Risks and financial performance of Indian banks: a cursory look at the COVID-19 period

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Abstract

Purpose – The novel coronavirus (COVID-19) has caused financial stress and limited their lending agility, resulting in more non-performing loans (NPLs) and lower performance during the II wave of the coronavirus crisis. Therefore, it is essential to identify the risky factors influencing the financial performance of Indian banks spanning 2018–2022.

Design/methodology/approach – Our sample consists of a balanced panel dataset of 75 scheduled commercial banks from three different ownership groups, including public, private and foreign banks, that were actively engaged in their operations during 2018–2022. Factor identification is performed via a fixed-effects model (FEM) that solves the issue of heterogeneity across different banks over time. Additionally, to ensure the robustness of our findings, we also identify the risky drivers of the financial performance of Indian banks using an alternative measure, the pooled ordinary least squares (OLS) model.

Findings – Empirical evidence indicates that default risk, solvency risk and COVAR reduce financial performance in India. However, high liquidity, Z-score and the COVID-19 crisis enhance the financial performance of Indian banks. Unsystematic risk and systemic risk factors play an important role in determining the prognosis of COVID-19. The study supports the “bad-management,” “moral hazard” and “tail risk spillover of a single bank to the system” hypotheses. Public sector banks (PSBs) have considerable potential to achieve financial performance while controlling unsystematic risk and exogenous shocks relative to their peer group. Finally, robustness check estimates confirm the coefficients of the main model.

Practical implications – This study contributes to the knowledge in the banking literature by identifying risk factors that may affect financial performance during a crisis nexus and providing information about preventive measures. These insights are valuable to bankers, academics, managers and regulators for policy formulation. The findings of this paper provide important insights by considering all the risk factors that may be responsible for reducing the probability of financial performance in the banking system of an emerging market economy.

Originality/value – The empirical analysis has been done with a fresh perspective to consider unsystematic risk, systemic risk and exogenous risk (COVID-19) with the financial performance of Indian banks. Furthermore, none of the existing banking literature explicitly explores the drivers of the I and II waves of COVID-19 while considering COVID-19 as a dependent variable. Therefore, the aim of the present study is to make efforts in this direction.

Keywords COVID-19, Systemic risk, Unsystematic risk, Financial performance, Indian banks

Paper type Research paper

1. Introduction

Crises like novel coronavirus (COVID-19), the 2007/2008 Global Financial Crisis and the recent Silicon Valley (2023) crisis are among the most immediate and critical issues for the banking sector, especially in emerging countries like India (Ahmed et al., 2022; Zhang et al., 2023). As a result, both the real estate and financial sectors in developed and developing...
nations are going through unprecedented levels of stress. According to World Bank figures for 2020, India’s gross domestic product (GDP) growth rate falls sharply from 3.7% in 2019 to −6.6% in 2020, which is far below the global GDP growth rate of 3.3%. The COVID-19 crisis’ second wave causes uncertainty in the Indian financial market, increasing its effects on the banking industry as well. The primary cause of this is that during a financial crisis, the bank fails to collect its debts as needed (Park and Shin, 2021). According to the Reserve Bank of India (2022), the ratio of non-performing loans (NPLs) to net advances of Indian commercial banks has reached 13.5% by the end of the fiscal year, which is the highest level since 2008 (2.25%) and lowers the bank’s financial performance. The top-level bank NPL ratio is a persistent problem in India that eventually has a detrimental influence on profitability and financial performance.

Apart from the accumulation of more debris in the bank’s balance sheet during the era of COVID-19, it faces a host of other risks such as liquidity, default, operational, foreign exchange, as well as market risks. Cornett and Saunders (1999) classify bank risks into three groups, namely operational, financial and strategic. Hussain and Al-Ajmi (2012) further claim that these are the most difficult risks for banks to manage during a crisis. All of these risks exacerbate the strain on the Indian banking industry and constitute a grave threat to the banks’ ability to make money. In essence, the COVID-19 crisis-induced economic slowdown in India raises concerns about the spillover effects of such an economic fallout on financial performance. This is because risks are becoming more systematic, systemic and unsystematic as a result of the macroeconomic recession. An increase in risk appetite by firms, individuals and households reduces the financial performance of banks. This argument suggests that it is important to understand how hazardous variables affect the financial performance of Indian banks.

The recent literature pertinent to the banking sector in the light of COVID-19 mainly focuses on the following areas: (1) examining the consequence of credit risk on financial performance in light of COVID-19 (Tran et al., 2022; Ahmed et al., 2022); (2) predicting systemic risk in the banking industry during the COVID-19 crisis (Rizwan et al., 2022; Baumohl et al., 2022; Zhang et al., 2023); (3) identifying systematic and systemic risk during the period of COVID-19 (Benoit et al., 2017; Duan et al., 2021; Chiang and Chen, 2022). Ahmed et al. (2022) assess the influence of credit risk on the financial performance of Islamic banks and conventional banks during the COVID-19 crisis. Tran et al. (2022) empirically examine the accounting- and market-based risks of banks during the COVID-19 pandemic. Fang et al. (2023) and Zhang et al. (2023) explore the impact of economic policy uncertainty on bank systemic risk with a distinction between systematic linkage and bank tail risk. Now, it is clear that the empirical evidence regarding the immediate effects of COVID-19 and other risky variables on bank financial performance is under-researched and unclear, with barely any effort from the banking system in an emerging market economy like India, which is one of the striking aspects of the existing research. Only Nayak and Chandiramani (2022), to the best of our knowledge, explain the significance of Indian bank digitization during COVID-19.

The riskiness of banks and their performance during an exogenous shock in the COVID-19 crisis remains an enduring concern and is subject to further empirical investigation (Tran et al., 2022). Given this background, the study addresses the following research questions: (1) What are the unsystematic risk, systemic risk and exogenous risky factors that affect financial performance in India during 2018–2022? (2) Does the financial performance of Indian banks remain unaffected by the external shock of COVID-19? (2) Does the financial performance remain consistent across ownership groups during the COVID-19 phases? (3) Are the same risk factors responsible during the first (I) and second (II) waves of COVID-19? To answer these questions, the following three research objectives are proposed: First, to estimate the impact of unsystematic risk, systemic risk and COVID-19 on the financial performance of Indian banks using a fixed-effects model (FEM). Second, to examine whether
the impact of the COVID-19 crisis is equally distributed across different ownership groups, such as public, private and foreign banks in India. Finally, to assess the key risk factors for COVID-19 during the I and II waves of COVID-19 using a bootstrapped truncated regression model (Algorithm #1) by Simar and Wilson (2007). The study period’s dataset spans the years 2018 through 2022. Earlier studies empirically used a shorter window of pandemic datasets to explore explainable variables of banks, although the epidemic arose well past, especially at the end dates of their windows. Therefore, the ongoing study extends the literature that covers both the I and II waves of the COVID-19 crisis, adding to the current stock of literature on Indian banks. The tendency of people to maintain more liquid assets than usual has restrained the increase of bank deposits in circumstances of great uncertainty, such as the COVID-19 pandemic. This, in turn, reduces the ability of borrowers to repay their loans, which negatively affects the ability of the banks to earn income. This argument forces us to explore as many risky factors as possible that hinder the financial performance of the banking industry when an exogenous shock occurs in the economy.

The study unquestionably adds significantly to the body of knowledge on Indian banking literature. First, this is the first study to assess the impact of exogenous shocks such as the COVID-19 crisis on bank financial performance in India. To dive deeper into this, we comprise our overall dataset considering pre-(2018–2020), during (2020–2021) and post-(2021–2022) COVID-19 periods. The dataset considered in the study is taken from the official data provided by the Reserve Bank of India. Research in the prior literature (such as Fujii et al., 2014; Tzeremes, 2015; Huang and Chung, 2017; Goswami, 2021a, b) is mostly limited to the Global Financial Crisis datasets. Second, we capture the effect of unsystematic risk (namely default risk, liquidity risk (LR), bank risk (Z-score), market risk and solvency risk), systemic risk and exogenous shock on the financial performance of Indian banks. Third, this study constructs all novel risky determinants in the FEM along with the exogenous shock of COVID-19 to explain their role in the financial performance of Indian banks. The FEM has been applied recently by several authors like Tarchouna et al. (2017), Khan et al. (2020), Demir and Danisman (2021), Tran et al. (2022), Cao and Chou (2022) etc. They prominently identify the influence of the COVID-19 crisis, along with other micro and macroeconomic variables on the banking industry in countries other than India in the literature (see Table 1 for detail variables). The FEM allows \( i \)th banks to have different constants, but the coefficients are fixed over time (Gujarati and Dawan, 2015). This model is used prominently to control for an unseen heterogeneity issue across different \( i \)th banks over time. While combining cross-section and time series in the panel datasets. The problem of heteroscedasticity mainly arises in the traditional “ordinary least squares (OLS) method” as residuals are correlated with time and different \( i \)th banks, and hence, predicted results are biased. We also identify the risky determinants of Indian banks using alternative measures such as the pooled OLS model and a bootstrapped truncated regression model to prove the robustness of the main model.

