The Effect of Bank Capital Constraints on Borrower Accounting Practices: Evidence from India's AQR

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Prateek Nahar
Ph.D. Scholar, Finance and Accounting, IIM Raipur
21fpm003@iimraipur.ac.in

Dr. Yogesh Chauhan
Associate Professor, Finance and Accounting, IIM Raipur
yogesh@iimraipur.ac.in

Prof. Chinmoy Ghosh
Gladstein Professor of Business and Innovation, University of Connecticut
chinmoy.ghosh@uconn.edu

Abstract

This study examines how an exogenous shock to bank capital affects borrowers' accounting practices. Following the Indian Asset Quality Review (AQR), which caused significant capital erosion in banks, we find that borrowers from AQR-exposed banks exhibit a substantial reduction in accounting conservatism. This suggests that undercapitalized banks adopt a defensive strategy to mitigate further capital shortfalls and avoid breaches of accounting-based debt covenants. We also find that the decline in conservatism is associated with higher interest rates, reduced opportunistic related-party transactions, and lower dividend payouts following the AQR. These results suggest that banks weigh the costs and benefits of relaxing the demand for accounting conservatism to stabilize their financial position.

Keywords: Bank capital, Accounting Conservatism, Indian Asset Quality Review (AQR); Debt Covenants

JEL Codes: G21, G28, M41, M48

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1. Introduction

This study examines whether the interaction between borrowers' accounting conservatism and lenders' regulatory capital adequacy generates a distinctive dynamic in debt contract design. Accounting conservatism—by accelerating the recognition of expected losses—provides lenders with timelier signals of downside risk (Basu, 1997; Watts, 2003). At the same time, however, the accelerated recognition of losses increases the likelihood of technical default through covenant violations (Watts, 2003). Such violations can trigger internal loan downgrades that reduce banks' reported regulatory capital (Chava & Roberts, 2008), intensifying the regulatory frictions that banks must manage when structuring covenants (Demerjian, Owens, & Sokolowski, 2023). We argue that under tighter capital constraints, banks respond not only by restricting credit supply (Chopra et al., 2021) but also by redesigning debt contract requirements to balance the informational benefits of conservatism against its costs in precipitating defaults and weakening regulatory capital (Van den Heuvel, 2002; Murfin, 2012; Qiang & Wang, 2024).

To test this argument, we exploit the Reserve Bank of India's (RBI) Asset Quality Review (AQR)—a large-scale banking clean-up initiative introduced in 2016 during a period of macroeconomic stability—that imposed a substantial and plausibly exogenous decline in regulatory capital across Indian banks. The nature of AQR is unique due to its vast scale, level of inquiry and minimal capital support from the government. The AQR required the recognition of previously concealed non-performing assets (NPAs) and forced banks to provision for these losses without sufficient capital support, directly eroding Tier 1 capital (Chari et al., 2021; Chopra et al., 2021).[1] This deterioration in reported asset quality simultaneously reduced

[1] Following the AQR, the ratio of gross NPAs to gross advances in the Indian banking system rose sharply from 4.6% to 11.5% (Chopra et al., 2021).

capital buffers, constrained credit supply, and increased the prevalence of "zombie lending"—the rolling over of loans to weak borrowers to avoid further write-downs (Chari et al., 2021; Chopra et al., 2021; Mannil et al., 2024). Collectively, these features establish the AQR as a powerful quasi-natural experiment that generated a large and unexpected regulatory capital shock, enabling us to examine how capital adequacy shapes lenders' contracting choices and responses to borrowers' accounting practices.

We posit two opposing views on how the erosion of regulatory capital adequacy affects accounting conservatism. On one hand, when banks experience adverse capital shocks, they typically respond by becoming more risk-averse and tightening lending standards (Chava & Purnanandam, 2011; Murfin, 2012; Lo, 2014). A key mechanism through which this risk aversion manifests is enhanced monitoring and greater reliance on accounting-based covenants that require timely and conservative loss recognition by borrowers (Watts, 2003; Ahmed, Billings, Morton, & Stanford-Harris, 2002; Qiang, 2007; Zhang, 2008; Gigler, Kanodia, Sapra, & Venugopalan, 2009; Nikolaev, 2010; Aier, Chen, & Pevzner, 2014). While such conservatism increases the likelihood of covenant violations by lowering reported earnings and net assets, it also disciplines borrower behavior. To avoid violations, borrowers often curtail dividend payouts, restrain leverage, and reduce risk-taking, thereby strengthening lenders' claims in liquidation and limiting expected credit losses. By influencing conservatism, banks can simultaneously temper perceptions of borrower credit risk and reduce covenant-triggering events, ultimately preserving regulatory capital buffers and mitigating the prospect of regulatory intervention.

From the borrower's perspective, adopting more conservative accounting policies can be strategically advantageous, as it facilitates continued access to credit, particularly in environments where banks are capital-constrained (Donelson, Jennings, & McLinnis, 2017; Qiang & Wang, 2024). In the post-AQR setting, this reciprocal adjustment between banks and borrowers suggests a contracting equilibrium in which accounting conservatism operates as a central mechanism for both credit risk mitigation and regulatory capital preservation.

On the other hand, although greater accounting conservatism facilitates early detection of borrower credit risk, banks facing acute regulatory capital pressure in the aftermath of the AQR may instead prefer borrowers to adopt less conservative reporting in order to minimize covenant violations and their consequences (Watts, 2003; Ahmed, Billings, Morton, & Stanford-Harris, 2002; Nikolaev, 2010; Lara, Osma, & Penalva, 2020). Covenant breaches typically trigger internal loan downgrades[2], elevate regulatory risk classifications, and mandate incremental equity capital—actions that directly weaken capital adequacy ratios and draw heightened regulatory scrutiny (Demerjian, Owens, & Sokolowski, 2023). In India's post-AQR environment, these costs are magnified, as regulatory guidance curtails banks' ability to renegotiate loan terms or grant covenant waivers[3]. As a result, covenant breaches may force the automatic reclassification of borrower's credit rating ~~loans as NPAs (sub-standard~~), leading to immediate capital requirements[4] and further erosion of already scarce capital buffers.

When external equity issuance is costly, as it is for many AQR-affected banks (Chopra et al., 2021) avoiding such capital hits becomes paramount. Further, strengthened Prompt

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[2]Rating agencies also explicitly evaluate firms' capacity to comply with covenant requirements. For example, Crisil Ratings notes that it assesses explicitly "the ability of the promoters to address all performance and capital structure covenants and maintain a steady drawdown from specified debt facilities."

[3] Li (2013) shows that without the possibility of renegotiation, greater accounting conservatism increases inefficient covenant-triggered liquidations, reducing overall surplus—costs that are magnified for capital-constrained lenders.

[4] In the Indian banking system, credit ratings play a pivotal role in assessing the health and performance of loans, both at the time of loan origination and throughout the life of the loan. These ratings directly influence the amount of risk-weighted capital a bank must hold under regulatory requirements. Loans with higher credit ratings (e.g., AAA) carry lower risk weights, requiring banks to set aside less equity capital. Conversely, a downgrade in a borrower's credit rating increases the loan's risk weight, compelling the bank to allocate a larger portion of its capital as a buffer. This reallocation effectively reduces the bank's available regulatory capital, which may constrain its ability to extend new credit or pursue other investment activities. In this way, deteriorating credit quality has immediate implications not only for risk management but also for a bank's lending capacity and overall financial flexibility. According to the Standardised Approach to credit risk under Basel regulations adopted by the Reserve Bank of India (RBI), banks must rely on credit ratings issued by approved external agencies to assign risk weights. The RBI has explicitly identified agencies that meet the eligibility criteria under its revised framework. As per RBI guidance, "the rating assigned by the eligible external credit rating agencies will largely support the measure of credit risk". This reliance places a strategic emphasis on external credit assessments in determining the capital adequacy of Indian banks. *https://rbidocs.rbi.org.in/rdocs/content/pdfs/NT08MC01042025_A.pdf.*

Corrective Action (PCA) framework regime after AQR, decrease in capital imposes stringent regulatory restrictions. In this context, relaxing demands for accounting conservatism may offer a relatively low-cost mechanism to sidestep covenant-related reclassifications and preserve capital adequacy. By encouraging delayed loss recognition, borrower's avoid covenant violations, reduce the likelihood of downgrades, and banks benefit by deferring recogninzing risky assets[5] without resorting to costly recapitalization. We refer to this response as the "capital-constrained monitoring channel", whereby banks under regulatory stress strategically soften their monitoring demands and shape borrower reporting choices to prioritize regulatory avoidance over timely recognition of credit risk.

From borrower's perspective decreasing conservatism offer various benefits without any additional cost regarding raising capital, avoiding lenders' intervention and penalties due to covenant violation. Further, decrease in conservatism will provide them survival chance by showing optimistic financial results and rasing capital. In post-AQR environment, where banks are intransigent to restructuring of loan, borrower will avoid the covenant violation and troubles attached with such violation by delaying loss recognition (Chodorow-Reich and Falato, 2022; Martin and Roychowdhury, 2015).

Alternatively, AQR-exposed banks could attempt to mitigate capital pressure by relaxing accounting-based covenants, thereby reducing the likelihood of borrower violations. However, in the post-AQR environment, regulatory restrictions substantially limited the feasibility of covenant restructuring, making this approach less effective.

Our empirical analyses consider the AQR process conducted between 2016 and 2019. Notably, although the AQR applied to all banks, the requiarement of additional provisioning requirements was contingent on materiality thresholds: banks were required to disclose (and

[5] In India, risk weight of corporate borrowers decided based on credit ratings. By avoding violations and delaying loss recignition firms can maintain ex-ante credit rating and risk weights in bank portfolio.

provision) only if (a) the additional provisioning mandated by the RBI exceeded 15% of the bank's reported net profit after tax, or (b) the additional gross non-performing assets (GNPAs) identified by the RBI exceeded 15% of the bank's incremental GNPAs for the reference period. Because not all banks crossed these thresholds in the same year, the variation in timing across banks generates plausibly exogenous, staggered shocks to regulatory capital. To isolate the causal effect of these shocks, we implement a staggered difference-in-differences (DiD) design with two-way fixed effects (firm and year).

We posit that the effect of the AQR on borrower accounting conservatism depends on two cross-sectional dimensions: (i) the extent to which a firm's borrowing is concentrated with AQR-exposed banks, and (ii) the severity of its banks' exposure to the AQR. Firms that rely more heavily on AQR-affected banks are more vulnerable, as their credit access and monitoring arrangements are disproportionately influenced by banks facing regulatory capital shocks. The magnitude of the AQR shock, however, varies across banks. Those with higher exposure—evidenced by a larger share of stressed assets or sharper capital erosion—face more binding capital adequacy constraints in the aftermath of the AQR. Borrowers connected to such banks will therefore be more likely to encounter adjustments in loan terms, covenant enforcement, and monitoring intensity.

To capture this channel empirically, we construct a firm-level exposure measure that links each borrowing firm to its banks' AQR exposure. Bank-level AQR exposure is measured as provisioning divergence, defined as the difference between the provisions mandated by the RBI and those initially reported by the bank, scaled by a bank's total assets. This measure reflects the extent to which a bank has previously under-recognized asset quality issues. A larger divergence indicates a greater capital adjustment following the AQR, making it a natural proxy for the severity of the bank's AQR-induced capital erosion and, by extension, the intensity of monitoring and reporting pressures transmitted to its borrowers. At the firm level, "treatment firms" are defined by their borrowing concentration with AQR-exposed banks before initiating the AQR. Specifically, firms with a larger share of outstanding loans from banks exhibiting higher provisioning divergence are classified as treatment firms (i.e., AQR-exposed firms).

Our staggered DiD design spans a six-year window, three years before and three after the AQR. The analysis compares borrowers' conditional conservatism changes between AQR-exposed and non-AQR-exposed firms. Conditional conservatism is measured using the asymmetric timeliness framework of Ball and Shivakumar (2005). All specifications control for key firm-level characteristics commonly associated with conservatism—firm size, sales growth, and leverage—and include both firm and year fixed effects to absorb unobserved heterogeneity. For robustness, we also employ the Khan and Watts (2009) firm-year *C-Score* model as an alternative measure of accounting conservatism.

We find that AQR-exposed firms experience a significant decline in accounting conservatism following the AQR. The effect is economically substantial, with conservatism decreasing by approximately 130 percent relative to pre-AQR levels. This pattern aligns with the "capital-constrained monitoring" channel, whereby banks facing binding capital pressures reduce their reliance on accounting-based monitoring mechanisms. Notably, the effect is transitory: the decline in conservatism dissipates within two years of the AQR, consistent with banks' capital positions recovering as buffers are rebuilt and regulatory frictions ease. These findings highlight the temporary but meaningful influence of regulatory capital shocks on firms' financial reporting behavior.

We further find that the decline in accounting conservatism is more pronounced for firms borrowing from AQR-exposed banks with low capital prior to the AQR. These results provide direct evidence for the "capital-constrained monitoring" channel, indicating that the effect of regulatory shocks on borrower conservatism is strongest where banks' balance sheet vulnerabilities are most binding.[6]

In the following analysis, we examine whether accounting-based debt covenants help explain the observed decline in borrower conservatism. Direct covenant-level data for Indian bank loans are not publicly available. Consistent with prior literature, we rely on indirect proxies that capture the tightness of lender oversight and monitoring frictions—factors that influence the presence and enforcement of covenants (Bharath et al., 2011; Murfin, 2012). Although these proxies do not directly measure covenant violations, they provide informative cross-sectional variation in lender–borrower contracting environments, enabling an assessment of how covenant-related pressures shape borrower reporting behavior.

The first proxy we use is the interest coverage ratio, which banks commonly employ as an accounting-based debt covenant (Demerjian, 2011). We find that borrowers closer to the breaching threshold of such covenants (i.e., with lower interest coverage ratios) tend to exhibit reduced accounting conservatism.

