominating for firms with high tangibility of assets. It appears that firms with high tangibility of assets are not ready to risk the threat of liquidation and the disciplining effect of IBC has brought down the leverage in these firms.

We also conduct a second DID analysis based on the likelihood of financial distress of a firm. Firms with high likelihood of financial distress are in the treatment group while firms with low likelihood of financial distress form the control group. Likelihood of financial distress is estimated through a combination of interest coverage ratio and leverage level of the firm. Firms having an interest coverage ratio of less than 1 and leverage in the highest quartile are

Table 4.5: Impact of IBC on Leverage - DID Analysis I

The table presents the difference-in-differences (DID) analysis of the impact of the IBC on Leverage (Column 1), long-term leverage (Column 2), short-term leverage (Column 3), secured leverage (Column 4) and unsecured leverage (Column 5). High Tang Ind is a binary variable that takes a value of 1 for firms that have tangibility value in the highest quartile of tangibility values for firms for a given year. It takes a value of 0 for firms that have tangibility value in the lowest quartile of tangibility values for firms for a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Total Leverage	(2) Long-Term Leverage	(3) Short-Term Leverage	(4) Secured Leverage	(5) Unsecured Leverage
Post IBC x High Tang Ind	-0.0401***	-0.0363***	-0.0151***	-0.0460***	-0.00683
	(-6.289)	(-5.958)	(-2.694)	(-8.268)	(-1.375)
Post IBC	0.0370***	0.0170***	0.0303***	0.0347***	0.00924**
	(7.839)	(3.387)	(6.542)	(7.645)	(2.243)
High Tang Ind	0.0769***	0.0446***	0.0418***	0.0524***	0.0332***
	(8.877)	(5.012)	(5.527)	(6.565)	(4.771)
Ln (Total Assets)	-0.00873*	0.0213***	-0.0386***	0.0323***	-0.0345***
	(-1.946)	(4.781)	(-9.934)	(8.684)	(-10.89)
Age	-0.00363***	-0.00775***	0.00248***	-0.00915***	0.00376***
	(-6.035)	(-13.50)	(4.665)	(-17.70)	(7.949)
Constant	0.564***	0.260***	0.415***	0.206***	0.334***
	(17.24)	(7.694)	(14.70)	(7.452)	(14.50)
Observations	67,872	51,777	51,777	54,635	54,629
R-squared	0.808	0.803	0.679	0.783	0.705
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

classified as the treatment group with a $HighFDInd$ value of 1. Firms having an interest coverage ratio of greater than 1 and leverage in the lowest quartile are classified as the control group with a $HighFDInd$ value of 0.[1] Equation (4.3) presents the regression specification.

[1]Interest Coverage Ratio (ICR) is a flow variable unlike the definition used by Bose et al. [2021] who use a stock variable called networth to define distress. They define it as a firm that has accumulated losses equal to or exceeding 50% of its average net worth in the immediately preceding four financial years, and 0 otherwise. In fact, a Zombie firm has also been defined to be one that obtained subsidized debt financing

$$
\begin{aligned}
Leverage_{i,t} =& \beta_0 + \beta_1 PostIBC_t \times HighFDInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighFDInd_{i,t} \\
&+ \beta_4 ln(TotalAssets)_{i,t} + \beta_5 Tangibility_{i,t} + \beta_6 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \qquad (4.3)
\end{aligned}
$$

Table 4.6 presents the results of this second DID analysis. In column (1), we find strong evidence of a differential increase in Leverage (of 10.7% on average) in firms having high likelihood of financial distress. Delving deeper, we observe from the results of columns (2) - (3) that for firms close to financial distress, there has been an incremental increase of 11.5% in short-term leverage while long-term leverage has witnessed a differential reduction of 2.0%. At the same time, both secured and unsecured leverage show a differential increase of 1.4% and 7.6%, respectively, post IBC.

4.2.2 IBC and the Cost of Debt

In this section, we turn our attention towards the impact of the IBC on the cost of debt. Figure 4.2 presents the trends in the mean value of cost of debt in the economy. For this part of analysis, we limit our focus on observations where the calculated cost of debt exceeds the yield on 10-year government bond rate. We observe that over the sample period, the yearly mean value of cost of debt has largely tended to be flat with some fluctuations around the overall average value of 16.7%.

and has a rating of BB or worse. We have considered a firm to be distressed if it is categorized as a zombie firm. Many benchmarks have been used to define a zombie firm, including profits, the nature of credit, and credit rating. However, for our purposes, we will consider the definitions involving the interest-to-coverage ratio (ICR) and financial leverage. McGowan et al. (2018) define distressed firms as "to have their ICR below 1 for three consecutive years and at the age of at least ten years". Through this definition, they aim to capture established firms that have shown signs of financial weakness in the recent past. Using the three-year timeline instead of considering ICR<1 for just one year has the disadvantage of cutting down the timeframe of our data by three years. However, it is crucial as one year of negative ICR, especially during the COVID-19 pandemic, did not necessarily indicate financial distress.

