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ORIGINAL ARTICLE

Identifying Financial Performance Drivers in the Indian Banking Sector During the COVID-19 Crisis

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Abstract

In order to shed light on the possible factors responsible for volatility in the financial performance of Indian banks, we primarily consider four novel variables in the study, including the COVID-19 crisis, NPLs, systemic risk, and government response. For this, we employ bank-level observations of 412 Indian commercial banks spanning 2018–2022. Using fixed-effects and 2SLS methods, we find that government response, COVID-19, and income diversification play a significant role in positively affecting the financial performance of Indian banks. However, non-performing loans, provisioning, systemic risk, and bank size are responsible for their poor performance. Projected macro-economic statistics suggest that the GDP growth rate and inflation have significantly increased the strength and resilience of Indian banks. The main evidence mainly supports the '*bad-management*', '*too-big-too-fail*', *and* '*diversification opportunity*' hypotheses. The heterogeneity test and robustness check results are nearly identical to those reported in the main evidence. Overall, our findings reduce the concern of policymakers, though not completely eliminated, that tighter government regulation and provisioning for Indian banks may expedite the bank's ability to withstand their credit risk, systemic risk, and exogenous shocks, which can lead to a rapid improvement in their performance.

Keywords COVID-19 · Non-performing loans · Systemic risk · Government response · Financial performance · Indian banks

JEL Classification G21 · C61 · C23

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Introduction

The Indian economy has been hit hard by the COVID-19 pandemic[1] with a GDP growth rate of 3.7 percent in 2019 to −6.6 percent in 2020, a major decline relative to world GDP growth rate, i.e., 3.3 for 2020 (World Bank, 2020). Despite various initiatives[2] by the Government of India to console the economy and financial system, millions lost their jobs due to the closure of many corporate firms. As a result, the ability of businesses to repay their loans was reduced, and more non-performing loans (NPLs) were added to the banking system (Park and Shin 2021). Huge and accumulated NPLs and increased provisions possibly suppressed banks' profitability in terms of poor capital, weaken balance-sheets and limited their ability to lend. (Kryzanowski et al. 2022). Reserve Bank of India (2022) revealed that the ratio of non-performing loans (NPL) to net advances of Indian commercial banks stood at 13.5 percent by the end of the financial year 2022, the highest since 2008 (2.25 percent), respectively, which reduces the financial performance of the bank. A top-level bank NPL ratio is a long-lasting issue in India which ultimately hampers the financial performance of the banks by pulling down the profitability levels. This issue prompts us to explain the influence of COVID-19, systemic risk, NPLs and government response on the performance of commercial banks in India.

Any global shock, such as the Asian financial crisis of 1996/97; the global financial crisis (GFCs) 2007/08, and more recently, the novel coronavirus crisis of 2019/20, creates a lot of room for academic research to examine its impact on the financial system. With this in mind, the ongoing research aims to answer various research questions related to the financial performance impact of Indian banks concerning the pandemic and other bank-centred risks. What drives the financial performance in the Indian banking industry during 2018–2022? Are non-performing loans, systemic risk, and the novel coronavirus crisis of 2019/20 affecting the performance of Indian banks? Are government policies more effective in maintaining the financial performance of Indian banks during the ongoing pandemic?

To answer these questions, the current study performs the fixed-effects model that has been recently applied by several studies, including those by Tarchouna et al. (2017), Khan et al. (2020), Demir and Danisman (2021), Cao and Chou (2022), and others. They prominently highlight the impact of the COVID-19 crisis, along with other micro–macro-economic variables on the banking industry in countries other than India in the existing literature (see Table 1 for detailed literature). Earlier studies have empirically examined a relatively shorter window of the pandemic dataset to explore explainable variables for banks. However, the epidemic continued well

[1] The current study uses the terms "COVID-19 pandemic", "COVID-19 crisis" and "pandemic" interchangeably to refer to the economic/financial turmoil associated with COVID-19.

[2] According to the report prepared by the Government of India (2022) and the Reserve Bank of India (2022) to encourage banks and inject additional money into the system, various initiatives include a 25 basis points (bps) cut in the reserve repo rate, raising repo rates by 50 basis points (bps) to 5.40 per cent from 5.15 per cent to fight inflation, COVID-19 provisions and introduction of new measures to take care of rising non-performing assets in India. Available at: https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=54236.

Table 1 Illustrating of dependent and independent variables used in regression analysis by recent academicians. *Source*: Authors' elaboration

Dependent/independent variables	Variables	Country	Literature	Model	Dataset
Dependent variables	Non-performing loans (NPLs)	Pakistan; US Commercial Banks; China	Khan et al. (2020), Tarchouna et al. (2017) and Kryzanowski et al. (2022)	Fixed effects; Principal component analysis and Dynamic Generalized Methods of Moments (GMM) model	2005–2017; 2000–2013; January 2020–March 2022
	Stock Return of banks	1927 publicly listed banks from 110 countries	Demir and Danisman (2021)	Fixed effects	January 11, 2020, to May 28, 2020
	Systemic Risk	1584 listed banks from 64 countries	Duan et al. (2021)	Fixed effects	February 6, 2020. to December 10, 2020
	Default Probabilities	12 Countries	Lee et al. (2022)	System Generalized Methods of Moments (GMM) model	2010–2021
	Asset, ROA, NPLs and Lerner Index	Cross-country data	Tan et al. (2021)	Fixed effects	2007–2017
	GDP per capita	Globally Systemically Important Banks (41 OECD)	Bitar and Tarazi (2022)	Regression analysis	2011–2019
	Total Loan	US banking sector	Cao and Chou (2022)	Fixed effects (Difference-in-difference method)	2017Q1–2021Q3
Independent variables	ROA, Efficiency, Capital, Diversification Index	Pakistan	Khan et al. (2020)	Fixed effects	2005–2017

Table 1 (continued)

Dependent/independent variables	Variables	Country	Literature	Model	Dataset
	COVID19; Capitalization; ROE; Non-interest Income; Size; NPLs; Deposit Share; GDP Growth Rate; Credit to Private Sector; Income Support; Debt Contract Relief; Fiscal measures; International Support; Stringent Index; Government Response Index; Containment Health Index; Economic Support Index; Environment; Social; Government; Corporate Social responsibility (CSR) Strategy	1927 publicly listed banks from 110 countries	Demir and Danisman (2021)	Fixed effects	January 11, 2020, to May 28, 2020
	COVID19; Size; Leverage; Return; Volatility; Network; Government Response; Log Z; Loan to total asset ratio; Capital ratio; Return on asset (ROA); NPLs; ACT_Restrict; Capital regulatory Index; Sup_Power; No_Dep; Bank Concentration Ratio; Power Distance Index; COL; MAS; UAI; LTO; Trust; GDP growth rate	1584 listed banks from 64 countries	Duan et al. (2021)	Fixed effects	February 6, 2020. to December 10, 2020

Table 1 (continued)

Dependent/independent variables	Variables	Country	Literature	Model	Dataset
	Risk appetite; Loan impairment charges; Environmental, social and governance; Return on Equity; Dividend pay-out ratio; Real GDP growth rate; Consumer Price Index; Exchange Rate (NEER); Dummy COVID19	12 Countries	Lee et al. (2022)	System Generalized Methods of Moments (GMM) model	2010–2021
	Corporate Governance Index (include the board size, the board independence, the CEO duality, the majority ownership as well as the directors and executive officers' ownership); Bank-specific factors (bank size; provision for loan losses; Diversification opportunity); Macro-economic factors (Interest rate; Unemployment; Global Financial Crisis); Control Variable (Financial Market Risk)	US Commercial banks	Tarchouna et al. (2017)	Principal component analysis and Dynamic Generalized Methods of Moments (GMM) model	2000–2013
	Intervention; Country fixed-effect; Time fixed-effect	Cross-country data	Tan et al. (2021)	Fixed effects	2007–2017

Table 1 (continued)

Dependent/independent variables	Variables	Country	Literature	Model	Dataset
	Capital ratio (Teir1 and Teir2); Size; ROA; Loan to total asset ratio; Equity to total asset ratio; NPLs ratio	US banking sector	Cao and Chou (2022)	Fixed effects (difference-in-difference method)	2017Q1–2021Q3
	Confirmed COVID-19 cases; Bank-specific (include, total loans to total deposits ratio, bank size, and return on assets ratio). The macro-economic control variables are the GDP growth rate and unemployment rate. The overnight rate is used to capture the liquidity support provided by the government to maintain the economy and the financial system during a crisis	China	Kryzanowski et al. (2022)	Fixed effects	January 2020–March 2022
	COVID-19; Tier 1 capital ratio; capital adequacy ratio; gross NPLs to gross loan ratio; ROA; liquid asset to total asset; banking sector policy response index; banking sector regulation; private sector debt to GDP ratio; current account to GDP ratio	Globally Systemically Important Banks (41 OECD)	Bitar and Tarazi (2022)	Simple regression (OLS) analysis	2011–2019

beyond, especially at the end dates of their observation windows. Consequently, the ongoing study contributes to the literature by encompassing both wave I and II of the pandemic datasets, thereby calculating robust coefficients in the current state of the Indian banking sector.

This study contributes to the existing body of knowledge in the literature in several novel ways. Firstly, it explores four distinctive variables at the bank-specific level, namely, COVID-19, NPLs, systemic risk, and government response, the study tries to rationalize empirical findings through prior literature. The economic and banking segment impact of COVID-19 and NPLs has been well-established in financial literature (Park and Shin 2021; Demir and Danisman 2021; Lee et al. 2022; Shabir et al. 2023). These studies argue that the severe economic and banking downturn caused by the COVID-19 pandemic, coupled with high debt levels globally, leads to concerns about the escalation of rising non-performing loans (NPLs) in global banking systems. This scenario poses a substantial risk to the earnings prospects and financial performance of banking businesses across economies. Therefore, this study looks the effect of COVID-19 and NPLs (that are likely outcomes of both the economic slowdown and weak risk management by banks) on the financial performance of Indian banks as unique bank-specific variables.

Secondly, our paper incorporates all novel variables into fixed-effects and Two-Stage least squares (2SLS)[3] models, along with other common bank-centric variables, aiming to enhance the understand of their impact on the financial performance of Indian banks. Undoubtedly, existing literature emphasizes that, in addition to macro-economic factors, a variety of bank-specific factors influence the performance of the banking industry globally (refer to Table 1 in the literature review). However, the current study contributes to a relatively limited body of literature on factors elucidating the financial performance of banks operating in both emerging and advanced economies. It is worth noting here that most of the studies on the subject matter are directed to US and cross-countries banks (see "Literature Review" section for more details); however, single country examination is hard to find. Therefore, apart from common macro-economic and bank-specific factors, this study explores the impact of changes in the COVID-19 crisis, systemic risk, NPLs, loan loss provisions, and government response on financial performance in Indian banks. None of the existing studies examines all the risk factors, along with government response, to explain the financial performance of Indian banks. Therefore, the scope of the present study is much wider than the earlier studies on the determinants of financial performance in Indian banks. For example, Rajaraman and Vasishtha (2002), Ranjan and Dhal (2003), Das and Ghosh (2007) and Arora et al. (2022) examines determinants of credit risk of public sector banks (PSBs) in their analyses. In line with current literature, we make use of bank-level data on drivers of financial performance and apply fixed-effects and 2SLS estimation approaches to find out key macroeconomic and microeconomic variables of financial performance of Indian

[3] Two-Stage least squares (2SLS) considers as an extensionn of the OLS method. It is usually use when the dependent variable's error terms are correlate with the independent variables (Chen and Gupta 2009; Tahir and Alam 2022; Burki and Tahir 2022).

banks. The potential use of all novel variables can help policymakers discuss different types of policies in a more comprehensive way.

Third, the study constructs a dummy to estimate the effect of government response on the financial performance of Indian banks. We expect that the prompt government response has reduced the rising NPL ratio and systemic risk during the crisis, thereby improving the performance of the banking system in India. Fourth, this is perhaps the first study that constructs an index of the price-to-book ratio to measure systemic risk (*PBR*) and its influence on the financial performance of Indian banks throughout the study period (Reserve Bank of India 2021a). The Reserve Bank of India (2021a) have recommended the *price-to-book ratio* (*PBR*) as a measure to check the systemic risk of Indian banks. The price-to-book ratio (PBR) is used to better understand the health, stability, and value of banks. In particular, changes in the price-to-book ratio help predict stressed assets. Following the Reserve Bank of India (2021a), the study is constructing price-to-book ratios to assess systemic risk (*PBR*) for each bank over the period of time as: $PBR_{i,t} = SA_{it} + DR_{it} + NIM_{it} + CAP_{it} + LTA_{it} + GDP_t + CTG_t$. The index includes the following as compositional variables: stressed assets ratio (SA), deposits ratio (DR), net interest margin (NIM), capital adequacy ratio (CAP), total assets (in natural logarithms), GDP growth rate (GDP), and credit-to-GDP ratio (CTG). PBR signifies the tail risk spillover of each bank$_i$ to the system, and it is measured by the average growth rate of the market value of assets for bank (i) over time (t). The index of price-to-book ratio reflects the efficacy of Indian banks in maximizing spreads and managing their credit risk; therefore, the study expects a positive association between banks' systemic risk and financial performance.