Second, we use relationship banking as a proxy for covenant reliance. Prior research shows that long-standing bank–borrower relationships reduce the need for formal covenants because lenders can supplement accounting information with soft information (Prilmeier, 2017). Gam and Liu (2024) document that relationship lenders are less likely to strictly enforce covenants, whereas non-relationship lenders rely more heavily on accounting-based triggers (Gormley, Kim, & Martin, 2012). We define a relationship bank as one with which a borrower maintains credit connections for the current year and at least the two preceding consecutive years (Bhue, Prabhala, & Tantri, 2015; Tantri & Vishen, 2025). Consistent with this view, the

[6] In case of breach of covenant, it provides an opportunity for banks to take punitive action by charging a higher interest rate and consider it as an event of default. Such technical events provide banks with bargaining power over firms, which influence firms' accounting and corporate decisions. https://bankofindia.co.in/documents/20121/0/Fair+Practices+code+on+Lenders+Liability.pdf

decline in accounting conservatism following the AQR is more pronounced for firms borrowing from non-relationship lenders.

Third, we consider geographic distance as a source of informational frictions. Hollander and Verriest (2016) show that geographically distant lenders rely more heavily on accounting-based covenants to monitor credit risk. If covenant-based monitoring is the channel through which AQR-exposed banks influence reporting, the effect should be stronger for borrowers whose lenders are farther away. In line with this prediction, our results indicate that the decline in conservatism is significantly larger when borrower–lender distance is greater.

Our study contributes to two broad strands of literature. First, we extend research on how capital-constrained banks manage regulatory capital. Prior studies show that banks actively adjust financial reporting and operational decisions to mitigate the risk of violating capital adequacy requirements. For example, Beatty, Chamberlain, and Magliolo (1995) and Ahmed, Takeda, and Thomas (1999) document that bank managers strategically use loan loss provisions to reduce expected regulatory costs. Owens and Wu (2015) demonstrate that banks alter real activities when capital buffers are thin, and more recently, Demerjian, Owens, and Sokolowski (2023) find a negative relationship between capital adequacy and lenders' reliance on covenants. Similarly, Plosser and Santos (2024) provide evidence that capital-constrained banks may even forgo positive-NPV opportunities to conserve capital.

Building on this literature, we identify a complementary channel of bank capital management—shaping the accounting practices of borrowing firms. We provide novel evidence that undercapitalized banks can influence borrowers to adopt less conservative reporting practices to reduce the likelihood of covenant violations, thereby alleviating pressure on regulatory capital ratios. This mechanism is particularly relevant when raising fresh equity is costly, making regulatory avoidance via borrower accounting a low-cost alternative. To our knowledge, this is the first study to show that banks facing acute capital constraints steer borrowers' accounting choices toward regulatory relief rather than prudent capital preservation, thereby extending the understanding of how capital adequacy pressures affect both lender and borrower behavior.

Second, we contribute to the accounting and banking literature by examining how an exogenous regulatory shock to bank capital affects both lenders' monitoring incentives and borrowers' financial reporting practices. Prior studies (e.g., Khan & Lo, 2019; Qiang & Wang, 2024) focus on capital shortfalls arising from banks' internal decisions—such as loan write-downs - which typically induce tighter lending standards and enhanced monitoring (Chava & Purnanandam, 2011). By contrast, we study the Indian AQR, an externally imposed audit that uncovered large volumes of previously unrecognized NPAs and prompted significant capital erosion (Chopra et al., 2021). Unlike internally driven shocks, the AQR constrained banks' strategic flexibility: raising external capital was costly, and post-AQR regulations limited the scope for loan renegotiation. In this environment, we argue that banks respond not by intensifying monitoring, but by reducing reliance on accounting-based monitoring. Consistent with this strategic adjustment, firms borrowing from AQR-exposed banks adopted less conservative financial reporting, helping banks preserve regulatory ratios without resorting to expensive capital raising.

The remainder of the paper is structured as follows. Section 2 provides a discussion of accounting conservatism and develops the associated hypotheses. Section 3 outlines the research design, data collection process, and identification strategy. Sections 4 and 5 present the baseline and robustness results. Sections 6, 7, and 8 discuss a series of tests for the accounting debt covenant violation channel. Section 9 provides the concluding remarks.

2. Background Literature and Hypothesis Development

In response to 1988 Latin American debt crisis, regulators from various countries introduced substantially more stringent capital adequacy standards under first Basel I Accord.

A central innovation of Basel I is that minimum capital requirements are now tied to risk-weighted assets (RWA). Assets with greater credit or market risk—such as unsecured loans or volatile securities—are assigned higher risk weights, which increase the denominator of the capital adequacy ratio. As a result, banks must hold larger amounts of Common Equity Tier 1 (Tier 1) capital to remain compliant. By directly linking capital requirements to asset risk, Basel norms raises the cost of holding risky assets and creates strong incentives for banks to shift portfolios toward safer assets and curb overall risk-taking (Hanson, Kashyap, & Stein, 2011; Gropp, Mosk, Ongena, & Wix, 2019; Lin, Xu, & Zhang, 2023).

To ensure that these strengthened standards are met in practice, regulators increasingly rely on asset-quality assessments that provide a clearer picture of bank balance sheets. In India, this took the form of the AQR, a system-wide reassessment of banks' asset quality and capital buffers. While designed to reinforce market discipline, the AQR also subjected banks to heightened regulatory and market scrutiny. Banks that fell short could be placed under the "Prompt Corrective Action" (PCA) framework, which restricts lending, caps compensation, and curtails strategic discretion (Acharya, 2020).

Faced with these risks, AQR-exposed banks have strong incentives to protect their capital positions—not only to satisfy regulators but also to preserve market confidence and maintain autonomy. One key way banks can adjust is through accounting choices. Banks could delay the reclassification of restructured loans into NPAs, underestimate expected credit losses (Kim et al. 2021; Kim et al. 2023; Gee et al. 2024; Chen et al. 2024), or smooth income to bolster reported profitability and retained earnings (Bhushan, 2024).

While banks respond to capital pressures through accounting discretion, the ripple effects of regulation can also extend to borrowers (Qiang & Wang, 2024). Because credit supply and monitoring practices are shaped by banks' capital positions (Diamond & Rajan, 2000), borrowing firms face parallel incentives to adjust their financial reporting in order to influence perceptions of creditworthiness (Khan & Lo, 2019) and reduce potential credit losses for lenders (Qiang & Wang, 2024). Consistent with this view, prior research shows that firms under covenant pressure frequently manage earnings or adopt more aggressive reporting strategies (DeFond & Jiambalvo, 1994; Sweeney, 1994; Dichev & Skinner, 2002; Christensen, Nikolaev, & Wittenberg-Moerman, 2016). In this environment, accounting discretion becomes a shared margin of adjustment for both banks and borrowers, shaping the evolution of credit relationships as regulatory capital requirements tighten.

The Indian AQR provides a compelling setting to examine this mechanism. By requiring banks to reclassify previously underreported or restructured loans as NPAs, the AQR directly increased provisioning requirements and reduced Tier 1 capital (Acharya & Steffen 2020; RBI 2016). Facing this erosion of capital adequacy, banks had strong incentives to prevent further depletion of Tier 1 ratios. One potential channel operates through borrower relationships: conservative accounting practices reduce reported earnings and net assets, heightening the likelihood of covenant violations (Ahmed et al. 2002; Nikolaev 2010). To mitigate such risks, borrowers avoid excessive dividend payouts, leverage, and risk-taking, thereby preserving banks' liquidation claims and limiting credit losses. More broadly, conservatism—particularly timely loss recognition—enhances the credibility of financial statements and strengthens the contracting role of accounting (Watts 2003; Qiang 2007; Zhang 2008; Gigler et al. 2009; Aier et al. 2014). Stronger borrower financial reporting can also support higher credit assessments (Ball & Shivakumar, 2005), which lower regulatory risk weights and ease capital requirements, ultimately helping banks conserve scarce Tier 1 capital.

From the borrower's perspective, conservative accounting policies also carry potential advantages. Conservatism operates as a commitment device that reduces information asymmetry, mitigates agency conflicts, and strengthens contractibility with lenders (Donelson, Jennings, & McLinnis, 2017; Qiang & Wang, 2024). In the post-AQR environment—marked by tighter capital supply (Chopra et al., 2021)—the interaction of bank incentives and borrower reporting choices could reinforce a contracting equilibrium in which conservatism aligns incentives, disciplines opportunistic behavior, and indirectly supports the preservation of regulatory capital.

While accounting conservatism enhances contract enforcement and strengthens creditor protection, it imposes costs on borrowers by increasing the likelihood of technical covenant violations (Martin & Roychowdhury, 2015). Such violations raise borrowing spreads, trigger collateral requirements, accelerate repayment obligations, and generate adverse effects on leverage, investment, and managerial turnover (DeFond & Jiambalvo, 1994; Sweeney, 1994; Dichev & Skinner, 2002; Chava & Roberts, 2008). These costs are amplified in the post-AQR environment, where regulatory interventions curtail banks' ability to restructure loans without immediately classifying them as NPAs (Chopra et al., 2021). In this regime, covenant breaches trigger loan downgrades, compel higher risk-weight and regulatory capital requirment, and erode Tier 1 capital ratio. The resulting decline in Tier 1 capital raises banks' cost of funding, which is likely to be transmitted to borrowers through tighter contract terms, higher refinancing risk, and reduced credit availability. Anticipating these consequences, borrowers of AQR-exposed banks will have stronger ex-ante incentives to reduce conservatism in financial reporting to lower breach risk and preserve financing flexibility.

Debt contracting theory also predicts that when renegotiation becomes exorbitantly costly, the contracting equilibrium shifts toward second-best arrangements that reduce covenant violation risk (Watts, 2003; Beatty, Weber, & Yu, 2008). Further, Chodorow-Reich and Falato, (2022) suggest that bank health transmit to borrowers through covenants and banks are more likely to take action for covenant violation, if they are in bad health In the post-AQR setting, less accounting conservatism can represent such an adaptation: it reduces the likelihood of covenant breaches and helps banks conserve regulatory capital. Therefore, borrowers and lenders both share incentives to move toward less conservative reporting. (Due to clear picture from intensive audit under AQR, banks requirement for conservatism decreases due to new age information environment, where auditor looks into borrower's laon performance across the banking sector.)

Given theoretical predictions from debt contracting and regulatory capital considerations, an open empirical question remains of how the AQR affects borrowing firms' accounting conservatism. Empirically testing this prediction is essential to understanding how regulatory interventions propagate through the credit channel and shape firm-level financial reporting decisions.

In examining this issue, it is important to consider why banks might prefer influencing accounting conservatism of borrowers rather than relying exclusively on debt covenants. While accounting-based covenants can help manage violations (Denerjian et al., 2023), post-AQR restrictions on loan restructuring constrain banks' ability to adjust Tier 1 capital through covenant renegotiation[7]. Under these conditions, influencing borrowers' conservatism provides a more direct mechanism to safeguard Tier 1 capital and mitigate the costs associated with covenant breaches.

H1: The undercapitalization of banks resulting from the AQR influences the accounting conservatism of borrowing firms, differentiating them from other firms.

3. Data and Method

We obtain our data from two primary sources. First, we manually collect firm-bank loan-level data from the Ministry of Corporate Affairs (MCA), which oversees an Index of Charges database.[8] In India, every creditor must register the loan against the assets of the borrowing firms (Mannil et al., 2024; Chopra et al., 2021). Table OA1 of the Online Appendix

[7] Further, changes in covenant requires costly renegotiation and covenant design and implementation for preserving credit risk is cotly affair. Where as change in damnd for conservatism is low cost mechanism ().
[8] The data are available at https://www.india.gov.in/official-website-ministry-corporate-affairs.

includes an overview of the MCA dataset. Second, we acquire firm-specific data from the Centre for Monitoring Indian Economy (CMIE) Prowess Dx. We match MCA data with CMIE using the CIN number. We also obtain bank-level information from CMIE Prowess Dx and manually match it with the MCA database. Our sample comprises all firms listed in India from 2013 to 2019. Table OA2 of the Online Appendix provides the sampling process. We restrict our sample to 2019 owing to the effects of the COVID-19 pandemic and resultant regulatory amendments. In the wake of the pandemic, banks were allowed to defer the recognition of NPA, and a moratorium on loan repayments was instituted. Additionally, we omit the financial firms identified with the National Industry Classification (NIC) codes 64 to 66 from our sample. To ensure the robustness of our results, we include only firms with more than one observation in the sample period. Our final sample comprises 19,105 firm-year observations after eliminating observations with missing variables. All variables are winsorized at the 1% level to reduce the impact of outliers.

Measurement of Accounting Conservatism

We measure conditional accounting conservatism following Ball and Shivakumar (2005), who estimate the asymmetry in the recognition of bad news relative to good news by examining the relationship between accruals and cash flows.

$$ACC_{it} = \beta_0 + \beta_1\ DCFO_{it} + \beta_2\ CFO_{it} + \beta_3\ DCFO_{it} \times CFO_{it} + \epsilon_{it} \quad (1)$$

ACC_{it} measures accruals for year *i* and firm *t,* calculated as (Net profit – Net Operating Cashflow, scaled by average total assets). CFO_{it} represents operating cash flows, derived from the cash flow statement and scaled by the average total assets. $DCFO_{it}$ is a dummy variable equal to 1 if CFO_{it} is negative and 0 otherwise. We expect β_2 to be positive if firms are engaged in the timely recognition of economic gains, and expect β_2 to be negative if firms utilize accruals to reduce the variability of cashflow (Ball & Shivkumar, 2005). Additionally, if firms are more prompt in recognizing economic losses than gains, we expect β_3 to be positive. This coefficient is the primary focus of our analysis.