Table 4.6: Impact of IBC on Leverage - DID Analysis II

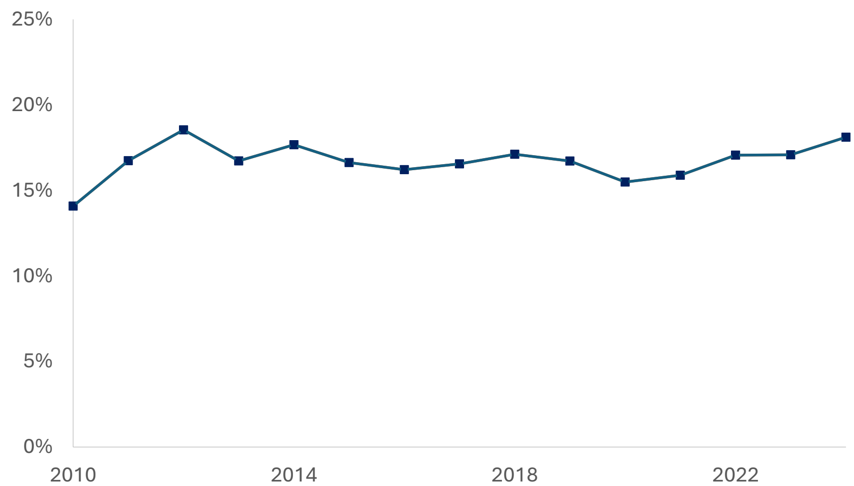
The table presents the difference-in-differences (DID) analysis of the impact of the IBC on Leverage (Column 1), long-term leverage (Column 2), short-term leverage (Column 3), secured leverage (Column 4) and unsecured leverage (Column 5). High FD Ind is a binary variable that takes a value of 1 for firms that have an interest coverage ratio in the lowest quartile of interest coverage ratios for firms for a given year. It takes a value of 0 for firms that have an interest coverage ratio in the highest quartile of interest coverage ratios for firms for a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Total Leverage	(2) Long-Term Leverage	(3) Short-Term Leverage	(4) Secured Leverage	(5) Unsecured Leverage
Post IBC x High FD Ind	0.107***	-0.0195**	0.115***	0.0140**	0.0758***
	(18.99)	(-2.319)	(15.55)	(2.088)	(10.75)
Post IBC	-0.0348***	-0.00400	-0.0286***	-0.00357	-0.0306***
	(-14.72)	(-1.174)	(-8.722)	(-1.389)	(-11.22)
High FD Ind	0.672***	0.351***	0.272***	0.392***	0.222***
	(55.45)	(20.79)	(16.58)	(24.98)	(13.20)
Ln (Total Assets)	-0.0652***	-0.0144***	-0.0515***	-0.00665*	-0.0514***
	(-20.78)	(-2.817)	(-10.78)	(-1.805)	(-13.64)
Tangibility	0.0767***	0.0630***	0.0107	0.0696***	0.00991
	(7.771)	(4.449)	(0.796)	(6.530)	(0.814)
Age	0.00675***	-0.000565	0.00631***	-0.00201***	0.00792***
	(13.94)	(-0.781)	(8.778)	(-3.806)	(13.81)
Constant	0.480***	0.216***	0.320***	0.170***	0.284***
	(22.85)	(5.981)	(9.643)	(6.781)	(10.93)
Observations	41,214	30,008	30,008	33,790	33,789
R-squared	0.963	0.894	0.830	0.912	0.841
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next, we explore the impact of the IBC on cost of debt in a regression setting. The final regression specification used is presented in Equation 4.4. In the equation, $CostofDebt_{i,t}$ is obtained as the ratio of Interest Expense to total debt in a given year. $PostIBC_t$ is a time dummy which takes the value 1 for years 2016–2024, and 0 otherwise. γ_i and ρ_n are firm

Figure 4.2: Cost of Debt Trends in the Economy
The figure shows trends in the mean value of cost of debt in the economy. Cost of debt is obtained as interest expense divided by total debt of a firm.



Source: Prowess

and industry fixed effects, respectively.

$$\begin{aligned} CostofDebt_{i,t} = & \beta_0 + \beta_1 PostIBC_t + \beta_2 ln(TotalAssets)_{i,t} + \beta_3 Tangibility_{i,t} + \\ & + \beta_4 Age_{i,t} + \gamma_i + \rho_n + \epsilon_{i,t} \end{aligned} \tag{4.4}$$

In Table 4.7, we see that while the overall impact of the IBC on the cost of debt seems to be negative, when all controls and fixed effects are added in column (4), the reduction is not significant. We extend our analysis to a DID setting similar to the approach taken in Section (4.2.1). We use two DID settings, one where the sample is partitioned based on its tangibility of assets and second where the sample is partitioned based on their proximity to

Table 4.7: Impact of IBC on Cost of Debt

The table presents the impact of IBC on cost of debt of firms. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond. Cost of debt is measured as the ratio of total interest expense to total debt of the firms.