Further, using an ownership dummy, we are also trying to show which ownership group of banks is more effective during the study period in terms of managing their financial performance, which is yet to be identified by the Indian literature. Finally, according to methodological concern, the study applies a '*fixed effects model*' that allows for the ith 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 ith banks over time. The problem of heteroscedasticity mainly arises while constructing panel regression and performing the 'ordinary least square method' because here we combine cross-section and time series; hence residuals are correlated with time and different ith banks, and predicted results are biased. Moreover, the endogeneity issue is being identified by using the Durbin–Wu–Hausman test, and the robustness of our main findings is being checked across alternative econometric estimation methodologies like 2SLS, OLS, and panel corrected standard error (PCSE) models.

The rest of the paper is organized as follows. "Literature Review" section illustrates the relevant literature and identifies the literature gaps in the study. "Methodological Framework" section explains the relevance of applying the fixed effects model to the study. "Sample Selection and Variable Specification" section briefly presents the dataset, variables specification, and hypothesis development for the estimated model. "Empirical Results" section presents and discusses the main findings, and a set of robustness exercises and extensions. Finally, "Conclusions and Recommendations for Policymakers" section concludes and shows optimal policies.

Literature Review

This section delves into the extensive literature and various themes encompassing numerous factors that impact the financial performance of banking systems across different countries. The considered factors are broadly classified into the following subsections, namely, government response to COVID-19, systemic risk, Non-Performing Loans (NPL), and single and cross-country analyses. There has been a noticeable expansion in the literature addressing COVID-19 and its influence on the banking industry and the economy. Broadly, the researchers identify macro and micro-economy (bank-specific) factors[4] that influence banks' lending decisions and financial performance when confronted with significant uncertainty and risks during the global pandemic. Studies by Demir and Danisman (2021), Duan et al. (2021), Lee et al. (2022), Bitar and Tarazi (2022), Kryzanowski et al. (2022) and Shabir et al. (2023) stand out as notable examples among others. These studies focus on both macro and micro-economic drivers of the banking industry, including factors such as the unemployment rate, GDP, stock index, inflation rate, and exchange rate movements, among others. Additionally, there are significant studies that specifically explore microeconomic factors as bank-specific influences, including works by Khan et al. (2020), Goswami (2021), Goswami (2022), Cao and Chou (2022), Abdelsalam et al. (2022), among others.

Theoretical Underpinning

This section thoroughly discusses the theoretical underpinnings of the '*bad management,*' *'too-big-to-fail,'* and *'diversification opportunity'* hypotheses.

Theories on Diversification Opportunity (DIV)

The theoretical linkage between diversification opportunity and financial performance finds support from numerous researchers. Louzis et al. (2012) and Chaibi and Ftiti (2015) argue that, in order to generate more income or to maintain a balance between conventional (interest income) and non-conventional income (non-interest income), banks need to invest in non-interest income activities. This, in turn, allows them to reduce various risks, including default risk and systemic risk, and improve their financial performance. Abbas and Ali (2021) assert that diversifying funds into different sources of income, such as investment banking, asset management, insurance underwriting, fee-paying and commission-paying services, trading and derivatives, can ensure bank stability even during financial

[4] Researchers (Berger and DeYoung 1997; Khemraj and Pasha 2009; Louzis et al. 2012; Messai and Jouini 2013; Khan et al. 2020; Goswami 2021; Goswami 2022; Cao and Chou 2022 among others) consider bank-specific factors (internal or controllable factors or idiosyncratic factors) to be microeconomy factors in the past few decades. Since the financial performance of banks can be affected by internal factors prevailing within an organization. Therefore, they are generally controllable in nature and are considered as micro-economic variables.

crises. VO (2020) considers the expansion of sources of funds in the bank's administration policy, emphasizing the importance of preserving bank funding diversity for maximizing bank performance. Markowitz (2015) highlights that the diversification of investments by banks can reduce unsystematic risk, ultimately contributing to an increase in their overall performance.

Theories on Too-Big-Too-Fail

The financial literature of bank size (*SIZE*) provides mixed evidence regarding the relationship between bank size and financial performance. Salas and Saurina (2002), Ranjan and Dhal (2003), Alhassan et al. (2014), Reserve Bank of India (2008), Reserve Bank of India (2020), Demir and Danisman (2021), Shabir et al. (2023) state that bank size is more resilient with financial performance. Larger banks do better in taking care of their financial performance in times of crises. This is probably because of prudent lending practices, adoption of stricter provisioning norms, and greater diversification of non-interest income in total assets by the bank, which reduces its default rate. Therefore, the size of the bank has a positive effect on its financial performance.

Contrary to this view, Stern and Feldman (2004) hypothesize the '*too-large-to-fail hypothesis*' and suggest that bank size is negatively related to financial performance. The study argues that in response to the prospect of government security, lenders reduce discipline, and banks take on excessive risk. As a result, large-sized banks increase their leverage and lend to borrowers with low creditworthiness even during times of crisis (pandemic, systemic risk, and default risk), have more bad loans, and thus eventually fall into the category of bad banks. (Laeven et al. 2016a, b; Duan et al. 2021; Abdelsalam et al. 2022; Shabir et al. 2023). In this context, Altunbas et al. (2007) and Chen and Wang (2015) identify that, with a view to achieving more interest income and mandate lending under government-sponsored schemes by large-sized banks, the risk of default may increase during periods of crisis, reducing the bank's profitability. Therefore, we expect the negative impact of *bank size* on financial performance in this study.

Theories on Bad Management

The 'bad management' hypothesis, initially proposed by Berger and DeYoung (1997), suggest that branch managers of banks tend to underestimate the creditworthiness of borrowers and provide them with poor-quality loans. This, in turn, leads to more non-performing loans and increased exposure to default risk. Consequently, the financial performance of the banks, in terms of profitability, is reduced. This hypothesis aligns with findings from other studies Podpiera and Weill (2008), Louzis et al. (2012), Chaibi and Ftiti (2015), Ghosh (2015), and Goswami (2021), all of which have observed a negative effect of non-performing loans and profitability.

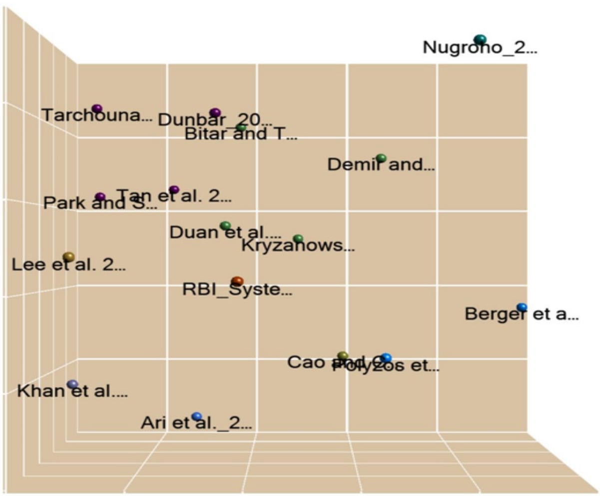

Fig. 1 Articles clustered by words similarity via NVivo Software. *Source*: Authors' construction

Theories on Covid-19 Pandemic

Al-Awadhi et al. (2020), Chen et al. (2020a, b), and Shabir et al. (2023) put forward a '*pandemic*' hypothesis, suggesting that the COVID-19 pandemic has had devastating impact on the banks' financial system, increasing its financial risks. Some literature has examined the influence of COVID-19 on the bank system. Elnahas et al. (2021) confirmed that the COVID-19 crisis has worsened the performance of many banks worldwide. Governments of various countries have taken significant steps to curb the spread of the virus, including implementing de-globalization by closing their borders between multiple countries. Consequently, this has severely affected economic activities, such as reduced trade and services, leading to a decline in business and household income and revenue. This, in turn, has reduced the ability of business owners to repay loans and the demand for banking services (Beck and Keil 2022; Duan et al. 2021). Lee et al. (2022) report strong empirical evidence indicating that the tightening of credit standards during the pandemic led to reduced demand for many types of loans. This reduction in demand is subsequently inversely associated with credit and systemic risks, impacting the banks' financial performance.

Relevant Themes on Literature Review

COVID-19 Crisis

Table 1 and Fig. 1 show the recent growing literature on COVID-19 in international banks, looking at the impact of the crisis and associated risks. Figure 1 illustrates items clustered by word similarities, depicting the extensive work undertaken by academics in the area of COVID-19 in the banking system. Table 1 includes various sub-sections, such as different financial sector policies implemented by regulators during the pandemic (Demirgüç-Kunt et al. 2021), systemic risk and its influence on the pandemic (Duan et al. 2021), sovereign default risk affecting government financially (Augustin et al. 2022), and fluctuations in bank deposits (Ding et al. 2021). Recent evidence highlighted by Eichenbaum et al. (2020), Chen et al. (2020a, b), and Barro et al. (2020) underscores that crises lead to an economic slowdown, which is likely to have a drastic influence on the stability of the banking sector. Beck and Keil (2022) conducted an examination revealing that U.S. banks with geographic exposure to the COVID-19 pandemic and lockdown measures experienced an increase in their non-performing loan (NPL) levels. Cao and Chou (2022) delved into the impact of bank capital on the NPL ratio during the COVID-19 crisis. Additionally, some literature reflects on the impact of COVID-19 on various countries and their financial systems (Fernandes 2020; Barua 2020; McKibbin and Fernando 2020). Berger et al. (2021) suggest that the impact of the COVID-19 shock was more severe for banks located outside the U.S.

Non-performing Loans and Its Association with the Macro–Micro Economy

Over the past two decades, there has been a huge amount of literature on NPLs and its influence on the banking system across various countries. Studies such as those by Berger and DeYoung (1997), Salas and Saurina (2002), Ahmad and Ariff (2007), Podpiera and Weill (2008), Nkusu (2011), Louzis et al. (2012) Beck et al. (2013), Makri et al. (2014), Ghosh (2015), Bawa et al. (2019), Goswami (2021), Goswami (2022), among others, have contributed to this body of research. These studies have empirically tested and found that high levels of NPLs lead to economic distress and fragility in both the macro–micro economies. This distress is generally associated with lower bank performance due to higher corporate funding costs and excess corporate debt (Kaminsky and Reinhart 1999; Aiyar et al. 2015). Other studies, such as those by Ari et al. (2021), recommend that higher levels of Non-Performing Loans (NPLs) reduce a country's output and GDP rate in the post-crisis period. This, in turn, can lead to increased cross-nation cash outflows from developing nation markets (Park and Shin 2021). On a micro-level, various studies (Tarchouna et al. 2017; Khan et al. 2020; Tan et al. 2021; Duan et al. 2021; Lee et al. 2022) have explored multiple factors, including income diversification, profitability, size, capitalization, and operating efficiency, that influence the levels of NPLs, Return on Assets (ROA), and systemic risk. However, the relationships between all dependent variables and independent variables remain unclear (see Table 1 and Fig. 1).

In the Indian context, Rajan (1994), Rajaraman and Vashishtha (2002), and Ranjan and Dhal (2003) were among the first researchers to examine the factors influencing Non-Performing Loans (NPLs) in public sector banks. Das and Ghosh (2007) accounted for the high persistence of credit risk in public sector banks in India. Similarly, Bardhan and Mukherjee (2016), Bawa et al. (2019), and Goswami (2021) found a high dynamic effect of Non-Performing Assets (NPAs) levels. Additionally, they pointed out that higher intermediation costs and Return on Assets (ROA) tend to lower NPAs, while credit growth and solvency ratio induce an increase in the level of NPAs. Goswami (2022) estimated the NPA drivers of Indian banks in the II-stage of the regression model, considering the factors of

COVID-19 and policy initiatives. The study found that serious policy actions and the negligible impact of the COVID-19 crisis led to a decline in the NPLs ratio during 1999–20.

Government Response During the Pandemic

The literature also underlines the importance of government responses to control the crisis situation, which includes measures such as quarantine for infected people, closure of public places for gatherings, restrictions on movement and travel, mandatory use of masks, and more. Ozili and Arun (2020) and Ding et al. (2020) identified that social distancing norms surged in response to large numbers of COVID-19 cases. Consequently, economic activity around the world declined, prompting governments to initiate numerous policies to mitigate the effects of the shock on the financial system. Hafiz et al. (2020) deliberated on numerous policy actions for handling COVID-19, addressing systemic risk, and considering micro- and macro-level risks. They summarized the intrinsic issues and trade-offs among these policies. Considering government and central bank responses, Berger et al. (2021) laid out a roadmap for banks during and after the pandemic period.

Systemic Risk and Financial System

Very few bodies of literature, such as Laeven et al. (2016a, b) and Zedda and Cannas (2020), analyze the grounds and implications of bank systemic risk. Acharya et al. (2012) and Acharya et al. (2017) identify the possibility and consequences of a capital shortfall in banks during the global financial crisis, reflecting the characteristics of systemic risk. Using the symbol ΔCOVAR, Adrian and Brunnermeier (2009) and Adrian and Brunnermeier (2016) provide a measure of systemic risk for each bank. ΔCOVAR allows for accounting changes in the market value of each considered bank's assets. It reflects "*the change in the value at risk of the financial system conditional on an institution being under distress relative to its median state*" (p. 1705 of Adrian and Brunnermeier 2016). Recently, Duan et al. (2020) identified the impact of the pandemic on systemic risk across 1584 listed banks of 64 countries.