Summary Statistics

Panel A of Table 2 presents the descriptive statistics of borrowing firms. The average *CFO* level is 0.05, similar for treatment and control firms. We use three control variables for accounting conservatism: *Size, Growth, and Leverage.* Panels B and C suggest that, on average, AQR-exposed firms are slightly larger, less financially leveraged, and have lower growth, but the differences are statistically insignificant.

Research design

As discussed above, both demand-side (proactive or defensive channel) and supply-side (firms' incentives for timely loss recognition—i.e., accounting conservatism) mechanisms can simultaneously influence timely loss recognition. The primary empirical challenge in isolating the effect of bank undercapitalization resulting from the AQR on borrowers' accounting conservatism lies in disentangling the supply-side response, as a shock to bank capital may also influence firms' accounting choices. However, as noted earlier, the Indian AQR was implemented during a period of macroeconomic stability (Chopra et al., 2021), making it less likely that firms independently adjusted their accounting conservatism in response to external economic conditions. We next exploit bank-level heterogeneity induced by the AQR to identify treatment firms—those borrowing from more severely affected banks—where the bank's bargaining power is likely to outweigh that of the firm. This empirical design will allow us to isolate variations in the accounting conservatism of borrowing firms primarily attributable to demand-side pressures from the lending bank.

We argue that the demand-side effect is more pronounced for firms with concentrated borrowing from banks that were severely affected by the AQR. Under the AQR process, banks are required to make additional provisions if either (a) the incremental provisioning requirement identified by the AQR exceeds 15% of the bank's net profits or (b) the additional gross Non-Performing Assets (NPAs) uncovered by auditors exceed 15% of the incremental gross NPAs for the year[9]. To quantify the extent of AQR exposure, we follow Chopra et al. (2021) and compute a divergence ratio (*Divergence ratio*), defined as the divergence in provisioning figures (as identified by the AQR) scaled by the bank's total assets. The divergence ratio is set to zero for lenders with no AQR-identified divergence or where the divergence falls below the specified threshold.

To measure a firm's exposure to AQR-affected banks, we use the following equation:

$$Bank\ Expsoure_{it} = \sum_{j=1}^{N} Loan\ Value_{j,i} * Divergence\ ratio_{jt} \qquad (2)$$

j and *i* represent bank *j* and firm *i*, respectively. A higher *Divergence ratio* indicates that the bank's capital has been substantially depleted due to the additional provisions required by the AQR; a higher *Loan Value* reflects the greater exposure of the firm to the bank. We estimate the pairings of a firm's loans and bank relationships based on the average amount of a firm's loans outstanding (*Loan Value*) from a bank in the years preceding the AQR (2013–2016). In sum, *Bank Exposure* captures the extent to which a firm is exposed to AQR-exposed banks. Thereafter, we create an indicator variable, *AQR_EXP* (treatment firms), which equals 1 if a firm's *Bank Exposure* is greater than the median value of *Bank Exposure* of our sample firms and zero otherwise. Note that *AQR_EXP* captures the joint effect of the extent to which a bank is exposed to the AQR and the extent to which a firm is exposed to the particular AQR-exposed bank. Therefore, *AQR_EXP* is a proxy for the demand-side effect on timely loss recognition.

Difference in Differences (DiD) test

[9] Chopra et al. (2021) find that the Indian AQR exercise leads to an average (median) additional provisioning of 86.3% (43.66%) of net profits, driven by an increase in gross NPAs.

We use the staggered Difference in Differences (DiD) regression combined with Ball and Shivkumar's (2005) model for the causal inference. We use the following regression model, which is an expanded version of equation (1):

$$ACC_{it} = \beta_0 + \beta_1\ DCFO_{it} + \beta_2\ CFO_{it} + \beta_3\ DCFO_{it} \times CFO_{it} + \beta_4\ AQR\_EXP_{it} + \beta_5\ DCFO_{it} \times AQR\_EXP_{it} + \beta_6\ CFO_{it} \times AQR\_EXP_{it} + \beta_7\ DCFO_{it} \times CFO_{it} \times AQR\_EXP_{it} + X_{it} + X_{it} \times DCFO_{it} + X_{it} \times CFO_{it} + X_{it} \times DCFO_{it} \times CFO_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it} \quad (3)$$

Here, i, t, and j represent firm i, year t, and industry j, respectively. ACC_{it}, $DCFO_{it}$, and CFO_{it} are defined similarly as in equation (1). Our coefficient of interest, β_7, measures the change in a borrowing firm's accounting conservatism due to the AQR exposure of its lending banks. We include firm-fixed effects (δ_i) to account for the firm time invariant supply effect (Khwaja and Mian, 2008; Chopra et al., 2021) and year-fixed effects (η_t) to control for time-invariant heterogeneity. Industry-specific, time-varying demand shocks (e.g., bank lending practices and regulations may differ across industries and evolve over time) can also influence firms' incentives to report timely loss recognition. We use industry-by-year fixed effects (γ_{jt}) to account for these shocks and absorb time-varying industry-level effects.

The Indian central bank conducted the AQR exercise at the end of the financial year 2016. Banks were promptly notified of any divergence identified during the exercise and were required to disclose these divergences in their subsequent annual reports. For instance, at the end of the financial year 2016, the central bank would conduct the AQR based on the annual report for the financial year 2015–2016, with banks disclosing the results of any divergence in their 2017 annual report. Therefore, we designate 2017 as the treatment year, during which the provisions resulting from the AQR divergence were recognized. Further, not all AQR-exposed banks crossed the threshold in the same year. Some banks crossed the threshold in 2017, while others did so in 2018 or 2019. We expect that once a bank is exposed to the AQR shock, it will actively seek to avoid further breaches of the threshold and the associated costs. Consequently, once a firm is classified as a treatment firm, it will remain a treatment firm throughout the sample period (see Callaway and Sant Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020).

We include several firm-level attributes (X_{it}): *Size*, measured by the natural logarithm of average total assets; *Growth*, measured by sales growth; and *Leverage*, calculated as total borrowings scaled by average total assets. Additionally, we include interactions between these variables and *CFO*, *DCFO*, and the interaction term *CFO* × *DCFO*. These interactions control for variation in timely loss recognition with firm-level attributes (LaFond & Watts, 2007; Roychowdhury & Watts, 2007; Gormley et al., 2012). With these controls, the coefficient (β_7) of *AQR_EXP* will capture the effect of the AQR on timely loss recognition that is not influenced by changes in firm-level attributes. Finally, we cluster standard errors at the firm level to correct for heteroskedasticity and ensure robust inference.

4. Results and Discussion

Table 3 presents the results of regression model (3). Our primary variable of interest is the coefficient of *DCFO×CFO×AQR_EXP*, which reflects the effect of the AQR on borrowing firms' timely loss recognition. The estimated coefficients are negative and significant across all model specifications (Columns 1 to 3). Notably, the coefficients are stable, ranging between -0.173 and -0.196, indicating that our estimates are not sensitive to model specification and are unlikely to be affected by omitted variables bias. The effect is also economically significant, indicating a 130% decrease in timely loss recognition, from 0.145 to -0.044 (0.145 + -0.189). This finding implies that AQR-exposed banks relax demand for timely loss recognition. The coefficient of *CFO* is negative and significant, indicating the role of accruals in reducing noise in cash flows (Dechow, Kothari, and Watts, 1998). However, the coefficients of *DCFO×CFO* are insignificant, except for column (1), which indicates that timely loss recognition is not significant before the AQR exercise for our sample firms during the study period. The coefficients of *AQR_EXP* are negative, suggesting that the levels of accruals decrease following the AQR. However, the coefficients of *CFO×AQR_EXP* are significantly positive, implying that the role of accruals in reducing noise in cash flows diminishes after the AQR.

De Chaisemartin and D'Haultfoeuille (2020) argue that the estimated treatment effect in a staggered DiD with two-way fixed effects might be biased when the treatment effect is heterogeneous (Baker et al., 2022). Our results are unlikely to be biased by heterogeneous treatment effects, as a substantial number of firm-year observations in the never-treated group (constituting 33% of the total sample) provides a robust control base for comparison (Baker et al., 2022). However, we estimate a stacked DiD model introduced by Gormley and Matsa (2011) to address the treatment heterogeneity issue. To do so, we create a stacked dataset that includes data from three years before and three years after the event year. For this, we primarily use the "STACKDID" command in Stata. Column (4) presents the results, where the coefficient of *DCFO×CFO×AQR_EXP* is negative and statistically significant at the 1% level, confirming our baseline findings. We also separately analyze each event year (2017 and 2018) and find consistent results[10].

5. Robustness analysis

Parallel trend assumption

To validate the parallel trends assumption of the DID analysis, we analyze the trend in timely loss recognition of borrowers before the AQR process. In the following regression model (4), we examine how the effect of the AQR varies depending on the year relative to its implementation year (see Autor, 2003).

[10] The results are available on request. We also follow Chopra et al. (2021) to define treatment firms and find consistent results.

$$ACC_{it} = \beta_0 + \beta_1 DCFO_{it} + \beta_2 CFO_{it} + \beta_3 DCFO_{it} \times CFO_{it} + \sum_{k=-4}^{3} \Gamma_{1,k} AQR\_EXP(k)_{it} + \sum_{k=-4}^{3} \Gamma_{2,k} DCFO_{it} \times AQR\_EXP(k)_{it} + \sum_{k=-4}^{3} \Gamma_{3,k} CFO_{it} \times AQR\_EXP(k)_{it} + \sum_{k=-4}^{3} \Gamma_{4,k} DCFO_{it} \times CFO_{it} \times AQR\_EXP(k)_{it} + X_{it} + X_{it} \times DCFO_{it} + X_{it} \times CFO_{it} + X_{it} \times DCFO_{it} \times CFO_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it} \quad (4)$$

AQR_EXP(k) is an indicator variable for the k^{th} year relative to the AQR exposure of firm *i*. For example, *AQR_EXP (1)* takes the value one for the first-year exposure of the firm *i* and zero otherwise, and *AQR_EXP (0)* indicates the year immediately before the AQR exposure of the firm. We set the year immediately before AQR exposure as the reference point by excluding *AQR_EXP(0)* and its interaction terms in the regression equation. Control variables and their interaction terms and fixed effects are the same as in equation (2). This model serves two purposes. First, by including a post-period AQR exposure indicator for each year, we can analyse the dynamics of firms' accounting conservatism after AQR exposure. Second, by including pre-AQR indicators (i.e., *AQR_EXP(-1,-2,-3)*, we can verify the parallel trend assumption—specifically, identify any trends in accounting conservatism in the treatment and control groups leading up to AQR exposure (pre-trend). The yearly point estimate of *DCFO×CFO×AQR_EXP* with a 95% confidence interval range is reported in Figure 3 (A). We find that the coefficients (k = -4, -3, -2, -1) of *AQR_EXP* before the AQR are insignificant, suggesting no systematic difference in timely loss recognition between the treatment and control firms in the pre-AQR period, and validates the parallel trends assumption.

Next, we observe that the estimated coefficients for *AQR_EXP* in years k = 1 and k = 2 are negative and statistically significant, while the coefficients in subsequent years are insignificant. This pattern suggests that the relaxation in banks' demand for accounting conservatism, driven by their exposure to the AQR, is concentrated in the first two years following the intervention and is absorbed thereafter. This result is consistent with the notion that by relaxing their demand for accounting conservatism, banks seek to avoid making provisions for losses in the short term and mitigate the immediate financial pressure caused by the expected capital shortfall.

Alternative proxy of timely loss recognition

Next, we use alternative proxies for timely loss recognition to ensure that our results are not sensitive to the choice of a specific proxy. Following Khan and Watts (2009), we measure timely loss recognition using the *C_Score*, which is based on Basu's (1997) model and designed to capture the asymmetric timeliness of earnings by using returns as a proxy for good or bad news. Appendix C outlines the methodology to estimate *C_Score*. We employ the following regression model to examine our hypothesis.

$$C\_Score_{it} = \beta_0 + \beta_1\, AQR\_EXP_{it} + X_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it} \qquad (5)$$

The dependent variable is *C_Score*. X_{it} is the control variables (*Mcap, MB, and Leverage)*. All variables are defined in Table 1. We include firm fixed effects (δ_i) for controlling time-invariant firm-level heterogeneity and year-fixed effect (η_t) for controlling macroeconomic changes. *Industry×Year fixed* effect (γ_{jt}) is used to capture the industry-level time-varying factors. β_1 is the coefficient of interest, which captures the impact of AQR-exposed banks. Since *C_Score* captures the timeliness of bad news, we expect β_1 to be negative.

Results are reported in Table 4. The coefficients of *AQR_EXP* are negative and significant, indicating a reduction in accounting conservatism among borrowers of AQR-exposed banks. Our results are also economically meaningful. The value of the coefficient (-0.32) suggests that firms borrowing from AQR-exposed banks reduce their timely loss recognition by approximately 290% (-0.32/0.11) relative to the average *C_score* (0.11).

Furthermore, we also examine the parallel trends assumption analysis using *C_score*; results are similar to the earlier model and reported in Figure 3(B).

Finally, we analyze three more supplementary accounting-based metrics for timely loss recognition: *Asset Write-Offs*, *Provision for Bad Debts*, and *Depreciation*, as defined in Table 1. These variables are used as dependent variables in equation (8), including all control variables, year-fixed effects, and firm-fixed effects. Table 5 reports the results. The coefficients of *AQR_EXP* are negative and significant at the 10% level, except for *Depreciation*. This result suggests that firms borrowing from AQR-exposed banks report lower *Asset Write-Offs* and *Provisions for Bad Debts* to inflate their reported profits. Taken together, the results are consistent with the findings from the other measures.

