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ARTICLE

# Financial deregulation, competition and cost efficiency of Indian commercial banks: is there any convergence?

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## Abstract
This paper investigates the convergence in cost efficiency among the Indian commercial banks during 1998–2015. We follow a two-step approach: We first employ the double bootstrap procedure of Simar and Wilson (J Econom 136:31–64, 2007) for estimating the bias-corrected cost efficiency scores. Using a dynamic panel framework, we then apply the concepts of $\beta$-convergence and $\sigma$-convergence from the growth convergence literature to evaluate the convergence process in the banking industry. Our results indicate large difference in mean efficiency among banks across various ownership categories. Further, we observe strong evidence favouring convergence in cost efficiency, driven by both "*catching-up*" and "*lagging-behind*" phenomena. The speed of convergence was found highest in state-owned banks, followed by foreign-owned and domestic private banks.

**Keywords** Convergence · Cost efficiency · Data envelopment analysis · Indian banks

**JEL Classification** D24 · G21 · G28

## 1 Introduction

Since the financial liberalisation of Indian banking industry in 1992, numerous studies have examined the effects of financial deregulation on Indian banking efficiency and productivity, and the relationship between ownership and efficiency. A majority of these studies have focussed mainly on the time period before Global Financial Crisis (GFC) (see Bhandari 2012; Bhattacharyya et al. 1997; Das and Ghosh 2006, 2009; Kumbhakar and Sarkar 2003; Ray and Das 2010; Sahoo and Tone 2009; Sensarma 2005; Zhao et al. 2010, among others). By contrast, only limited number of empirical studies have analysed the changes taken place within the Indian

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banking industry since GFC, i.e. after 2008 (Fujii et al. 2014; Gulati and Kumar 2016; Tzeremes 2015).

Although studies on banking efficiency and productivity analysis are voluminous, little attention has been paid to convergence in efficiency among banks. From a regulatory perspective, measurement of convergence process is important, since increase in integration fosters competition which in turn may result in improvement in cost efficiency (Guiso et al. 2004). Also, an integrated financial system plays an important role in promoting savings, investments and subsequently, economic growth of an economy (Mohan 2005). This study aims to fill this gap by investigating the convergence properties among Indian commercial banks during 1998–2015. In particular, we intend *inter alia* to address the following questions regarding the Indian banking industry. First, what is the overall cost efficiency of Indian commercial banks during the post deregulation period and how has it varied over time? Second, does efficiency vary among various ownership groups? Third, is there any convergence in cost efficiency among Indian banks? Fourth, if so, is it due to *catching up* or *lagging behind* processes? Fifth, has overall competition increased over time in the Indian banking industry?

This study contributes to the existing banking efficiency literature in many ways. Firstly, for measuring the efficiency or productivity of banking industry, it is essential that sample period must be large (Berger and Humphrey 1997). For this purpose, we use a time period that covers both pre and post GFC. This enables us to carry out a comprehensive analysis of cost efficiency among Indian banks during the time period consistent with the consolidation process. Secondly, to overcome the problems inherent in conventional two-stage analysis, we adopt the double bootstrap procedure (Simar and Wilson 2007), which provides bias-corrected cost efficiency scores and enables consistent inference. Thirdly, for estimating convergence in cost efficiency in the Indian banking industry, the concepts of $\beta$-convergence, and $\sigma$-convergence (Barro and Sala-i-Martin 1991; 1992) are employed in a dynamic panel framework. This is very important, since a number of structural and regulatory changes have been taking place in the Indian banking industry over the years. Finally, in order to estimate the intensity of competition in the banking industry, we deploy the Rosse and Panzar 1977 non-structural model, considered to be more comprehensive than $k$-firm concentration ratio or Herfindahl–Hirschman index (HHI).

The remainder of the paper unfolds as follows. Section 2 provides a brief overview of the Indian banking industry. Section 3 reviews the literature on banking efficiency and convergence. Section 4 presents the data and methodology we use for measuring efficiency and convergence. The empirical results are presented and discussed in Sect. 5, and Sect. 6 concludes.

## 2 Indian banking industry: an overview

Until the beginning of the 1990s, the banking sector in India was highly regulated, characterized by, among others, administered interest rates, large statutory pre-emptions, and other micro-regulations to direct the substantial portion of

**Table 1** Selected banking indicators (amount in ₹ millions)

| Indicator/Year | 1998 | 2002 | 2006 | 2010 | 2015 |
|---|---|---|---|---|---|
| CR5 | 0.447 | 0.437 | 0.405 | 0.379 | 0.379 |
| HHI | 0.072 | 0.073 | 0.056 | 0.056 | 0.053 |
| Interest spread | 0.051 | 0.048 | 0.037 | 0.042 | 0.034 |
| Advances growth rate | – | 0.24 | 0.32 | 0.08 | 0.10 |
| GNPLs growth rate | – | 0.11 | − 0.10 | 0.17 | 0.23 |
| Govt. sec/investment | 0.70 | 0.71 | 0.80 | 0.79 | 0.82 |
| Other income/total income | 0.14 | 0.16 | 0.16 | 0.16 | 0.12 |

Source: Authors' own compilation using RBI data

funds from financial intermediaries into sectors such as agriculture and small businesses. During the post-nationalization period,[1] most of the government deficit was financed through the money extracted out of the banking business in the form of high cash reserve ratio (CRR) and statutory liquidity ratio (SLR) (Sen and Vaidya 1997). Additionally, strict entry controls made the banking industry immune to the potential competition. The market share of state-owned banks (SOBs), in terms of total assets was more than 90 percent, whereas the share of privately-owned banks (POBs) and those under foreign-ownership (FOBs) remained abysmal. This whole scenario has been described as an ideal situation of *financial repression* (McKinnon 1973). The lack of competitive environment resulted in inefficient credit allocation by SOBs, which in turn deteriorated the balance sheets and profitability of banks. Consequently, the country undertook a major financial deregulation program in 1992 to meet these challenges on the basis of the recommendations of the (Narasimham Committee 1991).

Various policy initiatives have been introduced since then to enhance the efficiency of Indian banks. These include reduction of statutory pre-emptions in the form of CRR and SLR, deregulation of the administered interest rate, allowance of liberal entry of de novo domestic and foreign banks, among others. The broad aim of these reforms was to create a more diversified, profitable and efficient banking system. Further, the second stage of reforms, outlined in the recommendations of the (Narasimham Committee 1998) were introduced in 1998. The policy focus of these reforms aimed at strengthening the financial stability of the banking system. Subsequently, prudential norms on income recognition, capital adequacy, asset classification, and provisioning for loans were applied uniformly to all banks. Thus, making the entire banking industry a *level playing field* across ownerships, an era which researchers sometimes refer to as the *true liberalized* period (Barman 2007).

Table 1 provides the synopsis of changes that took place in the Indian banking industry since financial liberalization. The overall competition within the banking sector has improved, as is reflected in the substantial fall in both

[1] Fourteen commercial banks with a deposit base of more than ₹ 0.5 billion and another six banks with a deposit base exceeding ₹ 2 billion were nationalized in 1969 and 1980 respectively.

Herfindahl–Hirschman index (HHI)[2] and 5-bank concentration ratio (CR5) over the years.[3] The *interest spread*, which is measured by the difference between the *return on advances* and *cost of deposits* also decreased from 5.1% in 1998 to 3.4% in 2015, indicating an increase in competition fostered by the ongoing deregulation process.[4] However, in order to survive in such a competitive market, it is possible for the banks to lend money without undertaking any due diligence, which might in turn result in the accumulation of non-performing assets (NPAs).[5] Indian banks in general, and SOBs in particular, are plagued with huge stock of NPAs that piled up during these years. There has been a steady increase in the growth rate of NPAs since 2008 (e.g., from 17% in 2010 to 23% in 2015). In addition, the risk-averse behaviour of the banks in response to the strengthening prudential regulations led to a shift in the banks, preference for investments towards safer assets, as opposed to loans and advances. This is visible in the increasing share of government securities as a proportion of total investment over time and by the declining growth rate of advances (e.g., 32% in 2006 and 10% in 2015). Further, in order to find an alternative avenue for income generation, particularly after reforms, banks have shifted their business from traditional on-balance sheet business activities to non-traditional off-balance sheet business activities. Zhao et al. (2010) indicates that the ratio of fee-based income as a proportion of the total income by commercial banks in India increased from 13.4% in 1992 to 23.7% in 2004. Although a declining tendency is observed thereafter, since the overall income is found to be increasing gradually, the absolute volume of such component is largely increasing.