Fourth, we introduce the COVID-19 crisis as one of the dependent variables to measure the key drivers of the exogenous shock. Elnahass et al. (2021) and Goswami (2022) created a dummy to quantify outbreak that is equal to 1 if a sample bank was observed during the pandemic period of the first two quarters of 2020, or 0 otherwise. Unlike these studies, the study uses the natural log of total confirmed COVID-19 cases as our primary measure to predict the accurate measure of the exogenous shock. Lastly, to see the impact of risky determinants on different ownership groups in the light of the COVID-19 crisis, we create an ownership dummy for public sector banks (PUB) and for private banks (PVT), which are not yet identified in the Indian banking literature. Although the central bank directs almost the same policies for all ownership groups, their work culture, operations and risk management practices differ. Therefore, it is interesting to see whether risk determinants impact them equally during an unprecedented event or an external shock. To the best of our knowledge,
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<td>Goswami (2021a)</td>
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<td>Duan et al. (2021)</td>
<td>1 year dataset from February 6, 2020, to December 10, 2020</td>
<td>1,584 listed banks across 64 cross-countries</td>
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<td>Tan et al. (2021)</td>
<td>2007–2017</td>
<td>Cross-countries analysis</td>
<td>Fixed effects</td>
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<td>Demir and Danisman (2021)</td>
<td>1 year dataset from January 11, 2020, to May 28, 2020</td>
<td>1,927 publicly listed banks from 110 countries</td>
<td>Fixed effects</td>
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<td>Kryzanowski et al. (2022)</td>
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<td>Bitar and Tarazi (2022)</td>
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Source(s): Authors' elaboration
this is perhaps the first Indian study that identifies to what extent unsystematic risk, systemic risk, and the COVID-19 crisis impacts the banks’ financial performance. Interestingly, no efforts have been made so far to simultaneously take into account the risk factors and exogenous shocks affecting the financial performance of Indian banks. The findings of the study will be relevant for policymakers and regulators to craft preventive measures as early warning indicators against hazardous factors so that banks remain resilient even during crises.

The rest of the paper is organized as follows: Section 2 illustrates the relevant literature review, the theoretical underpinning and identifies literature gaps in the study. Section 3 explains the relevance of applying the FEM to the study. Section 4 briefly presents the dataset, variable specifications and hypotheses development for the estimated model. Section 5 presents and discusses the main findings, and it examines their heterogeneity and robustness. Section 6 presents discussion and implications. Finally, it shows concluding remarks and future courses of action.

2. Relevant literature review and theoretical framework

2.1 Theoretical framework

The study follows three theories to explain the role of risky determinants in the financial performance of Indian banks:

2.1.1 Theory of asymmetric information. Asymmetric information emerges from the “moral hazard” and “bad management” hypotheses. One of the cornerstones of Akerlof’s Lemon Theory (1970) is information asymmetry, which happens when owners or managers are more aware of the risks and benefits of their company than lenders are. Spence (1973) and Stiglitz (2002) define information asymmetry as a situation where one party (either a borrower or a lender) in an economic transaction has more information than the other party. For example, only a borrower knows better than the lender about their ability to repay a loan received, or vice versa. Asymmetric information is a difficulty in the financial industry, making it challenging to discern between good and bad borrowers. As a result, moral hazards and adverse selection may be problems.

Contrary to post-contractual knowledge asymmetries, pre-contractual information asymmetries result in unfavorable selection (Dari-Mattiacci et al., 2021; Kwashie et al., 2022). Adverse selection occurs when the profitability of a loan is influenced by the type of borrower and interest rate. This is because higher interest rates tend to draw fewer qualified borrowers. These borrowers are more likely to default since they frequently invest in high-risk projects (Laryea et al., 2016). Because they cannot see the borrower’s characteristics or behaviors, lenders that grant credit to borrowers encounter uncertainty over loan payback. This makes it challenging to assess the borrower’s creditworthiness. Due to the replacement of low-quality borrowers by high-quality borrowers, the quality of bank loan portfolios as a whole decline, NPLs increase and profitability declines. Louzis et al. (2012), Klein (2013), Makri et al. (2014), Chaibi and Fitt (2015), Ghosh (2015), Goswami (2021a, b), this study uses a ratio of bank equity to total assets to assess the impact of solvency risk on financial performance. According to studies, managers of bank branches with high levels of capital have a moral hazard incentive to participate in hazardous lending activities, as well as inadequate credit screening and monitoring of borrowers, all of which have the potential to negatively impact financial performance (Krugman, 2009). Gladwell (2005) indicates that the theory of moral hazard and adverse selection has a major effect on banks and may lead to lower profits, lower liquidity and higher pricing of loans. Moral hazard and adverse selection can result in borrowers not repaying loans, and this can cause a substantial increase in credit risk and thus impact the bank’s financial performance.
According to the “bad management” hypothesis put forward by Berger and DeYoung (1997), when NPLs rise, management tends to commit more resources to managing troubled loans, raising operational expenses above interest revenue. As a result, a higher cost-to-income ratio denotes subpar loan underwriting, monitoring and control on the part of the bank (Louzis et al., 2012; Ghosh, 2015; Goswami, 2021a).

2.1.2 Credit default theory. In situations where the impact of a default on a bank’s financial performance is indirect, the credit default theory is applicable. As it recognizes “delinquency” and “insolvency” as the causes of NPL, this theory seems to be consistent with studies on the association between NPL and financial performance. Delinquency is defined as failing to make a timely payment on an obligation, but insolvency is defined as having more liabilities than assets. The term “credit default” is rooted in the delinquency concept. This happens when a borrower lacks the liquidity necessary to make loan payments on time. Delinquency triggers a solvency review, which could lead to a negative equity position and the cancellation of the loan (Ahmed et al., 2022).

2.1.3 Risk-mitigation theory. Following Berger and DeYoung (1997) and Lee et al. (2022), the study assumes and supports the “risk mitigation theory” and “bad management” hypothesis, which hold that banks with more prudent lending are more cautious in lending and have stronger relationship management, which lowers the likelihood of bank default.

According to the theoretical framework provided, credit default is caused by asymmetric information, adverse selection of borrowers, bad management and moral hazard, which in turn affects the financial performance of the bank. These factors and the theoretical framework compel us to examine the novel objectives of this study to understand the key risky drivers impacting the financial performance of Indian banks during the exogenous crisis. Secondly, the study aims to see whether asymmetric information, bad management, moral hazard and systemic risk are responsible for undermining the financial performance of Indian banks in both the I and II waves of the COVID-19 crisis.

2.2 Literature review
A variety of issues are covered in the literature on banks’ performance during the COVID-19 outbreak, including bank lending, profitability and stability during the pandemic (Khan et al., 2020; Park and Shin, 2021; Ahmed et al., 2022), the impact of different bank-level factors on banking performance and banks’ resilience throughout the crisis (Cao and Chou, 2022), the impact of credit risk and systemic risk on banks’ performance (Duan et al., 2021; Baumohl et al., 2022; Ouyang et al., 2022; Chiang and Chen, 2022; Zhang et al., 2023; Fang et al., 2023), diversification of banking business from traditional to non-traditional based activities, corporate social responsibility (CSR) and financial performance (Maqbool and Zameer, 2018), the severity of financial regulations and regulatory response (Tan et al., 2021; Tran et al., 2022; Bitar and Tarazi, 2022), digitization effect (Nayak and Chandiramani, 2022) and so forth affect banks’ performance in the pandemic (see Table 1 and Figure 1).