	(1) Cost of Debt	(2) Cost of Debt	(3) Cost of Debt	(4) Cost of Debt
Post IBC	-0.000217	-0.00785***	-0.00854***	-0.00354
	(-0.117)	(-3.859)	(-4.206)	(-1.516)
Ln (Total Assets)		0.0117***	0.0104***	-0.0269***
		(7.789)	(7.255)	(-9.409)
Tangibility		-0.124***	-0.119***	-0.0647***
		(-26.92)	(-25.55)	(-8.324)
Age		0.00110***	0.00117***	0.00288***
		(8.171)	(8.510)	(7.302)
Constant	0.166***	0.0771***	0.0853***	0.344***
	(83.80)	(5.868)	(6.763)	(15.81)
Observations	76,907	76,907	76,907	74,795
R-squared	0.000	0.052	0.057	0.545
Industry Fixed Effects	No	No	Yes	Yes
Firm Fixed Effects	No	No	No	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

financial distress. The regression specifications are given in Equations (4.5) and (4.6).[2]

$$
\begin{aligned}
CostofDebt_{i,t} = &\beta_0 + \beta_1 PostIBC_t \times HighTangInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighTangInd_{i,t} \\
&+ \beta_4 ln(TotalAssets)_{i,t} + \beta_5 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \qquad (4.5)
\end{aligned}
$$

$$
\begin{aligned}
CostofDebt_{i,t} = &\beta_0 + \beta_1 PostIBC_t \times HighFDInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighFDInd_{i,t} \\
&+ \beta_4 ln(TotalAssets)_{i,t} + \beta_5 Tangibility_{i,t} + \beta_6 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \qquad (4.6)
\end{aligned}
$$

[2]The control and DID variables are defined in the same way as in Equations (4.2), (4.3) and (4.4).

In column(1) of Table 4.8, we see that while cost of debt went down post IBC across the sample, the benefit was largely limited to firms with low tangibility of assets. Firms with high tangibility of assets found their cost of debt increasing by 1.1% post IBC in comparison to firms with low tangibility of assets. However, the aggregate effect of IBC for firms with high tangibility of assets was negative (-0.5%) and significant.

On the other hand, firms with high financial distress show a decrease in the cost of debt by 3.3% when compared to the non-distressed firms after the implementation of the reform. This result is consistent with Bose et al. [2021] in which they find that cost of borrowing declined by 0.8% for distressed firms as compared to non-distressed firms. A possible explantion could be that distressed firms significantly improved their "credit channels" while experiencing lower cost of credit in the post IBC world with respect to their non-distressed counterparts.

4.2.3 IBC and Goverannce

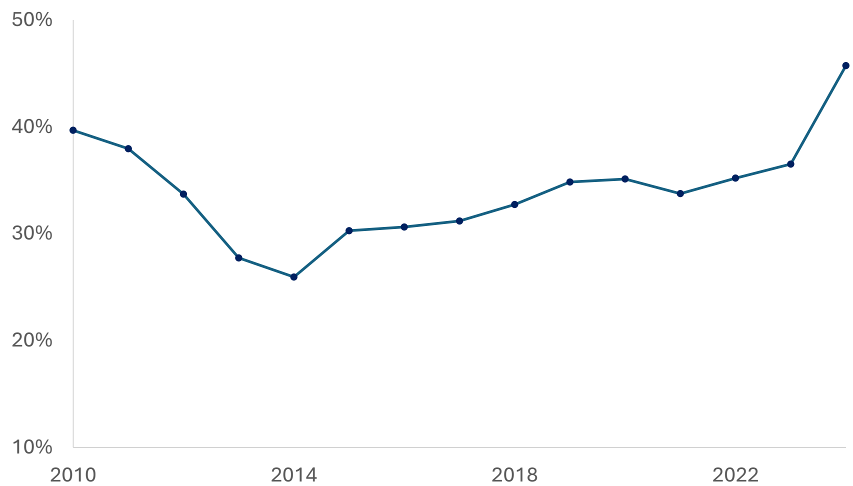
In this section, we evaluate the impact IBC had on governance of firms in the Indian economy. Jadiyappa and Kakani [2023] evaluate this question from a perspective of agency costs and show that the IBC has had a negative impact on dividend payout ratio, indicating a greater desire by firms to maintain financial slack. We explore the impact of IBC on another dimension of governance, using the proxy of the percentage of independent directors on the Board of Directors of a firm.[3]

For this part of the analysis, we focus only on public firms as the details of Board composition for private firms on Prowess is relatively sparse. In Figure 4.3, we plot the mean level of percentage of independent directors at firms in our sample. We observe that post IBC, the

[3]As per the Companies Act 2013, all listed public limited companies are mandatorily required to have at least one-third of the total number of directors as an independent directors. For Unlisted public companies, as per Rule 4 of the Companies (Appointment and Qualification of Directors) Rules, 2014, the following classes of companies must have at least 2 directors as independent directors: a. Public companies with aggregate outstanding loans, debentures, and deposits, exceeding Rs.50 crore. b. Public companies with paid-up share capital of Rs.10 crore or more. c. Public companies with a turnover of Rs.100 crore or more.

percentage of independent directors has increased from about 31% in 2017 to about 45% in 2024.

Figure 4.3: Trends in Independent Director (%)
The figure shows the trends in the mean level of independent directors at Indian firms.



Source: Prowess

Next, we evaluate the significance of this trend in a regression setting as specified by Equation (4.7). $Ind.Dir\%_{i,t}$. $PostIBC_t$ is a binary variable that takes the value of 1 for years – 2017 and beyond. Table 4.9 presents the results of these regression. It shows that post IBC, percentage of independent directors has increased as seen in Column (4) with Industry and Firm Fixed Effects. The percentage of independent directors has increased by 2.8% post IBC.

$$\begin{aligned} Ind.Dir\%_{it} =& \beta_0 + \beta_1 PostIBC_t + \beta_2 ln(TotalAssets)_{i,t} + \beta_3 Tangibility_{i,t} + \\ & + \beta_4 Age_{i,t} + \gamma_i + \rho_n + \epsilon_{it} \end{aligned} \tag{4.7}$$

Firms that are highly distressed have increased their percentage of independent directors by 2.52% post IBC reform. There is no significant effect being observed in the case of firms with high tangibility.