Alternative measure of accruals

Throughout the paper, we measure timely loss recognition with accruals, calculated as the difference between net profit and cash flow from operations. However, various studies measure accruals through working capital (Ball and Shivakumar, 2006; Gormely et al., 2012). Accordingly, we measure accruals using working capital as defined below.

$$WACC_{it}=[(\Delta CA_{it}-\Delta Cash_{it})-(\Delta CL_{it}-\Delta STD_{it})-\Delta DEP_{it}]/Total\ Assets_{it} \quad (6)$$

$WACC_{it}$ represents working-capital-based accruals, ΔCA_{it} is the change in current assets, $\Delta Cash_{it}$ is the change in cash and bank balances, ΔCL_{it} is the change in current liabilities, ΔSTD_{it} is the change in short-term debt and ΔDEP_{it} is the change in depreciation. We replace ACC from regression equation (3) with $WACC$ and re-estimate the model. Column 1 of Table 6 reports the result, where *AQR_EXP×DCFO×CFO* is statistically significant at the 10% level. The effects are also economically significant, indicating a 168% (-0.14/0.08) decrease in timely loss recognition, from 0.08 to -0.057 (0.08 + -0.14).

Entropy balancing

We next employ entropy-balanced weight-based regression to address the covariate imbalance problems between treatment and control firms (Hainmueller, 2012). The entropy balancing method ensures the retention of the whole sample while providing sufficient statistical power to minimize coefficient bias (McMullin & Schonberger, 2020). Entropy balancing is a matching technique like propensity score matching, but it assigns non-negative weights to each observation in the control group so that specified moments of covariates in the control group match the treatment group.[11] The results using the Staggered Difference-in-Differences (DiD) model with entropy-balanced weights results, reported in Column 2 of Table 6, are qualitatively and quantitatively consistent with the baseline regression findings.

Excluding Never-Treated Firms

To rule out the possibility that differential trends between treatment and control firms might drive our results, we restrict our sample to only firms borrowing from AQR-exposed banks (treatment firms). In column 3 of Table 6, we find that the coefficient of *DCFO×CFO×AQR_EXP* is negative and significant, and the magnitude of the coefficient is comparable to that reported in Column 3 of Table 3, corroborating that the treatment firms drive the observed association between timely loss recognition and the AQR.

Change in Accounting Policy- Ind-AS applicable firms

India adopted the International Financial Reporting Standards (IFRS)-driven accounting standards, known as Indian Accounting Standards (Ind-AS), in 2016. The implementation of Ind-AS was phased, starting with firms having a net worth greater than ₹500 crore (5 billion rupees) in 2017. In 2018, it was extended to firms with a net worth exceeding ₹250 crore (2.5 billion rupees). Starting from the financial year 2019, Ind-AS applied to all firms. Since the adoption of Ind-AS could potentially impact accounting conservatism, we exclude firm-year observations with a net book value greater than ₹5 billion and ₹2.5 billion

[11] Table OA3 of the Online Appendix details the covariate balancing results.

from our sample. We then run the regression model (3) with the subsample and find consistent results. The results are reported in Online Appendix Table OA5.

6. Mechanism Testing - Accounting-debt covenant violation

Interest coverage ratio

We posit that accounting-based debt covenant violations serve as a channel through which AQR-exposed banks influence the timely loss recognition of borrowing firms. To test this proposition, we examine a subsample of borrowing firms with a higher likelihood of accounting-based debt covenant violations. However, since the details of covenants are not available in India, we use proxies. First, we classify firms as having a high likelihood of covenant violation if their interest coverage ratio (earnings before interest and taxes/interest payment) before the AQR (Year = 2016) is less than 1; otherwise, they are classified as having a low likelihood of debt covenant violations.[12] In Table 7, we find that the coefficients of *AQR_EXP×DCFO×CFO* are negative in all models, but they are significant for firms with a high likelihood of covenant violations (high-interest coverage ratio). The coefficient is considerably larger (calculated as (0.496 - 0.189) / 0.189 = 162%) compared to the coefficient value reported in Column (3) of Table 3.

We next measure the sensitivity of firms' interest coverage ratios to assess the likelihood of accounting-based debt covenant violations. Firms are classified as having a high likelihood of violations if their interest coverage ratio is below 0.5, 2, or 3 before the AQR (Year = 2016). Firms with ratios above these thresholds are categorized as having a low likelihood. The results of this classification are presented in Table OA4 of the Online Appendix. Consistent with the findings in Table 7, we observe significantly negative coefficients for the interaction term *AQR_EXP×DCFO×CFO*. Specifically, the coefficient for *AQR_EXP×DCFO×CFO* is -0.541 for the subsample of firms with an interest coverage ratio below 0.5. This value decreases to -

[12] Stice (2018) shows that the average contracted covenant value for interest coverage for US firms is 2.58.

0.260 when the threshold is increased to 3. These results suggest that timely loss recognition decreases as a firm's interest coverage ratio declines (indicating a higher likelihood of accounting-based debt covenant violations) and reinforces the notion that the accounting-based debt covenant violation is an important channel through which the AQR impacts the timely recognition of losses of borrowing firms.

Relationship banking and Covenant violation

Next, we analyse the role of relationship banking to explore accounting-based debt covenant violations as a channel through which the AQR affects the timely loss recognition of borrowing firms. Prilmeier (2017) finds that relationship lending reduces the reliance on accounting-based debt covenants, as relationship lenders have access to more comprehensive (soft) information about borrowers beyond what is available in their financial statements. Additionally, in the case of covenant violations, relationship lenders are less likely to force action compared to transactional bankers (Gam and Liu, 2024). Building on this perspective, we expect the post-AQR effect to be more pronounced for non-relationship borrowers.

Following prior literature, we define relationship banking as a situation where a firm maintains a borrowing relationship with the same bank for the current and at least the previous two years. We divide the sample based on three measures of relationship lending. First, the exclusive relationship banking sample consists of firms that borrow only from the relationship bank. Second, the high (Low) relationship group includes firms with more (less) than 50% of their bankers being relationship bankers. Third, the high (low) relationship loan sample consists of firms with more (less) than 50% of total outstanding loans from relationship banks.

Table 8 reports the results. Consistent with our expectation, we find that the coefficients of $AQR\_EXP \times DCFO \times CFO$ are negative and significant for firms borrowing from non-relationship banks. This result suggests that AQR-exposed banks engaged in non-relationship banking and relying more heavily on accounting-based debt covenants tend to relax the demand for timely loss recognition to reduce the probability of violating these covenants.

Geographical distance and accounting-based debt Covenant

Next, we invoke the notion that banks derive ex-ante cost advantages from being geographically close to the borrowing firm, as distance reduces lenders' ability to acquire borrower-specific information (Agarwal and Hauswald, 2010; Carling and Lundberg, 2005). Consistent with this view, Hollander and Verriest (2016) document that banks rely more heavily on accounting-based debt covenants to assess borrowers' financial health in the presence of distance-related informational frictions. Given that the accounting-based debt covenant is a channel through which AQR-exposed banks affect timely loss recognition, we argue that the effect of the AQR process will be more pronounced when the geographical distance between the firm and the bank is greater.

We use a firm's headquarters as a proxy for its location based on prior studies (e.g., Tantri and Vishen, 2025; Malloy, 2005). The MCA data provides the bank branch's address from which the firm obtained the loan. Following Chopra et al. (2020), we measure the geographical distance between the bank branch and the borrowing firm's headquarters. Using a cab service company's website, which relies on the Google Maps API to calculate travel distances, we scrape latitude and longitude data for each address. We then estimate the geo-spatial distance for each bank branch-firm pair using Stata's 'geodist' command and compute the weighted average distance for each firm, using loan amounts as weights. Firms are classified as 'high distance' if their weighted average distance exceeds the median value of the sample and as 'low distance' if it falls below the median value.

We expect banks' lending to high-distance firms are likely depend more on accounting-based debt covenants. Thus, we predict that the decrease in accounting conservatism will be more pronounced for high-distance firms. Consistent with this notion, our findings, presented in Columns (1) and (2) of Table 9, show that the coefficients of *AQR_EXP×DCFO×CFO* are negative and significant for high-distance firms. In contrast, the coefficient of *AQR_EXP×DCFO×CFO* for low-distance sample firms is negative, albeit insignificant.

7. Auxiliary Evidence for Undercapitalized Banks' Defensive Strategy

Our analyses indicate that the reduction in accounting conservatism among borrowers of AQR-exposed banks reflects a defensive strategy adopted by the undercapitalized bank. In this section, we provide auxiliary evidence in support of this notion.

Bank Capital

First, we examine how the borrower's accounting conservatism changes with the lending bank's capital. We argue that AQR-exposed banks with lower equity capital are more vulnerable and likely to adopt a defensive strategy, as they lack the sufficient buffer needed to absorb provisions for expected losses (Chopra et al., 2021). This perspective aligns with the view that undercapitalized banks have stronger incentives to engage in risky activities (Diamond and Rajan, 2000; Admati and Hellwig, 2014). This dynamic arises because shareholders stand to gain from the upside of increased risk-taking, while the downside is limited by corporate liability structures and implicit or explicit protections for depositors (Caballero et al., 2008). Furthermore, if banks with lower levels of capital before the AQR are required to make additional provisions due to the AQR findings, they may fall short of meeting regulatory capital requirements or operate with capital levels below mandated thresholds post-AQR. In such scenarios, these banks are likely to face heightened regulatory scrutiny and operational constraints[13]. Therefore, one may expect them to adopt a defensive strategy—relaxing monitoring and screening of borrowers to defer further loss recognition, thereby mitigating the risk of additional capital erosion that could further violate their regulatory requirement. Advancing this view, we posit that the decrease in timely loss recognition among

[13] https://rbi.org.in/Scripts/NotificationUser.aspx?Id=1014&Mode=0

borrowing firms will be more pronounced for those who borrowed from AQR-exposed banks with lower levels of capital prior to the AQR.

To measure equity capital, we use the Capital Adequacy Ratio (CAR), which is calculated as the sum of Tier 1 and Tier 2 capital divided by Risk-Weighted Assets (Chopra et al., 2021). Since a firm can borrow from multiple banks, we compute a weighted average *CAR* ($WACAR$) of lending banks, using weights based on the average outstanding loan during the pre-AQR period (2013-2016), as follows:

$$WACAR_i = \sum_{j=1}^{N} Loan\ Value_{j,i} * CAR_j \quad (7)$$

j and i represent bank j and firm i, respectively. $Loan\ Value_{j,i}$ is the amount of a firm's outstanding loans over the pre-AQR period (2013-2016) of firm i from bank j. CAR_j is the mean capital adequacy ratio of bank i for the pre-AQR period. N represents the number of banks from which firm i has borrowed during the pre-AQR period. A higher value of *WACAR* indicates that firm i has borrowed more from banks with high *CAR*. We split our sample firms into two groups: *High_CAR* (*Low_CAR*) group, including all firms whose *WACAR* is greater (lower) than the median value of $WACAR$.

In Table 10, Panels A and B, we report the results of *Low_CAR* and *High CAR* firms, respectively. We find that the coefficient of *AQR_EXP×DCFO×CFO* is negative in all models; however, it is significant only for *Low_CAR* firms. The coefficient is considerably larger (calculated as (0.238 - 0.183) / 0.183 = 26%) compared to that reported in Column (3) of Table 3. Further, the coefficient of *DCFO×CFO* is positive and significant, which suggests that firms borrowing from low-capital banks exhibit timely loss recognition before the AQR. However, after the AQR, these firms do not report expected losses timely manner, as indicated by the total coefficient for timely loss recognition (*DCFO×CFO* + *AQR_EXP×DCFO×CFO* = 0.275 + -0.238 = 0.038). This result is consistent with our hypothesis.

Cost of borrowing

Our next test examines whether AQR-exposed, undercapitalized banks demand higher interest rates as the borrowers' timely loss recognition decreases. We posit that an increase in interest rates will serve two purposes. First, higher interest rates help banks build up their capital by transferring profits into capital reserves. Second, as the bank's loan risk increases as the borrowers' timely loss recognition reduces, banks demand higher interest rates as a defensive strategy to mitigate the increased risk (Ahmed et al., 2002; Li, 2015; Zhang, 2008). To test this proposition, we estimate the following regression model:

$$Interest\ cost_{it} = \beta_0 + \beta_1\ C\_Score_{it} + \beta_2\ AQR\_EXP_{it} + \beta_3\ AQR\_EXP_{it} \times C\_Score_{it} + X_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it} \quad (8)$$

The dependent variable is the interest cost (Interest amount/Total debt), and *C_Score* measures timely loss recognition. X_{it} is control variables (*Mcap, MB, Leverage, Profitability,* and *Age).* Our key explanatory variable is the interaction term between *AQR_EXP* and *C_Score*, and we expect a negative coefficient on this term. Panel A of Table 11, column (1) presents the results. We find that the coefficients of *AQR_EXP×C_Score* are negative and significant, which implies that AQR-exposed banks demand higher interest rates as timely loss recognition decreases. Specifically, a one standard deviation decrease in *C_Score* (0.375) leads to a 1.3% increase in the interest rate following the AQR. This increase is also economically significant, given that the average interest rate of our sample firms is 12.9%.

Dividend payout ratio

Next, we examine the effect of the AQR on borrowers' dividend distribution. We argue that AQR-exposed banks will restrict dividend payout to allow firms to accumulate cash reserves to reduce the default risk of loans. We estimate the following model:

$$Dividend\ payout_{it} = \beta_0 + \beta_1\ C\_Score_{it} + \beta_2\ AQR\_EXP_{it} + \beta_3\ AQR\_EXP_{it} \times C\_Score_{it} + X_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it} \quad (9)$$

The dependent variable in the above model is the dividend payout ratio, defined as the dividend amount divided by the average total assets. X_{it} is the control variable, same as equation (8). Our key explanatory variable is the interaction term between *AQR_EXP* and *C_Score*, with the expectation of a positive coefficient to support our hypothesis. Panel B of Table 11, column (2) presents the results. As expected, the coefficient for the interaction term *AQR_EXP×C_Score* is significantly positive, indicating that firms borrowing from AQR-exposed banks tend to choose lower dividend payouts as timely loss recognition decreases. Specifically, a one standard deviation decrease in *C_Score* (0.375) leads to a 0.08% reduction in the dividend-to-total-assets ratio. Given the average total assets of the sample firms (INR 2081 million), this reduction amounts to INR 1.66 million.