Various empirical studies are being conducted on the banking industry, considering several micro and macroeconomic factors during the COVID-19 crisis. Specifically, the issues of the banking sector’s ongoing response to the COVID-19 crisis are studies on the following factors: banks’ credit growth (Li et al., 2021; Çolak and Öztekin, 2021), credit risk (Goswami, 2022), systemic risk (Duan et al., 2021), stock market performance (Demirci-Kunt et al., 2021; Dadoukis et al., 2021) and performance (Tran et al., 2022; Elnahass et al., 2021) during the pandemic. Few studies emphasize the impact of various bank-level factors and country-specific factors on banks and the financial market’s resilience to the pandemic (Li et al., 2021; Çolak and Öztekin, 2021; Danisman et al., 2021; Demir and Danisman, 2021). Others assess the influence of government policy to mitigate the detrimental impact of the COVID-19 crisis on
banks’ performance (Demirgüç-Kunt et al., 2021; Demir and Danisman, 2021). Embaye et al. (2017), Herath et al. (2021), Kwashie et al. (2022), have identified that inflation, liquidity, size and stability improve the financial performance of banks, while Louzis et al. (2012) and Mushafiq et al. (2021) have indicated that size and leverage have a detrimental impact on banks’ financial performance. In the context of the Indian banking industry, Goswami (2022) estimates the drivers of credit risk in the II-stage of the regression model, taking into account the dummies of COVID-19 and policy initiatives. However, the study is limited to only the 2020 data period to explore the role of COVID-19 with NPLs. Continuing this, Figure 2 shows a graph of the most prominent authors working on the keys to COVID-19, systemic risk and NPLs in the banking literature over the past few years (Khan et al., 2020; Park and Shin, 2021; Ahmed et al., 2022). Figure 2 clearly shows the authors’ generosity in working on the most salient area of systemic risk and NPLs by covering the light of COVID-19 (Tarchouna et al., 2017; Duan et al., 2021; Tan et al., 2021; Lee et al., 2022). However, no one puts all the risky determinants in one basket, which can explain which risky factor mainly fragile the performance of banks when a crisis occurs; hence, the main aim of the study is to make efforts in this direction.

It is clearly seen from Figure 1 that the most studied topics in the context of the banking industry are COVID-19, NPLs and systemic risk. On the other hand, we can also find that most of the studies are conducted across nations and especially for China. This is also consistent with the presented literature Table 1. This highlights a glaring gap that needs to be filled for the Indian banking industry. Here, we can see that the frequency of the operation of Indian banking literature is very less but it should be increased considering all the emerging factors. It has become imperative to recognize the role of COVID-19, systemic risk, solvency risk, LR, market risk, bank risk (Z-score) and NPL in the banking sector. So that we can find out which factors need more attention by the policy makers to improve the performance of Indian banks. Hence, the terms COVID-19, systemic and NPL are garnering significant attention at the moment.
2.3 Research gap
The following research gaps are drawn from the literature review, Figures 1 and 2. First, unquestionably, the ongoing research of the banking industry across nations primarily focuses on the phenomenon of the COVID-19 crisis, but the literature on Indian banks is still untouched. The COVID-19 was heavily contained by the Indian government in order to slow its spread, but this resulted in a weakening of economic activity and a significant loss of income and revenue for enterprises and households (Tan et al., 2021; Tran et al., 2022; Goswami, 2022). In turn, this decreased consumer demand for financial services and weakened the solvency and repayment capacity of borrowers. However, not enough has been done to identify the risky factors at the micro- and macro-level that led to the Indian banks’ declining financial performance during the COVID-19 crisis. Second, we note that there is hardly any Indian study except by Goswami (2022) that identifies credit risk drivers in the recent period. However, the study is limited to only the 2020 data period to explore the role of COVID-19 with NPLs. The present study, using recent samples from 2018 to 2022 with other unsystematic risks, systemic risks and external shocks, aims to fill the gap in the Indian banking literature. Third, we summarize from the above that there are two stands of literature: one explores bank-centric factors, while the other explores both macro- and micro-factors across countries over the years. While no study collectively identifies the impact of unsystematic risk, systematic risk, systemic risk and exogenous shocks on financial performance in the banking system, the present study aims to make an effort in this direction. Identification of risky determinants is important for policymakers to focus on risk factors and cushion the financial performance of banks against an unprecedented event if it is likely to occur in the future.

3. Methodological framework
Consistent with previous literature (Tan et al., 2021; Demir and Danisman, 2021; Ahmed et al., 2022), we employ FEMs to explain the role of risky determinants with exogenous shock on the financial performance of Indian banks during 2018–2022.
3.1 Hausman specification test
Before jumping into the main FEM, we perform the Hausman specification test to decide between the FEM versus random effects model. In particular, the null hypothesis (Ho) prefers a random effects model ($\mu_{it} \neq \text{correlated } X_t$), while the alternate chooses FEM ($\mu_{it} = \text{correlated } X_t$). The Hausman specification test basically tells us if $\mu_{it}$ is correlated with the explanatory (Xs) variables, that is, whether the error components model (ECM) is the appropriate model or not (Ahmed et al., 2022). In the random effects model, the ECM comprises two (or more) error components ($\mu_{it} = \epsilon_i + w_{it}$). Here, $\epsilon_i$ is the cross-section, individual-specific and error component, $w_{it}$ is the combined time series and cross-section error component. $w_{it}$ is also known as the idiosyncratic term as it varies over cross-sections ($i$) and time ($t$). We perform the Hausman specification test and find $\chi^2$ statistics for the model of return on assets (ROA): 216.11 ($p$-value = 0.001) and for the model of ratio of return on equity (ROE): 251.99 ($p$-value = 0.000), signifying acceptance of the FEM. By rejecting the null hypothesis, the study confirms the specification of the FEM.

3.2 Fixed effects: a baseline model
The FEM allows individual bank-specific $\alpha_i$ coefficient in the baseline model. This model helps to control unseen variation over time ($t$) and allows for variation in behavior among individual banks ($i$), so the model permits different constants for individual Indian banks ($i$), but the coefficients are fixed over time (Gujarati and Dawan, 2015; Khan et al., 2020; Tan et al., 2021). Considering it, formalized baseline model is as follows:

$$\ln Y_{it} = \alpha_i + \sum_{n=1}^{N} \beta_n \ln X^a_{it} + \sum_{s=1}^{S} \beta_s X^s_{it} + \sum_{m=1}^{M} \beta_m X^m_{t-1} + \sum_{d=1}^{D} \phi_d X^d_{it} + \epsilon_{it}$$

where $i = 1, 2, 3, ...412; t = 1, 2, 3, 4, 5$; and $\epsilon_{it} = \nu_i + \xi_t + \mu_{it}$.

In model (1), the subscripts $i$ and $t$ denote the cross-sectional and time-dimensions of the panel, respectively, where $i$ in $\beta$ refers to the intercept values for each cross-section ($i$) unit that may be different over time ($t$). $\ln Y_{it}$ is an indicator of dependent variable, which shows both proxies of financial performance such as, ROA and ROE of Indian banks $i$ at time $t$. The $X^a_{it}$ stands for the $n$th controllable unsystematic (bank-specific) risky variables, such as default risk, solvency risk, LR and market risk. $X^s_{it}$ represents systemic risk of $i$th bank in the $t$ period. $X^m_{t-1}$ refers to the COVID-19 as exogenous shock ($m$) in the $t$-1 period, i.e. the natural log growth rate of confirmed COVID-19 cases during 2020–2022. $X^d_{it}$ displays dummy of “ownership group” ($d$) for the $i$th bank in the $t$ period, respectively (see next section for the detailed description of each variable). $\nu_i$ represents the unobserved bank-specific effects, $\xi_t$ is the unobservable time-effects and $\mu_{it}$ is the idiosyncratic error term. The $\beta$s, $\tau$s and $\phi$s are the coefficients to be estimated.