We further analyze the strength of this result in a DID setting based on regression specifications in Equations 4.8 and 4.9. The treatment and control groups are formed based on tangibility and financial distress in the same way as in Section 4.2.1. The results of the regression are presented in Table 4.10. We observe that while there is no differential increase in governance levels between the tangibility sub-groups, there is an incremental increase in governance levels post IBC for the sub-group of firms with high financial distress. Firms with high financial distress show a 2.8% higher level of independent directors in comparison to the low distress sub-group.

$$\begin{aligned} Ind.Dir\%_{i,t} =& \beta_0 + \beta_1 PostIBC_t \times HighTangInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighTangInd_{i,t} \\ &+ \beta_4 Leverage_{i,t} + \beta_5 ln(TotalAssets)_{i,t} + \beta_6 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \end{aligned} \tag{4.8}$$

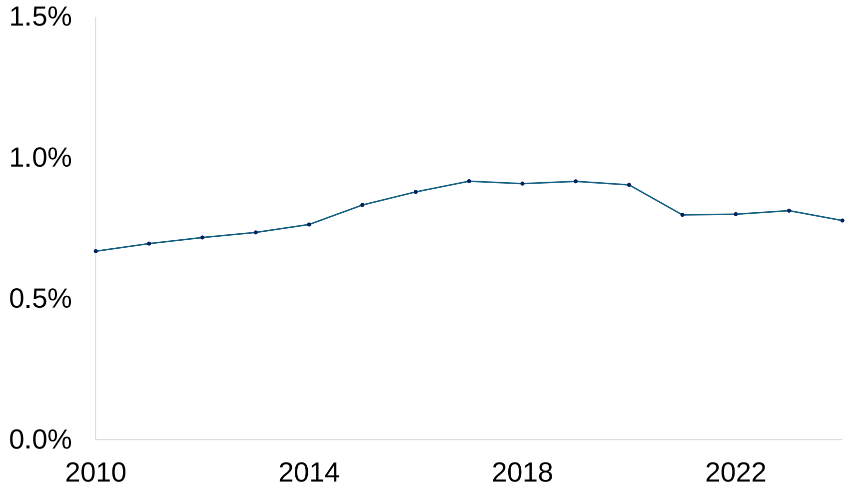
$$\begin{aligned} Ind.Dir\%_{i,t} =& \beta_0 + \beta_1 PostIBC_t \times HighFDInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighFDInd_{i,t} + \beta_4 Leverage_{i,t} \\ &+ \beta_5 ln(TotalAssets)_{i,t} + \beta_6 Tangibility_{i,t} + \beta_7 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \end{aligned} \tag{4.9}$$

4.2.4 IBC and Innovation

Acharya et al. [2011] show that when bankruptcy code is creditor-friendly, excessive liquidations cause levered firms to shun innovation, whereas by promoting continuation upon failure, a debtor-friendly code induces greater innovation. We aim to test this result in the Indian context when the IBC was proposed in 2016. The proxy for innovation is R&D Intensity which is measured by the ratio of R&D expenses to total assets. The Figure 4.4 shows that the R&D Intensity has slightly increased after IBC.

Next, we examine the significance of these trends in a regression setting. Equation 4.10 presents the full regression specification where the dependent variable is $R\&DIntensity_{i,t}$ and all controls, industry fixed effects, and firm fixed effects are included. In all four specifications

Figure 4.4: Trends in R&D Intensity
The figure shows the trends in the mean level of R&D Intensity in the economy.



Source: Prowess

shown in Table 4.11, R&D intensity is seen to increase post IBC. From the last column (4) in Table 4.11, we find that $R\&DIntensity_{it}$ has increased post IBC by 0.04%. This shows that strengthening of creditor rights is not a dampening factor for innovation for all firms. We have included firm fixed effects and Industry fixed effects to control for unobserved differences at firm-level and latent industry specific changes.

$$\begin{aligned} R\&DIntensity_{i,t} =& \beta_0 + \beta_1 PostIBC_t + \beta_2 ln(TotalAssets)_{i,t} + \beta_3 Tangibility_{i,t} + \\ & + \beta_4 Leverage_{i,t)} + \beta_5 Age_{i,t} + \gamma_i + \rho_n + \epsilon_{it} \end{aligned} \tag{4.10}$$

We further test the significance of these results in a DID setting. The treatment and control groups are formed based on tangibility and financial distress in the same way as in Section 4.2.1. The results of the regression are presented in Table 4.12. We observe that while there is no differential increase in R&D intensity between the tangibility sub-groups, there is an incremental reduction in R&D intensity post IBC for the sub-group of firms with high financial distress. Firms with high financial distress show a 0.2% lower level of R&D intensity in comparison to the low distress sub-group. Quite possibly, financially distressed firms are threatened by the IBC and its disciplining features and hence do not venture into risker innovative projects. This is consistent with Acharya et al. [2011] in which they say that a reform that strengthens creditor rights will bring down innovation as it can drive firms from not undertaking investments in newer and riskier projects.