In the context of literature related to Indian banks, studies by Ghosh (2009), Herwadkar and Pratap (2019), and the Reserve Bank of India (2021a) have recommended the use of the *price-to-book ratio* (*PBR*) as a measure to assess the systemic risk of banks. Ghosh (2009) examines the interrelationship between charter value and risk-taking by banks. To test the efficient market hypothesis, Herwadkar and Pratap (2019) use the price-to-book ratio as a key financial market indicator. Specifically, they explore whether equity markets provide salient information about banking stress and found that markets are capable of pricing in stress concurrently but not in advance. In summary, relative to other market-based measures, the PBR has emerged as a better indicator of impending distress, particularly for Indian banks; hence, this novel indicator has been assessed by this study.

Literature Gap

The literature has yielded several key insights. Firstly, the ongoing study significantly contributes to the growing body of literature on banking performance during the COVID-19 crisis, a topic that was not extensively explored by academia for the Indian banking system. The Government of India executed substantial containment measures to curb the spread of the novel coronavirus, leading to a weakening of economic activity and substantial losses in income and revenue for businesses and households (Tan et al. 2021; Goswami 2022). This, in turn, has eroded the solvency and repayment capability of borrowers, reducing the demand for banking services. However, there has been a lack of sufficient efforts to identify the drivers responsible for the deteriorating financial performance of Indian banks during the pandemic. Secondly, it is observed that, except for Goswami (2022), there is a scarcity of Indian studies identifying financial performance drivers in the recent period. Using recent samples from 2018 to 2022, the present study aims to fill this gap in the paucity of Indian banking literature. Thirdly, the study highlights from Table 1 that there are two strands of literature, one focusing on bank-centric factors and the other considering both macro–micro factors across countries over the years. Notably, none of the Indian and international studies collectively identify the impact of five controllable and uncontrollable variables (namely COVID-19, NPL, systemic risk, loan loss provisioning, and government response) on financial performance in the banking system.

Methodological Framework

The unbalanced panel data collected from the Reserve Bank of India (RBI) to assess the Eqs. (3) and (4) pose various challenges due to the inclusion of time and cross-sectional dimensions in the equations. To determine the correct estimators, the authors conducted preliminary checks on the panel dataset. Initially, to choose between a panel regression model of fixed effect, random effect, or Pooled OLS, the paper performed Breusch and Pagan's (1980) due to cross-sectional dependence. The test is based on the null hypothesis that implies no significant difference across cross-section dependence. If this is the case, then Pooled OLS is preferred over Fixed Effect (FE)/Random Effect (RE) or vice-versa. Second, since Eqs. (3) and (4) include time dimension, heteroscedasticity, and heterogeneity issues, panel data commonly suffer from autocorrelation issues (Burki and Tahir, 2022). Therefore, to fix this issue, Worrall (2010) suggested the use of fixed and random effects models. The key features of fixed and random effects modelling, as specified by Gujrati (2004) are: in fixed effects modeling, the intercept may vary across cross-sectional units, but it remains constant over time. In the random-effects model, the intercept represents the average value of all cross-sectional intercepts. Hill et al. (2011) and Burki and Tahir (2022) asserted that the fixed effects model works efficiently to estimate panel data models, especially when there is a chance of serial correlation between the independent variables (X's) and the disturbance error term. However, the random effects correction model is suitable if the error term and independent variables (X's) are independent. This is in line with Worrall (2010) suggestion that the random-effects model is suitable when there is zero correlation between the independent variables (X's) and the disturbance term. The fixed effects and random effects estimators' Eqs. (1) and (2) are specified below.

$$Y_{i,t} = \left(\alpha + \mu_i\right) + X_{i,t}\beta + \varepsilon_{i,t} \tag{1}$$

$$Y_{i,t} = \alpha + X_{i,t}\beta + \left(\mu_i + \varepsilon_{i,t}\right) \tag{2}$$

Further, a Hausman specification test (1978) is used to choose between fixed and random effects estimators (Worrall 2010; Baltagi 2014). The null hypothesis in the framework of the Hausman test shows no correlation between the error term and the independent variables in the panel data model (i.e., $Cov(v_i, X_{it}) = 0$, exogeneity, meaning random effects are consistent and efficient compared to fixed effects estimators. The fixed effects estimator will be used if the null hypothesis is not accepted. The Hausman specification test is given below in the following expression (3):

$$LM = \left(\beta_{LSDV} - \beta_{randoml}\right)W^{-1}\left(\beta_{LSDV} - \beta_{randoml}\right) \sim \chi^2(k) \tag{3}$$

The Breusch and Pagan's (1980) cross-sectional dependency test is utilized and supports Xts model (see Table 2). Further, the correct panel estimators are identified by employing Hausman test. The specification test supports the fixed effects estimator for the study as the null hypothesis is not accepted (see Table 2). Therefore, the specified models 4 and 5 are estimated by following the procedure of fixed effects modeling.

Breusch-Pagan test and Hausman specification test statistics are reported in Table 2. In Breusch-Pagan Test, we find χ^2 statistics of 282.40 (p-value = 0.001) in the case of the panel with the ratio of return on assets (ROA) as a dependent variable and 259.11 (p-value = 0.000) in the case of the ratio of return on equity (ROE). The null hypothesis is rejected, meaning the Pooled OLS model is not appropriate. The evidence of cross-section dependence from the Breusch-Pagan test is sufficient to switch from pooled OLS to -xt- suite. This aligns with the study by Baltagi et al. (2012), which advocates that the standard Breusch and Pagan (1980) LM test is not appropriate for testing cross-sectional dependence in a panel data model when the number of cross-sectional units (n) is large and the number of time periods (t) is small. Therefore, we performed the Hausman specification test and found χ^2 statistics of 216.11 (p-value = 0.000) in the case of the panel with a ratio of return on assets (ROA) as a dependent variable and 251.99 (p-value = 0.000) in the case of the ratio of return on equity (ROE), thereby rejecting the null hypothesis. This indicates that the fixed-effects estimation is accurate in estimating the panel model relative to the random effect and traditional panel estimator.

Fixed Effects Model: Baseline Model

To explore the key drivers of financial performance in the Indian banking system during 2018–2022, the current study uses the fixed-effects model (see Table 1 for a

Table 2 Hypothesis testing using and Breusch-Pagan Test and Hausman specification test. *Source*: Authors' calculations

Tests	Hypothesis	χ^2 value ROA	χ^2 value ROE	Selection of model
Breusch-Pagan test	Ho: not significant difference across cross-sections or vice-versa	282.40*** (0.001)	259.11*** (0.000)	Pooled OLS model is rejected
Hausman specification test	Ho: the individual effects are not correlated with the X_{it}	216.11*** (0.000)	251.99*** (0.000)	Random effect model is rejected

recent literature review for the popularity of the fixed-effects model among academics), which is also famous as the '*global regression model*' by Qiu and Wu (2011). For the purpose of the analysis in this study, the fixed-effects model is considered accurate because of the presence of multiple exogenous X variables. This model controls for heteroscedasticity and correlation issues between samples, thereby providing unbiased estimates. In this case, the use of the traditional OLS model is deemed to be seriously biased. Another reason for using the fixed-effects model is that it helps to control for unseen variation over time (t) and allows for variation in behaviour among individual banks (i), so that the model permits different constants for individual Indian banks (i), but the coefficients are fixed over time (Gujrati and Dawan 2015; Khan et al. 2020; Tan et al. 2021). Considering this, formalizing the baseline model is as follows:

$$\ln \mathrm{Y}_{it} = \alpha + \sum_{n=1}^{N} \beta_n \ln X_{it}^{n} + \sum_{m=1}^{M} \tau_m X_{t-1}^{m} + \sum_{mv=1}^{mv} \beta_{mv} \ln X_{t}^{mv} + \sum_{d=1}^{D} \phi_d X_{it}^{d} + \varepsilon_{it}$$
$$\text{where} \quad i = 1, \dots, J; \quad t = 1, \dots, T; \quad \text{and} \quad \varepsilon_{it} = v_i + \xi_t + \mu_{i,t}. \tag{4}$$

In Eq. (4), the subscripts i and t denote the cross-sectional and time dimensions of the panel, respectively. Here, $\ln Y_{it}$ is the dependent variable, representing the financial performance of Indian banks i at time t. The X_{it}^{n} stands for the nth controllable bank-specific variables, such as NPLs, LLP, Size, NOI, and systemic risk of ith bank in the t period, X_{t-1}^{m} represents uncontrollable variables (m) in the t-1 period, i.e., the average log growth rate of confirmed 'COVID-19' cases during $2020/2022_{t-1}$. The symbol $\ln X_{t}^{mv}$ considers the macro-economic variables that may affect the financial performance of Indian banks over time (t). $X_{i,t}^{d}$ displays dummy variables for the variable of 'government response' (d) for the ith bank in the t period, respectively (see next section for the detailed description of each variable). v_i represents the unobserved bank-specific effects, ξ_t is the unobservable time-effects, and μ_{it} is the idiosyncratic error term. The βs, τs, and ϕs are the coefficients to be estimated.

Moreover, to test the sensitivity of the fixed effects results of Eq. (4), we have also applied the Two-Stage Least Squares (2SLS) regression model with instrumental variables (IVs). The 2SLS model has the potential to address the issue of endogeneity and mitigate concerns about omitted variables in the panel data model (Chen and Gupta 2009; Tahir and Alam 2022; Burki and Tahir 2022). Following the previous literature (Tahir and Alam 2022; Burki and Tahir 2022), lagged values of regressors are used as instruments (IV) to address the issue of endogeneity in Eq. (4) while applying the 2SLS model. Using lagged regressor as IV, the 2SLS model Eq. 5 is given below:

$$\ln \mathrm{Y}_{it} = \alpha + \sum_{n=1}^{N} \beta_n \ln X_{it-1}^{n} + \sum_{ma=1}^{ma} \tau_{ma} X_{t-1}^{ma} + \sum_{d=1}^{D} \phi_d X_{it}^{d} + \varepsilon_{it} \tag{5}$$
$$\text{where} \quad i = 1, \dots, J; \quad t = 1, \dots, T; \quad \text{and} \quad \varepsilon_{it} = v_i + \xi_t + \mu_{i,t}.$$

In our 2SLS Eq. (5), $\ln X_{it-1}^{n}$ refers to the lagged value of bank-specific regressors considered as IVs. The interpretation of the rest of the symbols is as specified in the

Eq. (4). The specified Eqs. 4 and 5 are initially estimated through the fixed effect model using the Hausman specification test for panel data analysis. The results of the fixed effect model are depicted in columns (1–4) of Tables 8, 9, 10 and 11. The 2SLS model results are presented in columns (5–8) of Tables 8, 9, 10 and 11. Finally, the robustness check of Eqs. (4) and (5) is done through POLS pooled least squares (POLS) and PCSE models, and results are presented in Table 13.

Sample Selection and Variable Specification

Sample Selection

To examine bank-centric variables, the study uses an annual dataset of scheduled commercial banks in India spanning 2018 to 2022, obtained from the Indian Bank Association database [https://www.iba.org.in] and from the annual editions of ‘Statistical Table Relating to Banks in India’ [https://www.rbi.org.in]. The data on confirmed COVID-19 cases has been extracted from the ’Ministry of Health and Family Welfare’. These are reputable sources of databases and have been used by several major studies in the literature (Digal et al. 2015; Khan et al. 2020; Goswami 2021, 2022, among others). To run the statistical analysis, we first obtained and filtered the desired unbalanced bank-level data and then combined all bank-level data i.e., public, private and foreign banks, into a single unbalanced panel. In particular, the study uses 412 observations for further analysis. Definitions of selected variables, along with other information, are given in Table 3. Data on the real GDP growth rate (in percent) at constant prices for 2011–12 and the annual inflation rate (in percent) during the years 2018/22 have been obtained from the World Bank database. The data for exchange rates (REER) is sourced from the Bank for International Settlements (BIS). Later, the percentage of real GDP growth rate, annual inflation rate, and exchange rate are converted to log form to ensure consistency in the results.

Variable Specification and Hypothesis Development

In order to study the impact of controllable and uncontrollable variables on the financial performance of the Indian banking system during 2018–2022, we have developed and explained hypotheses among the dependent and independent variables in this section. Briefly, Table 3 reports the variable details.

