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Abstract: Examining the impact of ratio-based efficiency metrics, such as cost-to-income-ratio, and multifactor-based level efficiency on profitability can be potentially misleading. Our examination of Indian banks spanning the period from 2006 to 2023 reveals that profitability is significantly influenced by multifactor-based growth efficiency, rather than level efficiency. Notably, this finding remains robust when using either conventional or risk-adjusted measure of market power.

Keywords: Profitability; Level efficiency; Growth efficiency; Lerner index; Indian banking

JEL Classification: D2 (production and organization); G2 (financial institutions)

1. Introduction

In the extant empirical literature, bank profitability has often been modeled using multifactor-based level efficiency (LE) and conventional cost-to-income-ratio (CIR), a ratio-based measure of operational efficiency. We contribute to the literature by underscoring the significance of multi-factor-based growth efficiency (GE), a concept that has largely been overlooked but is closely linked to the notion of total factor productivity change (Sahoo et al., 2012), in analysing the performance of firms in hyper-competitive markets, such as the banking sector, characterized by high business uncertainties (Sengupta, 2002, 2003, 2004; Sengupta & Sahoo, 2006). To illustrate this contribution, we model the profitability of Indian banks from 2006 to 2023, incorporating CIR, LE, and GE, while controlling for market power and other bank-specific and macro determinants. To the best of our knowledge, this study represents the first attempt to highlight and address this issue in the literature.

Three broad sets of factors impact bank performance: bank-specific factors; sector-specific regulatory and policy initiatives; and domestic and global macroeconomic developments. The profitability of Indian banks, illustrated as a roller coaster ride (Fig. 1), reflects the intricate interplay of these three sets of factors. For instance, the policy stimuli post the Global Financial Crisis (GFC) contributed to sustained profitability in the years following the crisis. However, subsequent policy stagnation, combined with subpar underwriting standards, resulted in a decline in profitability over the next six years, with a Return on Assets (ROA) of 1.18 in 2015. The cessation of regulatory forbearance in 2014 and an asset quality review (AQR) conducted by the banking regulator from Aug-Nov 2015 led to a surge in non-performing loans (Misra, 2023), further denting bank profitability to a mere 0.45 by 2020. Policy initiatives, such as the enactment of the Bankruptcy Code in 2016, the establishment of new categories of banks, and the consolidation of public sector banks (reducing their number from 20 to 12 in 2020), have reshaped the banking landscape, impacting overall bank performance. The COVID-19 pandemic stands out as another black swan event affecting the Indian economy. Yet, it is the combined effect of policy responses and the proactive efforts of banks to mitigate the pandemic's negative impacts that restored the ROA of the banking system to the pre-AQR level of 1.18 by 2023. Despite this overall recovery, the performance of individual banks has exhibited significant variation during 2006-2023.