## 3 Literature on banking efficiency and convergence

In the last couple of decades, there has been a plethora of literature on the effects of financial deregulation on banking efficiency and productivity using both parametric and non-parametric approaches. Although the majority of these studies are confined to banking industries of the US and other European countries with well-developed financial markets (see Berger and Humphrey 1997; Berger and Mester 1997 for a detailed review), the number of such studies are not scanty for the developing countries either (see Leightner and Lovell 1998; Gilbert and Wilson 1998; Banker et al. 2010; Patti and Hardy 2005; Burki and Naizi 2010; Hsiao et al. 2010, among others) . However, most of the studies have produced mixed findings regarding the effectiveness of various policies implemented by regulators, such as financial deregulation and various consolidation programmes of banks.

[2] Market size can be measured either as decimal fraction or percentage. In our study we have taken market size as a decimal fraction.

[3] Both CR5 and HHI are calculated in relation to total assets.

[4] Return on advances refers to the ratio of interest received on advances to total advances, whereas cost on deposits refers to the ratio of interest paid on deposits to total deposits.

[5] We have run a Granger causality test that suggests the direction of causality is from HHI and CR5 to NPAs.

Another highly explored area in the literature on banking efficiency is the relationship between bank ownership and performance. Empirical studies in this area mainly focus on testing the validity of *property right hypothesis* (Alchain 1965; De Alessi 1980) and *public choice theory* (Niskanen 1975; Levy 1987). Both these theories complement each other and claim that private firms perform more efficiently than public firms since government employees are not incentivised. As for the empirical results are concerned, while Sturm and Williams (2004) argue that ownership structure becomes neutral in terms of productivity growth, Isik and Hassan (2003) were of the view that different ownership reacts with different speeds to the change of regulatory environment. Moreover, foreign banks often outperform their domestic counterparts in developing nations (Berger et al. 2009), however, it is the other way around in the developed countries (De young and Nolle 1996; Chang et al. 1998). A summary of literature review on banking efficiency studies related to Indian banking industry is provided in Table 11 11 in "Appendix".

It is important to note here that, despite numerous studies on banking efficiency and productivity analysis, convergence of efficiency among banking industries has received little attention. Majority of the empirical studies on convergence in efficiency across banking have analysed the banking industries of European Union (EU). These studies have resulted in mixed findings regarding convergence in banking efficiency across European countries. While estimating the cost and profit efficiency of banks across 10 new EU member countries, Mamatzakis et al. (2008) observed some evidence of convergence in cost efficiency but no convergence in profit efficiency. Weill (2009) found strong evidence of convergence in efficiencies across ten European countries. In their study for 15 EU countries, Casu and Girardone (2010) found evidence of convergence towards European average but not towards best frontier. Moreover, their results indicate that convergence was due to *"lagging-behind"* rather than *"catching-up"* effects. In line with this study, Andrieş and Căpraru (2014) examined the convergence of cost efficiency among central and eastern European countries and found strong evidence of both $\beta$- as well as $\sigma$-convergence. However, they found that convergence resulted because of both "*catching-up*" and "*lagging-behind*" phenomena. Recently, Matousek et al. (2015) investigated the convergence in banking efficiency in 15 EU and Eurozone countries. However, in contrast to the earlier findings, they failed to observe any evidence of overall convergence. Nonetheless, they found some weak evidence of club convergence.

As far as single country convergence studies are concerned, Fung (2006) investigated the convergence in productivity for the US bank holding companies (BHCs). Although, their findings didn't support the presence of absolute convergence, however, a strong evidence of conditional convergence among BHCs was observed. Matthews and Zhang (2010) found strong evidence of conditional $\beta$- and $\sigma$-convergence of productivity growth among nationwide banks in China. Similarly, Zhang and Matthews (2012) find convergence in cost efficiency over time among Indonesian banks, however, the speed of convergence was lower during and after financial crisis period.

In a study on Indian banking, Kumar and Gulati (2009) attempted to examine whether there has been convergence in the performance during the post deregulation regime in a static framework. They observed strong evidence of both $\beta$- and $\sigma$-convergence in efficiency levels among public sector banks. However, their focus was only on public sector banks and foreign and private banks were not included. Recently, Casu et al. (2013) formulated a catch-up index for banks and found that speed of catch-up process declined over time across all ownership categories in India. Although structural and regulatory changes are taking place in the Indian banking industry over the years, none of the above studies have examined the convergence phenomena of Indian banks using a dynamic framework that would take account of these changes. Our study aims to address this lacuna by investigating the convergence properties among all SOBs, POBs and FOBs operating in India using a dynamic panel framework.

# 4 Data and methodology

## 4.1 Data

Individual bank level data for inputs, outputs, input prices as well as bank-specific variables are collected from various issues of *Statistical Tables Relating to Banks in India*.[6] Our sample consists of all state, private and foreign owned commercial banks operating in India during financial year[7] 1998–2015 a period during which banking industry witnessed an intensified competition with more than 100 banks operating in the industry. However, we excluded the regional rural banks and some foreign banks (having less than three branches throughout the sample period) since their levels of operations are different vis-à-vis rest of the commercial banks in India. Further, we have aggregated the balance sheets of merged banks and treated them as a single composite entity for the entire sample period for data compatibility. This is a common practice in the literature (see for instance, Zhao et al. 2010). Moreover, data were cleaned to take care of inconsistencies and outliers. Our final sample is an unbalanced panel of 1062 observations. All nominal values of inputs and outputs are deflated using the wholesale price index with 2004–05 as the base year.

## 4.2 Specification of inputs and outputs

Although there are several approaches for the choice of inputs and outputs used in measuring efficiency or productivity of banking industry, *production approach* (*a* la Benston 1965) and *intermediation approach* (*a* la Sealey and Lindley 1977) dominate the literature. These differ based on whether a bank should ideally be considered as a service provider to its customers or an intermediating entity to channelize funds from savers to investors. In the production approach, banks produce loan and

[6] It is an annual publication of the Reserve Bank of India which provides annual data on balance sheets and profit and loss accounts of individual banks in India.

[7] The financial year 1998 refers to period from year April 1997 to March 1998 and the financial year 1999 refers to the period from April 1998 to March 1999.

deposit account services by using labour and capital as inputs, while in the intermediation approach, banks collect funds using labour and capital and transform them into the loans and other assets. However, there is a longstanding debate whether *deposits* should be treated as input or output because of their dual role. For instance, it may be considered as an *input* since it acts as raw material to produce loans and other investments, or alternatively may be treated as an *output* for its association with substantial amount of liquidity and payment services provided to customers (Berger and Humphrey 1997). The controversy over treatment of deposits has led to the foundation of three variants of the intermediation approach: *asset approach*, *user cost approach* and *value added approach*.[8]

Berger and Humphrey (1997) argue that the intermediation approach is more appropriate when the objective is to evaluate the performance of financial institutions as a whole since it is inclusive of interest expenses, which constitutes a significant share in total costs for these institutions. We use a variant of the intermediation approach to define our inputs and outputs and conceptualize a three output and two input model. We consider (1) Performing loan; (2) Investment; and (3) Other income, as our output variables.[9] Instead of total loans, we have treated *performing loan* as an output since it is the solely component of total loan that generates revenues for banks. Ignoring the quality of bank loans would inflate the efficiency values for banks having more loans even though majority of that is NPAs (Zhao et al. 2008). *Investment* is considered as an output in our study since it's an earning asset for a bank and also due to its overwhelming presence on balance sheets of Indian banks. Apart from loans, Indian banks, particularly in the post deregulation phase, are earning a substantial revenue from non-traditional activities.[10] To take this trend into account, we have included *other income* as one of the outputs. Clark and Siems (2002) highlighted that exclusion of such items underestimates the actual output, which might have implications on the derived efficiency and productivity estimates. Earnings which banks receive from the above outputs include both interest as well as non-interest income. Our two inputs include (1) loanable funds: sum of borrowing and deposits; and (2) Operating costs: sum of labour and capital expenses. The associated prices of these two inputs are measured by ratio of total interest expenses to total loanable funds and ratio of operating cost to total assets respectively. All of these variables are well supported in the literature (see Isik and Hassan 2003; Ray and Das 2010; Zhao et al. 2010; Casu et al. 2013, among others). Summary statistics of inputs and outputs used in our analyses are reported in the Table 2.