The Dependent Variables

In order to capture a bank’s financial performance using a single measure is not appropriate. Therefore, we followed the previous studies of Al-Musali and Ku Ismail (2014), Elnahass et al. (2021), Chen et al. (2022), Abdelsalam et al. (2022), Shabir et al. (2023) and optimized two alternative accounting-based measures in our empirical analysis as a dependent variable to evaluate the bank’s financial performance. These accounting-based measures that are used in the study are the log ratios of

Table 3 Sample selection and supportive literature for description of selected variables

Variables	Nomenclatures		Variable type	Description	Literature	Source	Proxy/hypothesis development
Return on assets	ROA		DV	It is used as a measure of the profitability and performance of Indian banks. ROA = net income/average assets	Ray and Goel (2023)	https://www.rbi.org.in	Financial Performance
Return on equity	ROE		DV	Ratio of income and equity. ROE = Net income/equity capital	Ray and Goel (2023)	https://www.rbi.org.in	Financial Performance
Non-performing loans	GNPL GNPA	NNPL NNPA	CV	Ratio of non-performing loans to total loans (GNPL, NNPL). Ratio of non-performing loans to total assets (GNPA, NNPA). Non-performing loans are the sum of loans past due more than 90 days and nonaccrual loans	Tarchouna et al. (2017), Goswami (2021) and Abdel-salam et al. (2022)	https://www.rbi.org.in	'Bad-management'
Loan loss provisions	LLP		CV	Ratio of loan loss provisions of Indian banks to total loans	Boudriga et al. (2009) and Tarchouna et al. (2017),	https://www.rbi.org.in	–
Systemic Risk	PBR		IV	Price-to-book ratio (PBR) of bank $_i$ over time $_t$	Adrian and Brunner-meier (2009, 2016) and Duan et al. (2021)	https://m.rbi.org.in/Scripts/BS_ViewBulletin.aspx?Id=20085	'Tail risk spillover of a single bank to the system/Franchise Value of banks'
Non-interest income	DIV		CV	Ratio of non-interest income to total income	Louzis et al. (2012), Tarchouna et al. (2017) and Khan et al. (2020)	https://www.rbi.org.in	'Diversification opportunity'

Table 3 (continued)

Variables	Nomenclatures	Variable type	Description	Literature	Source	Proxy/hypothesis development
L_Size	Size	CV	Natural Logarithms of Indian banks total assets	Tarchouna et al. (2017) and Ray and Goel (2023)	https://www.rbi.org.in	'Too-big-too-fail'
Ownership type	OT	CV	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	Goswami (2021)	Authors' construction	Ownership effect
Government Response	GR	IV	It is a dummy variable that is used to capture the effect of the government responsible for controlling the situation of a rising pandemic on Indian banks. Year 2020 = 1 and 0 otherwise	Duan et al. (2021) and Tan et al. (2021)	Asset classification and Income Recognition following the expiry of Covid-19 regulatory package [RBI April 7, 2021]	–
COVID19	COVID19	IV	Log growth rate of confirmed COVID-19 cases over time, represented as:$GR\_COVID19_t : \sum_{t=5}^{t} \left[\ln\left(1 + confirmed\ COVID19\ cases_t\right)\right]$	Ding et al. (2020), Demir and Danisman (2021) and Lee et al. (2022)	http://www.mohfw.gov.in WHO COVID19 Research Database	Pandemic
GDP growth rate	GDP	IV	Log growth rate in GDP per capita for each bank at time (t)	Park and Shin (2021), Abdelsalam et al. (2022) and Shabir et al. (2023)	https://data.worldbank.org/	

Table 3 (continued)

Variables	Nomenclatures	Variable type	Description	Literature	Source	Proxy/hypothesis development
Inflation	INF	IV	Log of annual inflation rate for each bank at time (t)	Park and Shin (2021), Abdelsalam et al. (2022) and Shabir et al. (2023)	https://data.worldbank.org/	
Exchange Rate	ER	IV	Log of annual real effective exchange rate for each bank at time (t)	Park and Shin (2021) and Lee et al. (2022)	Bis.org	

DV, dependent variable; IV, independent variable; CV, control variable the return on assets (ROA) and return on equity (ROE) as the dependent variables, serving as proxies for financial performance. These two measures are considered the banking sector's most accepted financial performance measures, providing better and robust predictions (Simpson and Kohers 2002).

The Independent Variables

Looking at prior and most recent literature (see Table 1), in addition to bank-centric determinants, the study examined three unique independent variables, including exposure to COVID-19, systemic risk, and government response. The detailed explanation of the development of the hypothesis between independent and dependent variables is as follows:

(i) *Non-performing loans* (*NPLs*): NPL, representative of default risk, has been measured by the ratios of gross non-performing loans (GNPLs) and net non-performing loans (NNPLs) to total gross loans, serving as proxies for default risk in the study. Recent banking literature following Bitar and Tarazi (2022), Abdelsalam et al. (2022) and Shabir et al. (2023), with gross NPLs specifications as a dependent variable, is defined as: $\ln GNPLs_{i,t}$. Likewise, another dependent variable is defined as: $\ln NNPLs_{i,t}$ in the case of net NPLs to net advances specifications. Additionally, the study considers other alternative measures, such as net NPLs as a percent of total assets and gross NPLs as a percent of total assets, as a proxies for NPLs to account for variation in results. This study expects that bank default risk is negatively correlated with financial performance. A high NPL indicates high default risk, which inhibits the development of banks' financial performance in response to generating revenue and income from traditional sources of income. This is supported by Ghosh (2015), who states that banks hold higher provisions for high-risk activities, lowering their incentives and profitability. Thus, bank profitability/financial performance is negatively related to default risk. This view corroborates with the theory of Berger and DeYoung (1997), who developed the 'bad management' hypothesis and pointed out that unprofitable banks generate more NPLs and are, therefore, more prone to default risk.

H1 We expect a negative relationship between default risk and financial performance.

(ii) *Non-interest income* (*NOI*): Other income of banks derived from non-traditional activities (such as investment banking, asset management and insurance underwriting, fee-paying and commission-paying services, trading and derivatives) is known as non-interest income. It is a good source of diversification of income opportunities for banks and hence referred to as a '*diversification opportunity*' in the study (Louzis et al. 2012; Chaibi and Ftiti 2015). This is evident from the fact that, in order to generate more income and maintain a balance between conventional (interest income) and non-conventional income, banks turn themselves towards non-conventional activities, thereby improving their financial performance (Salas and Saurina 2002; Ranjan and Dhal 2003; Hu et al. 2004; Alhassan et al. 2014; Chaibi and Ftiti 2015; and Ghosh 2015). This study uses the ratio of non-interest income to total income as a measure of diversification opportunity, and is expected to have a positive impact on financial performance.

DeYoung and Roland (2001) and Mamatzakis and Bermpei (2014) argue that more diversification in non-traditional relative to traditional loan-based activities induces bank fragility and may consequently reduce their performance level in the coming years. Therefore, the impact of revenue diversification (*DIV*) highly depends on the optimal mix of non-traditional and traditional activities by banks and is uncertain.

H2 The nature of the relationship between diversification opportunities and financial performance is uncertain and can vary. It could be either positive or negative depending on various factors.

(iii) *Loan loss provision* (*LLP*): The study a priori hypothesizes a negative relationship between loan loss provisioning and financial performance. It suggests that a high level of loan loss provision could diminish the profitability of banks, subsequently worsening their financial performance. Likewise, Boudriga et al. (2009) and Nikolaidou and Vogiazas (2014), Hasan and Wall (2004), Ahmad and Ariff (2007), Chaibi and Ftiti (2015) look at the retrospective behavior of provisioning, assuming that higher defaults provoke the creation of more provisioning, which in turn reduces the profitability of banks. So, the study expects that the financial performance of the Indian banks is negatively related to loan loss provisioning.

H3 The study anticipates a negative relationship between loan loss provisions and financial performance.

(iv) *COVID-19*: By a thorough review of the literature, it is found that the pandemic has a negative impact on the stability of the banking system. In this regard, Beck and Keil (2022), Ozili and Arun (2020), Barua (2020), Bartik et al. (2020) detail that governments around the world implemented significant control measures to reduce the spread of the virus, leading to a significant decline in economic activity and severe loss of revenue and income for corporate firms and households. As a result, the performance of the banking system went down due to the poor creditworthiness of borrowers and their inability to repay loans. The financial performance of banks was badly affected during the crisis years due to low credit offtake (from 6 percent in 2020 to 5 percent in 2021, respectively) and higher interest rates on lending imposed by the banks. Another reasons for deceleration in banks' financial performance was the muted growth in their off-balance sheet activities in line with subdued forward exchange investments. The Reserve Bank of India (2021a, b) reported that market anxiety about potential liquidity risks led to a loss of revenue and lower financial performance. Subsequently, as policy support measures were introduced by the Government of India and Central bank of India, reversals also became evident (Demirgüç-Kunt et al. 2021). Hence, the study expects that the financial performance of the banks is negatively related to COVID-19.

H4 The hypothesis posits a negative relationship between the pandemic and financial performance.

(v) *Systemic risk* (*PBR*)*:* It is observed that after the global financial crisis of 2008, a substantial body of banking literature from countries other than India analyzed the causes and consequences of systemic risk (Laeven et al. 2016a, b; Zedda and Cannas 2020; Duan et al. 2021).

Adrian and Brunermeier (2016) provide a factorization of systemic risk (ΔCOVAR) for each *i*th bank that measures systemic risk through changes in the market value of riskier assets. They suggest that changes in the risk value of the financial system affect an institution in crisis relative to its average position. However, the Reserve Bank of India (2021a) suggests *price-to-book-ratio* (*PBR*)[5] *as an* alternative measure of *systemic risk* (*PBR*). It indicates a close relationship of profitability with the viability of banks. Hence, this study employs PBR to better understand the health, stability and value of Indian banks. The *Price-to-book-ratio index* is constructed as follows: $PBR_{i,t} = SA_{it} + DR_{it} + NIM_{it} + CAP_{it} + LTA_{it} + GDP_t + CTG_t$. The index includes the following compositional variables: stressed assets ratio (SA), deposits ratio (DR), net interest margin (NIM), capital adequacy ratio (CAP), total assets (in natural logarithms), GDP growth rate (GDP) and credit-to-GDP ratio (CTG). The weighted average of the price-to-book ratios of each bank (*i*) over time (*t*) is calculated using the above equation. Further, the price-to-book ratios of each Indian bank are calculated by dividing the weighted average of the price/book ratios by the book value of total assets for bank (*i*) over time (*t*). Banks with negative price-to-book ratios are excluded from this calculation.

H5 We hypothesize a positive relationship between systemic risk and financial performance.

Given the bank-centric nature of the Indian financial system, the association of banks' systemic risk with financial performance is hardly anticipated in such assessments by the literature. However, since the index of price-to-book ratio reflects the efficacy of Indian banks to maximize spreads and manage their credit risk, the study expects a positive association between banks' systemic risk and financial performance.

(vi) *Bank size:* The financial literature of bank size (*SIZE*) provides mixed evidence about the relationship between bank size and financial performance. Demir and Danisman (2021) and Shabir et al. (2023) opined that bigger banks might be better equipped to handle their financial performance during the time of crises. This is probably because of prudential lending practices, the adoption of rigid provisioning norms, and more diversification of non-interest income to total assets by the banks in advance, which lowers their default rate. Therefore, they report a positive impact of bank size on financial performance.

[5] According to the Reserve Bank of India (2021a), PBR is defined as the ratio of market value of equity relative to the total book value of a firm.

Contrary to the view presented earlier, Stern and Feldman (2004) postulates the '*too-big-to-fail hypothesis*', suggesting that bank size is negatively related to financial performance. According to this perspective, large-sized banks take on excessive risks, increasing their leverage to unqualified borrowers and accumulating more bad loans (Louzis et al. 2012; Chaibi and Ftiti 2015; Adrian and Brunnermeier 2016; Billio et al. 2012; Black et al. 2016; Laeven et al. 2016a, b). Considering this opinion, one might expect a negative effect for bank size on the financial performance of Indian banks.

H6 The hypothesis suggests a mixed relationship between bank size and financial performance.

(vii) *Government response:* To capture the effect of government response on the financial performance of Indian banks, the study uses a dummy variable *GR* with a value equal to 0 during the years 2018/19, and 1 for the year 2019/20 only, and 0 for the years 2021/22. By using GR as a dummy, the study emphasizes the significance of tighter government policies primarily implemented during the pandemic to reduce systemic risk and default risk, thereby enhancing the financial performance of Indian banks. Various initiatives such as COVID-19 provisions, ploughing back of dividends, mega-mergers to strengthen capital position, regulatory tightening (i.e., resolution of large borrower accounts via the Insolvency and Bankruptcy Code), and successful write-offs and restructuring, have been launched primarily to improve the asset quality and financial performance of Indian banks (Reserve Bank of India 2018, 2020; Goswami 2022). Hence, we expect a positive correlation between the government response and financial performance.

H7 We hypothesize a positive relationship between government response and financial performance.

(viii) *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. The higher coefficient value of public sector banks as compared to private banks reflects the better financial performance of public sector banks, or *vice-versa.*

H8 We expect a positive relationship between ownership effect and financial performance.

(ix) *Macro-economic Indicators.*

In the literature, the real GDP growth rate, annual inflation rate, and exchange rate are commonly used to control for the effect of the macroeconomic environment. The variable *GDP*, measured by the logarithm of the annual *GDP* growth rate, serves as an indicator of cyclical output (Zhang and Daly 2014; Zhang et al. 2019; Wu et al. 2020; Shabir et al. 2023). A country with higher *GDP* growth rate is expected to be more efficient, reflecting a strong financial position and good creditworthiness of borrowers in the economy (Lee and Kim 2013; Zhang and Daly 2014; Zhang et al. 2019; Demir and Danisman 2021; Abdelsalam et al. 2022; Shabir et al. 2023). Thus, the study hypothesizes a positive impact of *GDP* on financial performance.