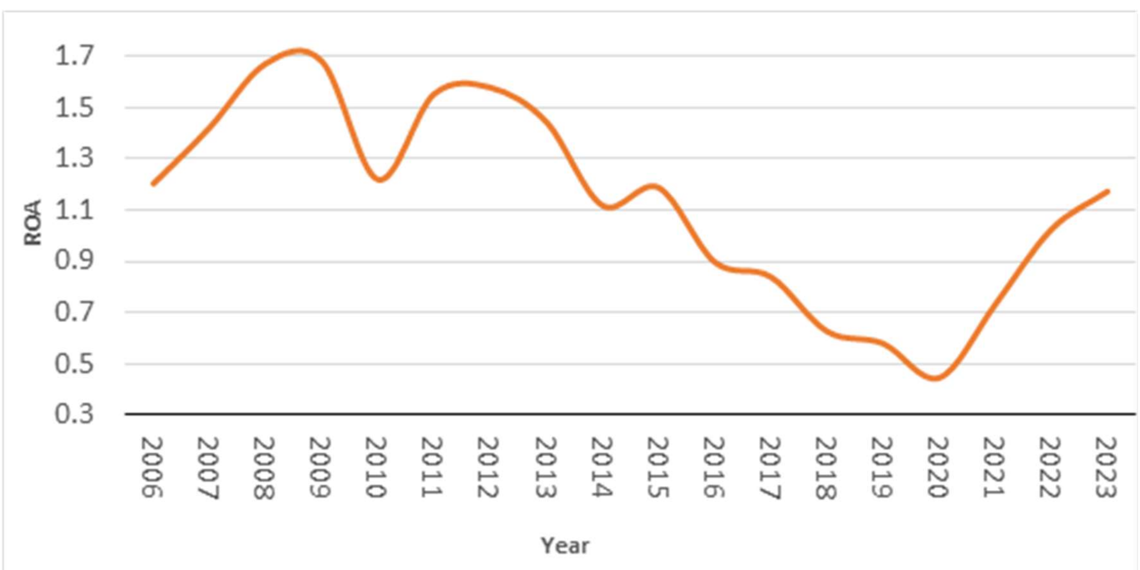

Fig. 1. ROA of Indian banks over years

Amidst the backdrop of policy initiatives and regulatory interventions, it is the agility of banks to adapt to a dynamic environment that would impact profitability. We therefore posit that this agility is mirrored in their efficiency and market power. Consequently, we argue that, given their market power, a multifactor-based GE, rather than LE, would better explain profitability after controlling for other bank-specific characteristics, macroeconomic developments, and black swan events such as the GFC and the COVID pandemic.

2. Data and methodology

Banks essentially aim to maximize their service provisions, given the resources available to them. Consequently, a service-oriented measure of the LE of bank h at time t (LE_h^t) is calculated as the reciprocal of the solution to the following linear program:

$$(LE_h^t)^{-1} = \max_{\theta,\lambda_j \geq 0} \theta \mid \textstyle\sum_{j=1}^{n} x_{ij}^t \lambda_j \leq x_{ih}^t \ (\forall i), -\sum_{j=1}^{n} y_{rj}^t \lambda_j + \theta y_{rh}^t \leq 0 \ (\forall r), \sum_{j=1}^{n} \lambda_j = 1 \quad (1)$$

wherein we have used three inputs – equity (x_1), employees (x_2), and fixed assets (x_3) and two outputs – net-interest income (y_1) and other income (y_2). Similarly, a service-oriented measure of the GE of bank h at time t (GE_h^t) is computed as the reciprocal of the solution to the following linear program:

$$(GE_h)^{-1} = \max_{\beta,\mu_j \geq 0} \beta \mid \textstyle\sum_{j=1}^{n} \hat{x}_{ij}^t \mu_j \leq \hat{x}_{ih}^t \ (\forall i), -\sum_{j=1}^{n} \hat{y}_{rj}^t \mu_j + \beta \hat{y}_{rh}^t \leq 0 \ (\forall r), \sum_{j=1}^{n} \mu_j = 1 \ (2)$$

where $\hat{x}_{ij}^t = \Delta x_{ij}^t / x_{ij}^{t-1} = \left(x_{ij}^t - x_{ij}^{t-1}\right)/x_{ij}^{t-1}$ $(\forall i)$ and $\hat{y}_{rj}^t = \Delta y_{rj}^t / y_{rj}^{t-1} = \left(y_{rj}^t - y_{rj}^{t-1}\right)/r_{rj}^{t-1}$ $(\forall r)$. These two programs (1) and (2) are solved once each for each bank in each year to compute LE and GE, respectively.

Note that estimates of LE and GE may be subject to bias if there are measurement errors in the input and output data. To mitigate these biases, following Tone (2013), we employed a triangular distribution for errors, which allowed us to generate resampled data through 2500 iterations. Subsequently, we utilized this resampled data in programs (1) and (2) to enhance the robustness of our analyses.