[8] For a detailed discussion on these approaches, see Kumar and Gulati (2014).

[9] *Performing loan* is defined as NPAs adjusted advances. *Investment* is the aggregate of government securities, other approved securities, debentures and bonds, shares, subsidiaries and joint ventures and other investments both inside and outside India. *Other income* includes non interest fee-based earnings from commission, exchange, and brokerages.

[10] Non-traditional activities include off-balance sheet items such as forward exchange contracts, guarantees, acceptances, endorsements among others.

**Table 2** Summary statistics of inputs, outputs and input prices 1998–2015

| Variables | Mean | Median | Minimum | Maximum | Std. Dev |
|---|---|---|---|---|---|
| Outputs | | | | | |
| Performing loans | 303,771 | 100,681 | 428 | 7,358,501 | 601,904 |
| Investments | 159,118 | 79,613 | 257 | 2,726,885 | 271,331 |
| Other income | 6785 | 3141 | 12 | 127,786 | 12,594 |
| Inputs | | | | | |
| Operating costs | 10,734 | 5158 | 35 | 272,118 | 22,632 |
| Loanable funds | 469,813 | 195,853 | 503 | 10,100,000 | 861,802 |
| Input prices | | | | | |
| Price of operating costs | 0.0268 | 0.0192 | 0.0054 | 2.8964 | 0.0994 |
| Price of loanable funds | 0.0685 | 0.0592 | 0.0085 | 2.8483 | 0.1222 |

All input and output variables are in ₹ millions and are deflated using 2004–2005 prices

### 4.3 Measuring banking efficiency

Empirical studies generally use two competing approaches for modelling banking efficiency, namely parametric approach, e.g., stochastic frontier analysis (SFA); and mathematical programming-based approach, e.g., data envelopment analysis (DEA). Berger and Humphrey (1997) argue that neither approach is superior to the other since the true level of inefficiency is unknown. While SFA involves the econometric estimation of a pre-specified production, cost or profit function, DEA allows formation of benchmark technology from the observed input output combinations of the banks in the sample without imposing any specific functional form. The potential level of performance is measured by the *envelope* or frontier which is formed by linear combinations of the best practice banks within the sample.

In this study, we use DEA to measure cost efficiency among Indian commercial banks. Instead of employing the static annual DEA frontiers, we employ sequential DEA (Tulkens and Eeckaut 1995; Casu et al. 2013), since static estimates only allow for cross-sectional comparisons without considering changes over time. Sequential DEA assumes that for every year, all previous year technologies are also feasible. Since sequential DEA incorporates past information as well, it is less sensitive than annual DEA indices to the presence or absence of a particular observation in the sample. Thus, sequential DEA frontiers provides a more adequate measure of performance than the standard DEA indices. We employ input-orientation approach since bank managers have more control over inputs (e.g., operating expenses) rather than outputs (e.g., performing loans; other income). Also, Casu and Girardone (2010) argue that it is appropriate to estimate input-oriented rather than output-oriented efficiency during periods of regulatory changes and heightened competition since banks are mainly interested in reducing costs. The input-oriented models aim at minimising the input quantity via improving performance without altering the target output.

Charnes, Cooper and Rhodes (CCR) (1978) introduced DEA to examine the relative performance of decision making units (DMUs). The CCR model is based on the assumptions of constant returns to scale (CRS), free disposability of inputs and outputs and convexity of production possibility set. This model was further extended by Banker, Charnes and Cooper (BCC) (1984) to accommodate variable returns to scale (VRS) technology[11]. We assume here a $p$-inputs—$m$-outputs technology for each bank. Suppose the input price vector for $s^{\text{th}}$ input faced by the $k^{\text{th}}$ bank is $w_s^k$ and $\tilde{x}_s^k$ is the (unknown) quantity of $s^{\text{th}}$ input for $k^{\text{th}}$ bank that minimizes the cost. The optimal value of $\tilde{x}_s^k$ to produce a target output under VRS can be obtained by solving the following linear programming problem.

$$\text{Min} \sum_{s=1}^{p} w_s^{kt} \tilde{x}_s^{kt}$$

s.t.

$$\sum_{i=1}^{n} \sum_{t=1}^{T} \lambda^{it} x_s^{it} \leq \tilde{x}_s^{kt} \quad \forall s = 1, 2, \ldots, p$$

$$\sum_{i=1}^{n} \sum_{t=1}^{T} \lambda^{it} y_r^{it} \geq y_r^{kt} \quad \forall r = 1, 2, \ldots, m \tag{1}$$

$$\sum_{i=1}^{n} \sum_{t=1}^{T} \lambda^{it} = 1$$

$$\lambda^{it}, \tilde{x}_s^{kt} \geq 0 \quad \forall i = 1, 2, \ldots, n; \ \forall t = 1, 2, \ldots, T$$

The above linear programming problem is solved $n$ times, once for each bank in each year in the sample, where $T$ is between 1 and 18. In particular, since we use a sequential frontier, $T$ is 1 for the first period's frontier (which is defined on the basis of the first period's observation alone), $T$ is 2 for the second period's frontier (which is defined on the basis of the first period's as well as second period's observations), and so on. The optimal solution of the above problem yields cost minimizing input bundle. $\tilde{x}_s^{*kt}$is the optimum value of $\tilde{x}_s^{kt}$ in the above linear programming problem. The cost efficiency of the $k^{\text{th}}$ bank is measured as $C = \frac{\sum_{s=1}^{p} w_s^{kt} \tilde{x}_s^{*kt}}{\sum_{s=1}^{p} w_s^{kt} x_s^{kt}} = \frac{c_i^*}{c_i} \leq 1$. An input efficient bank is the one that cannot reduce its input without reducing its output whereas input inefficient bank can reduce input without reducing its output. If $C=1$, the concerned bank is efficient and lies on the *envelope* or frontier, however if $C < 1$ the bank is inefficient. We use BCC model to accommodate more flexibility, since CCR model assumes the restrictive condition that all banks are operating at optimal scale (i.e., minimum point of long run average cost curve).

[11] Interested readers may look at Ray (2004) for an extended description on mathematical programming-based methodologies.

In order to obtain bias corrected cost efficiency scores, we follow the two stage double bootstrap approach proposed by Simar and Wilson (2007). The authors proposed a bootstrapping procedure that accounts for the bias in the efficiency scores in the first stage and the unknown serial correlation in the second stage DEA analysis. The bias corrected estimated efficiency scores estimated in the first stage are then used in a second stage truncated regression to improve statistical inferences. Finally, for identifying the outliers from our sample of banks, we follow the concept of super efficiency model (Anderson and Peterson 1993; Du et al. 2018).

### 4.4 Modelling convergence

We employ the concepts of $\beta$- and $\sigma$-convergences from the growth convergence literature (see Barro and Sala-i-Martin 1991, 1992). While $\beta$-convergence tests for possible catching up, $\sigma$-convergence measures the reduction in disparities among banks over time. $\beta$-convergence is the necessary, but not sufficient, condition for σ-convergence (Sala-i-Martin 1996). In the existing literature on convergence analysis a distinction is also made between unconditional and conditional $\beta$-convergence. While former refers to convergence towards the same point or steady-state, latter relates to convergence towards different points or steady states defined by different peer group characteristics. Since we have already included bank specific variables while estimating cost efficiency, unconditional $\beta$-convergence and $\sigma$-convergence are sufficient as far as our interests are concerned.[12]