An influence of the annual inflation (*INF*) rate on bank efficiency is captured using the log ratio of the annual inflation rate. Park and Shin (2021) and Abdelsalam et al. (2022) find that an increase in the inflation rate improves banks' financial performance. A rise in the inflation rate enhances the loan repayment capacity of the borrower by eroding the real value of outstanding loans, thereby improving banks' interest income and enhancing their financial performance.

However, Kjosevski et al. (2019), Texeira et al. (2020), Lee et al. (2022) and Shabir et al. (2023) argue that a rapid rise in the inflation rate could reduce the economies' real income and weaken the capacity of borrowers, resulting in added default risk and financial risk in banks. Therefore, the direction of the relationship between *INF* and financial performance is not clear in the literature.

Further, the study expects a positive relationship between the exchange rate (*ER*) and bank financial performance (Park and Shin 2021; Lee et al. 2022). The variable *ER* is measured by the annual log ratio of real effective exchange rate (*REER*). A rise in exchange rates signifies an appreciation in the country's currency, which improves banks' profitability, resulting in enhancement of performance. Therefore, the study anticipates a positive impact of *ER* on banks financial performance.

Empirical Results

Preliminary Check

Descriptive Statistics

Table 4 shows descriptive statistics of the variables used in the main analysis. GNPL and LLP have a mean of 2.354 and 2.764, and a standard deviation of 3.321 and 3.862, respectively. The mean of PBR is 1.252, and the standard deviation is 1.299. Non-interest income (diversification) has a mean of 1.995 and a standard deviation of 2.732. The mean of COVID-19 is 0.002, and the standard deviation is 0.015. The mean Size of Indian banks is −3.158, which is the log of total assets, indicating that the size of most Indian banks is smaller than average. The SFRANCIA test is a normality test crucial in statistical modeling. It helps in identify the variance or normality distribution among the considered variables. The distribution of *p*-value statistics for the variables is obtained by generating data from both a well-known normal distribution and a non-normal distribution at various sample sizes using the SFRANCIA test. Results from the SFRANCIA tests of normality indicate that all variables were non-normally distributed at the 1 percent significance level. This finding aligns with the studies of Alhassan et al. (2014) and Goswami (2021).

Table 4 Summary statistics of selected independent variables measured at the bank level. *Source*: Authors' calculation using MS-Excel

Variable(s)	N	Mean	SDV	25th	Median	75th	SFRANCIA (Z-statistics)
GNPL	412	2.354	3.321	19.890	57.342	99.532	10.53***
NNPL	412	0.167	1.190	11.888	43.271	60.537	9.010**
GNPA	412	3.629	7.914	29.909	61.529	71.484	12.902***
NNPA	412	1.936	4.130	22.264	44.678	74.310	20.516***
LLP	412	2.764	3.862	0.678	2.513	8.301	6.983***
PBR	412	1.252	1.299	3.542	9.012	19.345	6.739***
NOI	412	1.995	2.732	87.901	61.789	68.564	9.361***
Size	412	−3.158	2.210	67.102	89.590	101.374	14.672***
COVID19	412	0.002	0.015	45.90	56.21	63.10	9.520***
RGDP	412	4.621	8.460	22.630	46.892	60.538	10.893***
INF	412	5.002	5.110	13.614	33.792	50.173	07.901*
ER	412	2.063	0.017	09.172	21.571	49.089	13.563**

(i) N represent total number of observations; (ii) SDV signify the symbol of standard deviation; and (iii) *** reflects significance levels at 1 percent, respectively

Table 5 Stationarity tests: Fisher-ADF, Fisher-PP. *Source*: Authors' calculation

Tests	Fisher-ADF	Fisher-PP	IM-Pesaran
ROA	784***	791***	783***
ROE	732***	730***	561***
GNPL	539***	692***	442***
NNPL	483***	416***	382***
GNPA	503***	645***	619***
NNPA	782***	777***	752***
LLP	631***	674***	779***
PBR	890***	909***	803***
NOI	993***	731***	827***
Size	985***	630***	894***
COVID19	714***	519***	901***
RGDP	774***	795***	814***
INF	603***	667***	804***
ER	101***	184***	127***

***Reflects significance levels at 1 percent, respectively

Stationarity Tests

Additionally, to establish the degree of data integration, unit root tests (stationarity tests) are performed in Table 5 for all the predicted variables using the Fisher Augmented Dickey-Fuller (ADF), the Phillips-Peron (PP), and the Im–Pesaran–Shin (IPS) tests. The Im–Pesaran–Shin (2003) test is used to relax the assumption of a common autoregressive parameter. Moreover, the IPS test does not require balanced datasets; therefore, it provides a suitable approach to estimate the level of stationarity for the predicted variables. IPS assumes that ε_{it} is independently distributed normally for all i and t, and it allows ε_{it} to have heterogeneous variances across panels. The stationarity tests in Table 5 show that all the predicted variables are stationary at the level.

Pairwise Correlation Coefficient

Table 6 exhibits the pairwise correlation coefficients between selected variables used in the baseline regression model. All proxies of NPL are highly and significantly correlated. The correlation coefficient of LLP and GNPL is 2.374, and that of LLP with GNPA is 2.836, both significant at the 1 percent level and 5 percent level, respectively. This indicates that the gross NPL has come down due to higher provisions. The NPL ratio is positively affected by systemic risk during the study period. A similar trend of systemic risk is observed with LLP and the COVID-19 variable. Further, it can be seen that all the risky variables like NPL, systemic risk, and the COVID-19 have an inverse effect on the GDP growth rate.

Endogeneity Check Using Durbin–Wu–Hausman Test

This section focuses solely on the endogeneity check using the Durbin–Wu–Hausman (DWH) test. The Durbin–Wu–Hausman Test of Endogeneity is used to determine whether the applied regressors in the model are truly endogenous or not. Although the decision regarding the endogenous variables typically depends on theoretical considerations or a priori information. However, it is essential to identify that the regressors treated as endogenous in the model may be exogenous in reality. Therefore, this study adopts the Durbin–Wu–Hausman test to determine the endogeneity of the selected variables in the study (see Table 7). The following hypothesis is formulated:

$$\begin{aligned} Ho: &\quad \theta_1 = 0; \quad \textit{i.e.}, \text{ existance of } \textit{exogenous} \\ Ha: &\quad \theta_1 \neq 0; \quad \textit{i.e.}, \text{ existence of } \textit{endogenous} \end{aligned} \tag{6}$$

The null hypothesis (*Ho*) of the Durbin–Wu–Hausman Test of Endogeneity signifies that the extracted variables are exogenous, and the study can use Ordinary Least Squares (OLS) for efficient and consistent results. Whereas, if the null hypothesis is rejected, meaning the regressors are truly endogenous, then 2SLS should be used because OLS estimates would be biased and inconsistent.

The insignificant coefficient of the Durbin-Wu Hausman Endogeneity test confirms the exogeneity among variables. Hence, we conclude that, for the most part, variables are exogenous, and we can simply use OLS to estimate the performance of Indian banks. However, only ROA, NPLs, and PBR report the issue of endogeneity. Therefore, for a robustness check, the study applies the 2SLS model along with the fixed effect model in the main evidence. After confirming the endogeneity issue via the DWH test, we applied the two-stage least square (2SLS) to address potential

Table 6 Pairwise correlation matrix of selected independent variables. *Source*: Authors' calculation using STATA12

Variable(s)	GNPL	NNPL	GNPA	NNPA	LLP	PBR	DIV	Size	COVID-19	RGDP	INF	ER
GNPL	1.000											
NNPL	0.486*	1.000										
GNPA	9.046*	6.234**	1.000									
NNPA	4.046*	7.113**	4.414**	1.000								
LLP	2.374***	−0.001**	2.836**	−0.362*	1.000							
PBR	0.642*	0.431*	0.430*	0.328*	1.010	1.000						
DIV	−0.248**	−0.173*	−0.582*	0.026*	−0.681**	−8.632*	1.000					
Size	0.367*	−0.362*	0.187**	−0.003*	0.249**	4.619*	6.601***	1.0000				
COVID-19	0.456***	0.425***	0.185*	0.290**	0.486*	2.749**	−9.382*	−4.520*	1.0000			
RGDP	−0.250**	−0.345**	−0.291	−0.420**	0.247*	−0.006*	2.717**	2.483*	−0.702**	1.000		
INF	0.478*	0.684*	0.679*	0.235*	0.208**	0.447*	1.462**	1.347	2.641*	−3.330*	1.000	
ER	−0.114**	−0.154**	0.254*	0.864***	0.365*	0.325*	0.125*	0.062*	1.535*	0.903**	0.058*	1.000

***, **, and * denotes the level of significance at 10, 5 and 1 percent, respectively

Table 7 Endogeneity check using Durbin–Wu–Hausman Test: Ho: no endogenous. *Source*: Authors' calculations

Variables	Durbin Chi_2
ROA	1.401*
ROE	0.012
Independent variables: I Micro-economic (Bank-specific) variables	
GNPL	1.894**
NNPL	0.012*
GNPA	1.904*
NNPA	0.001
LLP	0.004
PBR	5.392*
DIV	3.516
Size	2.112
COVID19	2.772
GR	0.312
II Macro-economic variables	
GDP	1.540*
INF	0.058
ER	0.011

endogeneity issues as a sensitivity test. Ironically, in the panel data model, both the 2SLS and OLS estimator are not only consistent but are also efficient within the class of instrumental variable estimators.

Main Evidences

The study presents the results of fixed effects and 2SLS estimations using Eqs. (4) and (5) in Models 1–8, as detailed in Tables 8, 9, 10, and 11. The empirical assessment in this study focuses on the impact of NPLs, systemic risk, COVID-19, and government response on the financial performance of Indian banks, utilizing the baseline model represented by Eqs. (4) and (5). To showcase these empirical findings, the original baseline model [Eq. (1)] is further categorized into eight different models (Model 1-Model 8), and the corresponding results are presented in Tables 8, 9, 10 and 11. The entire discussion is based on the outcomes derived from these models.

The results presented in Tables 6 and 7 confirm a significant relationship between both ROA and ROE with the explanatory variables as dependent variables in the model. The adjusted R-squared values, ranging from 0.5 to 0.8 for ROA and ROE in Tables 8, 9, 10 and 11, respectively, indicate a high level of goodness-of-fit, signifying the accuracy of the linear model. Additionally, the study reveals that the selected regressor variables possess the capability to explain up to 50% and 80% of the variation in the model concerning ROA and ROE, respectively. These findings highlight the explanatory power of the chosen variables in accounting for the observed variations in the financial performance metrics.

Table 8 Statistics evidence on the determinants of financial performance of Indian banks during 2018–2022: using the fixed-effects and 2SLS estimators. *Source*: Authors' calculations

Estimators and independent variable	Fixed effects model dependent variable: return on asset				2SLS model dependent variable: return on asset			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	15.332*** (0.543)	15.88*** (0.673)	13.13*** (0.666)	15.47*** (0.321)	8.447*** (1.165)	5.157** (1.909)	0.612*** (1.817)	6.677** (1.021)
$GNPL_{i,t}$	−0.011* (0.000)			−0.105 (0.101)	−0.846*** (0.102)			0.614*** (0.078)
$NNPL_{i,t}$		−1.471*** (0.529)		−2.945 (1.934)		−0.811*** (0.081)		−0.132* (0.600)
$LLP_{i,t}$			−0.003** (0.002)	−0.538* (0.363)			−0.201* (0.006)	−0.001 (0.026)
$PBR_{i,t}$			−0.113* (0.011)	−0.033* (0.010)			−0.966** (0.413)	0.036 (0.003)
$DIV_{i,t}$	−0.004* (0.002)	−0.002 (0.000)	0.004 (0.001)	0.007 (0.003)	−0.322 (0.430)	−0.141 (0.066)	−0.112 (0.333)	0.058 (0.413)
$SIZE_{i,t}$	−0.762** (0.356)	−0.454 (0.121)	−0.559 (0.293)	0.793 (0.438)	−1.412 (0.838)	−0.984* (1.092))	0.377 (0.907)	−0.439 (0.014)
Government $Response_{i,t}$	0.015*** (0.109)	0.641 (0.291)	0.590*** (0.331)	0.102 (0.000)	0.914*** (0.070)	0.787** (0.453)	0.664 (0.032)	0.548 (0.026)
$COVID\text{-}19_{i,t}$	0.021*** (0.009)	0.007*** (0.003)	0.343 (0.177)	0.010 (0.005)	0.008 (0.0009)	0.005* (0.002)	−0.032 (0.008)	0.220 (0.091)
$PUBLIC_{i,t}$				0.563** (0.288)				0.421* (0.595)
$PRIVATE_{i,t}$				0.647 (0.441)				0.211 (0.081)
GDP_t	1.628 (0.754)			0.842 (0.329)	0.903 (0.682)			1.132** (0.407)
INF_t		−1.091 (0.372)		0.774 (0.215)		−0.041 (0.084)		−0.316 (0.371)
ER_t			0.982 (0.438)	0.371 (0.101)			0.203 (0.055)	−0.089 (0.027)
N	412	412	412	412	412	412	412	412
F statistics	11.23***	10.02***	12.56***	10.11***				