Related party transactions

Finally, we explore the effect of the AQR on related party transactions (RPTs). A substantial body of literature indicates that the prevalence of RPTs in emerging markets erodes firm value and leads to financial distress (Gopalan et al., 2023). The extant literature distinguishes between two types of RPTs: those driven by business requirements (efficient contracting hypothesis) and those motivated by opportunistic behavior (shareholder expropriation hypothesis) (Ryngaert & Thomas, 2012; Kohlbeck & Mayhew, 2010, 2017). We expect business-related RPTs that resolve market inefficiencies to be relatively stable post-AQR, as restricting these transactions would be detrimental to efficiency. In contrast, AQR-exposed banks are likely to impose constraints on borrowers' opportunistic RPTs as they reduce firm value and increase the risk of insolvency. We categorize RPTs into business-related and opportunistic, following Kohlbeck and Mayhew (2010, 2017) estimate the following regression model to examine the effect of AQRs on the borrower's RPT[14].

$$RPT_{it} = \beta_0 + \beta_1\ C\_Score_{it} + \beta_2\ AQR\_EXP_{it} + \beta_3\ AQR\_EXP_{it} \times C\_Score_{it} + X_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it} \quad (10)$$

[14] Table OA6 of the Online Appendix provides detailed classifications of related party transactions (RPTs).

The dependent variable is the level of Related Party Transactions (RPTs) rescaled by the average total assets. X_{it} is the control variable, same as equation (8). We use *C_Score* to measure timely loss recognition. Our key explanatory variable is the interaction term between *AQR_EXP* and *C_Score*, and we expect a positive coefficient on this term to be consistent with our hypothesis. Panel C of Table 11 presents the results. While the coefficients on the interaction term *AQR_EXP×C_Score* are positive for *Total RPTs* and *Business RPTs*, they are statistically significant only for *Opportunistic RPTs*. This suggests that firms borrowing from AQR-exposed banks reduce their involvement in opportunistic RPTs as timely loss recognition improves. Specifically, a one standard deviation decrease in *C_Score* (0.375) leads to a 0.26% reduction in opportunistic RPTs relative to total assets. Given the average total assets of sample firms (INR 2081 million), this reduction translates to INR 5.41 million.

Alternative explanations

Borrower–Lender Information Gaps in the Aftermath of the AQR

One may argue that the AQR process increased the information gap between borrowers and lenders, thereby allowing borrowers to delay the timely recognition of losses. Following the AQR, the cost of negotiation after debt covenant violations rose significantly. To mitigate this higher cost, borrowing firms may have reduced accounting conservatism, exploiting the widened information gap. However, we argue that this alternative explanation is unlikely to hold. During the AQR process, RBI-appointed auditors were mandated to thoroughly assess the quality of loan portfolios. Consequently, the AQR is more likely to have reduced information asymmetry between borrowers and lenders by enforcing stricter disclosure requirements and diagnostic standards.

Another argument with respect to information gap might reduce because auditor will thoroughly review the loan portfolio, repayment assumption and borrower's performance across all banks. In such case, banks should decrease demand for conservatism because they have information advantage. However, this argument cannot explain why AQR exposed banks (or banks which are hiding the losses in pre-AQR period) decrease demand for accounting conservatism from borrowers compared to other banks, since all the banks went to similar scrutiny.

The Supply of Conservatism Under Reduced Debt Capital Availability

An alternative explanation for our findings is that the AQR reduced the supply of capital to borrowers (Chopra et al., 2023), thereby altering their reporting incentives. In debt contracting, conservatism enhances contracting efficiency by facilitating timely loss recognition, improving covenant effectiveness, and mitigating agency conflicts between lenders and borrowers (Watts, 2003; Ball, Kothari, and Robin, 2000). Nevertheless, the benefits of conservatism depend critically on both the availability of credit and the extent to which lenders value such reporting. If the AQR constrained bank lending, the marginal value of conservative reporting for debt contracting would have declined, leading borrowers to reduce conservatism—particularly since conservative accounting is costly for firms, as it results in lower reported earnings and retained earnings (Watts, 2003).

Our evidence, however, is inconsistent with this capital supply channel. We find that the decline in conservatism is greater among firms whose leverage increased after the AQR, as reported in Table OA7 of the Online Appendix. If reduced credit supply were the primary driver, the sharpest declines in conservatism would have been expected among firms that deleveraged. Instead, the strongest reductions occur among firms that increased their debt levels following the AQR. This suggests that the observed changes in reporting behavior stem not from a contraction in credit supply but from a weakening of lenders' demand for conservative reporting.

8. Conclusion

This study sheds light on the relationship between bank capital and borrowers' accounting practices after an exogenous capital shock, specifically the Indian Asset Quality Review (AQR). Our findings indicate that a shock to bank capital affects banks' demand for accounting conservatism from borrowers. Using firms borrowing from AQR-exposed banks as treatment firms, we observe a reduction in accounting conservatism following the AQR in response to undercapitalization resulting from the shock. We also find that the tendency to reduce timely loss recognition increases as borrowing firms face a higher probability of accounting-based debt covenant violations, while AQR-exposed banks have lower equity capital. This suggests that AQR-exposed banks relax their demand for timely loss recognition to reduce accounting-based debt covenant violations, thus avoiding the need to make provisions for expected losses and further capital shortfalls. We next find that this decrease in accounting conservatism is associated with reduced opportunistic related-party transactions and lower dividend payouts among firms borrowing from these banks. We interpret these results as a counterbalancing strategy of banks to mitigate the adverse effects of relaxing timely loss recognition.

Our study emphasizes that the threat of undercapitalization can compel a bank to adopt a defensive strategy, affecting the accounting practices of borrowing firms. The implications of these findings extend to our understanding of how capital shocks affect bank governance and lending standards, suggesting that undercapitalized banks may prioritize short-term stability over stringent monitoring of borrower practices.

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Table 1: Variable Definition
This table defines the variables used in this study.

Variables	Description	Source
AQR_EXP	The dummy variable equals one if the firm's exposure to AQR is above the median and zero otherwise. It will remain one for subsequent years of exposure for the firm once exposed. The firm's exposure to AQR is the weighted average of lenders' exposure using weights of the firm's pre-AQR average outstanding loan amount with each lender. Lender exposure is the divergence in the lender's annual provisioning divided by total assets.	MCA
ACC	(Net profit-Net operating cash flow)/Average Total Assets	CMIE
CFO	Net Operating Cash Flow/ Average Total Assets	CMIE
DCFO	The dummy variable equals 1 if the CFO is negative and 0 otherwise	CMIE
Size	Natural Log of Average Total Assets	CMIE
Leverage	Borrowing/Average Total Assets	CMIE
Growth	Sales Growth	CMIE
Opportunistic RPT	Opportunistic Related Party Transactions are classified based on (Kohlbeck & Mayhew, 2017)	CMIE
Business RPT	Total Business-Related Party Transactions are classified based on (Kohlbeck & Mayhew, 2017)	CMIE
Total RPT	Total Related Party Transactions are classified based on (Kohlbeck and Mayhew, 2017)	CMIE
Interest Cost	Interest Expense/Total borrowing	CMIE
Profitability	PBIT/Average Total Asset	CMIE
Age	ln(1+(year-incorporation year)	CMIE
MB	Average Market to Book value ratio	CMIE
Mcap	Natural log of average market capitalization in the financial year	CMIE
Div	Dividend/Average Total Assets	CMIE
Asset Write-off	Asset written off divided by net fixed assets	CMIE
Bad Debt Provision	Provision for bad debt divided by trade receivables	CMIE
Depreciation	Depreciation divided by net fixed assets	CMIE

Table 2: Descriptive Statistics

The table provides descriptive statistics of the variables used in this study. Panel A reports descriptive statistics for the full sample. Panels B and C report descriptive statistics for treatment and control firms.

Variables	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
	Panel A: Full Sample			Panel A: AQR Firms (treatment firms)			Panel C: Firms Without AQR (control firms)		
Size	19105	7.641	2.007	5256	7.757	1.964	13849	7.598	2.022
Leverage	19105	0.371	0.351	5256	0.343	0.333	13849	0.382	0.357
growth	19105	0.156	0.712	5256	0.144	0.65	13849	0.16	0.734
CFO	19105	0.05	0.11	5256	0.05	0.106	13849	0.051	0.111
ACC	19105	-0.034	0.127	5256	-0.029	0.126	13849	-0.036	0.127
Opportunistic RPT	12739	0.026	0.069	3651	0.031	0.08	9088	0.023	0.064
Business RPT	12739	0.172	0.303	3651	0.162	0.291	9088	0.176	0.307
Total RPT	12739	0.204	0.34	3651	0.203	0.341	9088	0.205	0.339
Profitability	13287	0.073	0.089	3769	0.074	0.093	9518	0.073	0.088
Mcap	13,287	7.280	2.320	3769	7.614	2.289	9518	7.147	2.319
MB	13,287	2.437	3.734	3769	2.842	3.840	9518	2.277	3.680
Age	13,287	3.418	0.515	3769	3.475	0.504	9518	3.396	0.518
Interest cost	12934	0.131	0.2	3672	0.138	0.224	9262	0.129	0.189
Depreciation	13287	0.118	0.097	3769	0.119	0.103	9518	0.118	0.095
Bad debt provision	13287	0.049	0.177	3769	0.075	0.234	9518	0.039	0.148
Asset write off	13287	0.001	0.016	3769	0.001	0.012	9518	0.001	0.017
Dividend	6198	0.014	0.018	1685	0.013	0.016	4513	0.015	0.018
C_Score	13287	0.011	0.375	3769	0.044	0.522	9518	-0.002	0.296

Figure 1: Parallel Trends

Figure 1(A): Parallel trend

This figure plots the result regression equation (3) to show the dynamic trend in the difference in accounting conservatism of AQR-exposed and non-exposed firms. This figure plots only interest coefficients $DCFO_{it} \times CFO_{it} \times AQR\_EXP(k)_{it}$. Coefficients were used to plot this figure after using all control variables and interactions, firm-fixed effect, and Industry × Year fixed effect.

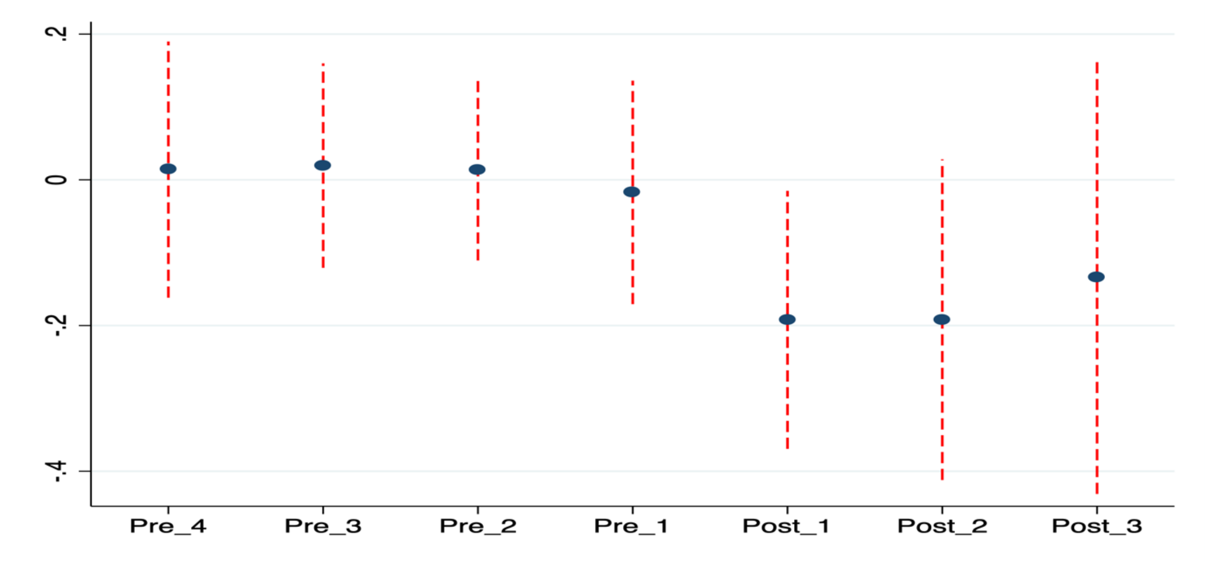

Figure 3 (B): Parallel trend with *C_Score*

This figure provides a plot of the result regression equation($Y_{it} = \beta_1 + \beta_2 \times AQR\_EXP(k)_{it} + \beta \times X_{it} + \delta_i + \eta_t + \gamma_{jt} + \epsilon_{it}$) where the dependent variable is *C_Score*. It shows the dynamic trend in the difference in accounting conservatism of AQR-exposed and non-exposed firms. This figure plots only interest coefficients $AQR\_EXP(k)_{it}$. The coefficient was used to plot in this figure after using all control variables and interactions, firm-fixed effect, and Industry × Year fixed effect.

