



# Systemic risk and Efficiency analysis of the banking sector: A comparative study of Indian Public and Private Banks

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## ARTICLE INFO

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## ABSTRACT

The academics, policymakers and regulators have shown significant curiosity in the study of systemic risk. Intra-country systemic risk has been studied in context of developed economies, but in the context of developing economies it seems to be rare. This research paper's objective is to present an innovative presentation of the complex interplay between efficiency and systemic risk in Indian banking sector- public and private banks. Due to disagreement among the scholars regarding the relationship between these two factors, we tried to investigate this issue by collecting data from banks listed on the Nifty PSU Bank Index and Nifty Private Bank Index over the period from 2003-04 to 2018-19. The fundamental connection between efficiency and systemic risk has been checked through granger causality. The results indicate that efficiency and systemic risk are significantly and negatively related, and the relationship is bi-directional for private banks and uni-directional for public banks. Both scholars and regulators could benefit from this article findings.

## Introduction

The financial system of an economy is the primary organ and crucial for its expansion. Prudent regulations have been set in place by the governments all over the world in order to maintain an effective financial system. By ensuring the best use of the nation's

resources, an effective financial system is required that fosters the economic growth (Levine, 2005). Banks, however, were unable to effectively carry out their roles during the Global Financial Crisis (GFC). The GFC's aftermath, featuring a global liquidity crisis, an average rise in unemployment of 7%, a 9.3% decline in GDP per capita spanning roughly 1.9 years, and an 86% increase

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in public debt (Reinhart & Rogoff, 2009), highlighted the miscalculation of risk by banks, regulatory authorities, and investors. The global financial crisis (GFC) of 2007–2008 was a significant event that led to a reevaluation of the rationale for risk management in the arena of banking. However, the risk assessment in the realm of banking is complex due to numerous shifts that have occurred in the financial world, including increased competition, integration, consolidation, globalization, financial liberalisation, and ongoing innovations (Zahra, 2016). A vital aspect of risk assessment is the macro-prudential approach, which accentuates the significance of ensuring financial stability. The integration of world economy substantiates GFC contagious effect to developed as well as developing economies.

Efficiency is an essential gauge of a bank's performance. An ineffective banking sector has the potential for escalating financial crises resulting in the reduction of the money supply and significant losses to the economy. Effective management can help steer a bank through challenging times, adapt to changes in industry, and capitalize on growth opportunities. The caliber of bank management is crucial, a bank's effectiveness is also shaped by the interplay of market forces. Skillful management can navigate market dynamics, capitalize on opportunities, and mitigate risks, ultimately contributing to bank's overall effectiveness. This is the case why a commercial bank's actual value is based on the way well it does on the securities exchange. The stock market is extremely contagious, and its detrimental effect creates systemic danger for other people.

Studies that attempt to explore the intricate relationship between risk and efficiency of banks in emerging economies are relatively few. Although some studies in developed economies have found a positive relationship between the two (Ben Zeineb & Mensi, 2018; Le et al., 2018; Sarkar et al., 2019), others (Podpiera & Podpiera, 2006; Fiordelisi et al., 2010; Fiordelisi & Mare, 2013; Saeed & Izzeldin, 2016; Avkiran, 2018) have found an unfavourable relationship. The backdrop of these studies that they neglected the developing nations, where banking rules are distinct from those in developed economies. The current study aims to plug this research vacuum by investigating intra-country systemic risk and its link with banking efficiency in the world of Indian Banking sector across different owner-

ship groups, where no prior research have investigated this causal relationship. The implications of this study will provide valuable perspectives for policymakers in the banking sector.

In a nutshell, this study aims to respond to the following key query:

- Is there a relationship between efficiency and intra-country systemic risk for public and private banks in India?

The term “systemic risk” is ill-defined. According to Ben S. Bernanke, (2009) and De Nicolò et al. (2012), systemic risk refers to the adverse implications that bank distress have on remaining financial system elements. Alternatively systemic risk can be defined as a bank's role in exacerbating an decline of the country's capital system amid an economic downturn (Acharya et al., 2012; Brownlees et al., 2012) or as the evident and immediate risk of problems in the financial system swiftly propagating to other institutions or markets, causing harm to institutions themselves, their customers, and, ultimately, the economy at large (Bach & Nguyen, 2012). In accordance with the literature review, systemic risk can be gauged using five different models, including the Early Warning System (EWS) and Credit Default Swap (CDS) Indexes; Liquidity Measures of Systemic Risk; Capital Measures of Systemic Risk; Contagion Measures of Systemic Risk; and Network Measures of Systemic Risk (Ellis, 2019).