To measure the unconditional $\beta$-convergence or whether the improvement in bank's efficiency levels exhibits a negative correlation with the initial level of efficiency we employ the following dynamic equation, following the specification of Casu and Girardone (2010):

$$\Delta \ln \hat{\theta}_{k,t} = \alpha + \beta\left(\ln \hat{\theta}_{k,t-1}\right) + \gamma\left(\Delta \ln \hat{\theta}_{k,t-1}\right) + \varepsilon_{k,t} \tag{2}$$

where $\Delta ln\widehat{\theta}_{k,t} = ln\widehat{\theta}_{k,t} - ln\widehat{\theta}_{k,t-1}$; $\Delta ln\widehat{\theta}_{k,t-1} = ln\widehat{\theta}_{k,t-1} - ln\widehat{\theta}_{k,t-2}$; $\widehat{\theta}_{k,t}$ is the bias corrected cost efficiency of bank $k$ at time $t$; $\widehat{\theta}_{k,t-1}$ is the bias corrected cost efficiency score of bank $k$ at time $t$-1. α, β and γ are parameters to be estimated and $\varepsilon_{k,t}$ is the error term. A statistically significant negative sign for parameter β implies unconditional β-convergence. The higher the coefficient of β in absolute terms the faster is the speed of convergence. However, Eq. (2) tells only whether there is unconditional β-convergence or not. It does not tell us the way through which convergence has occurred, i.e., via least efficient banks or via most efficient banks or from both. In order to find out the direction of convergence, Eq. (2) is modified after following Andries and Capraru (2014):

[12] The bank specific variables, $z_i$ (used in bootstrapping) include size, capital adequacy ratio, liquidity, ownership, whether the bank is listed on the stock market or not, net-NPA to advance ratio and other income to assets ratio. We have not reported second stage results here since our objective is not to find determinants of cost efficiency, however, such results would readily be produced upon readers request.

$$\hat{\theta}_{k,t} - \hat{\theta}_{k,t-1} = \alpha + \beta_1 \hat{\theta}^{-}_{k,t-1} + \beta_2 \hat{\theta}^{+}_{k,t-1} + \in_{k,t} \tag{3}$$

$$\hat{\theta}^{-}_{k,t} = \begin{cases} \hat{\theta}_{k,t}, \text{ if } \hat{\theta}_{k,t} < \bar{\hat{\theta}}_t \\ 0, \text{ if } \hat{\theta}_{k,t} > \bar{\hat{\theta}}_t \end{cases} \tag{4}$$

$$\hat{\theta}^{+}_{k,t} = \begin{cases} \hat{\theta}_{k,t}, \text{ if } \hat{\theta}_{k,t} > \bar{\hat{\theta}}_t \\ 0, \text{ if } \hat{\theta}_{k,t} < \bar{\hat{\theta}}_t \end{cases} \tag{5}$$

where $\bar{\hat{\theta}}_t$ = mean efficiency of Indian banking industry at time $t$. If $\beta_1 < 0$, convergence is said to occur from banks with less mean efficiency than mean score of industry *(catching- up)*. On the other hand, if $\beta_2 < 0$, convergence occurs from banks with more mean efficiency than the industry mean *(lagging-behind)*.

For measuring the σ-convergence, which tests for convergence towards the industrial average we adopt the following autoregressive distributed lag model following Casu and Girardone (2010):

$$\Delta E_{k,t} = \varphi + \sigma E_{k,t-1} + \gamma\left(\Delta E_{k,t-1}\right) + \xi_{k,t} \tag{6}$$

where $\Delta E_{k,t} = E_{k,t} - E_{k,t-1}$; $\Delta E_{k,t-1} = E_{k,t-1} - E_{k,t-2}$;$E_{k,t} = ln(\hat{\theta}_{k,t}) - ln(\bar{\hat{\theta}}_t)$; $E_{k,t-1} = ln(\hat{\theta}_{k,t-1}) - ln(\bar{\hat{\theta}}_{t-1})$; $\bar{\hat{\theta}}_t$ and $\bar{\hat{\theta}}_{t-1}$ refers to mean efficiency of Indian banking industry at time $t$ and $t$-1 respectively; φ, σ and γ are parameters to be estimated and $\xi_{k,t}$ is the error term. A negative value of parameter σ implies unconditional σ-convergence of $\hat{\theta}_{k,t}$ towards $\hat{\theta}_t$. Again, higher the coefficient of σ in absolute terms the greater is the speed of convergence.

## 5 Results and discussion

### 5.1 Empirical findings

The sequentially estimated average BCC-DEA and bias corrected (bootstrap-based) cost efficiency scores for the industry as a whole as well as across different ownership categories are reported in Tables 3 and 4 respectively. The double bootstrap model is estimated using rDEA package in R software. Algorithm #2 of Simar and Wilson (2007) produces bias corrected estimates of efficiency scores and solves the serial correlation simultaneously. We use it with 1500 bootstrapped replications in B1 and 2000 bootstrapped replications in B2.[13] While Simar and Wilson (2007) consider only output oriented technical efficiency, however we use its input oriented counterpart following Badunenko and Tauchmann (2019).

[13] Please see the Appendix A.2 for further clarity on the Algorithm #2 of Simar & Wilson (2007).

**Table 3** BCC-DEA and bias corrected (average) cost efficiency for Indian banking sector

| Year | BCC-DEA | Bias corrected | Lower bound | Upper bound | Bias |
|---|---|---|---|---|---|
| 1998 | 0.945 | 0.922 | 0.903 | 0.952 | 0.020 |
| 1999 | 0.916 | 0.879 | 0.852 | 0.914 | 0.030 |
| 2000 | 0.934 | 0.902 | 0.876 | 0.936 | 0.028 |
| 2001 | 0.916 | 0.879 | 0.851 | 0.915 | 0.031 |
| 2002 | 0.918 | 0.880 | 0.851 | 0.919 | 0.033 |
| 2003 | 0.931 | 0.899 | 0.874 | 0.933 | 0.027 |
| 2004 | 0.928 | 0.899 | 0.875 | 0.933 | 0.026 |
| 2005 | 0.887 | 0.861 | 0.840 | 0.892 | 0.021 |
| 2006 | 0.867 | 0.838 | 0.815 | 0.871 | 0.022 |
| 2007 | 0.872 | 0.842 | 0.819 | 0.874 | 0.023 |
| 2008 | 0.887 | 0.852 | 0.825 | 0.888 | 0.025 |
| 2009 | 0.884 | 0.851 | 0.827 | 0.883 | 0.024 |
| 2010 | 0.884 | 0.853 | 0.831 | 0.885 | 0.021 |
| 2011 | 0.895 | 0.869 | 0.850 | 0.896 | 0.017 |
| 2012 | 0.908 | 0.883 | 0.863 | 0.909 | 0.017 |
| 2013 | 0.912 | 0.888 | 0.869 | 0.911 | 0.018 |
| 2014 | 0.891 | 0.868 | 0.850 | 0.891 | 0.017 |
| 2015 | 0.884 | 0.864 | 0.849 | 0.883 | 0.016 |
| 1998–2015 | 0.903 | 0.874 | 0.851 | 0.904 | 0.023 |

**Table 4** Bias corrected DEA (average) cost efficiency scores

| Year | SOBs | POBs | FOBs |
|---|---|---|---|
| 1998 | 0.952 | 0.859 | 0.951 |
| 1999 | 0.907 | 0.839 | 0.878 |
| 2000 | 0.921 | 0.851 | 0.928 |
| 2001 | 0.909 | 0.862 | 0.848 |
| 2002 | 0.916 | 0.867 | 0.836 |
| 2003 | 0.919 | 0.861 | 0.912 |
| 2004 | 0.912 | 0.858 | 0.928 |
| 2005 | 0.910 | 0.792 | 0.870 |
| 2006 | 0.908 | 0.763 | 0.821 |
| 2007 | 0.917 | 0.788 | 0.791 |
| 2008 | 0.911 | 0.792 | 0.832 |
| 2009 | 0.905 | 0.793 | 0.838 |
| 2010 | 0.907 | 0.801 | 0.833 |
| 2011 | 0.924 | 0.815 | 0.851 |
| 2012 | 0.938 | 0.832 | 0.859 |
| 2013 | 0.943 | 0.828 | 0.874 |
| 2014 | 0.934 | 0.823 | 0.821 |
| 2015 | 0.931 | 0.822 | 0.813 |
| 1998–2015 | 0.920 | 0.825 | 0.860 |

**Table 5** Statistical tests for difference in cost efficiency across different ownerships

| | SOBs vs FOBs | | SOBs vs POBs | | FOBs vs POBs | |
|---|---|---|---|---|---|---|
| | *t* test | Mann–Whitney *U* test | *t* test | Mann–Whitney *U* test | *t* test | Mann–Whitney *U* test |
| 1998–15 | − 5.4*** | − 3.5*** | − 11.8*** | − 5.1*** | 2.7*** | 2.1** |

*** and **Denote significant at 1% and 5% levels respectively

As expected, the average bias corrected cost efficiency of the Indian banking industry was less than the BCC-DEA efficiency estimates. Hence, we use these bias corrected cost efficiency score for inference. The average overall bias corrected cost efficiency (inefficiency) for the Indian banking industry for the entire sample is 87.4% (14.4%).[14] This means that the average Indian bank could have produced the same level of output using only the 87.4% of resources they use, if producing on the frontier. In other words, on an average there was 14.4% input wastage among Indian banks during our sample period. Table 4 indicates a large difference in mean efficiency across various ownership groups. These differences are statistically significant following paired *t* test and Mann–Whitney *U* test as reported in Table 5. State owned banks (SOBs) are found to be most cost efficient, followed by the foreign banks (FOBs). However, domestic private banks (POBs) are observed to be the least cost efficient. The average cost efficiency (inefficiency) during our sample period for state, private and foreign owned banks is 92% (8.6%), 82.5% (21.2%) and 86% (16.2%) respectively. The high cost efficiency of SOBs in India in our study corroborates the findings of Ray and Das (2010) and Sensarma (2005).