4. Sample selection and variable specification
4.1 Sample selection
The Indian Bank Association database [https://www.iba.org.in] and the annual editions of “Statistical Table Relating to Banks in India” [https://www.rbi.org.in] are used to compile an annual dataset of scheduled commercial banks in India for the study, which spans from the years 2018–2022. COVID-19 data is culled from the “Ministry of Health and Family Welfare.”

We first gathered the needed unbalanced panel data, filtered it, and then aggregated all bank-level balanced panel data – 12 PSBs, 22 private banks and 41 foreign banks – for the analysis. The study specifically uses 75 scheduled commercial banks operating during 2018–2022. Table 2 provides detailed definitions of selected risky variables. The limitations of the total
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<td>Return on assets</td>
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<td>DV</td>
<td>It used as a measure of profitability and performance of Indian banks. ROA = net income/average assets</td>
<td>Ray and Goel (2022)</td>
<td><a href="https://www.rbi.org.in">https://www.rbi.org.in</a></td>
<td>Performance</td>
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<td>Non-performing loans (credit risk)</td>
<td>NPLs</td>
<td>CV</td>
<td>Ratio of gross non-performing loans to gross advances. Non-performing loans are the sum of loans past due more than 90 days and nonaccrual loans</td>
<td>Tarchouna et al. (2017), Goswami (2021ab)</td>
<td><a href="https://www.rbi.org.in">https://www.rbi.org.in</a></td>
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<td>Z-score</td>
<td>CV</td>
<td>Sum of the ratio of return on assets and leverage to dispersion of return on assets (where σROA was calculated, by using three years rolling time window for jth bank in the tth year</td>
<td>Boyd and Runkle (1993), Beck et al. (2013) and Ahamed and Mallick (2017)</td>
<td><a href="https://www.rbi.org.in">https://www.rbi.org.in</a></td>
<td>Soundness</td>
</tr>
<tr>
<td>Market risk</td>
<td>MR</td>
<td>EV</td>
<td>Repo rate for entire bank over tth year</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variables</td>
<td>Nomenclatures</td>
<td>Variable type</td>
<td>Description</td>
<td>Literature</td>
<td>Source</td>
<td>Proxy/ hypothesis development</td>
</tr>
<tr>
<td>-----------</td>
<td>---------------</td>
<td>---------------</td>
<td>-------------</td>
<td>------------</td>
<td>--------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>COVID-19</td>
<td>COVID-19</td>
<td>MV</td>
<td>Log growth rate of confirmed COVID-19 cases over time, represent as: $GR_{COVID19} = \frac{\sum_{t=5}^{T} \ln(1 + \text{confirmed COVID19 cases}_t)}{C138}$</td>
<td>Ding et al. (2021), Demir and Danisman (2021), Lee et al. (2022), Ahmed et al. (2022)</td>
<td><a href="http://www.mohfw.gov.in">http://www.mohfw.gov.in</a></td>
<td>Pandemic</td>
</tr>
<tr>
<td>Ownership type</td>
<td>OT</td>
<td>CV</td>
<td>To capture the ownership effect on Indian banks dummy of OT is created. Public bank = 1 if public, and 0 otherwise; private bank = 1 if private, and 0 otherwise</td>
<td>Goswami (2021ab)</td>
<td>Author’s construction</td>
<td>Equality</td>
</tr>
</tbody>
</table>

**Note(s):** DV = dependent variable; IV = independent variable; CV = control variable, EV = exogenous variable; MV = moderating variable

**Source(s):** Authors’ construction
number of bank samples in this paper come from two aspects. (1) The lack of observations of risky variables is excluded from the sample. (2) The study has considered only actively engaged, scheduled commercial banks during 2018–22.

4.2 Variable specification and hypotheses development
This section interprets the study variable information and develops relevant hypotheses in detail, considering the theoretical framework and the literature review as a whole. Specifically, Table 2 reports the variable’s information in brief.

4.2.1 The dependent variables. Following Berger and DeYoung (1997), Maqbool and Zameer (2018) and Kwashie et al. (2022), the study uses the log ratios of ROA and ROE as dependent variables as proxies for financial performance.

4.2.2 The independent variables. The study examines nearly all risky factors that impact the financial performance of the banking industry by reviewing both traditional and contemporary literature (see Section 2 for more information). A more detailed explanation of the connection between financial performance and risky variables is provided below:

(1) **Default risk**: In the study, NPLs are used as a proxy for default risk, calculated using the ratio of gross loans to gross advances. According to this study, there is a negative relationship between financial performance and bank default risk. The development of banks’ financial performance in response to generating revenue and income from conventional sources is hampered by high NPL levels, which imply high default risk. The argument that banks keep more provisions for high-risk activities, which lowers their incentives and affects their profitability, is backed by Ghosh (2015). Thus, the relationship between default risk and bank profitability or financial performance is adverse. The ‘bad management’ hypothesis, proposed by Berger and DeYoung (1997), which argues that unprofitable banks produce more NPLs and are hence more readily harmed, has been supported by this point of view.

\[ H1 \quad \text{Default risk impacts financial performance negatively, ceteris paribus.} \]

(2) **Market risk**: In the study, the concept of market risk is captured by the variable of the repo rate for scheduled commercial banks over the period from 2018–2022. A rise or drop in the repo rate can significantly affect inflation and borrowers’ purchasing power, which, in turn, affects the financial performance of banks. For example, an increase in the repo rate means that commercial banks borrow less money at a higher rate from the Bank of India, which also signals an increase in the lending interest rate for borrowers. This, in turn, negatively impacts the buying and pay-off power of borrowers and adds more default risk, thereby reducing the financial performance of banks. Hence, we predict that market risk and bank financial performance are negatively correlated.

\[ H2 \quad \text{High repo rates (market risk) negatively impact the financial performance of banks.} \]

(3) **Solvency risk**: The ratio of equity capital to total assets (EQTA) is used in the study to quantify the solvency risk that is taken into account. According to Mester (1996) and Chortareas et al. (2011), keeping a high amount of equity capital lowers excessive bankruptcy risk and boosts the banks’ financial performance. On the other hand, Berger and DeYoung (1997) formulated the “moral hazard” hypothesis, which predicts that profitability will be negatively associated with EQTA. Under the “moral hazard” hypothesis, a risk-averse manager retains sizable sums of equity capital on
hand as readily available funds for high-revenue projects, which involve high credit risk and, in turn, have a negative effect on the bank’s financial performance. Therefore, it is evident that the literature is ambiguous about the direction of the relationship between solvency risk and the financial performance of banks. Thus, the study hypothesizes:

**H3a.** A large amount of equity capital involves high credit risk, which has a negative impact on the financial performance of banks.

**H3b.** A positive association prevails between the solvency risk and financial performance.

(4) **Liquidity risk (LR):** Following Ghosh (2015), the current study uses the ratio of total loans to total deposits to capture the impact of LR. Ghosh (2015) defined LR as “the ratio of loans to deposits” and stated that total loans are less liquid and riskier than other deposits and assets, such as government securities in banks’ portfolios, but they also have a higher expected return. Studies by McKillop et al. (2002) and Zeineb and Mensi (2018) showed that increasing LR had a detrimental impact on bank performance. In contrast, Altunbas et al. (2007) and Goswami (2021a) described that liquidity has the potential to generate more interest revenue, which has a favorable impact on bank performance levels. The study hypothesizes:

**H4a.** Aggressive lending (LR) is accompanied by negative financial performance.

**H4b.** Higher credit growth creates more revenue, thereby having a positive impact on financial performance.

(5) **Bank risk:** The study uses the Z-score as a proxy for “bank risk” or “bank soundness”, following Beck et al. (2013). The variable can be seen as “the number of standard deviations (σ) below the mean (X) by which a bank’s asset returns would fall before all equity capital in the bank gets wiped out” (Boyd and Runkle, 1993; Beck et al., 2013; Ahamed and Mallick, 2017). The chance of failure is lower, and financial performance is better when the Z-score is higher and positive. So, we anticipate a favorable correlation between the Z-score and bank financial performance.