The characterization of bank's efficiency is outlined as the production of given output with the use of minimal amount of inputs, or by maximizing output levels using a given amount of inputs (Minsky et al., 1992). Efficiency refers to how well a bank produces its services. Various techniques have been used to measure efficiency, which can be broadly categorized into traditional and modern approach. The traditional technique aims to focus on accounting ratios such as cost to income ratio (Beccalli et al., 2006), whereas the modern technique concentrates on economical effectiveness using parametric statistics like Stochastic Frontier Analysis (SFA), Distribution Free Approach (DFA), and Thick Frontier Approach (TFA) and non-parametric approaches (Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH)).

## Literature Review

Over the past few years, financial institutions have been primarily preoccupied with the following concern of stability and efficiency relationship. Hyman Minsky established the financial instability hypothesis, which reinforces how efficiency affects systemic risk (Minsky et al, 2008). Four hypotheses—the bad luck hypothesis, the bad management hypothesis, the skimping hypothesis, and the risk-averse hypothesis—have been put forth in the banking literature to shed light on how efficiency and risk share a connection. The bad luck hypothesis, the bad management hypothesis, the skimping hypothesis were put forth by Berger and DeYoung (1997), and risk-averse hypothesis was put forth by Jeitschko & Jeung (2005). According to the bad luck hypothesis, efficiency and risk are negatively correlated, exhibiting that with exogenous events problem loans for banks increases leading to jacking up costs and managerial work while decreasing the efficacy of the bank. Outside shocks are the trigger of this instability. Pursuant to the bad management hypothesis, an increase in default risk follows with fall in efficiency level of bank as the management team of the bank may not be able to handle business operations and risk management. According to the skimping theory, rising efficiency raises the likelihood of bank's default, as senior managers may stress on increasing their power, which is more advantageous to managers than owners. This method could provide immediate advantages, but it may ends up in putting the bank at greater risk. According to the risk-averse hypothesis, bank management may put a higher priority on short-term default risk reduction by pursuing approaches that raise operational expenses and decrease efficiency.

The study conducted by Podpiera and Podpiera (2006) looks at the outcome of inefficient cost management on the likelihood of bankruptcy for banks in the Czech banking industry, utilizing a sample of 50 banks and have encountered a strong correlation between the two. The three efficiency measures are effective predictors of the likelihood of bank failure. The danger of bank failure rises when efficiency drops, and conversely the opposite is also true. The “bad management” hypothesis has been corroborated by Fiordelisi et al. (2010) while investigating into the associa-

tion between bank capital, risk and its efficiency for the EU's 26 banks between 1995 and 2007. They found that banks with less efficiency in terms of both expenses and earnings are granger-causal factors for high bank pitfalls. The researchers also observed that more efficient banks tends to improve their capitalization level across time, and there is favourable impact on bank's efficiency due to their strong captilization base. Saeed & Izzeldin, (2016) probed on the association between efficiency and default risk in 23 Islamic and 83 conventional banks and concluded that causality from profit efficiency to default risk is inversely related for all categories, thus enhancing profit efficiency lead to reduction in default risk. There is causality between banking stability and efficiency (Alber, 2017). Ding (2018) examined the relationship between banks' capital, risk and cost efficiency on US banks and found that causal relationship between efficiency and default risk is positive, when NPL is used to represent risk and the situation when RWA is used to measure risk then efficiency and default risk shows negative relation. According to an analysis of 314 different U.S. financial institutions, banks with more productivity corresponds to higher systemic risk (Le et al., 2018).