$$\begin{aligned} R\&DIntensity_{i,t} = \beta_0 &+ \beta_1 PostIBC_t \times HighTangInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighTangInd_{i,t} \\ &+ \beta_4 Leverage_{i,t} + \beta_5 ln(TotalAssets)_{i,t} + \beta_6 Age_{i,t} \\ &+ \gamma_j + \rho_i + \epsilon_{i,t} \end{aligned} \tag{4.11}$$

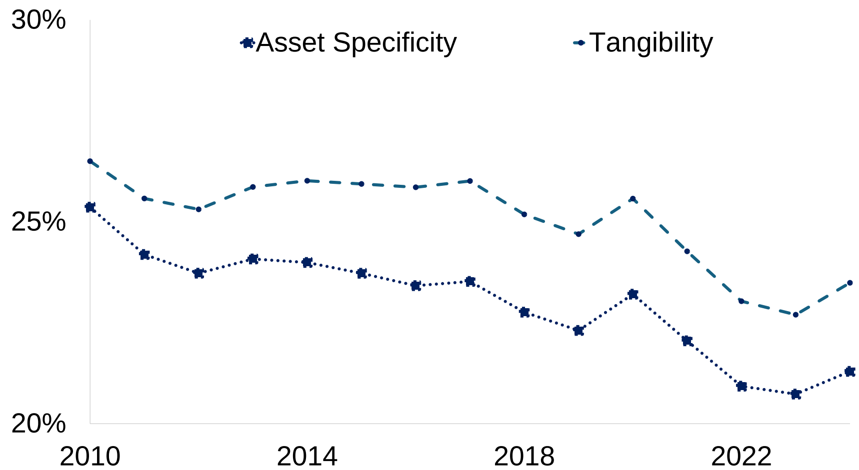
$$\begin{aligned} R\&DIntensity_{i,t} = \beta_0 &+ \beta_1 PostIBC_t \times HighFDInd_{i,t} + \beta_2 PostIBC_t + \beta_3 HighFDInd_{i,t} \\ &+ \beta_4 Leverage_{i,t} + \beta_5 ln(TotalAssets)_{i,t} + \beta_6 Tangibility_{i,t} \\ &+ \beta_7 Age_{i,t} + \gamma_j + \rho_i + \epsilon_{i,t} \end{aligned} \tag{4.12}$$

4.2.5 IBC and Tangibility and Asset Specificity

Tangibility is measured by the ratio of net fixed assets to total assets. Asset specificity is defined as the ratio of Net Plant, Property and Equipment to total assets. It measures the repurposability of the assets of a firm, and firms with high asset specificity are expected to face lower borrowing costs as these assets have higher liquidation value. From the Figure 4.5, we notice that tangibility and asset specificity has come down after the IBC reform. The ability to borrow at lower costs due to the existence of collateral has reduced. However, this needs to be more carefully analysed in the multivariate analysis using the Difference-in-Difference framework.

We examine the trends in a regression setting in Table 4.13. We observe that once firm fixed effects are accounted for, there has been an increase in asset tangibility and asset specificity in the economy post IBC. However, only the former increase is observed to be statistically

Figure 4.5: Trends in Tangibility and Asset Specificity
The figure show the trends in the mean level of tangibility and asset specificity across firms.



Source: Prowess

significant in the presence of firm fixed effects.

4.3 Conclusion

Post IBC, we see an increase in total leverage by 0.40%, decrease in long term leverage by 0.68%, increase in short term leverage by 1.29% and increase in unsecured leverage by 0.38%. Among firms with high tangibility, Leverage fell by 4.01%, long-term leverage by 3.63%, short-term leverage by 1.51%, and secured leverage by 4.6%, indicating a broad-based deleveraging response. These patterns strongly reflect a demand-side effect, where firms appear reluctant to assume excessive debt due to the disciplining mechanisms introduced by the Insolvency and Bankruptcy Code (IBC). The threat of inefficient liquidation under the IBC seems to have discouraged firms from increasing leverage.

Conversely, highly distressed firms witnessed an 8.24% increase in Leverage, primarily driven by a 7.68% rise in short-term leverage. This suggests that the IBC may have facilitated greater capital access or risk tolerance among distressed firms, contributing to increased capital formation post-reform.

Regarding the cost of debt, the IBC does not exhibit a significant effect once firm fixed effects are accounted for. However, distressed firms show a 2.07% reduction in their cost of debt compared to non-distressed peers following the reform, implying a relative benefit for financially weaker firms.

The proportion of independent directors increased by 2.84% on average after the IBC was enacted. Among highly distressed firms, this increase was 2.52%, suggesting that governance adjustments were more pronounced in financially vulnerable firms. In contrast, no statistically significant change in board composition was observed among firms with high tangibility.

R&D intensity marginally increased by 0.04% in the overall sample post-IBC. However, distressed firms experienced a notable decline of 0.264% in R&D intensity, possibly reflecting a reallocation of resources toward immediate solvency concerns. Meanwhile, asset tangibility increased by 0.432% following the reform, but there was no observable impact on asset specificity.