Finally, we employed the following model specification to estimate profitability:

$$ROA_j^t = \alpha_1 ROA_j^{t-1} + \alpha_2 EFF_j^t + \alpha_3 MP_j^t + \alpha_4 RISK_j^t + \alpha_5 SIZE_j^t + \alpha_6 DIV_j^t + \alpha_7 RGDPG_j^t + \alpha_8 INF_j^t + \alpha_9 YR\_2009 + \alpha_{10} YR\_2021 + \varepsilon_j^t \quad (3)$$

In this specification, subscript j denotes banks, and superscript t signifies years. ROA serves as a proxy for profitability. We employed three efficiency (EFF) variants – one conventional, namely, CIR, and two multifactor-based efficiencies, namely, LE and GE. Market power (MP) is denoted by two variants: conventional Lerner index (LI) and risk-adjusted Lerner index (ALI). The riskiness ($RISK$) of a bank's portfolio is gauged by provisions for bad loans as a proportion of the loan portfolio. In the specification utilizing ALI, $RISK$ is included as an explanatory variable. The $SIZE$ of a bank (natural log of total assets), the degree of diversification, DIV (non-interest income as ratio of operating expenses), real-GDP growth ($RGDPG$) and inflation, INF (annual change in GDP deflator) are all employed as control variables. We include year dummies to account for key events such as the GFC and COVID pandemic.

We estimated Model (3) using panel-data econometric methods. Initially, following Coccorese and Misra (2021), we employed the least-square dummy-variable corrected ($LSDVC$) method to incorporate bank-specific effects. In our framework, the $LSDVC$ estimator, initialized by the Arellano and Bond (1991) estimator, relies on a recursive correction of the fixed-effects estimator's bias. The bias approximation is accurate up to $O(1/T)$, and we adopted bootstrapped standard errors with 1000 iterations (Bruno, 2005). Additionally, following Tan (2018) and Misra and Coccorese (2022), we applied the system GMM (Blundell & Bond, 1998) to estimate Model (3). Due to the limited size of our sample, we utilized the two-step system GMM, incorporating the finite-sample correction proposed by Windmeijer (2005) to enhance the reliability of coefficient estimates and correct standard errors. The estimation covers 50 commercial banks, including 12 public, 16 foreign, and 22 private ones, spanning the period 2005-2023. Detailed summary statistics for the variables used in the estimation are provided in the Annexure.

3. Results and discussion

Table 1 presents the findings on the influence of various efficiency metrics (CIR, LE and GE) and market power indicators (LI and ALI) on profitability. Columns 1-6 showcase $LSDVC$ estimates, while columns 7-12 display GMM estimates. The persistence of the profitability is underscored by the statistically significant coefficient for the lagged ROA. We find presence of first order serial correlation and absence of second order serial correction along with validity of the instruments used in estimation for the system GMM results (Cols7-12). We find that in the specifications where CIR or LE measure of efficiency is used, we get inconsistent results. The results unequivocally demonstrate that GE positively drives profitability, observed in both GMM (columns 11-12) and $LSDVC$ estimates (column 3 and column 6) when either LI or ALI is employed. Conversely, LE shows no discernible impact in either GMM or $LSDVC$ estimates, regardless of the use of LI or ALI. Additionally, as anticipated, higher risk diminishes profitability in models utilizing ALI, evident in both $LSDVC$ (columns 4-6) and GMM estimations (columns 10-12). Consistent with prior literature, $SIZE$ exerts a negative influence on profitability in specifications incorporating GE under GMM estimations (columns 11-12). Conversely, DIV exhibits a robust positive influence on profitability across both sets of estimations. Further, we find that both GFC and the COVID pandemic had adversely impacted profitability in the GE combined with ALI specification.

4. Conclusions

The banking landscape is characterized by dynamic competition, emphasizing GE as opposed to static competition, which focuses on LE. Consequently, scrutinizing the effects of factors such as market power, CIR, and LE $-$ commonly employed in the existing literature on profitability can be problematic. Our empirical findings suggest that profitability is predominantly driven by GE rather than LE, in conjunction with either LI or ALI.