Table 8 (continued)

Estimators and independent variable	Fixed effects model dependent variable: return on asset				2SLS model dependent variable: return on asset			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
R^2	0.656	0.879	0.821	0.543	0.894	0.993	0.871	0.801
D–W test	2.126	2.124	2.137	2.184				
White-adjusted panel FE	16.782**	16.341*	15.864**	15.002**				
Wald Chi2 value					341.11***	210.12***	365.16***	229.23***

This table shows the fixed effects results and the results of instrumental variable (IV) regression with two-stage least squares (2SLS) estimators of financial performance of Indian banks. The IVs are lagged values of all the regressors that are used in Eq. (4) and (5). (i) GNPA: Ratio of gross non-performing asset to gross advances; LLP: loan loss provisions; PBR: Systemic risk measure as price-to-book ratio; DIV: Diversification index measure as ratio of non-interest income to total assets; SIZE: Log of total assets; Government Response: Dummy; COVID-19: log growth rate of confirmed COVID-19 cases; (ii) Autocorrelation is examined from the statistics of D–W test and compare with the critical values of DW (0.05, K, n), here, $d > du = Ho$: there is no autocorrelation or vice-versa; (iii) White-adjusted panel fixed effect (FE) is the test for the assumption of homoscedasticity (H_0: errors are homoscedastic); (iv) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; and (v) Figure in parentheses in columns (1)–(4) are clustered standard errors, respectively

Table 9 Statistics evidence on the determinants of financial performance of Indian banks during 2018–2022: using the fixed-effects and 2SLS estimators. *Source*: Authors' calculations

Estimators and independent variable	Fixed effects model dependent variable: return on equity				2SLS model dependent variable: return on equity			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	10.127*** (0.236)	12.789*** (0.521)	10.891*** (0.389)	14.431*** (0.518)	5.988* (0.273)	3.261** (0.523)	3.263** (0.588)	2.313** (3.132)
$GNPL_{i,t}$	−0.021* (0.002)			−0.007 (0.003)	−0.547** (0.139)			−0.601*** (0.163)
$NNPL_{i,t}$			−0.207 (0.037)	0.378 (0.142)			−0.120* (0.017)	0.3308 (0.4661)
$LLP_{i,t}$		−0.261*** (0.120)		−0.111* (0.171)		−0.008* (0.010)		−0004** (0.020)
$PBR_{i,t}$			0.273** (0.141)	0.390 (0.173)			2.738 (0.983)	0.831 (0.334)
$DIV_{i,t}$	−0.163 (0.002)	−0.152 (0.010)	0.197 (0.083)	0.100 (0.005)	0.107** (1.180)	−0.688 (0.483)	−0.398 (0.261)	1.007 (0.341)
$SIZE_{i,t}$	−0.291 (0.031)	−0.310* (0.0582)	−0.489 (0.062)	0.439 (0.037)	−3.271 (0.702)	−0.2576** (0.529)	0.131 (0.783)	−2.0593 (1.4946)
Government $Response_{i,t}$	−0.113** (0.059)	−0.260 (0.013)	0.672* (0.018)	−0.768 (0.024)	0.212 (0.143)	1.120* (0.976)	0.667** (0.253)	1.916 (0.349)
$COVID\text{-}19_{i,t}$	0.101* (0.100)	0.006 (0.003)	0.118 (0.001)	0.100 (0.002)	−0.289 (0.222)	0.583 (0.237)	0.967 (0.186)	−0.366 (0.284)
$PUBLIC_{i,t}$				0.483 (0.396)				−0.247 (0.244)
$PRIVATE_{i,t}$				0.690* (0.237)				0.640 (1.515)
GDP_t	0.126 (0.111)			0.983 (0.349)	0.025 (0.068)			−0.132 (0.323)
INF_t		1.191** (0.672)		0.364 (0.152)		0.637 (0.017)		−0.159*** (0.057)
ER_t			0.001 (0.000)	0.006 (0.002)			0.002 (0.005)	0.003 (0.005)
N	412	412	412	412	412	412	412	412
F statistics	10.31***	09.88***	08.62***	09.61***				
R^2	0.128	0.189	0.232	0.299	0.672	0.873	0.902	0.548

Table 9 (continued)

Estimators and independent variable	Fixed effects model dependent variable: return on equity				2SLS model dependent variable: return on equity			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
D–W test	2.173	2.188	2.123	2.121				
White-adjusted panel FE	15.175***	14.832**	15.442***	13.738***				
Wald Chi2 value					535.56***	505.62***	93.69***	448.21***

(i) GNPA: Ratio of gross non-performing asset to gross advances; LLP: loan loss provisions; PBR: Systemic risk measure as price-to-book ratio; DIV: Diversification index measure as ratio of non-interest income to total assets; SIZE: Log of total assets; Government Response: Dummy; COVID-19: log growth rate of confirmed COVID-19 cases; (ii) Autocorrelation is examined from the statistics of D–W test and compare with the critical values of DW (0.05, K, n), here, $d > du = Ho$: there is no autocorrelation or vice-versa; (iii) White-adjusted panel fixed effect (FE) is the test for the assumption of homoscedasticity (H_0: errors are homoscedastic); (iv) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; and (v) Figure in parentheses in columns (1)–(4) are clustered standard errors, respectively

Table 10 Statistics evidence on the determinants of financial performance of Indian banks during 2018–2022: using the fixed-effects and 2SLS estimators. *Source*: Authors' calculations

Estimators and independent variable	Fixed effects model dependent variable: return on asset				2SLS model dependent variable: return on asset			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	13.832*** (0.543)	17.987*** (0.673)	12.213*** (0.666)	10.437*** (0.321)	15.42** (0.561)	− 19. 894** (0.659)	14.68** (0.676)	15.45** (0.320)
$GNPA_{i,t}$	− 0.012 (0.001)			− 0.005 (0.001)	− 0.460** (0.156)			0.417 (0.060)
$NNPA_{i,t}$		1.672** (0.342)				0.626*** (0.474)		
$LLP_{i,t}$		− 0.023** (0.002)		− 0.348* (0.003)		− 0.116 (0.030)		0.232 (0.378)
$PBR_{i,t}$			− 0.173* (0.010)	− 0.043* (0.013)			− 0.006** (0.002)	− 0.004* (0.002)
$DIV_{i,t}$	0.024* (0.001)	− 0.012 (0.001)	0.024 (0.001)	0.007 (0.001)	0.001 (0.006)	0.007* (0.006)	0.003 (0.001)	0.001 (0.006)
$SIZE_{i,t}$	− 0.271** (0.056)	− 0.444 (0.021)	− 0.532 (0.093)	0.438 (0.038)	0.424 (0.340)	0.244 (1.304)		− 0.326* (1.223)
Government $Response_{i,t}$	0.225*** (0.095)	0.897 (0.066)	0.543*** (0.031)	0.142 (0.006)	0.286** (0.197)	0.150 (0.064)		0.396 (0.090)
COVID-$19_{i,t}$	0.221*** (0.019)	0.167*** (0.013)	0.243 (0.097)	0.010 (0.005)	0.004* (0.002)	0.377 (0.293)	0.713 (0.461)	0.189* (0.088)
$PUBLIC_{i,t}$				0.164** (0.028)			0.638 (0.490)	0.630 (0.441)
$PRIVATE_{i,t}$				0.279 (0.041)			1.122 (0.413)	− 0.611 (0.377)
GDP_t	2.638 (1.116)			0.149 (0.010)	8.400** (4.127)			8.252* (4.001)
INF_t		0.155 (0.539)		0.172* (0.063)		− 8.181* (4.527)		− 0.323 (0.290)
ER_t			0.004 (0.002)	0.002 (0.001)			0.942 (0.163)	0.991 (0.269)
N	412	412	412	412	412	412	412	412
F statistics	08.22***	08.01***	10.66***	09.38***				
R^2	0.456	0.772	0.579	0.493	0.880	0.753	0.716	0.693

Table 10 (continued)

Estimators and independent variable	Fixed effects model dependent variable: return on asset				2SLS model dependent variable: return on asset			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
D–W test	3.262	3.749	3.893	2.404				
White-adjusted panel FE	24.817**	36.441*	39.854**	26.371**				
Wald Chi2 value					264.37***	293.53***	437.28***	385.90***

This table shows the fixed effects results and the results of instrumental variable (IV) regression with two-stage least squares (2SLS) estimators of financial performance of Indian banks. The IVs are lagged values of all the regressors that are used in Eq. (4) and (5). (i) GNPA: Ratio of gross non-performing asset to gross advances; LLP: loan loss provisions; PBR: Systemic risk measure as price-to-book ratio; DIV: Diversification index measure as ratio of non-interest income to total assets; SIZE: Log of total assets; Government Response: Dummy; COVID-19: log growth rate of confirmed COVID-19 cases; (ii) Autocorrelation is examined from the statistics of D–W test and compare with the critical values of DW (0.05, K, n), here, $d > du = Ho$: there is no autocorrelation or vice-versa; (iii) White-adjusted panel fixed effect (FE) is the test for the assumption of homoscedasticity (H_0: errors are homoscedastic); (iv) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; and (v) Figure in parentheses in columns (1)–(4) are clustered standard errors, respectively

Table 11 Statistics evidence on the determinants of financial performance of Indian banks during 2018–2022: using the fixed-effects and 2SLS estimators. *Source*: Authors' calculations

Estimators and independent variable	Fixed effects model dependent variable: return on equity				2SLS model dependent variable: return on equity			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	10.101*** (0.306)	10.889*** (0.611)	09.891*** (0.266)	11.431*** (0.709)	4.858*** (3.829)	3.531*** (4.508)	2.585*** (3.865)	3.781*** (3.869)
$GNPA_{i,t}$	−0.321* (0.162)			−0.071 (0.005)	0.5896 (0.0709)			0.6239 (0.0875)
$NNPA_{i,t}$		1.531*** (0.018)				0.4295** (0.1978)		
$LLP_{i,t}$			−0.101 (0.020)	−0.102* (0.072)			−0.491** (0.120)	−0.0763 (0.151)
$PBR_{i,t}$		0.196 (0.061)		0.203** (0.004)		−0.0031* (0.0016)		
$DIV_{i,t}$	−0.078 (0.002)		0.112* (0.083)	0.101 (0.005)	0.007** (0.003)		0.006* (0.003)	0.004 (0.002)
$SIZE_{i,t}$	−0.291 (0.031)	−0.310* (0.0582)	−0.489 (0.062)	0.439 (0.037)	0.1168 (0.290)	−0.0211 (0.443)	−0.045* (0.025)	0.036 (0.001)
Government $Response_{i,t}$	0.185 (0.059)	0.390** (0.013)	0.267 (0.018)	−0.371* (0.024)	0.396 (0.598)	0.302 (0.797)	1.123*** (0.421)	0.1502 (0.5647)
COVID-$19_{i,t}$		0.106* (0.037)	0.138 (0.061)	0.109 (0.022)		0.392*** (0.657)	1.232*** (0.113)	−0.2665 (0.088)
$PUBLIC_{i,t}$				0.548 (0.283)				0.371 (0.159)
$PRIVATE_{i,t}$				0.439* (0.217)				0.992 (0.557)
GDP_t	0.264 (0.010)			−0.517 (0.138)	−1.168 (0.002)			0.027* (0.0001)
INF_t		0.173 (0.001)		0.421 (0.182)		−0.329 (0.184)		0.662 (0.312)
ER_t			0.003* (0.001)	0.748 (0.391)			0.0001* (0.0001)	0.025 (0.007)
N	412	412	412	412	412	412	412	412
F statistics	11.23***	10.02***	12.56***	10.11***				
R^2	0.656	0.879	0.821	0.543	0.894	0.993	0.871	0.801

Table 11 (continued)

Estimators and independent variable	Fixed effects model dependent variable: return on equity				2SLS model dependent variable: return on equity			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
D–W test	2.126	2.124	2.137	2.184				
White-adjusted panel FE	16.782**	16.341*	15.864**	15.002**				
Wald Chi2 value	–	–	–	–	341.89***	538.90***	365.43***	429.24***

This table shows the fixed effects results and the results of instrumental variable (IV) regression with two-stage least squares (2SLS) estimators of financial performance of Indian banks. The IVs are lagged values of all the regressors that are used in Eq. (4) and (5). (i) GNPA: Ratio of gross non-performing asset to gross advances; LLP: loan loss provisions; PBR: Systemic risk measure as price-to-book ratio; DIV: Diversification index measure as ratio of non-interest income to total assets; SIZE: Log of total assets; Government Response: Dummy; COVID-19: log growth rate of confirmed COVID-19 cases; (ii) Autocorrelation is examined from the statistics of D–W test and compare with the critical values of DW (0.05, K, n), here, $d > du = Ho$: there is no autocorrelation or vice-versa; (iii) White-adjusted panel fixed effect (FE) is the test for the assumption of homoscedasticity (H_0: errors are homoscedastic); (iv) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; and (v) Figure in parentheses in columns (1)–(4) are clustered standard errors, respectively

In Models (1–4) of Tables 8, 9, 10 and 11, the problem of autocorrelation, as assessed by the Durbin-Watson (D-W) tests, does not appear. To detect autocorrelation, the study checks the estimated results using D-W statistics and compares them with the critical values of 'DW(0.05, K, n),' where K represents the independent variables (excluding the intercept), and n denotes the total number of observations used in the study. The D-W test values observed are close to $\rho = 0$, with d $\approx$ 2, indicating no evidence of serial correlations in the models. Despite using log-linear functions to address the issue of heteroscedasticity in the fixed effect model, the study adds heteroscedasticity test statistics in Tables 8, 9, 10 and 11 using the White-adjusted Panel Fixed Effect model. The assumption that the Lagrange multiplier (LM) stat is less than the Chi-square critical value is satisfied. Therefore, the study concludes that the null hypothesis can be accepted, indicating no evidence of heteroskedasticity in the models. Broadly, our investigation extends the finding of prior studies that have identified that NPL, bank size, systemic risk, COVID-19, NOI, and government response make a substantial and meaningful impact on the financial performance of banks.