**H5.** Bank soundness (Z-score) pushes the banks’ financial performance in a positive way.

(6) **Systemic risk (ΔCOVAR):** This study uses ΔCOVAR indicator as given by Adrian and Brunnermeier (2009, 2016), to quantify the systemic risk of ith bank over time (t) concerning the whole banking system as an independent variable. Systemic risk is a measure of the expected capital shortage of an individual bank relative to its own size. In this study, Moody’s Kealhofer-McQuown-and-Vasicek (KMV) model is applied to calculate Indian banking systemic risk and the contribution of Indian banks to systemic risk during the study period. This model serves as a valuable early warning system.

According to the KMV model, under the assumption that all debts are risk-free, the study uses the log ratio of the market value of the bank’s stock return (SRi,t) and return on an equity investment (EIi,t), calculated as the weighted average of daily returns of all sample banks in bank (i) over time (t). The weight is determined by the market value of each bank and is
represented as: $\Delta \text{COVAR} = \text{stock return (SR)}_i, t / \text{equity investment (EI)}_i, t$. COVAR is the “value-at-risk” of equity investments in the financial system, defined as the loss on a unit investment. This model indicates the relationship between the volatility of the bank’s stock return and its ROE investment in the financial system (Yang et al., 2013; Laeven et al., 2016; Zedda and Cannas, 2020; Duan et al., 2021; Zhang et al., 2023).

This study also considers the “tail risk spillover of a single bank to the system” hypothesis proposed by Van Oordt and Zhou (2019). Different ownership groups undertake risk-taking practices and accumulate more liquidity in pursuit of higher stock returns and returns on equity investments. This behavior increases the “tail risk spillover of a single bank into the system,” consequently raising systemic risk. According to Yang et al. (2013), when an economic shock occurs, banks’ individualistic and short-term orientations make them more susceptible to systemic risk. Therefore, this study anticipates an inverse correlation between banks’ systemic risk and their financial performance.

**H6.** Large variations in $\Delta \text{COVAR}$ lead to deterioration in the financial performance of banks.

(7) **COVID-19:** Following Duan et al. (2021) and Ahmed et al. (2022), this study assess the impact of COVID-19 on the financial performance of Indian banks using the log growth rate of confirmed COVID-19 cases over time, represented as: $\text{GR}_{\text{COVID19}}(t) = \sum_{i=5}^{t}[\ln(1+\text{confirmed COVID19 cases}_i)]$ which is collected from the World Health Organization (WHO) COVID-19 research database. The government’s COVID-19 preventative measures have led to a significant decrease in economic activity and substantial revenue and income losses for corporate enterprises and households. Consequently, due to borrowers’ diminished creditworthiness and their inability to repay loans, the banking system’s performance has been adversely affected (Beck and Keil, 2022; Ozili and Arun, 2020; Barua, 2020; Baumohl et al., 2022). Hence, the study expects that the financial performance of banks is negatively related to COVID-19.

**H7.** COVID-19 negatively affects banks’ financial performance.

(8) **Ownership effect (PUBLIC or PRIVATE):** By creating dummies to identify the ownership effect, the study examines differences in the level of financial performance across different ownership groups using two ownership dummies: public and private. A higher coefficient value for PSBs compared to private banks reflects the better financial performance of PSBs, or vice versa.

**H8.** Financial performance is distributed equally across the ownership group.

### 5. Empirical results

#### 5.1 Preliminary check

**5.1.1 Summary statistics.** Table 3 exhibits summary statistics of the variables used in the main analysis. The average values for default risk, LR, solvency risk, market risk and bank risk are 7.71, 11.52, 2.84, −6.82 and 1.12, respectively, while their standard deviation also exhibits volatility during the analysis period. The average values for COVID-19 and $\Delta \text{COVAR}$ are 0.005 and 1.36, with a standard deviation of 0.015 and 1.29, respectively. On average, low values of risk determinants indicate that Indian banks effectively manage their revenues. The SFRANCIA test for normality shows that all tested variables are not normally distributed at the 5% level of significance, which aligns with the findings of Alhassan et al. (2014) and Goswami (2021a, b).
5.1.2 Stationarity tests. Table 4 reports the results of the Augmented Dickey–Fuller (ADF) and Phillips–Peron (PP) tests, which assess the stationarity of all unsystematic, systemic and exogenous factors. The stationarity tests indicate that all the estimated factors are stationary and stable at level. The finding is consistent with the research of Ibicioglu and Kapusuzoglu (2012), Goswami (2021a, b) and Ahmed et al. (2022), who have reported that all the series of the variables remain stable at a 1% level of significance. Fisher-ADF and Fisher-PP stationarity tests were used in both studies, as they are better measures for balanced panel and time-series data. Both tests check whether the average value of data points remains the same over the analysis period. If the mean value is constant, then the time series of the estimated variables are stationary, or vice versa.

5.1.3 Pairwise correlation coefficient. The pairwise-correlation-coefficients between the selected variables used in the baseline regression model are examined in this sub-section. A negative relationship is observed between few risky determinants and ROA and ROE (see Table 5). Specifically, we can clearly see that NPL, LR and ΔCOVAR are inversely related to ROA and ROE. On the other hand, the coefficients of solvency risk, market risk, bank risk (Z-score) and COVID-19 are positively associated with ROA and ROE.

Concerning the issue of multicollinearity among the variables, most of the coefficient values are less than 70%, which does not indicate the existence of the problem of multicollinearity. However, the coefficient value between the variables of ROE and solvency risk is very high (i.e. 85%), which raises concerns about multicollinearity. The finding is consistent with the observations of Alhassan et al. (2014) and Ahmed et al. (2022), who suggest that multicollinearity becomes a concern when the correlation values between

### Table 3.
Summary statistics of selected independent variables

<table>
<thead>
<tr>
<th>Variable(s)</th>
<th>N</th>
<th>Mean</th>
<th>SDV</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
<th>SFRANCIA (Z-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPLs</td>
<td>375</td>
<td>7.71</td>
<td>4.12</td>
<td>19.890</td>
<td>57.342</td>
<td>99.532</td>
<td>10.53***</td>
</tr>
<tr>
<td>LR</td>
<td>375</td>
<td>11.52</td>
<td>8.94</td>
<td>0.678</td>
<td>2.513</td>
<td>8.301</td>
<td>6.983***</td>
</tr>
<tr>
<td>SR</td>
<td>375</td>
<td>2.84</td>
<td>1.52</td>
<td>0.231</td>
<td>0.348</td>
<td>0.886</td>
<td>0.08***</td>
</tr>
<tr>
<td>MR</td>
<td>375</td>
<td>-6.82</td>
<td>3.35</td>
<td>67.102</td>
<td>89.590</td>
<td>101.374</td>
<td>14.672***</td>
</tr>
<tr>
<td>ΔCOVAR</td>
<td>375</td>
<td>1.36</td>
<td>1.299</td>
<td>3.542</td>
<td>9.012</td>
<td>19.345</td>
<td>6.739***</td>
</tr>
<tr>
<td>Z-score</td>
<td>375</td>
<td>1.12</td>
<td>0.14</td>
<td>87.901</td>
<td>61.789</td>
<td>68.564</td>
<td>9.361***</td>
</tr>
<tr>
<td>COVID-19</td>
<td>375</td>
<td>0.002</td>
<td>0.015</td>
<td>45.90</td>
<td>56.21</td>
<td>63.10</td>
<td>9.520***</td>
</tr>
</tbody>
</table>

**Note(s):** (1) N represent total number of observations; (2) SDV signify the symbol of standard deviation; and (3) *** reflects significance levels at 1%, respectively

**Source(s):** Authors’ calculation using MS-Excel and STATA-12

<table>
<thead>
<tr>
<th>Tests</th>
<th>Fisher-ADF</th>
<th>Fisher-PP</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROA</td>
<td>684***</td>
<td>891***</td>
</tr>
<tr>
<td>ROE</td>
<td>532***</td>
<td>530***</td>
</tr>
<tr>
<td>NPLs</td>
<td>539***</td>
<td>692***</td>
</tr>
<tr>
<td>LR</td>
<td>631***</td>
<td>674***</td>
</tr>
<tr>
<td>SR</td>
<td>551***</td>
<td>486***</td>
</tr>
<tr>
<td>MR</td>
<td>985***</td>
<td>630***</td>
</tr>
<tr>
<td>ΔCOVAR</td>
<td>890***</td>
<td>909***</td>
</tr>
<tr>
<td>Z-score</td>
<td>993***</td>
<td>731***</td>
</tr>
<tr>
<td>COVID-19</td>
<td>714***</td>
<td>519***</td>
</tr>
</tbody>
</table>

**Note(s):** *** reflects significance levels at 1%, respectively

**Source(s):** Authors’ calculation

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Indian banks’ financial performance
coefficients are approximately 80% or greater. Overall, the pairwise correlation coefficients suggest that there is no significant multicollinearity among the variables used in the analysis, except for the high correlation between ROE and solvency risk.