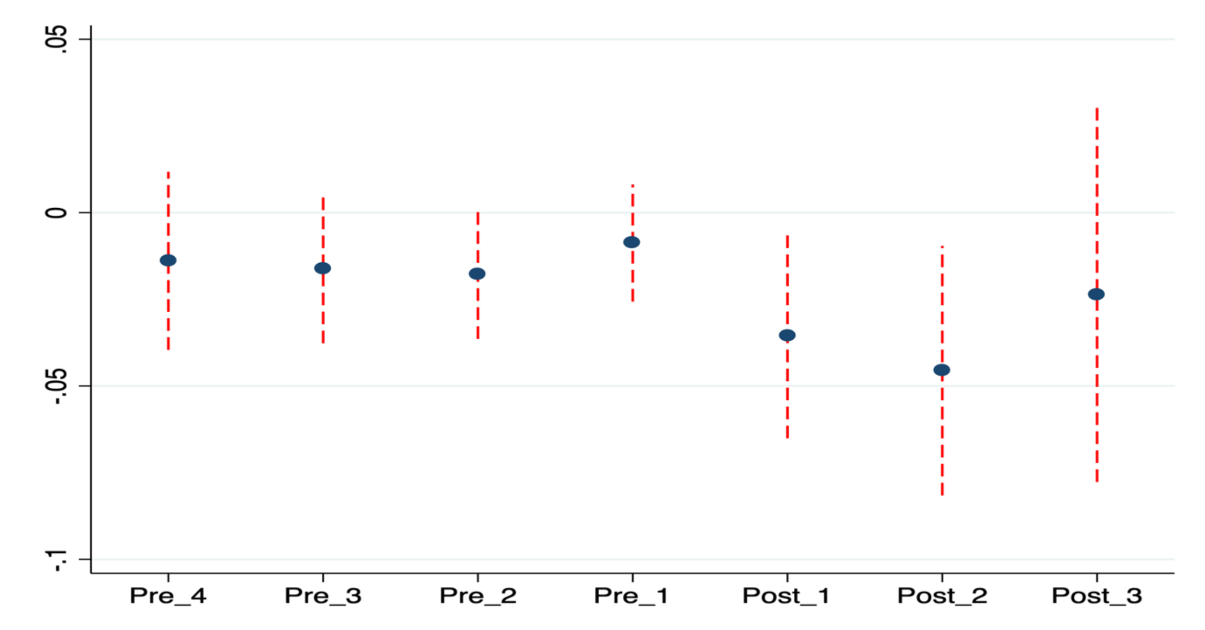

Table 3: Main Baseline Regression Result

This table reports regression equation (3) results, where the dependent variable is ACC. The primary coefficient of interest is the interaction term DCFO×CFO×AQR_EXP, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, along with their interactions with CFO, DCFO, and CFO×DCFO. Definitions of all variables are provided in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of interest variable.

	(1)	**(2)**	**(3)**	**(4) Stack DiD**
VARIABLES	**ACC**	**ACC**	**ACC**	**ACC**
CFO	-0.915***	-1.149***	-1.147***	-1.126***
	(0.017)	(0.072)	(0.073)	(0.0358)
DCFO	-0.000	-0.014	-0.012	-0.00708
	(0.003)	(0.012)	(0.012)	(0.00658)
*DCFO*CFO*	-0.059*	0.154	0.145	0.139**
	(0.032)	(0.134)	(0.131)	(0.0596)
AQR_EXP	-0.021***	-0.018***	-0.019***	-0.0201***
	(0.004)	(0.004)	(0.004)	(0.00279)
*AQR_EXP*CFO*	0.205***	0.167***	0.173***	0.174***
	(0.033)	(0.033)	(0.034)	(0.0200)
*AQR_EXP*DCFO*	0.008	0.008	0.009	0.00731*
	(0.006)	(0.006)	(0.006)	(0.00404)
AQR_EXP*DCFO*CFO	**-0.196*** **	**-0.173** **	**-0.189*** **	**-0.220*** **
	(0.073)	**(0.070)**	**(0.069)**	**(0.0354)**
Constant	0.013***	0.017	0.019	0.0344**
	(0.002)	(0.031)	(0.031)	(0.0167)
Control Variables and Interactions	No	Yes	Yes	Yes
*Year Fixed Effect (*Cohort Time)	Yes	Yes	Yes	Yes
*Firm Fixed Effect (*Cohort Unit)	Yes	Yes	Yes	Yes
*Industry*Year Fixed Effect*	No	No	Yes	Yes
Observations	19,105	19,105	19,063	29,099
R-squared	0.738	0.751	0.759	0.806

Table 4: C_Score and AQR Bank

This table reports the results from the DiD regression, where the dependent variable is C_Score, a measure of timeliness in recognizing bad news. The primary coefficient of interest is AQR_EXP. Control variables include Market Capitalization (Mcap), Market-to-Book ratio (MB), and Leverage. All variable definitions are provided in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	**(2)**	**(3)**
VARIABLES	**C_Score**	**C_Score**	**C_Score**
AQR_EXP	**-0.028***	**-0.032****	**-0.032****
	(0.016)	**(0.014)**	**(0.014)**
Mcap		-0.046***	-0.046***
		(0.007)	(0.007)
Leverage		1.055***	1.058***
		(0.036)	(0.037)
MB		-0.009***	-0.009***
		(0.002)	(0.002)
Constant	0.018***	0.062	0.062
	(0.004)	(0.049)	(0.050)
Year Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
*Industry*Year Fixed Effect*	No	No	Yes
Observations	13,060	13,060	13,016
R-squared	0.544	0.613	0.655

Table 5: Alternative Measures

This table reports the results from the DiD regression (equation 8), where the dependent variables are Asset Write-Off, Bad Debt Provision, and Depreciation. The primary coefficient of interest is AQR_EXP. Control variables include Market Capitalization (Mcap), Market-to-Book ratio (MB), and Leverage. All variable definitions are provided in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	**(2)**	**(3)**
VARIABLES	**Asset Write off**	**Bad Debt Provision**	**Depreciation**
AQR_EXP	**-0.001***	**-0.020***	**-0.005**
	(0.001)	**(0.010)**	**(0.003)**
Mcap	-0.000	-0.039***	-0.009***
	(0.000)	(0.006)	(0.002)
MB	-0.000	0.005***	0.001***
	(0.000)	(0.002)	(0.000)
Leverage	0.000	0.026	-0.015
	(0.002)	(0.037)	(0.012)
Constant	0.004	0.320***	0.188***
	(0.003)	(0.044)	(0.015)
Year Fixed Effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Observations	13,762	13,762	13,762
R-squared	0.315	0.523	0.708

Table 6: The robustness analysis

This table reports regression equation (3) results, where the dependent variable is ACC. The primary coefficient of interest is the interaction term DCFO*CFO*AQR_EXP, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, along with their interactions with CFO, DCFO, and CFO*DCFO. Definitions of all variables are provided in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	**(2)**	**(3)**
	Working Capital Accruals	**Entropy-based DiD**	**Exc. Never treated**
VARIABLES	**WACC**	**ACC**	**ACC**
CFO	-0.835***	-1.193***	-1.220***
	(0.091)	(0.078)	(0.080)
DCFO	-0.015	-0.017	-0.029*
	(0.014)	(0.014)	(0.015)
*DCFO*CFO*	0.083	0.174	0.132
	(0.161)	(0.153)	(0.165)
AQR_EXP	-0.013***	-0.015***	-0.017***
	(0.005)	(0.004)	(0.004)
*AQR_EXP*CFO*	0.088**	0.135***	0.170***
	(0.037)	(0.032)	(0.033)
*AQR_EXP*DCFO*	0.005	0.006	0.009
	(0.007)	(0.006)	(0.006)
AQR_EXP*DCFO*CFO	**-0.140***	**-0.151****	**-0.183****
	(0.076)	**(0.069)**	**(0.072)**
Constant	-0.050	0.059*	0.066*
	(0.037)	(0.033)	(0.036)
Control Variables and Interactions	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Observations	18,689	19,105	13,854
R-squared	0.476	0.753	0.747

Table 7: Firms' Probability of Covenant Violation and Accounting Conservatism

This table reports regression equation (3) results, where the dependent variable is *ACC*. The primary coefficient of interest is the interaction term *DCFO*CFO*AQR_EXP*, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, along with their interactions with *CFO, DCFO,* and *CFO*DCFO*. Definitions of all variables are provided in Table 1. Standard errors are reported in parentheses and are clustered at the firm level. Columns 1 and 2 show the results for firms with *ICR* < 1 in 2016, while Columns 3 and 4 display the results for firms with *ICR* > 1 in 2016. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	(2)	(3)	(4)
	ICR<1		ICR>1	
VARIABLES	ACC	ACC	ACC	ACC
CFO	-1.257***	-1.283***	-1.167***	-1.158***
	(0.157)	(0.165)	(0.075)	(0.076)
DCFO	-0.003	0.006	-0.022*	-0.020
	(0.028)	(0.030)	(0.013)	(0.012)
*DCFO*CFO*	0.490	0.462	0.023	0.024
	(0.340)	(0.337)	(0.139)	(0.128)
AQR_EXP	-0.047***	-0.057***	-0.008**	-0.008**
	(0.011)	(0.011)	(0.003)	(0.003)
*AQR_EXP*CFO*	0.412***	0.481***	0.113***	0.119***
	(0.104)	(0.106)	(0.029)	(0.029)
*AQR_EXP*DCFO*	0.009	0.012	0.010	0.010
	(0.014)	(0.015)	(0.006)	(0.006)
AQR_EXP*DCFO*CFO	**-0.496***	**-0.645***	**-0.039**	**-0.049**
	(0.181)	**(0.180)**	**(0.074)**	**(0.074)**
Constant	-0.084	-0.102	0.075**	0.079***
	(0.091)	(0.093)	(0.029)	(0.030)
Control Variables and Interactions	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
*Industry*Year Fixed Effect*	No	Yes	Yes	Yes
Observations	3,881	3,800	12,936	12,893
R-squared	0.614	0.652	0.816	0.824

Table 8: Relationship vs. Transactional Banking

This table presents the results of a regression equation (3), where the dependent variable is ACC. The primary coefficient of interest is the interaction term DCFO * CFO * AQR_EXP, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, as well as their interactions with CFO, DCFO, and CFO * DCFO. Definitions of all variables are provided in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Columns 1, 3, and 5 present the results for firms with high relationship bank borrowing, while Columns 2, 4, and 6 show the results for firms with low relationship bank borrowing. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Exc. Relationship bank	**Remaining**	**High Rln Bank**	**Low Rln Bank**	**High Rln Loan**	**Low Rln Loan**
VARIABLES	**ACC**	**ACC**	**ACC**	**ACC**	**ACC**	**ACC**
CFO	-1.160***	-1.132***	-1.105***	-1.320***	-1.152***	-1.133***
	(0.165)	(0.086)	(0.118)	(0.125)	(0.110)	(0.112)
DCFO	-0.030	-0.007	-0.001	-0.026	-0.013	-0.017
	(0.026)	(0.015)	(0.020)	(0.018)	(0.019)	(0.017)
*DCFO*CFO*	0.135	0.116	0.189	0.358*	0.169	0.129
	(0.319)	(0.157)	(0.247)	(0.211)	(0.226)	(0.183)
AQR_EXP	-0.022***	-0.018***	-0.024***	-0.017***	-0.022***	-0.013**
	(0.008)	(0.004)	(0.006)	(0.006)	(0.006)	(0.005)
*AQR_EXP*CFO*	0.139**	0.182***	0.190***	0.150***	0.181***	0.155***
	(0.059)	(0.040)	(0.057)	(0.051)	(0.052)	(0.046)
*AQR_EXP*DCFO*	-0.000	0.009	0.006	0.007	0.006	0.008
	(0.012)	(0.007)	(0.010)	(0.009)	(0.009)	(0.009)
AQR_EXP*DCFO*CFO	**-0.061**	**-0.224*** **	**-0.139**	**-0.232** **	**-0.133**	**-0.173** **
	(0.143)	**(0.080)**	**(0.129)**	**(0.095)**	**(0.118)**	**(0.077)**
Constant	-0.044	0.039	0.034	0.050	0.034	0.029
	(0.079)	(0.035)	(0.068)	(0.047)	(0.055)	(0.042)
Control Variables and Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,231	15,195	7,337	7,588	8,318	9,368
R-squared	0.777	0.755	0.734	0.808	0.758	0.805

Table 9: Bank monitoring and covenant violation

This table reports the results of a regression equation (3), where the dependent variable is ACC. The coefficient of interest is the interaction term DCFOCFOAQR_EXP, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, along with their interactions with CFO, DCFO, and CFO*DCFO. Definitions of all variables can be found in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Columns 1 and 2 show the results for firms with a high distance from the bank branch, while Columns 3 and 4 show the results for firms with a low distance. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	(2)	(3)	(4)
	High Distance Firms		Low Distance Firms	
VARIABLES	**ACC**	**ACC**	**ACC**	**ACC**
CFO	-1.356***	-1.355***	-1.024***	-1.030***
	(0.108)	(0.109)	(0.094)	(0.096)
DCFO	-0.009	-0.003	-0.014	-0.011
	(0.017)	(0.017)	(0.016)	(0.016)
*DCFO*CFO*	0.663***	0.700***	-0.105	-0.124
	(0.226)	(0.223)	(0.173)	(0.168)
AQR_EXP	-0.021***	-0.021***	-0.017***	-0.018***
	(0.005)	(0.006)	(0.005)	(0.006)
*AQR_EXP*CFO*	0.185***	0.190***	0.156***	0.170***
	(0.044)	(0.046)	(0.047)	(0.048)
*AQR_EXP*DCFO*	0.015*	0.017**	0.002	0.003
	(0.008)	(0.008)	(0.008)	(0.008)
AQR_EXP*DCFO*CFO	**-0.307***	**-0.321***	**-0.098**	**-0.144**
	(0.099)	**(0.092)**	**(0.095)**	**(0.098)**
Constant	0.089*	0.091*	-0.030	-0.032
	(0.046)	(0.048)	(0.041)	(0.041)
Control Variables and Interactions	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
*Industry*Year Fixed Effect*	No	Yes	No	Yes
Observations	8,032	7,976	11,073	11,025
R-squared	0.761	0.774	0.748	0.760