In models (1) and (4), as reported in Tables 8 and 9, the coefficients of Non-Performing Loans (NPLs) ratio and Loan Loss Provisions (LLP) are found to be negatively associated with Return on Assets (ROA) and Return on Equity (ROE) when utilizing fixed effects and Two-Stage Least Squares (2SLS) models. This suggests that the larger size of NPLs and higher loan loss provisions act as constraints on the performance of Indian banks. The negative associations imply that a substantial presence of Non-Performing Loans and elevated levels of loan loss provisions are linked to reduced profitability in Indian banks. This observation aligns with the findings of Acharya and Thakor (2012), who proposed that high bank leverage can lead to excess provisions, contributing to default risk, especially in situations where creditors face liquidation. The negative impact on performance may arise from the financial strain associated with managing and covering non-performing assets and provisioning for potential losses. The negative relationship observed between GNPL and NNPL with ROA and ROE suggests that branch managers of Indian banks may have engaged lax lending practices, paying less attention to evaluating the creditworthiness of borrowers. This, in turn, leads to higher default risk and exerts a negative impact on the profitability of the banks. The study's finding aligns with the perspective put forth by Berger and DeYoung (1997), as well as the more recent studies by Park and Shin (2021), Goswami (2021), Goswami (2022), and Shabir et al. (2023), supporting the *'bad management'* hypothesis for the banking industry.

Similarly, we observe that the financial performance of Indian banks, as measured by ROA, is negatively corelated with bank Size and systemic risk (*PBR*). This favours the presumption of '*too-big-to-fail*' in the banking industry for bank size, suggesting that the failures of large banks can lead to greater economic losses than those of small banks. Consequently, larger banks may have higher exposure to systemic risk exposure (*PBR*), resulting in a worsening condition of the financial performance of Indian banks. This observation is consistent with the perspectives presented by Adrian and Brunnermeier (2016), Das and Ghosh (2006) and Batir et al. (2017).

On the other hand, the positive relationship of PBR with ROE found in Table 9 of Model 3 may be attributed to banks being exposed to credit and operational risks (such as frauds) and facing challenges in accurately estimating the true value of risks in their loan portfolio and earnings. The accurate accounting of such risks becomes crucial. In essence, the delay in recognition 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; Vishwanathan 2018; Reserve Bank of India 2021a). This interpretation suggests that the positive association between PBR and ROE may be a result of delayed recognition rather than an actual improvement in financial performance.

The study also revealed that the coefficient of log_COVID19 with ROA is positive and statistically significant at the 1 percent level. The interaction of log_COVID19 with ROE is positive and significant at the 5 percent level. The log_COVID-19 coefficients authorize the findings related to PBR and indicate that the proactive measures taken by the Indian Government and Central Bank have positively moderated the impact of the pandemic. This moderation, in turn, is associated with a reduction in default and systemic risk, ultimately leading to an enhancement in financial performance during the analysis period (Reserve Bank of India 2021b; Duan et al. 2021; Goswami 2022). The concerted efforts through measures such as COVID-19 provisions, dividend retention, mega-mergers, regulatory tightening via the Insolvency and Bankruptcy Code, loans moratorium, restructuring policies, and successful write-offs were aimed at improving the overall health and resilience of the banking sector. These strategies were considered essential to address the growing issue of Non-Performing Assets (NPAs) and enhance the soundness of the banking system. This necessity was emphasized in reports from the Reserve Bank of India in 2018 and 2020, as well as by directives from the Honourable Supreme Court of India.

Furthermore, columns (1) and (3) of Table 8, the relationship between government response and ROA is positive and statistically significant at the 1 percent level. However, in columns (2) and (4) of Table 9, it is observed that the government response has a negative relationship with Return on Equity (ROE) at the 5 percent level, respectively. A higher coefficient value dictates more policies and successful recovery of defaults, reflecting stronger responses by the government to the performance of Indian banks. This suggests that strict government responses were effective in reducing the number of future COVID-19 cases, defaults, and systemic risk ultimately enhancing the performance of the banking system in India (Duan et al. 2021; Tan et al. 2021). Furthermore, a negative association of ROE with government response may not necessarily be unfavorable, especially when operating costs (free cash flow) and interest on loans are improving the business of Indian banks through loan restructuring efforts, as highlighted by Nugroho (2019) and Zhang (2021).

The diversification opportunity, represented by non-interest income (*NOI*), is found to play an insignificant role in ROE. However, ROA demonstrates a negative and statistically significant coefficient with diversification at the 10 percent level, suggesting that Indian banks capitalized on the diversification opportunity during the period from 2018 to 2022. This implies that the profitability and interest rate of Indian banks, generated from traditional sources of income, are less than those from other sources of income. This finding aligns with the perspective put forth by DeYoung and Roland (2001) and supports the *'diversification opportunity'* hypothesis for the Indian banking industry.

Moreover, to assess the diverse behavior of ROA and ROE across different ownership groups, the ownership effect has been captured by including public and private dummies in Tables 8 and 9. The findings indicate that public sector banks exhibit superior financial performance in terms of achieving higher ROA as compared to private banks and foreign banks in India during the pandemic period. This corroborates the above findings of COVID-19 and the financial performance of the study. However, private Indian banks maintained higher returns on equity compared to their peer groups over the analyzed period. This implies that, while public sector banks outperformed in terms of ROA, private Indian banks demonstrated greater efficiency in generating returns on equity during the specified period.

Macro-economic Indicators Discussion

As anticipated, a positive relationship between Gross Domestic Product (GDP) and the financial performance of Indian banks is observed in the fixed-effects model, while an insignificant coefficient is reported in the Two-Stage Least Squares (2SLS) model. The financial performance of banks is influenced by the business cycle, represented by the real GDP growth rate. The positive coefficient of GDP growth rate on financial performance in Table 8 indicates that active economic growth reduces the likelihood of bank defaults, thereby enhancing the profitability of Indian banks. This finding is consistent with the work of Kohler (2015), Baselga-Pascual et al. (2015), Kjosevski et al. (2019), and Lee et al. (2022).

Additionally, there are mixed findings regarding the impact of inflation (INF) on the financial performance of Indian banks. A positive impact of inflation on bank financial performance, especially with the proxy of Return on Equity (ROE), is noted. High inflation is associated with a reduced probability of bank defaults. This scenario is attributed to the recent conditions in the Indian economy, where inflationary pressures arose from the high interest rates charged on government borrowings. To address this, the Government of India revised policy rates, increasing the net interest margin for banks and leading to higher profitability. The positive and significant coefficient of inflation on bank performance aligns with the findings of Otasevic (2013), Kjosevski et al. (2019), Teixeira et al. (2020), and Lee et al. (2022). Simultaneously, a negative impact of inflation on financial performance is reported with Return on Equity (ROE) in Table 9. This suggests that high inflation adversely affects the indicator of banks' Return on equity (ROE) in generating equity interest income over the analysis period. This finding is in line with recent research by Abdelsalam et al. (2022).

Variation Check Using an Alternative Measure of NPLs

In this section, the study conducts a variation check by considering an alternative measure of the NPLs ratio. In particular, we use Gross Non-performing Assets (GNPA) and Net Non-performing Assets (NNPA) are used as proxies for gross and net non-performing loans to total assets ratio. The results presented in Tables 10 and 11 largely support the findings obtained from Tables 8 and 9. Examining the coefficients of NNPA, it is observed that the profitability of Indian banks increases. This may be attributed to Indian banks effectively managing their provisions (increased by 6 percent to 10.1 percent, respectively) and total assets (increases 10 to 13 percent, respectively), thus maintaining their profit levels. Furthermore, this finding aligns with the *'diversification hypothesis'*, especially considering the behavior of NNPA with ROE. It indicates that, during the analysed period, Indian banks diversified their operations to generate more non-interest income relative to interest income, aiming to achieve profitability targets. In support of this context, the Reserve Bank of India (2020) reports a decline in net interest income (NII) from 16 percent in 2019 to 13 percent in 2020, while other income (NOI) has increased from 9.5 percent to 11.6 percent, respectively. The results of GNPA, government response, COVID-19, GDP, and INF coefficients are fairly similar to those in Tables 8 and 9, indicating a positive relationship between GNPA and NNPA with the financial performance of Indian banks. However, the scale and significance level of the coefficients for GNPA and NNPA exhibit slight variations. This could be attributed to better asset management by Indian banks in handling bad loans, resulting in a lesser impact on profit decline during the analysis period. The coefficient of the REER estimate appears to be positive and statistically significant with the financial performance (proxy of ROE) of Indian banks (see Table 11). This infers that an incline in the domestic currency leads to an appreciation of the net worth of import-oriented corporation, resulting in reduced bank distress and enhanced financial performance of Indian banks due to a better creditworthiness of corporate borrowers during the analysis period. This finding supports the result of Park and Shin (2021) and Lee et al. (2022).

Check Period Effects: I and II Waves of COVID-19 Crisis

In this section, we extend our analysis by estimating additional results to investigate whether the main evidence remains consistent when considering heteroskedasticity across time on the same variables, as detailed in "Methodological Framework" section. An innovative aspect of our analysis is the inclusion of a time dimension that distinguishes between Wave I and Wave II of the COVID-19 crises. However, given that our sample of banks is almost equally distributed between the first and second waves of the COVID-19 crisis, we anticipate that our main results will be equally weighted each time (t) in the estimates presented in Table 12.

In addition to time, we add NPLs in column 3 of Table 12 as another dependent variable to see the robustness with the same explanatory variables. Additionally, we introduce NPLs as another dependent variable in column 3 of Table 12 to evaluate the robustness of our findings with the same explanatory variables. This approach allows us to observe variations over time and across different phases of the crisis, providing a comprehensive understanding of the impact on Indian banks. To observe heterogeneity and examine the impact of bank-centric variables on Indian bank performance and NPLs during the I and II waves of the COVID-19 crisis—we adopt a time-study design using fixed effects models:

Table 12 Statistics evidence on the determinants of financial performance of Indian banks: I and II waves of COVID-19 crisis. *Source*: Authors' calculations

Dependent variables:	Return on asset (1)	Return on equity (2)	Non-performing loans (3)
Panel A: I Wave of COVID-19 (*2018–2020*)			
Constant	18.67*** (0.989)	15.32*** (0.888)	14.93*** (0.723)
GNPL	−0.012* (0.001)		
NNPL		−0.490 (0.236)	
ROA			−0.002 (0.001)
ROE			
LLP	−0.023** (0.010)	0.386 (0.021)	0.985 (0.055)
PBR	0.732 (0.037)	0.863 (0.071)	0.998* (0.261)
DIV	−0.001 (0.010)	−0.011 (0.004)	0.101 (0.001)
Size	−0.161* (0.082)	0.444 (0.095)	0.472 (0.026)
PUBLIC			yes
PRIVATE			yes
N	225	225	225
F statistics	8.436***	8.749***	7.391***
Adjusted-R^2	0.188	0.271	0.479
D–W test	2.132	2.124	2.198
White-adjusted panel FE	14.882**	14.672*	11.716*
Panel B: II Wave of COVID-19 (*2020–2022*)			
Constant	10.888*** (0.476)	10.548*** (0.444)	12.683*** (0.629)
GNPL	0.104 (0.022)		
NNPL		−0.201* (0.047)	
ROA			
ROE			0.371 (0.052)
LLP	0.947 (0.099)	−0.127* (0.095)	0.999 (0.098)
PBR	−0.401** (0.058)	0.606 (0.074)	−0.208* (0.033)
DIV	0.666 (0.071)	−0.931 (0.082)	0.589* (0.084)
Size	0.752 (0.055)	0.639 (0.053)	0.008 (0.085)
PUBLIC			yes
PRIVATE			yes
N	187	187	187
F statistics	6.593***	6.799**	6.526**
Adjusted-R^2	0.348	0.219	0.311
D–W test	2.165	2.188	2.132
White-adjusted panel FE	12.491*	12.212*	09.811**

This table presents fixed-effects estimates of Eq. (2) at bank-level data of Indian scheduled commercial banks as explained in "Methodological Framework" section. The I wave of Covid-19 refers to the period before Covid-19 in India, from 2018 to 2020. Wave II of COVID-19 refers to the year immediately following the COVID-19 crisis (i.e., 2020–2022). Autocorrelation is detected from the statistics of the D–W test and compared with the critical values of DW (0.05, K, n); here, *Ho* implies: there is no autocorrelation or vice-versa. Figure in parentheses in columns (1)–(4) are clustered standard errors, respectively. $*p<0.1$, $**p<0.05$, $***p<0.01$

$$\ln(d)_{j,t} = \beta_0 + \sum_{n=1}^{n} \beta_n \ln(i^n)_{j,t} + \varepsilon_{j,t} \tag{7}$$

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. Here, the dependent variables $(d_{j,t})$ are the estimated log values of the ratio of return on assets (ROA), return on equity (ROE) and the ratio of gross non-performing assets to gross advances (NPLs), respectively. The vector of contextual variables (namely, loan loss provisions, systemic risk, non-interest income, bank size, and ownership effect) that affect the bank's assets quality and performance level throughout the study period. The β's are the coefficients to be estimated using fixed effects model.