To explain, as compared to SOBs, the FOBs and POBs have taken lead in investing in sophisticated technology, computerisation of branches, training of their employees, among others. Although, POBs and FOBs might have made these costly investments with an eye on earning higher revenue, this has resulted in higher costs for these banks. According to Berger and Mester (2003), banks who try to improve the quality of services to their customers incur huge costs, which in turn results in decline in cost efficiency. However, reduction in cost efficiency doesn't mean reductions in profitability. The revenue-based bank operations are not captured in the cost function. In fact, Sensarma (2005) also observes that, state owned banks were cost efficient as compared to privately owned banks, however, it was opposite when profit efficiency was measured. In order to see how profitably the funds have been deployed by the banks, we use *cost to income ratio*. The lower the ratio, more efficiently a bank operates, which results in increasing profitability. The cost to income ratio of banks across different ownership categories is shown in Fig. 1. Two important findings come out of it: (a) cost to income ratio for POBs and FOBs has consistently declined throughout; (b) FOBs have consistently the lowest value of it throughout, however, although

[14] It is important to note that efficiency ($E$) and inefficiency ($IE$) are defined as $E = 1/(1 + IE)$ or alternatively $IE = (1\text{-}\ E)/E$. Thus, 87.4% efficiency means 14.4% inefficiency not 12.6%.

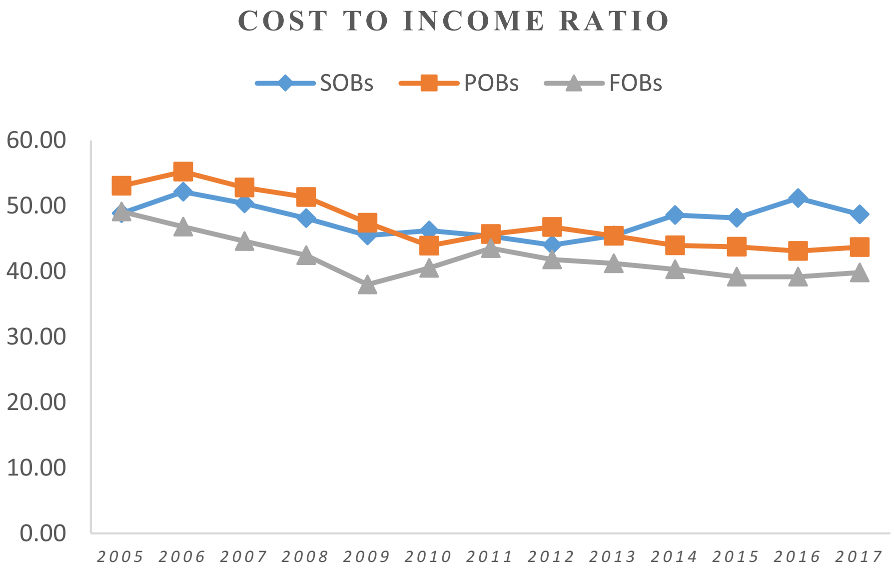


**Fig. 1** Cost to income ratio across different ownership groups. Source: Authors' own compilation using RBI data. Cost to Income Ratio = Operating Expenses/(Other Income + Net Interest Margin)

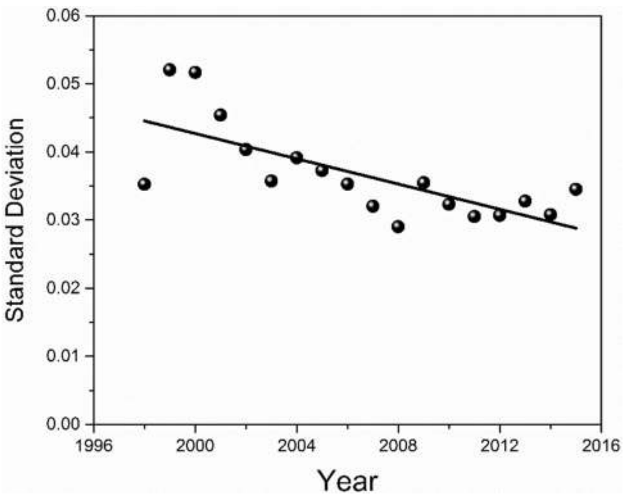


**Fig. 2** Dispersion of efficiency scores amongst SOBs

it is higher for the POBs than that of the SOBs during 2005-09, it has altered afterwards. Thus, our findings are consistent with the hypothesis that private and foreign banks provided additional services or higher service quality, which may have raised costs but also raised revenues by more than the cost increases. Again, less efficiency scores of private banks can be explained by the wave of mergers during 2005–2010,

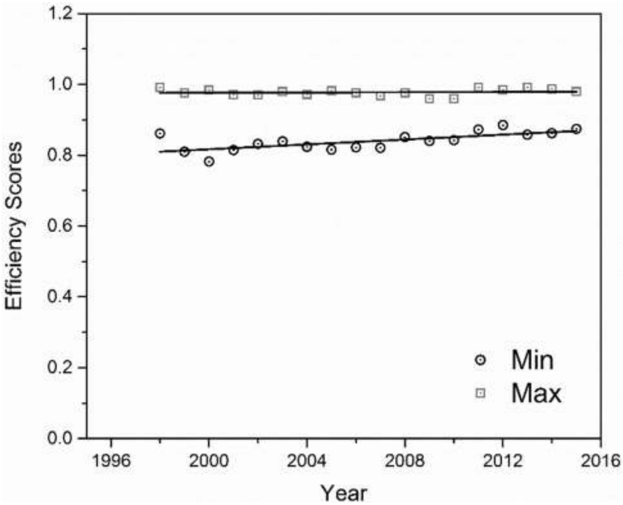


**Fig. 3** Range of efficiency scores amongst SOBs

which might have resulted in higher costs for banks. During 2005–2010, 11 banks underwent mergers, out of which 8 were of privately owned banks, thereby decreasing cost efficiency. The yearly results reflect an improvement in input utilisation in the initial years (1998–2005) when efforts were made by banks towards cost cutting fostered by deregulation and increased competition. However, there has been some increase in input wastage during the financial crisis period (2006–2010).

Before moving to the formal rigorous analyses on the issue of convergence in Indian banking sector, we analyse the dispersion and trends in efficiency levels across different banks. Figure 2 maps the year-wise standard deviation of efficiency scores for state owned banks in our sample.[15] It shows that deviation from average values has declined significantly, thus reflecting convergence in cost efficiency across public sector banks. Since SOBs hold the lions share in the Indian banking sector, we anticipate that there may be the convergence in the performance of overall banking sector as well.

Figure 3 shows the cost efficiency range (i.e., the difference between the highest and the lowest efficiency scores) of public sector banks in India. While highest cost efficiency scores across years have remained fairly stable, the lowest cost efficiency scores have witnessed a slightly increased trend, thereby favouring possible *catching up* of less efficient banks towards the best performing ones.

We evaluate the $\beta$-convergence for our sample of banks by sequential estimation of Eq. (2) using pooled OLS, Fixed effects and GMM models.[16] For making a choice between fixed effect model and random effects model we have conducted

[15] We have done similar prior analysis for all banks in our sample, however, it fails to show any visual trend (in standard deviation of the cost efficiency scores) from which we can formulate some hypothesis.