Table 10: Bank's Capital Adequacy Ratio (CAR) and Firms' Accounting Conservatism
This table presents the results of a regression equation (3), where the dependent variable is ACC. The primary coefficient of interest is the interaction term *DCFO*CFO*AQR_EXP*, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, along with their interactions with *CFO*, *DCFO*, and CFO * DCFO. Definitions of all variables are provided in Table 1. Standard errors are reported in parentheses and clustered at the firm level. Columns 1 and 2 show the results for firms that borrowed from Low CAR banks, while Columns 3 and 4 present the results for firms that borrowed from High CAR banks. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	(1)	(2)	(3)	(4)
	Low CAR		**High CAR**	
VARIABLES	**ACC**	**ACC**	**ACC**	**ACC**
CFO	-1.188***	-1.179***	-1.181***	-1.177***
	(0.087)	(0.089)	(0.117)	(0.119)
DCFO	-0.004	-0.001	-0.027	-0.023
	(0.016)	(0.016)	(0.020)	(0.020)
*DCFO*CFO*	0.287*	0.275*	0.112	0.106
	(0.164)	(0.164)	(0.224)	(0.212)
AQR_EXP	-0.021***	-0.023***	-0.011**	-0.013***
	(0.006)	(0.006)	(0.005)	(0.005)
*AQR_EXP*CFO*	0.213***	0.215***	0.112***	0.125***
	(0.049)	(0.050)	(0.042)	(0.042)
*AQR_EXP*DCFO*	0.016**	0.016**	0.001	0.004
	(0.008)	(0.008)	(0.009)	(0.009)
AQR_EXP*DCFO*CFO	**-0.231****	**-0.238****	**-0.098**	**-0.135**
	(0.097)	**(0.098)**	**(0.102)**	**(0.100)**
Constant	0.041	0.040	0.029	0.033
	(0.048)	(0.048)	(0.041)	(0.041)
Control Variables and Interactions	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
*Industry*Year Fixed Effect*	No	Yes	Yes	Yes
Observations	8,832	8,771	8,812	8,758
R-squared	0.745	0.756	0.755	0.771

Table 11: Auxiliary Analysis

This table reports the results for equation (9), where the dependent variables are Interest Cost, Dividend, Opportunistic RPT, Business RPT, and Total RPT. The coefficient of primary interest is *AQR_EXP*C_Score*. Control variables include Market Capitalization (Mcap), Leverage, Market-to-Book ratio (MB), Profitability, and Age. Definitions of all variables can be found in Table 1. Standard errors are reported in parentheses and are clustered at the firm level. Statistical significance is denoted by *, **, and *** for significance levels of 10%, 5%, and 1%, respectively. We bold the coefficient of the interest variable.

	Panel A	**Panel B**	**Panel C**		
VARIABLES	**Interest cost**	**Dividend**	**Opportunistic RPT**	**Business RPT**	**Total RPT**
C_Score	-0.009	-0.001	-0.005	-0.014	-0.019
	(0.011)	(0.001)	(0.003)	(0.011)	(0.012)
AQR_EXP	-0.006	-0.000	0.000	-0.019**	-0.016*
	(0.007)	(0.001)	(0.003)	(0.009)	(0.010)
AQR_EXP*C_Score	**-0.039*** **	**0.002***	**0.007***	**0.007**	**0.014**
	(0.014)	**(0.001)**	**(0.004)**	**(0.013)**	**(0.014)**
Mcap	-0.017***	0.001	-0.003**	0.013***	0.006
	(0.004)	(0.000)	(0.001)	(0.005)	(0.006)
Leverage	-0.342***	-0.014***	0.025***	0.044	0.082**
	(0.028)	(0.002)	(0.009)	(0.031)	(0.035)
MB	0.002***	0.000	0.000	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Profitability	0.058*	0.062***	0.043***	0.133***	0.212***
	(0.033)	(0.006)	(0.012)	(0.047)	(0.053)
Age	-0.035	-0.013**	0.014	-0.112	-0.117
	(0.052)	(0.005)	(0.018)	(0.070)	(0.074)
Constant	0.470***	0.050***	-0.012	0.442*	0.523**
	(0.182)	(0.017)	(0.063)	(0.246)	(0.265)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	12,686	5,960	12,502	12,502	12,502
R-squared	0.517	0.835	0.563	0.729	0.739

Appendix A: The Overview of Indian Asset Quality Review

Chopra et al. (2021) identify four distinct approaches to bank clean-up that are commonly employed by countries to assess the asset quality of banks during periods of financial crisis. First, the government injects capital into banks without assessing their asset quality, as seen in the U.S. Capital Purchase Program (CPP) in 2008. Second, an independent auditor evaluates banks' asset quality, and the government subsequently provides capital support to undercapitalized banks based on the findings of the asset quality review. This approach is illustrated by the European stress tests of 2011 and 2014, Japan (2003), and the U.S. Capital Assistance Program (CAP) in 2008. Third, this category combines stress tests, asset quality reviews, and capital backstops. A notable example is the European Comprehensive Program of 2014, although its effectiveness was limited due to a flawed incentive structure and the challenges of supranational regulation (Steffen, 2014; Haselmann et al., 2022). Lastly, the fourth category involves asset quality reviews conducted without a capital backstop during non-crisis periods. This is an example of the Indian Asset Quality Review (AQR).

The trigger for the Indian AQR can be traced back to the global financial crisis 2008. Governments and regulatory bodies worldwide employed various mechanisms and tools to mitigate the effects of the crisis. Similarly, in response to the Global Financial Crisis, the Reserve Bank of India (RBI) introduced forbearance measures for loan restructuring, offering relief from the automatic classification of restructured loans as Non-Performing Assets (NPAs), a practice that had been in place before 2008. Chari et al. (2021) examined the forbearance regime and found that it led to a decline in credit extended to healthy firms, which was reallocated to weaker firms. This environment allowed banks to conceal their losses (Flanagan and Purnanandam, 2019) and fostered a "band-aid" culture, resulting in the evergreening of loans (Mannil et al., 2024). In 2015, the RBI revoked the forbearance policy;

however, banks remained hesitant to disclose their NPA-related losses, contributing to sluggish credit growth. Following continued deterioration in asset quality and governance after the end of forbearance, the RBI introduced the "Deep Surgery" in the form of the AQR. Raghuram Rajan, the incumbent governor of the Indian Central Bank, stated, "*Forbearance is ostrich-like behavior, hoping the problem will go away. It is not realism but naiveté, for the lesson from across the world is that the problems only worsen as one buries one's head in the sand… As we found banks reluctant to recognize problems, we decided not just to end Forbearance but also to force them to clean up their balance sheets. The Asset Quality Review, initiated in 2015, was the first major exercise of this nature in India*" (Rajan, 2017, ch.6, p. 70).

The AQR was conducted after the end of the 2016 financial year, with disclosure requirements to be made in the 2017 financial statements. Disclosure and provisioning are mandated if a bank exceeds certain divergence thresholds. Under the AQR process, banks are required to make additional capital provisions and disclose if (a) the additional provisioning requirements assessed by the RBI exceed 15 percent of the published net profits after tax for the reference period or (b) the additional Gross NPAs identified by the RBI exceed 15 percent of the published incremental Gross NPAs for the reference period, or both.[15] The effect of the Indian AQR was significant, as Gross NPAs to total advance (net NPAs to total advance) increased dramatically following its implementation. Figure A1 provides the time series of Gross and Net NPAs.

However, considering the potential for misuse near the cutoff, the RBI revised the threshold in April 2019. Additionally, in response to the COVID-19 moratorium and other forbearance measures granted to banks, the RBI lowered the limits to 5% for commercial banks. Recently, the RBI expressed concerns regarding banks' asset quality, given the impact of the COVID-19 moratorium and forbearance policies. In response, it increased the risk

[15] https://www.rbi.org.in/Scripts/NotificationUser.aspx?Id=10932&Mode=0

weights for several asset categories to curb the accumulation of such assets and prevent the concealment of losses. Table A1 provides year-wise thresholds.

Figure A1: Non-Performing Assets of Indian Banks

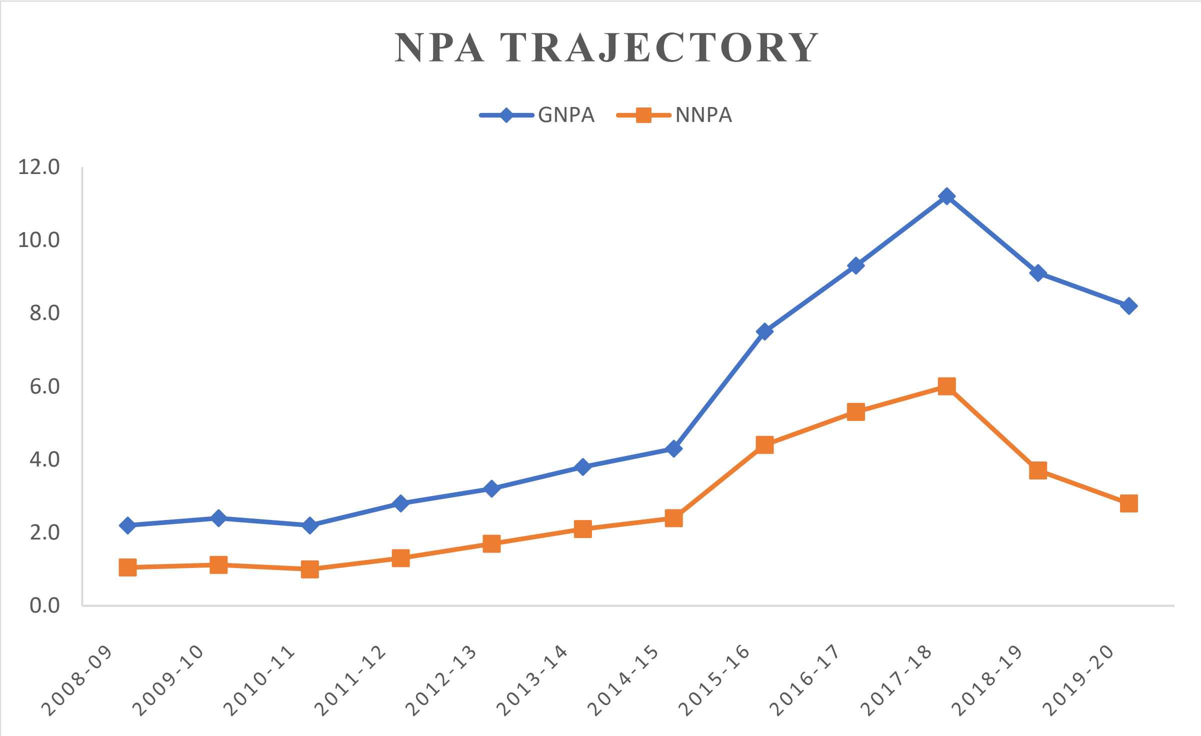

Table A1

Threshold	2017-19	2020-2023	2024 onwards
Additional Provisioning % of net profit	15%	10%	5%
Additional NPA % of gross NPA	15%	15%	5%

Appendix B: Anecdotal Evidence

In the initial years following the AQR, there is substantial evidence that firms attempted to conceal their losses. A prominent example is Infrastructure Leasing and Financing Services Limited (IL&FS). Before defaulting on loan repayments in 2018, IL&FS reported profitable financial statements for the fiscal year 2017-18 and held the highest-grade credit rating just before its default. After the default, restatements of IL&FS's financials revealed significant irregularities and hidden losses. For instance, the following two leading Indian financial newspapers report highlights the extent of these irregularities:

"Following the massive restatement of accounts, IL&FS's loss has now been estimated at Rs 9,600 crore during the five financial years ending 2017-18. Originally, a profit of Rs 1,869 crore had been shown by the company management and board -- which were later superseded following revelations of huge irregularities that left India's financial sector shaken." The Economic Times (2023, March 22).

"The government in its court filing said IL&FS was 'indiscriminately" borrowing money. IL&FS "has been presenting a rosy picture and camouflaging its financial statements by hiding severe mismatch between its cash flows and payment obligations, total lack of liquidity and glaring adverse financial ratios," according to the 44-page filing. " Bhat, R. (2018, October 1)

The IL&FS case illustrates how firms attempted to conceal losses to avoid the consequences of covenant violations or debt defaults. The default by IL&FS significantly drained liquidity from the market. Even a month before the default, IL&FS maintained a high credit rating, primarily due to its efforts to hide losses, which benefited both the company and its creditors.

Appendix C: The estimation of *C_score*

Appendix C provides details on the estimation process used to calculate C_Score. We follow the methodology Khan and Watts (2009) outlined to estimate *C_Score*.

The following equation presents the model:

$$Earnings_i = \beta_0 + \beta_1 \times D_i + \beta_2 \times Return_i + \beta_3 \times D_i \times Return_i + \epsilon_{it} \qquad \text{(C1)}$$

In equation (C1), the dependent variable is earnings (profit after tax scaled by the market value of equity at the beginning of the year). *Return* represents the annual rate of return of firm *i*, and *D* is a dummy variable that takes the value one if *Return*<0 (indicating bad news) and zero otherwise (indicating good news). The coefficient β_3 measures the timeliness of bad news compared to good news, also called conditional conservatism. Specifically, β_3 captures how quickly bad news (negative returns) is incorporated into earnings compared to good news (positive returns). A positive and significant β_3 suggests that firms recognize bad news more quickly than good news, indicating greater accounting conservatism, which is the essence of timely loss recognition.