The mixed result regards to direction of causality between risk and efficiency has driven attention of researchers. Some of studies exhibit positive association (Ben Zeineb & Mensi, 2018; Le et al., 2018; Sarkar et al., 2019), while some studies propose a negative association between the two (Avkiran, 2018; Fiordelisi et al., 2010; Fiordelisi & Mare, 2013; Podpiera et al., 2006; Saeed & Izzeldin, 2016). Most of earlier studies focused on measuring the relationship between risk and efficiency as proxied by individual banks level risk measure in contrast to systemic risk measure. Referring to the literature review mentioned above, the following hypotheses can be put forth:

**H<sub>0</sub> (a): Banking efficiency has no substantial impact on systemic risk in private banks.**

**H<sub>0</sub> (b): Systemic risk has no substantial impact on banking efficiency in private banks.**

**H<sub>0</sub> (c): Banking efficiency has no substantial impact on systemic risk in public banks.**

**H<sub>0</sub> (d): Systemic risk has no substantial impact on banking efficiency in public banks.**

## Research Design

This study focuses on analyzing the causal relationship between financial stability and efficiency in the Indian banking sector. The research relies on secondary data sourced from the Nifty PSU Bank Index and Nifty Private Bank Index as of March 31, 2019, covering a period of 15 financial years from FY 2003-2004 to FY 2018-2019. This time frame includes the Global Financial Crisis (GFC) that occurred between 2008-2012, providing a complete picture of the variables before and after the crisis and aiding in framing reforms to manage systemic risk. The study's data collected from the Centre for Monitoring Indian Economy's Prowess database. The study focuses on the two key variables of systemic risk and efficiency, with intra-country systemic risk measured using the capital measure  $\Delta\text{CoVaR}$ , and non-parametric methodology is used to quantify efficiency- Data Envelopment Analysis, a modern method of determining the economic efficiency.

The method of quantile regression will be utilized to figure out CoVaR, the capital gauge of systemic risk. The computation of  $\Delta\text{CoVaR}_{i,t}(\alpha)$  will involve using an alpha value of 0.05. Equation 1 is used to compute the value of  $\Delta\text{CoVaR}_{i,t}(\alpha)$  as difference between the conditional value at risk of the financial system with firm i in distress and the conditional value at risk of the system with firm i in its median state.

$$\Delta\text{CoVaR}_{i,t}(\alpha) = \text{CoVaR}_{i,t}^{m \vee r_{i,t} = \text{VaR}_{i,t}(\alpha)} - \text{CoVaR}_{i,t}^{m \vee r_{i,t} = \text{median}(r_{i,t})} \quad (1)$$

In this study, modern approach to banking efficiency will be utilized. The efficiency frontier will be expressed in the transcendental logarithmic (translog) form, represented by Equation 2, where  $TC_{i,t}$  denotes the total costs, including employees related expenses, other operating expenses and administrative expenses and of Bank  $i$  at year  $t$ .  $E_{it}$ , In OEA, In T Loan, and In Deposits are total bank equity, napierian logarithm of bank's other income-generating assets, bank's total loans, and bank's entire deposits respectively. Furthermore,  $y_i \wedge w_i$  represents the vectors of output and inputs for the  $i^{\text{th}}$  bank. The coefficients  $\alpha, \beta, \gamma, \varphi, \theta, \rho, \xi, \psi, \lambda, \eta, \wedge \kappa$  are to be estimated and  $\beta_{mn} = \beta_{nm}$ .

$$\begin{aligned} \ln TC_{i,t} = & \alpha + \beta_m y_{imt} + \sum_j \gamma_j w_{ijt} + \frac{1}{2} \sum_m \sum_n \beta_{mn} y_{im} y_{in} + \frac{1}{2} \sum_j \sum_k \beta_{jk} y_{ijt} y_{ikt} + \\ & \sum_m \sum_j \psi_{mj} \ln y_{imt} \ln w_{ijt} + \varphi_1 \ln E_{it} + \frac{1}{2} \varphi_2 \ln E_{it}^2 + \sum_m \lambda_m \ln y_{imt} \ln E_{it} + \sum_j \xi_j \ln w_{ijt} \ln E_{it} + \\ & \theta_1 T + \theta_2 T^2 + \sum_m \kappa_m \ln y_{imt} T + \sum_j \rho_j \ln w_{ijt} T + \eta \ln E_{it} + \ln OEA + \ln T \text{Loan} + \ln \text{Deposits} + \\ & v_{it} + v_{it} \end{aligned} \quad (2)$$

While computing a bank's efficiency using the DEA, different inputs and outputs are taken into consideration. The publicized Financial Statements provide convenient access to these inputs and outputs. The weights specified to these inputs and outputs are derived endogenously, meaning they are not subjective or externally imposed based on other samples. In order to minimize the influence of measurement inaccuracies, it is advisable to avoid the outlier's effect.