Table 4.8: Impact of IBC on Cost of Debt - DID Analysis

The table presents the difference-in-differences (DID) analysis of the impact of the IBC on cost of debt. In column (1), we divide the sample based on High Tang Ind. High Tang Ind is a binary variable that takes a value of 1 for firms that have tangibility value in the highest quartile of tangibility values for firms for a given year. It takes a value of 0 for firms that have tangibility value in the lowest quartile of tangibility values for firms for a given year. In column (2), we divide the sample based on High FD Ind. High FD Ind is a binary variable that takes a value of 1 for firms that have an interest coverage ratio in the lowest quartile of interest coverage ratios for firms for a given year. It takes a value of 0 for firms that have an interest coverage ratio in the highest quartile of interest coverage ratios for firms for a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1)	(2)
	Cost of Debt	Cost of Debt
Post x High Tang Ind	0.0109*	
	(1.837)	
Post x High FD Ind		-0.0326***
		(-3.840)
Post IBC	-0.0165***	0.0240***
	(-3.077)	(2.726)
High Tang Ind	-0.0299***	
	(-2.871)	
High FD Ind		-0.215***
		(-9.619)
Ln (Total Assets)	-0.0266***	-0.0231***
	(-6.327)	(-3.399)
Tangibility		-0.0744***
		(-4.135)
Age	0.00379***	0.00144
	(7.473)	(1.341)
Constant	0.334***	0.485***
	(9.754)	(8.593)
Observations	35,758	23,609
R-squared	0.658	0.591
Industry Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Impact of IBC on Governance

The table presents the impact of IBC on governance of firms. Governance is proxied by the percentage of independent directors in a firm in a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Ind. Dir. %	(2) Ind. Dir. %	(3) Ind. Dir. %	(4) Ind. Dir. %
Post IBC	0.0382***	0.0192***	0.0208***	0.0284***
	(15.43)	(7.055)	(7.755)	(12.35)
Leverage		-0.0647***	-0.0461***	-0.0190***
		(-8.871)	(-6.388)	(-2.710)
Ln (Total Assets)		0.00934***	0.0158***	0.0424***
		(5.636)	(9.806)	(15.01)
Tangibility		0.0126	0.0227**	0.00182
		(1.385)	(2.336)	(0.209)
Age		0.00247***	0.00210***	0.00254***
		(20.51)	(17.33)	(6.487)
Constant	0.312***	0.198***	0.141***	-0.115***
	(101.3)	(13.18)	(9.481)	(-5.081)
Observations	70,464	62,074	62,074	61,309
R-squared	0.006	0.069	0.100	0.705
Industry Fixed Effects	No	No	Yes	Yes
Firm Fixed Effects	No	No	No	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4.10: Impact of IBC on Governance - DID Analysis

The table presents the difference-in-differences (DID) analysis of the impact of the IBC on governance level of firms. Governance is proxied by the percentage of independent directors in a firm in a given year. In column (1), we divide the sample based on High Tang Ind. High Tang Ind is a binary variable that takes a value of 1 for firms that have tangibility value in the highest quartile of tangibility values for firms for a given year. It takes a value of 0 for firms that have tangibility value in the lowest quartile of tangibility values for firms for a given year. In column (2), we divide the sample based on High FD Ind. High FD Ind is a binary variable that takes a value of 1 for firms that have an interest coverage ratio in the lowest quartile of interest coverage ratios for firms for a given year. It takes a value of 0 for firms that have an interest coverage ratio in the highest quartile of interest coverage ratios for firms for a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Ind. Dir. %	(2) Ind. Dir. %
Post x High Tang Ind	-0.00662	
	(-1.046)	
Post x High FD Ind		0.0276***
		(3.335)
Post IBC	0.0338***	0.0142***
	(6.417)	(2.918)
High Tang Ind	0.00822	
	(0.822)	
High FD Ind		-0.0208
		(-1.041)
Leverage	-0.00669	0.000977
	(-0.706)	(0.0591)
Ln (Total Assets)	0.0339***	0.0301***
	(8.679)	(5.874)
Tangibility		0.00270
		(0.179)
Age	0.00416***	0.00234***
	(6.983)	(3.270)
Constant	-0.113***	-0.00373
	(-3.451)	(-0.0906)
Observations	30,812	19,524
R-squared	0.714	0.767
Industry Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11: Impact of IBC on R&D Intensity

The table presents the impact of IBC on R&D Intensity of firms. R&D Intensity is calculated as the ratio of R&D expense of the firm to its total assets in a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) R&D Intensity	(2) R&D Intensity	(3) R&D Intensity	(4) R&D Intensity
Post IBC	0.000951***	0.000869***	0.000763***	0.000429**
	(3.993)	(3.055)	(2.659)	(1.996)
Leverage		-0.00556***	-0.00498***	-0.00236***
		(-5.260)	(-4.712)	(-3.041)
Ln (Total Assets)		-0.000315	-0.000210	-0.00171***
		(-1.541)	(-0.971)	(-4.785)
Tangibility		-0.00193	-0.00195	-0.000536
		(-1.636)	(-1.576)	(-0.528)
Age		-8.01e-05***	-7.70e-05***	8.95e-05**
		(-7.280)	(-7.033)	(2.314)
Constant	0.00764***	0.0153***	0.0141***	0.0210***
	(26.00)	(8.711)	(7.801)	(7.832)
Observations	19,437	17,604	17,604	17,103
R-squared	0.001	0.030	0.044	0.846
Industry Fixed Effects	No	No	Yes	Yes
Firm Fixed Effects	No	No	No	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.12: Impact of IBC on R&D Intensity - DID Analysis