Khan and Watts (2009) develop two additional measures to assess the timeliness of good and bad news in earnings. These measures, *G_Score* and *C_Score*, respectively, capture the asymmetry in the recognition timeliness for the good and bad news. *C_Score* measures the incremental timeliness of bad news, reflecting how firms recognize negative news more quickly than positive news.

$$C\_Score = \beta_3 = \lambda_1 \times Mcap_i + \lambda_2 \times M/B_i + \lambda_3 \times Leverage_i \qquad \text{(C2)}$$
$$G\_Score = \beta_2 = \delta_1 \times Mcap_i + \delta_2 \times M/B_i + \delta_3 \times Leverage_i \qquad \text{(C3)}$$

Here*,* *Mcap* is the natural log of the market value of equity, *M/B* is the market value of equity divided by the book value of equity, and *Leverage* is the total borrowing divided by the average total asset. For estimating *C_Score,* equations (C2) and (C3) are substituted in equation (C1), to obtain equation (C4).

$$X_i = \beta_0 + \beta_1 \times D_i + R_i \times (\lambda_1 \times Mcap_i + \lambda_2 \times M/B_i + \lambda_3 \times Leverage_i) + D_i \times R_i \times (\lambda_1 \times Mcap_i + \lambda_2 \times M/B_i + \lambda_3 \times Leverage_i) + (\delta_1 \times Mcap_i + \delta_2 \times M/B_i + \delta_3 \times Leverage_i + \delta_4 \times D_i \times Mcap_i + \delta_5 \times D_i \times M/B_i + \delta_6 \times D_i \times Leverage_i) + \epsilon_{it} \quad \text{(C4)}$$

We estimate the regression equation (C4) using annual cross-sectional data to capture the relationship between earnings and market returns, accounting for firm characteristics. Next, we use equation (C2) estimates to obtain *C_Score* for each firm. *C_Score* is calculated as the incremental timeliness of bad news, following the methodology proposed by Khan and Watts (2009) and Ahmed and Duellman (2013). Specifically, the coefficient β_3 (C_Score) Equation (C2) captures the differential timeliness in recognizing bad news compared to good news, thus serving as a measure of conditional conservatism. We also control for firm-level characteristics—market value (MV), market-to-book ratio (M/B), and Leverage—separately, as per the methods outlined by Khan and Watts (2009) and Ahmed and Duellman (2013).

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Online Appendix

Table OA1: Sample MCA Data Format

This table reports the Bank-Firm loan level data for one Indian company.

Sr. No	SRN	Charge Id	Charge Holder Name	Date of Creation	Date of Modification	Date of Satisfaction	Amount	Address	Whether charge registered
1	A66312588	90168447	BANK 1	11/11/1991	-	08/07/2009	1,14,00,000	SECTOR - 17 B,CHANDIGARH, Chandigarh, India,	No
2	Y10270320	90168421	BANK 2	05/04/1991	31/08/1991	10/04/2002	60,00,000	S A S NAGAR,MOHALI,MOHALI, Punjab, India, 142009	No
3	A65973398	90170491	BANK 3	05/12/1989	-	13/07/2009	30,00,000	THE MALL BRANCH,PATIALA, Punjab, India,	No
4	Y10269949	90168050	Bank 1	21/10/1986	11/11/1991	30/03/2002	50,00,000	SECTOR - 17 B,CHANDIGARH, Chandigarh, India, 160009	No
5	Y10269897	90167998	Bank 2	12/03/1986	30/11/1989	10/04/2002	1,25,00,000	S A S NAGAR,MOHALI, Punjab, India, 142009	No

Table OA2: Sample Selection Process

This Table defines the sample selection process.

Particulars	Number of Firms	Number of Transactions (Firm-Year Observations)
Extracted CIN Number of listed superset of companies from CMIE prowess Dx	9033	
MCA Data Availability	6363	157116
MCA Data after removing loans settled before 2012 and matched with bank data	6076	122159
Firms with outstanding borrowing during the sample period	5736	
Final sample for the Baseline model (after removing missing observations for variables of the baseline model and financial industry firm observations and ensuring at least one observation in the sample period)	3406	19105
AQR-exposed bank borrowing firms (Treatment firms)	2278	13854
Never Treated Firms (Control firms)	1128	5251
Final Sample for C_Score	2625	13287

Table OA3: Entropy Balancing

Before Matching	Treatment			Control		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	7.757	3.857	0.2507	7.598	4.089	0.2969
Leverage	0.3425	0.1106	3.144	0.3822	0.1275	2.975
Growth	0.1445	0.4223	5.301	0.1599	0.5383	4.838
After Matching	Treatment			Control		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	7.757	3.857	0.2507	7.756	3.858	0.2506
Leverage	0.3425	0.1106	3.144	0.3427	0.1108	3.143
Growth	0.1445	0.4223	5.301	0.1446	0.4231	5.298

Table OA4: ICR based regression

This table reports regression equation (3) results, where the dependent variable is *ACC*. The primary coefficient of interest is the interaction term *DCFO*CFO*AQR_EXP*, which captures the effect of bank AQR exposure on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, along with their interactions with *CFO, DCFO,* and *CFO*DCFO*. Definitions of all variables are provided in Table 1. Standard errors are reported in parentheses and are clustered at the firm level. Columns 1, 3 and 5 show the results for firms with *ICR* < 0.5, <2, and <3 in 2016, respectively, while Columns 2, 4 and 6 display the results for firms with *ICR* > 0.5, >2, >3 in 2016, respectively. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively

	(1)	(2)	(3)	(4)	(5)	(6)
	ICR<0.5	ICR>0.5	ICR<2	ICR>2	ICR<3	ICR>3
VARIABLES	ACC	ACC	ACC	ACC	ACC	ACC
CFO	-1.190***	-1.198***	-1.250***	-1.133***	-1.294***	-1.048***
	(0.184)	(0.073)	(0.122)	(0.077)	(0.101)	(0.086)
DCFO	-0.003	-0.020	-0.010	-0.026	-0.011	-0.030*
	(0.031)	(0.013)	(0.019)	(0.016)	(0.016)	(0.018)
DCFO*CFO	0.359	0.089	0.307	-0.105	0.271	-0.059
	(0.375)	(0.136)	(0.210)	(0.169)	(0.182)	(0.194)
AQR_EXP	-0.054***	-0.009**	-0.033***	-0.006*	-0.027***	-0.008*
	(0.012)	(0.003)	(0.007)	(0.003)	(0.006)	(0.004)
AQR_EXP*CFO	0.461***	0.114***	0.312***	0.089***	0.261***	0.102***
	(0.120)	(0.028)	(0.068)	(0.028)	(0.054)	(0.032)
AQR_EXP*DCFO	0.008	0.010	0.014	0.007	0.011	0.011
	(0.016)	(0.006)	(0.010)	(0.007)	(0.008)	(0.007)
AQR_EXP*DCFO*CFO	-0.541***	-0.044	-0.340***	-0.000	-0.260**	-0.036
	(0.200)	(0.073)	(0.120)	(0.079)	(0.104)	(0.090)
Constant	-0.132	0.067**	-0.058	0.129***	-0.023	0.136***
	(0.102)	(0.029)	(0.057)	(0.034)	(0.047)	(0.041)
Control Variables and Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,123	13,694	7,853	8,964	10,109	6,708
R-squared	0.616	0.807	0.692	0.823	0.717	0.813

Table OA5: Sample excluding reporting requirement under Ind-AS

This table reports the result of a regression equation (3) where the dependent variable is ACC. Our coefficient of interest is the interaction term DCFO*CFO*AQR_EXP, which captures the effect of bank AQR on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage, and their interactions with CFO, DCFO, and CFO*DCFO. All variables are defined in Table 1. Columns 1 and 2 report results for firms with net book value less than 5 billion rupees and 2.5 billion rupees, respectively. Standard errors are given in parentheses and clustered at the firm level. *, **, and *** represents the statistical significance level at 10%, 5% and 1% respectively.

	(1)	(2)
	Net<5000	Net<2500
VARIABLES	ACC	ACC
CFO	-1.042***	-0.988***
	(0.096)	(0.108)
DCFO	-0.013	-0.009
	(0.015)	(0.017)
DCFO*CFO	0.034	-0.006
	(0.163)	(0.179)
AQR_EXP	-0.017***	-0.018***
	(0.004)	(0.005)
AQR_EXP*CFO	0.162***	0.166***
	(0.037)	(0.041)
AQR_EXP*DCFO	0.007	0.009
	(0.006)	(0.007)
AQR_EXP*DCFO*CFO	-0.156**	-0.169**
	(0.076)	(0.079)
Constant	-0.014	-0.027
	(0.031)	(0.033)
Control Variables and Interactions	Yes	Yes
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
Observations	15,551	13,803
R-squared	0.760	0.767

Table OA6: Panel A Types of Related Parties

Panel A

This table presents different kinds of related parties and their classification into Directors, Officers, Shareholders (DOS), and Investees.

Related Party Name	**DOS/Investee**
1. Holding Company	Investee
2. Ultimate Holding Company	Investee
3. Intermediate Holding Company	Investee
4. Subsidiary	Investee
5. Fellow Subsidiary Company	Investee
6. Associate	Investee
7. Joint Venture	Investee
8. Parties where control exists	DOS
9. Key Personnel	DOS
10. Relatives of Key Personnel	DOS
11. Enterprises over which KMP (Key Managerial Personnel) have control or significant influence	DOS
12. Individuals having significant influence over the company	DOS
13. Promoters	DOS
14. Shareholders	DOS
15. Others	Investee

Table OA6: Panel B: Nature of Related Party Transactions

TONE is a transaction with a higher probability of opportunism, and BUSINESS has a lower probability of opportunism. Therefore, TONE implies opportunistic transactions, and BUSINESS suggests no opportunism. Any transaction of the firm with DOS or Investees of a Tone nature is classified as Opportunistic RPT. However, any firm transaction with Investees or DOS of a Business nature transaction is classified as Business RPT. Furthermore, few transactions depend on the type and party involved to be classified as Tone and Business RPT. Classification of the transaction into Business and Opportunistic RPT is shown in the table below.

Variable Name	Party	Grouping
Income from the sale of goods to related parties	DOS/Investee	BUSINESS
Income from services to related parties	DOS/Investee	BUSINESS
Rent income from related parties	DOS/Investee	BUSINESS
Interest income from related parties	DOS/Investee	TONE
Dividend income from related parties	DOS/Investee	TONE
Reimbursement of expenses by related party	DOS/Investee	TONE
Other income from related parties	DOS/Investee	TONE
Payment for raw materials/finished goods	DOS/Investee	BUSINESS
Payment for energy, power, and fuel	DOS/Investee	BUSINESS
Payment for salaries and wages to related parties	DOS/Investee	TONE
Payment for marketing expenses	DOS/Investee	BUSINESS
Payment for processing charges/job works	DOS/Investee	BUSINESS
Payment for rent	DOS/Investee	BUSINESS
Payment for royalties/technical know-how fees	DOS/Investee	BUSINESS
Payment for interest	DOS/Investee	TONE
Expenses reimbursed to a related party	DOS/Investee	TONE
Payment for other revenue expenses	DOS/Investee	TONE
Payment for other operating expenses	DOS/Investee	BUSINESS
Payment for dividends	DOS/Investee	TONE
Share capital issued during the year	DOS/Investee	DOS-TONE, Investee-BUSINESS
Receipts from the sale of fixed assets	DOS/Investee	DOS-TONE, Investee-BUSINESS
Receipts from the sale of investments	DOS/Investee	DOS-TONE, Investee-BUSINESS
Total capital account payments	DOS/Investee	DOS-TONE, Investee-BUSINESS
Borrowings received during the year	DOS/Investee	DOS-TONE, Investee-BUSINESS
Loans and advances given during the year	DOS/Investee	DOS-TONE, Investee-BUSINESS
Guarantees given during the year	DOS/Investee	DOS-TONE, Investee-BUSINESS
Guarantees taken during the year	DOS/Investee	DOS-TONE, Investee-BUSINESS

Table OA7: Change in Debt and 'Firms' Accounting Conservatism

This table reports the result of a regression equation (6) where the dependent variable is ACC. Our coefficient of interest is the interaction term DCFO*CFO*AQR_EXP, which captures the effect of bank AQR on firm-level asymmetric timely loss recognition. Control variables include Size, Growth, and Leverage and their interactions with CFO, DCFO, and CFO*DCFO. All variables are defined in table 1. Standard errors are given in parenthesis and clustered at the firm level. Column 1 and 2 shows the results for firms which increased the debt and column 3 and 4 shows the results for firms which decrease the debt. *, **, and *** represents the statistical significance level at 10%, 5% and 1% respectively.

	(1)	(2)	(3)	(4)
	Increase Debt		Decrease Debt	
VARIABLES	ACC	ACC	ACC	ACC
CFO	-1.111***	-1.118***	-1.177***	-1.167***
	(0.098)	(0.101)	(0.117)	(0.110)
DCFO	-0.008	-0.006	-0.065*	-0.070**
	(0.014)	(0.013)	(0.034)	(0.033)
DCFO*CFO	0.081	0.100	0.134	0.146
	(0.162)	(0.153)	(0.312)	(0.319)
AQR_EXP	-0.016***	-0.016***	-0.014**	-0.014**
	(0.005)	(0.005)	(0.006)	(0.006)
AQR_EXP*CFO	0.154***	0.159***	0.156***	0.155***
	(0.042)	(0.043)	(0.055)	(0.054)
AQR_EXP*DCFO	0.004	0.004	0.014	0.013
	(0.007)	(0.007)	(0.011)	(0.011)
AQR_EXP*DCFO*CFO	-0.161*	-0.186**	-0.093	-0.104
	(0.084)	(0.083)	(0.140)	(0.140)
Constant	-0.029	-0.024	0.113	0.109
	(0.038)	(0.038)	(0.073)	(0.074)
Control Variables and Interactions	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Industry*Year Fixed Effect	No	Yes	Yes	Yes
Observations	12,283	12,228	5,675	5,630
R-squared	0.783	0.792	0.786	0.808