Table 6 provides a diagnosis of multicollinearity through the variance inflation factor (VIF). The VIF suggests that if any value in the estimated model exceeds the VIF threshold of 5 or 10, it indicates high variance inflation, which, in turn, means that the variable is redundant with other variables. Overall, Table 6 shows that none of these variables have VIF values above the moderate threshold. However, in the VIF2 model, the variables SR and ΔCOVAR appear to be slightly redundant with other variables, but their VIF values are below the threshold of 5. As a precaution, all the models in Table 8 have been rearranged to address the issue of multicollinearity.

### 5.2 Main evidences

The main evidence for the estimated coefficients using FEMs is reported in Tables 7 and 8. In general, we observe that the expected signs and outcomes of financial performance with indicators of risky determinants and exogenous shocks align with the existing banking literature. The adjusted R-squared values for ROA and ROE range from 0.5 to 0.7, respectively, indicating the goodness-of-fit of the models. Specifically, in Table 7, higher adjusted R-squared values indicate a better fit of regression models (3) and (4) to the data. Gujarati and Dawan (2015) state that a higher value of adjusted R-squared (above 0.7 or 0.8) serves as a better measure of goodness-of-fit (model accuracy) for linear models. This shows how well the other independent variables in the model explain the dependent variable.
Tables 7 and 8 clearly indicate that default risk has a negative impact on ROA at a 5% significance level and on ROE at a 10% significance level. This implies that an increase in default risk and higher provisioning for NPLs by Indian banks led to lower ROA and ROE.
performance during the period from 2018 to 2022. Other than this, bad management and a greater involvement of Indian banks in hazardous investments result in the accumulation of NPLs, which negatively affects both proxies of the financial performance of Indian banks. As per the result, the study confirms hypothesis H1, which suggests that an upsurge in default risk leads to a deterioration in the financial performance of Indian banks. This finding is consistent with the results of Demir and Danisman (2021), Tran et al. (2022) and Kwashie et al. (2022). These studies indicate that bad management of banks leads to NPLs, which, in turn, require more provisions and write-offs, restricting their ability to generate income. This finding supports the theory of “asymmetric information” and validates the “bad management” hypothesis of Berger and DeYoung (1997) in the context of the Indian banking industry. The inverse relationship between default risk and financial performance reflects the extent to which managers of Indian banks take risk-aversion measures to maximize their earnings. The asymmetric information theory posits that there may be a possibility of information asymmetry between borrowers and banks seeking loans, leading to higher levels of NPLs and lower financial performance.

Similarly, while analyzing the effect of solvency risk on a bank’s profitability, it is observed that a 1% increase in EQTA leads to a decline in the bank’s capacity to maintain its ROA by approximately \((-0.019\%)\) to \((-0.034\%)\). This suggests that when Indian banks become more profitable, they may engage in aggressive lending and become less diligent in monitoring and screening the creditworthiness of their borrowers. This behavior may increase the risk of default and lead to a decline in their financial performance. This finding is consistent with Goswami’s findings (2021a) and lends credence to Gladwell (2005) and Krugman (2009)’s contention that banks with lower asset LR frequently make riskier investments, raising the likelihood that they will fail. This finding supports the “moral hazard” hypotheses, which indicate that moral hazard and adverse selection by banks result in borrowers not paying their loans, and this significantly increases default risk, leading to adverse effects on a bank’s financial performance.

Furthermore, a strong and negative association is observed between systemic risk and the financial performance of Indian banks, which supports the existence of the “tail risk spillover of a single bank to the system” hypothesis. This claims the possibility of the spillover of tail risk, such as lower market share, lower asset value and bad loans, from a single bank to the entire system of the Indian banking industry, impairing their performance. To further elaborate, the delay in the recognition of credit risk and subsequent understatement of risks and losses could be a reason for exaggerating financial performance and systemic risk in the Indian banking system (Huizinga and Laeven, 2012; Reserve Bank of India, 2021). Another reason could be that larger banks are more sensitive to severe shocks in the financial system, indicating a negative relationship between financial performance and systemic risk (Van Oordt and Zhou, 2019). This observation is supported by the research of Adrian and Brunnermeier (2016), Das and Ghosh (2006) and Batir et al. (2017). Additionally, it is noted that the market risk variable has a negligible relationship with any measure of the financial performance of Indian banks.

On the other hand, the analysis reveals a positive association between LR and ROA and ROE, suggesting that increasing lending will enhance the financial performance of Indian banks by boosting interest revenue and ROE (Altunbas et al., 2007; Burki and Niazi, 2010; Hou et al., 2014). Additionally, the study finds that the Z-score coefficient has a favorable and statistically significant impact on both measures of Indian banks’ financial performance, indicating a reduced risk of failure and a sustained improvement in financial performance over the period from 2018 to 2022. This finding aligns with the research of Ahamed and Mallick (2017).

Interestingly, it is observed that the coefficient of COVID-19 is positively associated with ROA and ROE at the 1% and 5% significance levels. This illustrates the effective measures
taken by the Indian Government and the Central Bank, including the implementation of sound credit policies for banks during the pandemic situation. These policies have reduced the default risk and enhanced the financial performance of banks in terms of maintaining the levels of ROA and ROE. These actions are in line with those of the Reserve Bank of India (2021), Duan et al. (2021) and Goswami (2022). Some of the credit policies that have contributed to this positive outcome include COVID-19 provisions, the ploughing back of dividends, mega-mergers to strengthen capital positions, regulatory tightening (such as the resolution of large borrower accounts via the Insolvency and Bankruptcy Code) and successful write-offs. These measures have become inevitable tools to curb the rising levels of NPLs in the pre-during and post-COVID-19 period, as documented by the Reserve Bank of India (2018, 2019, 2020). Despite the challenges posed by the COVID-19 pandemic, improvements in credit risk soundness continued until 2020 from 2017 to 18 due to the loan moratorium and restructuring policies initiated by the Honorable Supreme Court. Likewise, Duan et al. (2021) and Tan et al. (2021) assert that stringent government responses were effective in mitigating the impact of exogenous shocks (COVID-19) and default risk, thereby enhancing the financial performance of banks.

In model (4) of Tables 7 and 8, two clusters of ownership groups are utilized, which consist of dummies for public, private and foreign bank groups. These dummy variables help in identifying variations in coefficients between ownership groups concerning the maintenance of financial performance levels during 2018–2022. The results across ownership groups indicate that, in comparison to private banks and foreign banks, PSBs demonstrate better sustainability in terms of financial performance contribution. The main reason for this is that, compared to private and foreign banks in India, PSBs tend to be more cautious about taking higher risks while making investments. Consequently, the study rejects the hypothesis H8, which posits that the results across distinct bank groups in India are equal.