[16] We have also done similar analysis for yearly frontiers as well. The results are roughly the same. For reasons of space we have not reported annual frontier results, however, the results would be readily available upon request.

**Table 6** Beta convergence

| Coefficients | Without lagged term | | With lagged term | | |
|---|---|---|---|---|---|
| | Pooled OLS | Fixed effects | Pooled OLS | Fixed effects | Two step system GMM |
| β | − 0.1262*** (0.0174) | − 0.3885*** (0.0258) | − 0.1026*** (0.0189) | − 0.4153*** (0.0311) | − 0.7305*** (0.0068) |
| $\gamma$ | | | − 0.0729** (0.0335) | 0.0561* (0.0338) | 0.1656*** (0.0041) |
| $\alpha$ | − 0.0206*** (0.0032) | − 0.0561*** (0.0040) | − 0.0155*** (0.0034) | − 0.0581*** (0.0047) | − 0.0994*** (0.0012) |
| $R^2$ | 0.0506 | | 0.0496 | | |
| $R^2$ Within | | 0.1964 | | 0.1923 | |
| $F$ test | | 226.76*** | | 102.24*** | |
| AR1 $p$ value | | | | | 0.000 |
| AR2 $p$ value | | | | | 0.868 |
| Sargan | | | | | 1.000 |

Standard errors are presented in the parentheses

*, ** and ***Indicate significant at 10%, 5% and 1% respectively

**Table 7** Direction of β-convergence

| Fixed effects model | |
|---|---|
| $\alpha$ | 0.2485*** (0.0279) |
| $\beta_1$ | − 0.2636*** (0.0343) |
| $\beta_2$ | − 0.3143*** (0.0328) |

***Indicate significant at 1% level. Standard errors are presented in the parentheses.

Hausman selection test for both unconditional $\beta$-as well as $\sigma$-convergence. In both the cases, Hausman test allowed us to reject the random effects. We estimate Eq. (2) first without the lagged dependent variable and then with lagged dependent variable for accounting structural and regulatory changes that have taken place in the Indian banking over the years. The results of various models are reported in Table 6. The last column shows the two step system GMM results for the estimated Eq. (2) that attempts to account for endogeneity problem and the omitted variable bias in the estimates (see, Arellano and Bover 1995; Blundell and Bond 1998).[17] For all the models considered, the coefficient of $\beta$ is negative and statistically significant, thus suggesting the presence of unconditional convergence in cost efficiency across banks in India.

As mentioned earlier, results of Eq. (2) only tell us about the presence or absence of $\beta$-convergence, it does not provide any information about the direction of convergence. To investigate the direction of convergence, we estimate Eq. (3) as suggested by Andries and Capraru (2014) and the results are reported in the Table 7. The coefficients of both $\beta_1$ and $\beta_2$ are negative and statistically significant, thereby suggesting that convergence occurs from both sides i.e., from banks with lower efficiency as compared to industry average, as well as from banks having more efficiency than industry average. Thus, our findings validate both "*catching up*" and "*lagging behind*" hypotheses as the sources of the overall convergence scenario in Indian banking. Hence, the above results confirm the presence of strong unconditional $\beta$-convergence in Indian banking industry.

Friedman (1992) argues that for true convergence to exist, $\beta$-convergence has to coincide with $\sigma$-convergence. The results from estimating Eq. (6) have been reported in Table 8. These results complement the results of $\beta$-convergence and show some reduction in dispersion of mean efficiency scores among Indian banks over the entire sample period 1998–2015. The coefficient of $\sigma$ is negative and significant in all the alternative models tested, thereby indicating convergence of individual cost efficiency towards industry average.

One may recall that higher absolute value of the coefficient of $\beta$ and $\sigma$ stand for greater speed of $\beta$ and $\sigma$-convergence respectively. In order to test for the speed of convergence across different ownership categories, we run similar analysis separately for each of such categories and the results are reported in Table 9. The speed of convergence was found highest in SOBs, followed by FOBs and domestic POBs. Thus, results

[17] The system GMM satisfies all the 3 additional conditions i.e., a significant AR (1) serial correlation, lack of AR (2) serial correlation and a valid over identifying restrictions for GMM estimators.

**Table 8** Sigma convergence

| Coefficients | Without lagged term | | With lagged term | | |
|---|---|---|---|---|---|
| | Pooled OLS | Fixed effects | Pooled OLS | Fixed effects | Two step system GMM |
| σ | − 0.1136*** (0.0170) | − 0.3859*** (0.0262) | − 0.0946*** (0.0185) | − 0.4264*** (0.0316) | − 0.7420*** (0.0028) |
| $\gamma$ | | | − 0.0887** (0.0339) | 0.0530 (0.0343) | 0.1548*** (0.0031) |
| $\alpha$ | 0.00005 (0.0021) | 0.00005 (0.0020) | − 0.00003 (0.0022) | 0.0001 (0.0020) | 0.0010 (0.0010) |
| $R^2$ | 0.0430 | | 0.0495 | | |
| $R^2$ Within | | 0.1900 | | 0.1989 | |
| $F$ test | | 217.66*** | | 106.63*** | |
| AR1 $p$ value | | | | | 0.000 |
| AR2 $p$ value | | | | | 0.697 |
| Sargan | | | | | 1.000 |

Standard errors are presented in the parentheses

** and ***Indicates significant at 5% and 1% respectively

**Table 9** Speed of convergence across different ownership categories

| Bank type | Convergence Type | Pooled OLS | Fixed effects | Pooled OLS | Fixed effects | Two step system GMM |
|---|---|---|---|---|---|---|
| SOBs | β-Convergence | – 0.378 | – 0.603 | – 0.295 | – 0.526 | – 0.852 |
| | σ-Convergence | – 0.315 | – 0.481 | – 0.307 | – 0.498 | – 0.788 |
| POBs | β-Convergence | – 0.044 | – 0.249 | – 0.045 | – 0.242 | – 0.203 |
| | σ-Convergence | – 0.037 | – 0.268 | – 0.028 | – 0.240 | – 0.214 |
| FOBs | β-Convergence | – 0.246 | – 0.449 | – 0.234 | – 0.545 | – 0.637 |
| | σ-Convergence | – 0.228 | – 0.437 | – 0.223 | – 0.547 | – 0.602 |

SOBs, POBs, FOBs refer to state owned, private owned and foreign owned banks respectively

of our formal analyses validate our preliminary hypotheses drawn on the basis of graphical plots. However, observed cost efficiency convergence in Indian banking seems to be a combined effect of both "*catching-up*" and "*lagging-behind*" phenomena.

As a robustness check, three input (viz., employees, loanable funds and capital) and three output (viz., investments, performing loans and other income) model is also estimated. The input prices are defined as the ratios of payments and provisions for employees to total employees; the interest expenditure on loanable funds to the total loanable funds; and rent, taxes, lightning, insurance and other administrative expenses to total fixed assets,[18] respectively. The results are reported in the Tables 12, 13, 14, 15 and 16 in "Appendix". The results are similar to our two inputs and three outputs model and reaffirms the robustness of our results.

## 5.2 Measuring competition in banking: Rosse–Panzar model

We employed the Rosse–Panzar test (Rosse and Panzar 1977) to investigate the competition scenario in the Indian banking industry. This is a non-structural test for measuring competition, which takes into account the actual behaviour of banks instead of simply using information regarding the structure of the industry and has been widely applied in banking competition literature (see Matousek et al. 2015; Matthews et al. 2007; Weill 2009 among others). The banking competition is measured by estimating the following log linear revenue equation:

$$\ln TR_{kt} = \alpha_0 + \sum_{s=1}^{p} \gamma_s \ln w_{skt} + \sum_{i=1}^{n} \beta_i \ln X_{ikt} + \varepsilon_{kt} \tag{7}$$

where TR represents the total revenue, $w_s$ denotes the $s^{\text{th}}$ input price *and* $X_i$ denotes the $i^{\text{th}}$ bank-specific characteristics. Subscripts $k$ and $t$ refer to $k^{\text{th}}$ bank at the $t^{\text{th}}$ time period. The model assumes a one-way error component $\varepsilon_{kt} = \mu_k + v_{kt}$ where $\mu_k$ denotes the unobservable bank-specific effect and $v_{kt}$ denotes a random term which is assumed to be IID. Our bank specific factors include *assets*, equity to asset ratio

[18] We follow Ray & Das (2010) to define price of the fixed asset.