To investigate the causal link between efficiency and systemic risk, Granger-causality analysis will be conducted to address the query regarding the presence of causal relationship between these two variables. This analysis will be based on Model 1 & 2, which has been developed for this purpose. For these models, we will consider n lags of efficiency and systemic risk, to examine causative link between them.

**Model 1: To examine the causative link between efficiency and systemic risk for Private sector banks**

$$\begin{aligned} SR_{jp,t} &= f(SR_{jp,t-a}; Eff_{jp,t-a}) + e_{i,t} \\ Eff_{jp,t} &= f(Eff_{jp,t-a}; SR_{jp,t-a}) + e_{i,t}, \\ &\text{where } a=0,1,2,3,\dots,n \end{aligned}$$

**Model 2: To examine the causative link between efficiency and systemic risk for Public sector banks**

$$\begin{aligned} SR_{jpb,t} &= f(SR_{jpb,t-a}; Eff_{jpb,t-a}) + e_{i,t} \\ Eff_{jpb,t} &= f(Eff_{jpb,t-a}; SR_{jpb,t-a}) + e_{i,t}, \\ &\text{where } a=0,1,2,3,\dots,n \end{aligned}$$

**Where,**  $SR_{jp,t-a}$  = Systemic risk faced by  $j^{\text{th}}$  private bank at time t with lag a

$Eff_{jp,t-a}$  = Efficiency of  $j^{\text{th}}$  private bank at time t with lag a

$SR_{jpb,t-a}$  = Systemic risk faced by  $j^{\text{th}}$  public bank at time t with lag a

$Eff_{jpb,t-a}$  = Efficiency of  $j^{\text{th}}$  public bank at time t with lag a

$e_{i,t}$  = Random error

## Empirical Results

### Descriptive Statistics

Table 2 provides for the descriptive statistics for the sampled banks based on their ownership classification. Table 2 exhibits the mean, standard deviation, maximum and minimum value of variables.

**Table 2:** Descriptive Statistics by ownership

	Private banks		Public banks	
	$\Delta\text{CoVar}$	DEA	$\Delta\text{CoVar}$	DEA
<b>N</b>	160	160	192	192
<b>Minimum</b>	-3.353	0.00	-3.5972	0.00
<b>Maximum</b>	0.00	1.00	.5179	1.00
<b>Mean</b>	-1.2370	.8299	-1.4495	.9262
<b>Standard Deviation</b>	.9208	.3033	.9197	.1768

According to the findings in Table 2, private banks are less vulnerable to intra-country systemic risk since their average mean is -1.24 which is lower than that of public banks, which is -1.45 (Verma et al., 2019). This suggests that when compared to their public counterparts, private banks are more prepared to manage systemic risk. Additionally, with a mean efficiency of 92.61% and 82.99%, respectively, public and private banks differ in efficiency between 0 and 1. In the past, the public suffered from poor asset quality as a result of reckless lending practises. However, over time and because of RBI regulations, the quality of the assets increased and they generally outperformed their private counterparts (Das & Kumbhakar, 2016; Trade Brains, 2022).

**Table 3:** Results of stationarity

Method	Private banks		Public banks	
	Statistic	Prob.*	Statistic	Prob.*
<b>Null: Unit root (assumes common unit root process)</b>				
Levin, Lin & Chu t*	-8.19566	0.0000	6.22589	0.0000
<b>Null: Unit root (assumes individual unit root process)</b>				
Im, Pesaran and Shin W-stat	-3.38894	0.0004	3.16558	0.0008
ADF - Fisher Chi-square	67.9645	0.0002	60.0519	0.0019
PP - Fisher Chi-square	126.960	0.0000	86.5432	0.0000

\*Significant at 5%.

### Panel Unit Root Test Results

In order to check causality between the research variables, firstly stationarity of the variables is checked. If data is not stationary, it must be differentiated in order to make it stationary. Levin, Lin, and Chu t unit root test, ADF-Fisher Chi-square, PP-Fisher Chi-square, and Fisher Chi-square are used in our study to test the stationarity of the data. All of above tests does not accept the  $H_0$  of non-stationary at 5 per cent level of significance. Table 3, describes series is stationary.