5.2.1 Heterogeneity test across time: I and II waves of the COVID-19 crisis. By splitting the sample into I and II waves of the COVID-19 crisis, Table 9 reports the variations in the coefficients of the COVID-19 model. In this analysis, with COVID-19 considered the dependent variable, the study examines the key unsystematic factors responsible for the genesis of COVID-19. It is also interesting to see whether all these drivers exhibit the same behavior as determined in the main model of the study, as shown in Tables 7 and 8. To assess the drivers of the I and II waves of COVID-19, we utilized two models: In the first model, the I wave of COVID-19 is treated as the dependent variable and financial performance, along with risky determinants, serves as the independent variable. In the second model, the II wave of COVID-19 is used as the dependent variable, while the remaining explanatory variables are consistent with those set in Model 1 of Table 9. To empirically examine the determinants of COVID-19, we followed the approach given by Simar and Wilson (2007). The parametric regression equation (2) of the bootstrapped truncated regression algorithm (Algorithm #1) by Simar and Wilson is as follows:

$$\ln (d)_{jt} = \beta_0 + \sum_{n=1}^{n} \beta_n \ln (\bar{p})_{jt} + \varepsilon_{jt}$$  

(2)

where \(j = 1, \ldots, n; \ t = 1, \ldots, T\). The subscripts \(j\) and \(t\) denote the cross-sectional and time-dimensions of the panel respectively. In this context, the dependent variables \((d)_{jt}\) represents the log growth rate of confirmed COVID-19 cases during the I (2019/20) and II (2020/21) waves of COVID-19, denoted as: \(GR_{COVID19} \equiv \sum_{t=3}^{T} \ln (1 + \text{confirmed COVID19 cases}_t)\). The vector \(\bar{p}_{jt}\) is comprised of all the unsystematic, systemic and financial performance variables used in equation (1) of the study. The \(\beta\)'s coefficients are assessed through a bootstrapped truncated
The estimated $\beta$'s coefficients will help determine whether risky determinants and financial performance have a different impact on the COVID-19 crisis in different time intervals.

The analysis models elucidate similar analogous results, as shown in Tables 7 and 8. Default risk and solvency risk have a negative impact on both the I and II waves of COVID-19, with significance levels of 5 and 10% respectively. The variables ROA, $\Delta$COVAR, LR and Z-score negatively and significantly influence the II wave of the COVID-19 crisis. High systemic risk, LR and bank risk are constrained in maintaining ROA levels during the II wave of the COVID-19 crisis, hence showing negative coefficients during that period.

Our results can be explained by the findings of Bilgin et al. (2021) and Ahmed et al. (2022), who found a significant decline in credit growth by banks during the pandemic period of COVID-19, hindering their ability to achieve ROA levels. However, their ROE remained resilient to financial uncertainties. This evidence supports the report of the Reserve Bank of India’s (2022), which reported a marginal contribution of credit growth from $-0.6\%$ in 2021 to 2.1$\%$ in 2022, along with a decrease in provisions from $-18\%$ in 2021 to $-15\%$ in 2022. Lower levels of credit growth during the II wave of the crisis have exacerbated the levels of NPLs and negatively affected the financial performance of Indian banks.

### Table 9.

Statistics evidence on the determinants of I and II waves of COVID-19 crisis: Bootstrapped truncated regression model

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>COVID-19 I wave</th>
<th>COVID-19 II wave</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>18.67*** (0.989)</td>
<td>15.32*** (0.888)</td>
</tr>
<tr>
<td>ROA</td>
<td>0.104*** (0.022)</td>
<td>-0.201*** (0.047)</td>
</tr>
<tr>
<td>ROE</td>
<td>0.401 (0.058)</td>
<td>0.606 (0.074)</td>
</tr>
<tr>
<td>NPLs</td>
<td>-0.012*** (0.001)</td>
<td>-0.490** (0.236)</td>
</tr>
<tr>
<td>LR</td>
<td>0.888*** (0.476)</td>
<td>-0.548** (0.444)</td>
</tr>
<tr>
<td>SR</td>
<td>-0.947*** (0.099)</td>
<td>-0.127* (0.095)</td>
</tr>
<tr>
<td>MR</td>
<td>0.732 (0.037)</td>
<td>0.863 (0.071)</td>
</tr>
<tr>
<td>$\Delta$COVAR</td>
<td>0.023 (0.010)</td>
<td>-0.386** (0.021)</td>
</tr>
<tr>
<td>Z-score</td>
<td>0.666*** (0.071)</td>
<td>-0.931** (0.082)</td>
</tr>
<tr>
<td>MR</td>
<td>0.452 (0.297)</td>
<td>0.346 (0.209)</td>
</tr>
<tr>
<td>Bank and year fixed effect</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>F-statistics</td>
<td>6.490***</td>
<td>6.101***</td>
</tr>
<tr>
<td>Adjusted-$R^2$</td>
<td>0.263</td>
<td>0.250</td>
</tr>
</tbody>
</table>

**Note(s):** Table 8 presents a bootstrapped truncated regression estimates by Simar and Wilson (2007). The I wave of Covid-19 refers to the period immediate before Covid-19 period in India which is from 2019 to 2020. Wave II of COVID-19 refers to the year immediately following the COVID-19 crisis (i.e. 2020–2021). ROA: ratio of return on assets; ROE: ratio of return on equity; GNPA: Ratio of gross non-performing asset to gross advances; LR: ratio of total loans to total deposits; SR: equity to total assets ratio; MR: market risk: repo rate during 2018–2022; Systemic risk measure as $\Delta$COVAR: VAR banks stock return ($SR_i,t$/VAR equity investment ($EI_i,t$)); Z-score: sum of the ratio of return on assets and leverage to dispersion of return on assets; COVID-19: log growth rate of confirmed COVID-19 cases; figure in parentheses in columns (1)–(2) are clustered standard errors, respectively. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ 

**Source(s):** Authors’ calculations
The OLS regression equation used to assess the influence of the risky factors on the performance of Indian banks over time is as follows:

$$\ln (d)_{jt} = \beta_0 + \sum_{n=1}^{n} \beta_n \ln (i^n)_{jt} + \epsilon_{jt}$$

(3)

where, \(j = 1, ..., n\); and \(t = 1, ..., T\). The subscripts \(j\) and \(t\) denote the cross-sectional and time-dimensions of the panel, respectively. Here, \(d_{jt}\) represents the estimated log values of ROA and ROE, serving as proxies for financial performance. ROA and ROE are used as indicators of a bank’s profitability and financial performance. The vector \(i^n_{jt}\) comprises unsystematic risk, systemic risk and exogenous shock variables that may influence the bank’s performance during 2018–2022. The \(\beta\)'s coefficients are to be estimated using the simple OLS method.

The results of the third-stage panel regression analysis are presented in Table 10. It is important to note that in all the panel model specifications, the \(F\)-statistics are statistically significant. This implies that the combined set of explanatory variables \(X\) significantly influences the level of bank performance. The empirical results confirm that, in most cases, the explanatory variables \(X\) have the expected signs as anticipated, as shown in the main evidence in Tables 7 and 8. Specifically, we observe that the negative relationship between default risk and solvency risk with ROA and ROE is statistically significant at the 5% and 10% levels, respectively. Default risk once again affirms a negative association with bank performance. This suggests that a higher ratio of NPLs raises the demand for higher provisioning and write-offs, ultimately eroding the profitability and performance of Indian banks.

However, unlike our previous results in Tables 7, 8 and 9, the robustness analysis reveals a negative relationship between public sector banks and financial performance. This indicates that the financial performance of PSBs is significantly weaker than that of their peer groups, primarily due to an increase in the quantum of NPLs. Capitalized PSBs become more involved in risk-taking performance, resulting in higher toxic-loan ratios and, consequently, a decline in stability compared to private and foreign banks in India.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Return on assets (1)</th>
<th>Return on equity (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.3674*** (0.268)</td>
<td>0.2905*** (0.174)</td>
</tr>
<tr>
<td>NPLs</td>
<td>-0.676** (0.079)</td>
<td>-0.895*** (0.069)</td>
</tr>
<tr>
<td>LR</td>
<td>-0.765** (0.139)</td>
<td>-0.917 (0.154)</td>
</tr>
<tr>
<td>SR</td>
<td>-0.690*** (0.438)</td>
<td>-0.985*** (0.509)</td>
</tr>
<tr>
<td>MR</td>
<td>0.457 (0.061)</td>
<td>0.877 (0.063)</td>
</tr>
<tr>
<td>ΔCOVAR</td>
<td>-0.474* (0.196)</td>
<td>-0.603* (0.236)</td>
</tr>
<tr>
<td>Z-score</td>
<td>0.330** (0.086)</td>
<td>0.409 (0.102)</td>
</tr>
<tr>
<td>COVID-19</td>
<td>-0.673*** (0.375)</td>
<td>-0.732* (0.316)</td>
</tr>
<tr>
<td>PUBLIC</td>
<td>-0.860*** (0.028)</td>
<td>-0.792** (0.020)</td>
</tr>
<tr>
<td>PRIVATE</td>
<td>0.515 (0.209)</td>
<td>0.584* (0.364)</td>
</tr>
<tr>
<td>(N)</td>
<td>375</td>
<td>375</td>
</tr>
<tr>
<td>(F)-statistics</td>
<td>15.73***</td>
<td>19.18***</td>
</tr>
<tr>
<td>Adjusted-(R^2)</td>
<td>0.2907</td>
<td>0.2170</td>
</tr>
</tbody>
</table>

**Note(s):** (1) GNPA: Ratio of gross non-performing asset to gross advances; LR: ratio of total loans to total deposits; SR: equity to total assets ratio; MR: market risk: repo rate during 2018–2022; Systemic risk measure as ΔCOVAR: VAR banks stock return (SRi,t)/VAR equity investment (EIi,t); Z-score: sum of the ratio of return on assets to dispersion of return on assets; COVID-19: log growth rate of confirmed COVID-19 cases; (2) *p < 0.1, **p < 0.05, ***p < 0.01 and (3) figure in parentheses in columns (1)–(4) are clustered standard errors, respectively.