**Table 10** Rosse–Panzar tests for measuring competition in Indian banking industry

| Coefficients | 1998–2007 | 2008–2015 | 1998–2015 |
|---|---|---|---|
| Constant | – 0.0403 | – 1.311*** | – 0.833*** |
| | (0.368) | (0.208) | (0.149) |
| Ln(POE) | – 0.152*** | 0.217*** | – 0.0524** |
| | (0.0489) | (0.0313) | (0.0252) |
| Ln(PLF) | 0.211*** | 0.147*** | 0.163*** |
| | (0.0464) | (0.0227) | (0.0242) |
| Ln(ASSETS) | 0.818*** | 1.061*** | 0.924*** |
| | (0.0322) | (0.0153) | (0.0120) |
| Ln(EQASS) | 0.0134 | 0.184*** | 0.0902*** |
| | (0.0459) | (0.0314) | (0.0254) |
| Ln(LFASS) | 0.902*** | 0.599*** | 0.832*** |
| | (0.0854) | (0.0531) | (0.0509) |
| No. of obs | 574 | 488 | 1,062 |
| R-squared within | 0.572 | 0.930 | 0.884 |
| Hypothesis I: H = 0 | F(1, 507) = 3.49* | F(1, 421) = 128.71*** | F(1,995) = 27.61*** |
| Hypothesis II: H = 1 | F(1,507) = 907.90*** | F(421) = 395.95*** | F(1,995) = 1773.96*** |
| H statistic | 0.0585 | 0.3630 | 0.1109 |

Standard errors are presented in parentheses

*, **, and ***Indicate significant at 10%, 5% and 1% respectively

(*EQASS*) and loanable funds to asset ratio (*LFASS*). *Assets* capture the size of a bank, whereas *EQASS* and *LFASS* are used to account for the risk factor. POE and PLF represent the input prices for operating expenses and loanable funds respectively and $\varepsilon_{kt}$ is the stochastic error term. We estimate market power by the estimation of H-statistic which aggregates the elasticities of total revenue to input prices.

$$H = \sum_{s=1}^{p} \gamma_s$$

where H-statistic indicates monopoly, monopolistic or perfect competition if the H takes the value less than or equal to 0, $0 < H < 1$ and 1 respectively. However, some criticism of this model is also there in the literature (e.g., see Bikker et al. 2012).

Table 10 shows results of estimated Eq. (7). We have divided our sample period into two sub-samples, viz., 1998–2007 (i.e., before the GFC) and 2008–2015 (i.e., after the GFC). The results provide some interesting findings. First, the significance test on the sum of the input price elasticities show that the 'H' statistic lies between zero and unity, thus indicating that Indian commercial banks operate under monopolistically competitive market structure. Secondly, H statistic for the post-GFC period has increased significantly to 0.3630 compared to 0.0585 during pre-GFC era, indicating substantial increase in the competition level over time. Thus, the results of H statistic also confirm our prior findings of CR5 and HHI that overall competition level in the Indian banking industry has increased over time. This may be one important influencing factor for the observed convergence of cost efficiency.

## 6 Conclusions

We have investigated convergence in cost efficiency among the Indian commercial banks during 1998–2015. We use sequential DEA frontier approach to measure cost efficiency of banks and the Simar and Wilson (2007) double bootstrap procedure to obtain bias-corrected cost efficiency scores. Since Indian banking has gone through several structural and regulatory changes during this period, we have analysed convergence using a dynamic panel data econometric framework. Further, we have also used non-structural Rosse and Panzar (1977) model to analyse Indian banking, with an effort to link it with the convergence phenomenon.

Our results indicate an improvement in input utilisation among Indian commercial banks during the initial years of our study period. However, it slightly deteriorates during 2006–2010, perhaps due to wave of mergers that happened during this time. We also observe considerable difference in cost efficiency across various ownership categories. The banks under state ownership are the most efficient ones, followed by their counterparts under foreign and domestic private ownerships. As for the convergence in such cost efficiencies is concerned, we observe strong evidence favouring both $\beta$ and $\sigma$-convergence. Further, our findings show that both the *catching-up* and *lagging-behind* processes are responsible for the convergence. Moreover, the speed of convergence is the highest for the state owned banks, followed by foreign owned banks and domestic private banks. Since our findings also indicate gradual improvement in competition over time, we conclude that more competition amongst the banks is one of the influencing factors of convergence of their cost efficiency performance.

Hence, the liberal entry of de novo private and foreign banks and their increased investment on technology have enhanced the level of competition in the Indian banking industry and resulted in convergence in the performance of banks. Our findings, thus, corroborate those of Kumar and Gulati (2009) that financial deregulation programme in India has been successful in achieving its desired goal.

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### Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

## Appendix

### Appendix A.1

See in Table 11.

**Table 11** Summary of efficiency studies in India

| Authors | Sample | Methodology | Approach | Main finding/s |
|---|---|---|---|---|
| Bhattacharyya et al. (1997) | 1986–1991 | DEA | VAA | Financial deregulation had resulted in marginal improvement in the efficiency of Indian banks |
| Khumbhakar and Sarkar (2003) | 1985–1996 | Shadow cost function | VAA | TFP growth in Indian banks in general and PSBs in particular was gloomy during the deregulation period |
| Ataullah and Le (2006) | 1992–1998 | DEA | IA | Economic reforms have created an environment that enabled Indian banks, particularly foreign banks to improve their efficiency after liberalisation period |
| Das and Ghosh (2006) | 1992–2002 | DEA | IA,VAA, OA | Medium sized banks with less non-performing assets performed better during the deregulation period |
| Ray (2006) | 1997–2003 | DEA | IA | A reasonable number of banks in India are too large in size and therefore efficiency gains may be achieved by splitting them into smaller entities |
| Sensarma (2005) | 1986–2003 | SFA | VAA | Cost inefficiencies of Indian banks in general and that of public banks in particular has decreased since deregulation |
| Das and Ghosh (2009) | 1992–2004 | DEA | IA | Liberalisation has resulted improvement in cost and profit efficiency of Indian banks |
| Sahoo and Tone (2009) | 1998–2005 | DEA | IA | Although reforms have a positive impact of Indian banks as a whole however, the nationalised and old private sector banks did not performed well as for as output and resource allocation performances are concerned |
| Zhao et al. (2010) | 1992–2004 | SFA | IA | Deregulation has fostered competition in the industry which in turn had resulted in improvement in the performance of banks |
| Ray and Das (2010) | 1997–2003 | DEA | AA | High level of cost efficiency and relatively lower level of profit efficiency was found among Indian banks. Also, public sector banks were found more efficient than their counterparts under private ownerships |
| Bhandari (2012) | 1999–2007 | DEA, MPI | PA, IA | Public sector banks were found to be more efficient than their private and foreign counterparts |

**Table 11** (continued)

| Authors | Sample | Methodology | Approach | Main finding/s |
|---|---|---|---|---|
| Bhandari (2014) | 1999–2007 | DEA | PA, IA | Size of a bank has a positive impact on the efficiency levels of a bank. Moreover, ownership structure do affect the performance of banks |
| Casu et al. (2013) | 1992–2009 | DEA, MPI | IA | Financial deregulation have resulted in sustained productivity growth in Indian banks. Productivity growth was mainly driven by technological progress |
| Fujii et al. (2014) | 2004–2011 | Russell directional distance model | IA | Foreign sector banks performed reasonably well compared to public and private banks and have pushed the frontier in the banking industry |
| Tzeremes (2015) | 2004–2012 | Conditional directional distance model | IA | Ownership structure do influence the efficiency of banks. Foreign banks performed better compared to national and domestic private banks |
| Gulati and Kumar (2016) | 2004–2013 | DEA | IA | Global financial crisis didn't have an enduring detrimental effect on the performance of Indian banks. However, different ownership groups had adjusted differently to the changes of global financial crisis |
| Badunenko and Kumbhakar (2017) | 1992–2009 | SFA | IA | Banks across different ownerships have reacted differently to both financial deregulation and reregulation. While foreign banks have benefited the most from technological progress, state banks were found to be most cost efficient |

VAA, IA, PA, AA, OA and MPI refer to value-added, intermediation, production, asset and operation approaches and Malmquist productivity index respectively.