The results obtained in this analysis closely resemble those reported in Tables 8 and 9, with notable exceptions in the coefficients of systemic risk and the diversification index. During both the I and II waves of the COVID-19 crises, high systemic risk and a greater reliance on non-interest income contribute to elevated levels of non-performing loans. This evidence aligns with the findings reported by the Reserve Bank of India (2022), which indicates that other income increased from −0.6 percent in 2021 to 2.1 percent in 2022. Additionally, provisioning declined from −18 percent in 2021 to −15 percent in 2022. These trends suggest that lower provisioning levels and a heightened diversification of the bank's traditional income to other sources negatively impact asset quality and lower the financial performance of Indian banks during the analysis period.

Robustness Check

As explained in "Methodological Framework" section, we validate our main results using both the simple ordinary least squares (OLS) model and panel-corrected standard errors (PCSE) model across the same set of samples. Gujarati and Dawan (2015) demonstrate that the use of a simple OLS regression can yield valid estimates and perform well when the relevant variables significantly impact the performance level of a bank. However, the issue of heteroscedasticity may arise due to the combination of cross-section and time series data. In this context, the residuals are correlated with time and different ith banks, potentially leading to exaggerated and biased predicted results (Nickell 1981).

The OLS and PCSE regression equation of Gujarati and Dawan (2015) and Goswami (2021) to examine the relevant factors influencing the performance of Indian banks over time is as follows:

$$\ln(d)_{j,t} = \beta_0 + \sum_{n=1}^{n} \beta_n \ln(i^n)_{j,t} + \varepsilon_{j,t} \tag{8}$$

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. Here, $d_{j,t}$ is the estimated log values of ROA and ROE as a proxy of financial performance. The variables ROA and ROE, measured by return on assets and return on equity, have been used as indicators of a bank's profitability and financial performance. The $i^n_{j,t}$ is a vector of contextual vari-

Table 13 Determinants of financial performance for Indian banks during 2018–2022: using simple pooled OLS model and PCSE model. *Source*: Authors' calculations

Model estimates	Simple pooled OLS		Panel corrected standard error (PCSE)	
Variables	Return on assets (1)	Return on equity (2)	Return on assets (1)	Return on equity (2)
Constant	0.1858* (0.945)	0.1932 (0.5318)	0.3754 (0.2899)	0.5632 (0.2990)
GNPL	−0.531** (0.026)	−0.552*** (0.061)	−0.765** (0.139)	−0.941** (0.056)
NNPL	−0.525 (0.020)	−0.792*** (0.060)	−0.877** (0.063)	−0.676*** (0.079)
LLP	−0.457 (0.061)	−0.565** (0.028)	−0.721 (0.032)	−0.067*** (0.054)
PBR	−0.908** (0.083)	0.689 (0.374)	−0.478* (0.184)	0.336 (0.172)
DIV	0.708 (0.383)	−0.459*** (0.085)	0.539** (0.056)	0.1481 (0.024)
SIZE	0.908 (0.083)	0.991 (0.547)	−0.917 (0.154)	0.882 (0.563)
Government Response	0.345** (0.123)	0.391** (0.273)	0.297* (0.136)	0.371 (0.121)
COVID-19	−0.945*** (0.548)	0.589 (0.217)	0.786 (0.342)	−0.895*** (0.069)
PUBLIC	0.885 (0.437)	0.774** (0.590)	0.328** (0.112)	0.376 (0.101)
PRIVATE	0.541 (0.179)	0.756 (0.428)	0.311 (0.167)	0.407 (0.135)
GDP	0.643** (0.389)	0.429* (0.220)	0.383* (0.109)	0.394 (0.003)
INF	0.692 (0.481)	0.290** (0.173)	0.483 (0.161)	0.189** (0.034)
ER	0.273 (0.202)	0.245 (0.138)	0.113 (0.002)	0.179 (0.010)
N	412	412	412	412
F statistics	18.98***	20.22***	–	–
R^2	0.1697	0.1605	0.4290	0.5612
D–W test	2.189	2.112	No autocorrelation	No autocorrelation
Wald Chi^2			541.17***	473.90***
BP-CW Hettest	20.002***	20.581***		

(i) GNPA: Ratio of gross non-performing asset to gross advances; LLP: loan loss provisions; PBR: Systemic risk measure as price-to-book ratio; DIV: Diversification index measure as ratio of non-interest income to total assets; SIZE: Log of total assets; Government Response: Dummy; COVID-19: log growth rate of confirmed COVID-19 cases; (ii) Autocorrelation is detected from the statistics of D–W test and compare with the critical values of DW (0.05, K, n); here, *Ho* implies: there is no autocorrelation or vice-versa; (iii) The Wald test is a test of the null hypothesis that the coefficients in the given equation are all zero (iv) BP-CW Hettest is the test for the assumption of homoscedasticity (H_0: errors are homoscedastic); (v) *$p<0.1$, **$p<0.05$, ***$p<0.01$; and (vi) Figure in parentheses in columns (1) and (2) are clustered standard errors, respectively

ables that influence the bank's performance level during the entire study period. The β's are the coefficients to be estimated using simple OLS. The relevant factors affecting the financial performance of Indian banks are the same as those used in Eq. (1). Furthermore, to conduct a robustness check, the study employs the Wald test procedure using the PCSE model. The chi-squared and its *p*-values are associated with *k* degrees of freedom generated by the Wald test. Based on the *p*-values, we are able to reject the null hypothesis, indicating that the evaluated coefficients are not simultaneously equal to zero. This implies goodness of fit in all model specifications, as the null hypothesis of joint insignificance of parameters is rejected across models.

The results of the third-stage panel regression analysis are offered in Table 13. It is noteworthy that, across all panel model specifications, the values of F-statistics and Wald Chi2-statistics for both simple pooled OLS and PCSE models are statistically significant. This implies that the combined set of explanatory variables (Xs) has a significant influence on the bank performance level. The empirical results confirm that, in most of the cases, the explanatory variables (X_s) exhibit the expected signs, aligning with the a priori expectations and as shown in the main evidence of Tables 8 and 9. Concerning LLP, the variable NPLs confirms a negative association with bank performance. This implies that a higher NPLs ratio deteriorates the asset quality of banks, necessitating higher provisioning, and consequently, erodes the profitability and performance of Indian banks. In contrast to the findings in the main Tables 8 and 9, the simple pooled OLS statistics report that COVID-19 and systemic risk correlate negatively with performance. This suggests that greater capital infusions under recapitalization scheme and COVID-19 provisions by the government (like the Indradhanush scheme, Insolvency and Bankruptcy Code, loans moratorium and restructuring policies initiated by the Honourable Supreme Court in 2020) may reduce the incentives for bank managers to adopt best lending practices, potentially inducing moral hazard and lowering bank performance. This finding of this study is supported by Harris et al. (2013). The findings show that systemic risk and the COVID-19 outbreak have significantly reduced the financial performance of banks. The COVID-19 may heighten systemic fragility across Indian banks through government policies and channels related to bank default risk. The Reserve Bank of India (2021a, b) highlighted factors such as low credit offtake (from 6 percent in 2020 to 5 percent in 2021, respectively), higher interest rates on lending, and muted growth in banks' off-balance sheet activities, resulting in higher credit risk and systemic fragility, ultimately impacting the financial performance of banks adversely. These findings are consistent with the studies by Duan et al. (2021), Elnahass et al. (2021), Beck and Keil (2022), and Shabir et al. (2023). Additionally, the economic slowdown resulting from the pandemic led to a decline in Indian trade and services, business activities, household income, and consequently reduced demand for banking services. This, in turn, contributed to a decrease in the revenues of Indian banks (Beck and Keil 2022; Duan et al. 2021).

In macro-economic variables, both GDP and inflation (INF) exhibit positive and statistically significant associations with both indicators of financial performance of Indian banks, confirming the aforementioned findings of the study. Furthermore, as anticipated, we observe inflated coefficients with identical signs in both Ordinary Least Squares (OLS) and Panel-Corrected Standard Errors (PCSE) models for bank size, diversification (*DIV*), exchange rate (*ER*), and ownership effects. The results of the robustness investigation align with the main findings and are expected to be reliable for policymakers for further consideration.

Conclusions and Recommendations for Policymakers

The COVID-19 crisis contributed to the deterioration of the financial performance of Indian banks, owing to a spate of domestic and firm bankruptcies and their weakened ability to repay loans. Indian governments and the central bank took a variety of initiatives (such as; moratorium on loan payment, Covid-19 provisions and plough back of dividends, optimization of the use of capital, and voluntary write-off NPAs in 2019–20) to support banks and avoid a financial crisis that could have worsened the severe economic downturn brought on by the pandemic. In the context of higher risk, bank-loss growth could be a side effect of such government initiatives. Hence, this paper studies to gain insights into the factors impacting the performance of Indian banks during 2018–2022. Specifically, it accounts for four unique variables such as COVID-19, NPLs, systemic risk, and government response, using bank-level data for 412 observations across 3 bank groups between 2018 to 2012 through fixed effects and 2SLS models. The robustness check of the main evidences is further checked using OLS and PCSE models in the study.

Both the fixed-effects and 2SLS models confirm our findings. According to fixed-effects and 2SLS models, our analysis shows that the financial performance of Indian banks is increasing significantly due to the government response, COVID-19, and systemic risk exposure. It suggests that strict government responses are able to reduce the number of future COVID-19 cases, defaults, and systemic risk, thereby increasing the performance of the banking system in India. On the other hand, especially for ROA, we find that higher levels of NPL, provisioning, bank size, and non-interest income drag down the financial performance of Indian banks. For this reason, the study supports the presumptions of '*bad-management*', '*too-big-too-fail*', *and* '*diversification opportunity*' for the Indian banking industry throughout the study period. The ownership effect is more pronounced for public sector banks relative to their peer groups, which experience better financial performance during the study period. Macroeconomic factors including the GDP growth rate, inflation, and exchange rate play an important role in determining Indian financial performance. The estimated macro-economic statistics confirm lower exposure to bank risks and higher financial performance during periods of inflation and when the Indian rupee appreciates. A similar trend has also been observed for GDP and the financial performance of Indian banks.

The results of the variation check are slightly different when considering alternative measures of NPLs ratio. While accounting for GNPA and NNPA in the model using the fixed-effects and 2SLS models, we find that NNPA has a positive relationship with ROE. This suggests that, relative to default risk, assets are better managed by Indian banks, portraying a rosy picture of ROE over the period of analysis. The coefficient of the exchange rate also has a positive impact on the financial performance of Indian banks, indicating the appreciation of the Indian currency and better wealth in the financial system of the economy. Moreover, the results of the time heterogeneity test suggest that higher systemic risk and non-interest income contributed to higher levels of non-performing loans during the

I and II waves of the COVID-19 crisis. This is validated by the Reserve Bank of India (2022) report, which indicates that lower levels of provisioning and greater diversification of bank traditional income to other income contribute to poorer asset quality and lower financial performance of Indian banks during the analyzed period. The empirical results of the robustness check finally confirm that in most cases, except for COVID-19 and systemic risk, the explanatory variables exhibit signals similar to those predicted by the prior analysis.

Indian policymakers need to be more vigilant and stricter in policy formulation and implementation to ensure that the effects of the pandemic, systemic risk, and default risk do not adversely impact the financial performance of the banking system. In particular, policymakers should focus on the use of loan loss provisions and restructuring policies. Besides, the bank-level efforts are also needed to achieve sustainable banking growth that does not further harm their performance. Overall, our findings reduce, though do not completely eliminate, the concern that future government intervention towards Indian commercial banks could lead to a sharp decline in bank performance due to high provisioning, leading to increased costs for lenders. An Indian bank is considered safe if it diversifies its income-generating opportunities from various sources and maintains a low funding cost. This approach can help mitigate future pandemic, credit risk, and systemic risk, contributing to the overall safety and stability of the bank.

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