**Source(s):** Authors’ calculations
The negative associations of COVID-19 and ΔCOVAR with bank performance indicate that increased capital infusions under recapitalization schemes and the COVID-19 provisions initiated by the Central Bank of India (such as the Indradhanush scheme, the Insolvency and Bankruptcy Code, the loan moratorium and restructuring policies initiated by the Honorable Supreme Court in 2020) may reduce the incentives for bank managers to adopt best lending practices. This could potentially induce moral hazard and lead to lower bank performance. This result aligns with the claim made by Ahmed et al. (2022) that COVID-19 has increased the earnings of large pharmaceutical and technology companies, while smaller companies have experienced losses or bankruptcy. Consequently, smaller companies were unable to repay their bank loans on time, leading to an increase in bad debts and a deterioration in their financial performance.

6. Empirical discussion and policy implications
This study provides new evidence regarding the risky determinants that may affect the financial performance of Indian banks during the COVID-19 crisis period. The analysis supports the validity of the hypotheses of “bad management”, “moral hazard” and “tail risk spillover of a single bank to the system” for Indian banks in the light of the COVID-19 pandemic. LR and Z-score positively influence financial performance. This evidence holds during the I wave of the COVID-19 crisis and is consistent when examining robustness, except for the second wave. Furthermore, it is observed that COVID-19 is positively associated with the financial performance of Indian banks throughout the study period. This indicates the significant efforts made by the Indian Government and Central Bank in formulating effective credit policies for banks during the pandemic situation, which, in turn, reduced the default risk and enhanced their financial performance in terms of maintaining the levels of ROA and ROE (Reserve Bank of India, 2021; Duan et al., 2021; Goswami, 2022).

The coefficient of the ownership dummy shows that financial performance is positively associated with PSBs in India relative to their peer group. This supports the hypothesis (H8) of the study regarding the non-uniform distribution of financial ownership in Indian banks. The adaptation to stringent policies of the Central Bank of India and Government of India since the 1990s (e.g. Indradhanush Scheme, 2014; S4A, 2016; IBC Act, 2016; COVID-19 provisions, etc.) has helped PSBs maintain their dignity in the market (Goswami, 2022).

The coefficients of systemic risk, LR and z-score are negatively associated with ROA during the II wave of the COVID-2020–21 crisis. The significant decline in credit growth during the COVID-19 pandemic period hindered the financial performance of Indian banks in maintaining ROA. However, the coefficient of ROE is not negatively impacted. This observation is supported by the official data from the Reserve Bank of India’s (2022) report, which indicated that the level of credit growth in 2021 reached −0.6% and the level of provisions in 2021 reached −18%, respectively. Lower levels of credit growth and provisions worsened the levels of NPLs and negatively affected the financial performance of Indian banks during the II wave of the COVID-19 crisis.

Our results suggest that Indian banks should implement careful screening and monitoring of borrowers at the branch level to mitigate the harmful effects of credit risk on financial performance. Further, the central bank should formulate and implement new win-win strategies related to provisions, loan restructuring, NPLs and solvency risk, which can create a novel value framework for Indian commercial banks.

7. Conclusion and future course of action
Despite a plethora of research that illustrates the relationship between various risky indicators and financial performance, the literature on the banking industry across countries
fails to provide conclusive evidence. Thus, this study provides comprehensive empirical evidence that may help explain divergences in prior work. Using a FEM, the current study explores the impact of unsystematic risk, systemic risk and exogenous shocks on the financial performance of Indian banks. To identify the drivers of financial performance, the study uses a panel data set of scheduled Indian commercial banks that have been actively involved in their operations for the last five years. Similarly, the study employs a two-year panel data set representing both I (2019–20) and II (2019–20) waves of COVID-19, which has not yet been analyzed in the Indian context. To measure the robustness of the main model, a pooled OLS model is applied in the study.

Our analysis reveals a strong and negative association between NPLs and financial performance in the Indian banking industry. The same impact also applied during the I and II waves of the COVID-19 crisis. This implies that if the default risk of Indian banks increases, their chances of generating profitability are less. This supports the theory of “asymmetric information” that unprofitable banks are more sensitive to default risk and hence approves of Berger and DeYoung’s the “bad management” hypothesis in the Indian banking industry. Interestingly, banks with high equity tend to take excessive risks and, under the perception of “moral hazard”, facilitate their loans without proper scrutiny and monitoring of the borrower’s creditworthiness, leading to deterioration in their asset quality and profitability. We also observe a strong and negative association between systemic risk and the financial performance of Indian banks, which supports the existence of the “tail risk spillover of a single bank to the system” hypothesis. This suggests the possibility of spillover of tail risk (like lower market share, lower value of assets and bad NPLs) from a single bank to the entire system of the Indian banking industry, impairing their performance.

On the other hand, the results show that LR and bank risk (Z-score) have a positive impact on profitability, indicating that a more significant flow of liquidity and greater bank soundness are improving the financial performance of Indian banks. This suggests that the level of default risk has reduced due to good and significant changes in credit policy during the COVID-19 phase, which is having a positive impact on financial performance. Similarly, the COVID-19 factor is also playing an important role in explaining the financial performance of Indian banks. However, market risk had no significant impact on the financial performance of Indian banks during the study period. COVID-19 provisions, loans moratorium and restructuring policies initiated by the Honorable Supreme Court in 2020, ploughing back of dividends, mega-mergers to strengthen capital position and successful write-offs have become inevitable tools to control the rising level of NPLs over the last few years (Reserve Bank of India, 2018; Reserve Bank of India, 2020). Comparing the ownership group coefficients, we find that PSBs have considerable potential to achieve financial performance while preserving unsystematic risk and external shocks relative to their peer group. Finally, robustness check estimates confirm the coefficients of the main model. In a nutshell, the results suggest that the Central Bank of India should give adequate concern to unsystematic risk and systemic risk to maintain its financial performance.

The results of this study have important implications for strategic bank managers, policymakers and stakeholders. To manage unsystematic risks, such as default risk and solvency risk, banking management must make strict changes to its credit policies. Asymmetric information between borrowers and bank managers should be reduced, allowing banks to thoroughly evaluate borrowers’ references throughout the credit analysis, thereby reducing the probability of default. The management of banks should timely monitor the loan installments of the borrowers via early warning indicators and check the liquidity position. To mitigate the level of default risk, the bank must maintain a healthy capital structure. Policymakers need to pay more attention to loan loss provisions and restructuring policies. The outlook of the study is also relevant to investors, as it explains the key drivers that affect profitability in the banking industry, thereby instilling more confidence in their investment behavior.
The current analysis is limited to the years 2018–2022. Consequently, future studies may take into account larger data sets to conduct more in-depth analysis. Specifically, future research can explore the drivers of the financial performance of Indian banks by comparing the impact of the global financial crisis of 2007/08 with the COVID-19 crisis. Further, future research can enhance the drivers of the financial performance of Indian banks by considering macroeconomic variables along with CSR. In particular, the impact of CSR, dividend payout ratio and fluctuations in market share could be a future research direction. Other than this, instead of treating ownership as a dummy variable, future studies can explore risky determinants for different ownership groups. Finally, concerns related to a dynamic effect (or endogeneity) can be further examined.

References


Further reading


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