### Kao's residual co-integration test

The next step is to run a test for cointegration, which is the long-term equilibrium that exists between more than one non-stationary time series variables. Kao's test used to check residual co-integration. The last step of analysis comprises VAR model estimation and granger causality test. The length of lag was determined at the outset. All variables employed in this model exhibited significance in rejecting the conjecture of no co-integration at the 5% alpha, as per Kao's tests (1999) for the homogeneous panel co-integration. The empirical findings of the panel co-integration test demonstrate that there is cohesive integration (relationship) between the factors at play.

**Table 4:** Kao's residual co-integration test

	Private banks		Public banks	
	t-statistic	Prob.	t-statistic	Prob.
<b>ADF</b>	0.507385	0.0059	-2.400354	0.0082

\*Significant at 5%

### Granger Causality

The VAR model must be estimated in order to establish the causal relationship between the variables as there is co-integration among them. The first step is to find the optimal lag that generates minimal value for statistical purposes among the following criteria: FPE (Final prediction error), AIC (Akaike information criterion), SC (Schwarz information criterion), and HQ (Hannan-Quinn information criterion). The lag length is chosen by the lowest SC number, which is 4 for private banks and 6 for public banks, as shown in Table 5. Table 6 sums up the coefficient estimated result for VAR (4) and VAR (6). The independent variable is the granger cause of the dependent variable if any independent variable's coefficient is significant as determined by the t-statistic (Koop, 2013). The value in the bracket represents the t-statistic value. Thus, Efficiency and systemic risk granger cause each other in case of private banks and from systemic risk to efficiency in case of public banks.

**Table 5: Lag Determination**

Private banks				
Lag	FPE	AIC	SC	HQ
0	0.095922	3.331530	3.384954	3.353125
1	0.083089	3.187873	3.348145	3.252658
2	0.072109	3.045995	3.313115	3.153969
3	0.054057	2.757514	3.131482	2.908678
4	0.038229*	2.410487*	2.891302*	2.604840*
Public banks				
Lag	FPE	AIC	SC	HQ
0	0.026428	2.042434	2.095858	2.064029
1	0.012095	1.260734	1.421005	1.325518
2	0.008920	0.956115	1.223235	1.064089
3	0.008335	0.887899	1.261866	1.039062
4	0.007445	0.774464	1.255279	0.968817
5	0.005144	0.403738	0.991401	0.641281
6	0.003814*	0.103398*	0.797909*	0.384130*

**Table 6: Estimates of Model VAR**

D.V. and its lag	Private banks		D.V. and its lag	Public banks	
	I.V. and their coefficient			I.V. and their coefficient	
	CoVar	DEA		CoVar	DEA
CoVar(-1)	0.01707 [ 0.14517]	0.216632 [ 5.03107]*	DEA(-1)	0.691256 [ 1.82616]	-0.170021 [-2.12512]*
CoVar(-2)	-0.27083 [-2.06179]*	0.100425 [2.08722]*	DEA(-2)	0.178391 [ 0.37874]	-0.135050 [-1.35657]
CoVar(-3)	0.223125 [ 1.64854]	0.045703 [0.92190]	DEA(-3)	0.250723 [ 0.52466]	-0.020642 [-0.20437]
CoVar(-4)	0.476360 [ 4.23851]*	-0.234260 [-5.69065]*	DEA(-4)	-0.139411 [-0.38854]	0.144981 [ 1.91174]
DEA(-1)	0.907161 [ 3.06373]*	0.068305 [ 0.62980]	DEA(-5)	-0.031163 [-0.07629]	0.352758 [ 4.08587]*
DEA(-2)	-0.744829 [-1.95392]	0.379717 [ 2.71954]*	DEA(-6)	-0.392423 [-0.68433]	0.113550 [ 0.93687]
DEA(-3)	-1.415330 [-4.67557]*	0.268808 [ 2.42440]*	CoVar(-1)	-0.395228 [-3.44145]*	-0.035453 [-1.46059]
DEA(-4)	0.956483 [ 3.33744]*	0.122461 [-1.16659]	CoVar(-2)	-0.359214 [-3.13998]*	-1.61812 [-0.039125]
C	-0.277202 [-0.59904]	0.465687 [ 2.74749]*	CoVar(-3)	-0.178695 [-1.58357]	-0.060709 [-2.54543]*
			CoVar(-4)	--0.257412 [-2.55916]*	-0.055106 [-2.59209]*
			CoVar(-5)	-0.008382 [-0.08703]	-0.060395 [-2.96693]*

	<b>CoVar(-6)</b>	0.018698 [ 0.22789]	-0.024810 [-1.43063]
	<b>C</b>	-0.109052 [-1.80228]	0.041476 [ 3.24310]*

\*Significant at 5%.