The table presents the difference-in-differences (DID) analysis of the impact of the IBC on R&D Intensity level of firms. R&D Intensity is calculated as the ratio of R&D expense of the firm to its total assets in a given year. In column (1), we divide the sample based on High Tang Ind. High Tang Ind is a binary variable that takes a value of 1 for firms that have tangibility value in the highest quartile of tangibility values for firms for a given year. It takes a value of 0 for firms that have tangibility value in the lowest quartile of tangibility values for firms for a given year. In column (2), we divide the sample based on High FD Ind. High FD Ind is a binary variable that takes a value of 1 for firms that have an interest coverage ratio in the lowest quartile of interest coverage ratios for firms for a given year. It takes a value of 0 for firms that have an interest coverage ratio in the highest quartile of interest coverage ratios for firms for a given year. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) R&D Intensity	(2) R&D Intensity
Post x High Tang Ind	0.000576	
	(0.846)	
Post x High FD Ind		-0.00195**
		(-2.011)
Post IBC	-0.000637	0.000770**
	(-0.993)	(2.274)
High Tang Ind	-0.000758	
	(-0.902)	
High FD Ind		0.00366**
		(2.080)
Leverage	-0.00104	-0.00225
	(-0.784)	(-1.567)
Ln(TA)	-0.000985*	-0.00264***
	(-1.768)	(-4.694)
Tangibility		0.000426
		(0.249)
Age	9.62e-05*	0.000189***
	(1.911)	(3.134)
Constant	0.0131***	0.0256***
	(2.589)	(6.212)
Observations	4,810	6,138
R-squared	0.872	0.884
Industry Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4.13: Impact of IBC on Tangibility and Asset Specificity

The table presents the impact of IBC on tangibility of assets and asset specificity of firms. Tangibility is obtained as the ratio of tangible assets of the firm to total assets. Asset specificity is obtained as the ratio of net PP&E of the firm to total assets of the firm. Post IBC is a binary variable that takes the value of 1 for years – 2017 and beyond.

	(1) Tangibility	(2) Tangibility	(3) Asset Specificity	(4) Asset Specificity
Post IBC	-0.00946***	0.00432***	-0.0148***	0.00150
	(-5.118)	(2.935)	(-8.567)	(1.142)
Ln (Total Assets)	-0.00573***	0.00598***	-0.00968***	-0.00187
	(-4.630)	(2.814)	(-8.128)	(-0.992)
Age	-0.000915***	-0.00275***	-0.000366***	-0.00228***
	(-10.66)	(-10.24)	(-4.420)	(-9.365)
Constant	0.327***	0.264***	0.329***	0.300***
	(31.72)	(17.49)	(33.06)	(22.18)
Observations	146,209	144,859	145,569	144,228
R-squared	0.176	0.808	0.167	0.826
Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Appendix

Table 4.14: Predictive variables of the classification model

This table lists the different variables used in the analysis from the literature.

Category of variables	Variables	Formula
LEVERAGE	Total Leverage	Total Debt to total assets
	Long Term Debt Percentage	long-term debt/total assets
	Interest Coverage Ratio	EBIT/interest expense
	Secured Debt Percentage	Secured Debt/total assets
	Short Term Debt Percentage	short-term debt/total assets
LIQUIDITY	Current Ratio	Current Liabilities/Current Assets
	Quick Ratio	(Current Assets-Inventory)/Current Liabilities
	R&D Intensity	R&D expense/total expenses
PROFITABILITY	NITA	Net Income/total assets
	PBITDASA	PBITDA / Sales
	Cash Flow Intensity	CFO/Total assets
TANGIBILITY	FATA	Fixed assets/Total assets
	Asset Specificity	Net PP&E / Total Assets
GOVERNANCE	Percentage of Institutional Ownership	
	Board of Directors	Independent Directors percentage
Size Related Metrics	Log Sales	Natural Logarithm of sales
	Log Total Assets	Natural Logarithm of Assets
Market Related Metrics	Market Cap	
	Tobin's Q	
Group Indicator	Ownership Code	