Table 1. Determinants of profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable: ROA^t											
ROA^{t-1}	0.673***	0.735***	0.735***	0.529***	0.573***	0.584***	0.483***	0.183*	0.859***	0.276**	0.777***	0.275***
	(28.916)	(31.587)	(31.533)	(24.488)	(26.596)	(26.526)	(3.711)	(1.681)	(10.667)	(2.056)	(9.731)	(3.197)
LI^t	0.108	0.400***	0.393***				-2.360***		1.211**		0.716**	
	(0.899)	(3.289)	(3.382)				(-2.848)		(2.128)		(2.598)	
ALI^t				-0.079	0.018	0.021		0.102		0.556		0.644**
				(-1.081)	(0.237)	(0.286)		(0.157)		(0.718)		(2.017)
LE^t		-0.154			0.032				1.252	1.829		
		(-0.807)			(0.191)				(1.144)	(0.712)		
GE^t			0.266*			0.270*					0.661***	0.590*
			(1.646)			(1.769)					(3.031)	(1.921)
CIR^t	-0.014***			-0.014***			-0.067**	-0.018				
	(-5.462)			(-6.069)			(-2.247)	(-0.727)				
$RISK^t$				-0.162***	-0.165***	-0.166***		-0.374***		-0.398**		-0.388***
				(-13.403)	(-13.633)	(-13.627)		(-4.224)		(-2.676)		(-4.189)
$SIZE^t$	-0.068**	-0.124***	-0.070**	-0.037	-0.030	-0.047	-0.640*	0.036	-0.137	-0.185	-0.107***	-0.069*
	(-2.299)	(-3.201)	(-2.336)	(-1.499)	(-1.197)	(-1.579)	(-1.923)	(0.258)	(-1.665)	(-0.876)	(-4.631)	(-1.701)
DIV^t	0.002**	0.003***	0.003***	0.004***	0.005***	0.005***	0.015*	0.024***	0.001	0.028***	0.007***	0.022***
	(2.454)	(4.933)	(4.462)	(5.895)	(8.581)	(8.829)	(1.889)	(3.473)	(0.898)	(3.013)	(3.372)	(4.636)
$RGDPG^t$	-0.016	-0.079***	-0.025	-0.008	-0.017	-0.012	1.294**	-0.015	-0.010	-0.108**	0.020	-0.062**
	(-0.878)	(-3.097)	(-1.132)	(-0.507)	(-0.989)	(-0.513)	(2.540)	(-0.363)	(-0.509)	(-2.098)	(1.493)	(-2.611)
INF^t	0.041***	0.010	0.006	0.022*	0.026**	0.019	-0.201*	0.006	0.047***	0.009	0.012	0.036
	(3.296)	(0.859)	(0.527)	(1.855)	(2.224)	(1.531)	(-1.726)	(0.237)	(4.853)	(0.280)	(1.170)	(1.553)
YR_2009	-0.015	-0.257*	0.009	-0.001	-0.028	-0.008	6.473**	-0.189	0.111	-0.566*	0.136	-0.428**
	(-0.138)	(-1.899)	(0.071)	(-0.012)	(-0.276)	(-0.060)	(2.382)	(-0.846)	(0.777)	(-1.987)	(1.099)	(-2.330)
YR_2021	-0.215	-1.100***	-0.472	-0.0876	-0.184	-0.121	19.02**	-0.120	-0.116	-1.064*	0.221	-0.722**
	(-0.873)	(-3.152)	(-1.559)	(-0.400)	(-0.820)	(-0.388)	(2.546)	(-0.246)	(-0.384)	(-1.928)	(1.209)	(-2.444)
No. of instruments							47	47	47	47	47	47
$AR(1)$ (*p*-value)							0.087	0.061	0.098	0.099	0.094	0.092
$AR(2)$ (*p*-value)							0.618	0.506	0.731	0.843	0.769	0.321
Hansen-J (*p*-value)							0.228	0.224	0.123	0.145	0.119	0.293
No. of observations	850	850	850	850	850	850	850	850	850	850	850	850

Notes:

- *t*-stats are in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$
- The $AR(1)$ and $AR(2)$ tests check for the presence of first-order and second-order serial correlation in the residuals of the estimated equations, respectively, while the Hansen J statistic tests the instruments' joint validity.
- Columns 1-6 present the $LSDVC$ estimates for LI and CIR, LI and LE, LE and GE, ALI and CIR, ALI and LE, ALI and GE specification, respectively. Columns 7-12 present the specifications in the same order under the GMM estimation.
- We have used 3-year moving average of the variables used in the estimation.

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