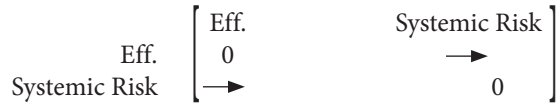
As per Table 7, in the case of private banks, causality operates in both directions, i.e., from systemic risk to efficiency and back, and results are negatively significant, confirming both the bad luck theory and bad management theory. The poor luck theory is supported by the fact that, for public sampling banks, the direction of causality is unidirectional, i.e., from systemic risk to efficiency, and the outcome is negatively significant. Inefficiency is brought on by the rise in systemic risk for both private and public institutions (Avkiran, 2018; Tan & Floros, 2018). Therefore, to lower risk and increase efficiency, private banks must strengthen their managerial attributes, notably their risk management capabilities in the context of investing or extending credit, poor managerial decisions.

**Table 7:** Granger Causality test among the sampled banks on basis of ownership

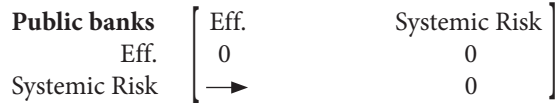
<b>Private Banks</b>			
<b>H0(a): Systemic Risk does not granger cause Efficiency</b>			
<b>Dependent Variable: CoVar</b>			
Excluded	Chi-sq	Df	Prob.
DEA	36.25	4	0.0000*
<b>H0(b): Efficiency does not granger cause Systemic Risk</b>			
<b>Dependent Variable: DEA</b>			
Excluded	Chi-sq	Df	Prob.
CoVar	64.0186	4	0.0000*
<b>Public banks</b>			
<b>H0(c): Systemic Risk does not granger cause Efficiency</b>			
<b>Dependent Variable: CoVar</b>			
Excluded	Chi-sq	Df	Prob.
DEA	9.6526	6	.1401
<b>H0(d): Efficiency does not granger cause Systemic Risk</b>			
<b>Dependent Variable: DEA</b>			
Excluded	Chi-sq	Df	Prob.
CoVar	40.9698	6	0.0000*

The matrix information is represented below:

**Private banks**



**Public banks**



In cases where the value is  $\rightarrow$ , indicates a significant causality running from the row-variables to the column-variables and, where the value is 0, it signifies the absence of significant causality running from the row- variables to the column-variables.

## Conclusion

In this study, we evaluate the manner in which intra-country systemic risk and efficiency commune across time in the context of Indian private and public banks. The findings of this research contributed to an existing reservoir of literature on the relationship between systemic risk and bank efficiency in India’s emerging market. The significance of this matter is crucial for the country, as the occurrence of bank failures in India could lead to disruptions in the interbank market, payment systems, reduce credit availability and have an adverse impact on the country’s economic growth (PTI, 2019). As per our study, we found that bad management hypothesis is supported; implying that poor cost efficiency has a detrimental effect on systemic risk for private banks. Additionally, we also found support for bad luck hypothesis, which suggests a reverse causality between two variables for both public and private banks.

The study has several limitations. Firstly, the study only uses specific measures to calculate systemic risk and efficiency such as CoVar and DEA, respectively. It would be worthwhile to investigate whether using different measures of these variables would exhibit different results. Secondly, Granger causality approach used

in the study has certain limitations, and it would be valuable to explore other statistical ways to review the causative connection between intra-country systemic vulnerability and efficiency.

These findings emphasize the significance of surveillance and management of systemic risk in the Indian banking industry, to guarantee its stability and resilience. Based on this findings, it can be inferred that improving efficiency in private banks can lead to reduction in systemic risk, and reducing systemic risk can lead to improved efficiency in the public and private banking sector. Therefore, policymakers can use this information to develop strategies that focus on enhancing efficiency and reducing systemic risk simultaneously to promote sustainable growth and stability in the Indian banking industry.

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