Table 4.15: Bank-wise Net NPAs to Net Advances

Bank	Mean	Median	SD	Min	Max
UNITED BANK OF INDIA	6.382	6.22	4.59	1.42	16.49
INDIAN OVERSEAS	5.502	3.2	4.97	0.57	15.33
DENA BANK	4.798	3.085	4.18	1.01	11.95
CENTRAL BANK OF	4.763	3.75	3.37	0.65	11.1
UCO BANK	4.663	3.17	3.78	0.89	13.1
ORIENTAL BANK OF	4.506	3.34	3.21	0.87	10.48
IDBI BANK LIMITE	4.413	1.97	5.04	0.34	16.69
PUNJAB NATIONAL	4.409	4.06	3.20	0.53	11.24
ALLAHABAD BANK	4.396	4.15	2.86	0.66	8.92
CORPORATION BANK	4.132	3.08	3.69	0.31	11.74
ANDHRA BANK	3.751	3.11	2.79	0.17	8.48
PUNJAB AND SIND	3.715	3.35	2.61	0.36	8.03
LAKSHMI VILAS BA	3.691	2.43	2.92	0.9	10.04
BANK OF MAHARASH	3.605	2.03	3.76	0.2	11.76
UNION BANK OF IN	3.597	2.71	2.45	0.81	8.42
BANK OF INDIA	3.476	2.34	2.50	0.91	8.28
CANARA BANK	3.315	2.65	2.16	1.06	7.48
SYNDICATE BANK	3.197	1.9	2.44	0.76	7.37
NAINITAL BANK LI	2.991	1.84	2.13	0.94	5.77
STATE BANK OF IN	2.791	1.94	2.89	0.57	11.61
VIJAYA BANK	2.597	1.82	1.40	1.3	4.8
INDIAN BANK	2.357	2.27	1.41	0.23	4.39
DHANLAXMI BANK L	2.319	2.58	1.30	0.3	4.76
JAMMU & KASHMIR	2.271	2.49	1.91	0.14	4.9
BANK OF BARODA	2.269	1.72	1.76	0.34	5.49
KARNATAKA BANK L	2.221	2.11	0.63	1.31	3.19
CSB BANK LIMITED	2.191	1.74	1.61	0.35	5.51
ICICI BANK LIMIT	1.866	1.24	1.61	0.45	5.43
SOUTH INDIAN BAN	1.859	1.45	1.39	0.28	4.71
IDFC BANK LIMITE	1.740	1.69	0.63	1.14	2.39
KARUR VYSYA BANK	1.679	0.74	1.70	0.07	4.98
CITY UNION BANK	1.599	1.7	0.83	0.44	2.97
YES BANK LIMITED	1.385	0.58	2.02	0.01	5.88
DCB BANK LIMITED	1.187	0.96	0.72	0.57	3.11
IDFC FIRST BANK	1.177	1.105	0.47	0.6	1.86
TAMILNAD MERCANT	1.127	0.89	0.71	0.24	2.4
BANDHAN BANK LIM	1.070	0.58	1.03	0.08	3.51
AXIS BANK LIMITE	1.011	0.46	0.99	0.27	3.64
FEDERAL BANK LIM	0.993	0.96	0.41	0.48	1.69
KOTAK MAHINDRA B	0.924	0.92	0.35	0.34	1.73
RBL BANK LIMITED	0.818	0.69	0.62	0.11	2.12
INDUSIND BANK LI	0.525	0.5	0.26	0.27	1.21
HDFC BANK LIMITE	0.299	0.31	0.07	0.18	0.4
Total	2.708	1.700	2.802	0.010	16.690

Table 4.16: Yearwise Transitions across Categories for Large Loan Contracts

The table presents the percentage of transitions made by large loan contracts originating in the starting category to each of the four ending categories. The percentages add up to 100% row-wise. The final column of the panel presents the total number of transitions out of the category specified in the first column in that year. Each panel presents the transition matrix for the specified year.

	Panel A: 2019					Panel B: 2020					
	N	O	D	S	Total (k)		N	O	D	S	Total (k)
N	96%	4%	0%	-	295	N	21%	66%	13%	1%	110
O	18%	78%	3%	0%	77	O	18%	78%	3%	0%	77
D	0%	0%	100%	-	2	D	11%	8%	81%	1%	64
S	-	-	-	100%	0	S	1%	0%	1%	98%	4

	Panel C: 2021					Panel D: 2022					
	N	O	D	S	Count (k)		N	O	D	S	Count (k)
N	97%	3%	1%	0%	1,105	N	96%	4%	0%	0%	1,406
O	24%	71%	5%	0%	145	O	24%	73%	3%	0%	220
D	6%	5%	90%	0%	95	D	6%	4%	90%	0%	85
S	1%	0%	0%	99%	14	S	2%	2%	3%	93%	8

	Panel E: 2023					Panel F: 2024					
	N	O	D	S	Count (k)		N	O	D	S	Count (k)
N	97%	3%	0%	0%	1,927	N	97%	3%	0%	0%	3,154
O	34%	62%	3%	0%	250	O	26%	72%	1%	0%	299
D	6%	5%	89%	0%	137	D	6%	1%	93%	0%	190
S	1%	4%	4%	92%	14	S	1%	0%	0%	99%	18

Table 4.17: Yearwise Transition Times across Categories for All Loans

The table presents the details of the time spent by loan accounts in a category before they transition into the next category, based on the full sample of loans (large and small). It captures the average, median and standard deviation of time spent in the category prior to the transition.

Transition	Metric	2019	2020	2021	2022	2023	2024
	Mean Transition Time (Days)	405	277	209	116	83	31
O $\rightarrow N$	Median Transition Time (Days)	210	149	138	74	60	29
	Std. Dev. of Transition Times	427	292	206	124	70	15
	Mean Transition Time (Days)	218	225	185	130	82	37
O $\rightarrow D$	Median Transition Time (Days)	75	90	102	97	53	31
	Std. Dev. of Transition Times	307	289	191	143	77	15
	Mean Transition Time (Days)	373	365	219	193	81	32
D $\rightarrow N$	Median Transition Time (Days)	114	156	120	120	57	29
	Std. Dev. of Transition Times	441	373	237	168	73	10
	Mean Transition Time (Days)	441	232	215	105	95	43
D $\rightarrow O$	Median Transition Time (Days)	175	89	95	75	88	34
	Std. Dev. of Transition Times	454	291	191	88	59	19
	Mean Transition Time (Days)	563	712	506	221	194	-
D $\rightarrow S$	Median Transition Time (Days)	263	867	435	179	217	-
	Std. Dev. of Transition Times	445	435	310	172	92	-
	Mean Transition Time (Days)	847	654	292	32	83	29
S $\rightarrow D$	Median Transition Time (Days)	854	670	216	27	83	29
	Std. Dev. of Transition Times	377	306	235	38	-	-