## Appendix A.2

Input oriented counterpart of Simar and Wilson (2007)

Algorithm #2

The steps consistent with the input-oriented algorithm are presented below:

1. Estimate the input-oriented efficiency scores $\hat{\theta}_i$ for each bank using (1).

2. Using maximum likelihood method (MLE), estimate the truncated regression of $\hat{\theta}_i$ on $\boldsymbol{z_i}$ to obtain an estimate $\hat{\beta}$ of $\beta$ as well as an estimate $\hat{\sigma}_\varepsilon$ $of$ $\sigma_\varepsilon$ using $m<n$ observations for which $\hat{\theta}_i < 1$.

3. Loop over the next four steps (3.1- 3.4) to obtain a set of B1 bootstrap estimates $\{\hat{\theta}^*_{ib}$ b = 1,…, B1$\}$

3.1. For each bank $i$ = 1,…, n draw an $\varepsilon_i$ from the N(0,$\hat{\sigma}^2_\varepsilon$ ) two sided truncated distribution with left truncation at - $z_i\hat{\beta}$ and right truncation at 1- $z_i\hat{\beta}$.

3.2. Compute $\theta^*_i = z_i\hat{\beta} + \varepsilon_i$ ; $\forall\ i = 1, \ldots, n$

3.3. Generate a pseudo data set $(x^*_i, y^*_i)$ such that $y^*_i = y_i$ and $x^*_i = \frac{x_i}{\theta^*_i}\hat{\theta}$. $\forall\ i = 1,2, \ldots, n$

3.4. Calculate the new DEA estimate $\hat{\theta}^*_i$ from the pseudo data $(x^*_i, y^*_i)$ by replacing

$$Y^* = \{ y^*_i, \ldots, y^*_n \} \text{ and } X^* = \{x^*_i, \ldots, x^*_n\}.$$

4. For each bank $i$ = 1 ,…, n calculate bias corrected efficiency score estimate $\hat{\hat{\theta}}_i = \hat{\theta}_i - \widehat{Bias}\ (\hat{\theta}_i)$ where;

$$\widehat{Bias}\ (\hat{\theta}_i) = \frac{1}{B1}\sum_{b=1}^{B1}\hat{\theta}^*_{ib} - \hat{\theta}_i .$$

5. Use the MLE to obtain estimates ( $\hat{\hat{\beta}}$ , $\hat{\hat{\sigma}}$) from the truncated regression of $\hat{\hat{\theta}}_i$ on $z_i$.

6. Loop the next three steps (6.1-6.3) to obtain set of B2 bootstrap estimates $\{\hat{\hat{\beta}}^*_b, \hat{\hat{\sigma}}^*_b$ , b=1,…, B2$\}$

6.1. For each bank $i$= 1,…,n $\varepsilon_i$ is drawn from N(0, $\hat{\hat{\sigma}}^2_\varepsilon$) two sided truncated distribution with left truncation at - $z_i\hat{\hat{\beta}}$ and right truncation at 1- $z_i\hat{\hat{\beta}}$

6.2. Compute $\theta^{**}_i = z_i\hat{\hat{\beta}} + \varepsilon_i\ \forall\ i = 1, \ldots, n$

6.3. Again using MLE, estimate the truncated regression of $\theta^{**}_i$ $on$ $z_i$ to obtain estimates of $\hat{\hat{\beta}}^*$ $and$ $\hat{\hat{\sigma}}^*$.

7. Calculate confident intervals and standard errors for $\hat{\hat{\beta}}$ $and$ $\hat{\hat{\sigma}}$ from the bootstrap distribution of $\hat{\hat{\beta}}^*$ $and$ $\hat{\hat{\sigma}}^*$.

## Appendix A.3

Input 3 Output Model see in Tables 12, 13, 14, 15 and 16

**Table 12** Bias corrected DEA (average) cost efficiency scores

| Year | SOBs | POBs | FOBs | ALL |
|---|---|---|---|---|
| 1998 | 0.957 | 0.844 | 0.903 | 0.908 |
| 1999 | 0.902 | 0.811 | 0.890 | 0.871 |
| 2000 | 0.919 | 0.845 | 0.921 | 0.891 |
| 2001 | 0.901 | 0.845 | 0.901 | 0.884 |
| 2002 | 0.913 | 0.869 | 0.872 | 0.889 |
| 2003 | 0.922 | 0.862 | 0.928 | 0.905 |
| 2004 | 0.922 | 0.845 | 0.944 | 0.903 |
| 2005 | 0.918 | 0.802 | 0.894 | 0.874 |
| 2006 | 0.914 | 0.755 | 0.838 | 0.842 |
| 2007 | 0.919 | 0.766 | 0.819 | 0.843 |
| 2008 | 0.914 | 0.755 | 0.852 | 0.845 |
| 2009 | 0.904 | 0.763 | 0.846 | 0.843 |
| 2010 | 0.914 | 0.786 | 0.854 | 0.856 |
| 2011 | 0.928 | 0.779 | 0.831 | 0.853 |
| 2012 | 0.937 | 0.809 | 0.846 | 0.871 |
| 2013 | 0.933 | 0.807 | 0.856 | 0.872 |
| 2014 | 0.922 | 0.795 | 0.842 | 0.862 |
| 2015 | 0.916 | 0.800 | 0.836 | 0.858 |
| 1998–2015 | 0.920 | 0.807 | 0.870 | 0.870 |

**Table 13** Beta convergence

| Coefficients | Without lagged term | | With lagged term | | |
|---|---|---|---|---|---|
| | Pooled OLS | Fixed effects | Pooled OLS | Fixed effects | Two step Sys GMM |
| β | – 0.1172*** (0.0164) | – 0.3866*** (0.0260) | – 0.0890*** (0.0173) | – 0.3902*** (0.0299) | – 0.6695*** (0.0033) |
| $\gamma$ | | | – 0.1313*** (0.0329) | 0.0092 (0.0337) | 0.1128*** (0.0036) |
| α | – 0.0197*** (0.0031) | – 0.0571*** (0.0041) | – 0.0142*** (0.0032) | – 0.0562*** (0.0046) | – 0.0932*** (0.0018) |
| $R^2$ | 0.0493 | | 0.0634 | | |
| $R^2$ Within | | 0.1928 | | 0.1995 | |
| $F$ test | | 221.68*** | | 107.01*** | |
| AR1 $p$ value | | | | | 0.000 |
| AR2 $p$ value | | | | | 0.659 |
| Sargan | | | | | 1.000 |

Standard errors are presented in the parentheses

***Indicate significant at 1% level

**Table 14** Direction of β convergence

| Fixed effects model | |
|---|---|
| α | 0.2521*** (0.0270) |
| $\beta_1$ | – 0.2712*** (0.0333) |
| $\beta_2$ | – 0.3196*** (0.0321) |

Standard errors are presented in the parentheses

***Indicate significant at 1% level

**Table 15** Sigma convergence

| Coefficients | Without lagged term | | With lagged term | | |
|---|---|---|---|---|---|
| | Pooled OLS | Fixed Effects | Pooled OLS | Fixed Effects | Two step Sys GMM |
| σ | – 0.1082*** (0.0161) | – 0.3955*** (0.0265) | – 0.0818*** (0.0170) | – 0.4090*** (0.0306) | – 0.6417*** (0.0036) |
| $\gamma$ | | | – 0.1493*** (0.0330) | 0.0071 (0.0340) | 0.0947*** (0.0027) |
| $\varphi$ | – 0.0002 (0.0021) | – 0.0002 (0.0019) | – 0.0002 (0.0021) | – 0.0001 (0.0020) | 0.0046* (0.0020) |
| $R^2$ | 0.0436 | | 0.0655 | | |
| $R^2$ Within | | 0.1936 | | 0.2110 | |
| $F$ test | | 222.80*** | | 114.89*** | |
| AR1 $p$ value | | | | | 0.000 |
| AR2 $p$ value | | | | | 0.696 |
| Sargan | | | | | 1.000 |

Standard errors are presented in the parentheses

* and ***Indicate significant at 10 and 1% respectively

**Table 16 Speed of convergence across different ownership categories**

| Bank type | Convergence type | Pooled OLS | Fixed effects | Pooled OLS | Fixed effects | Two step system GMM |
|---|---|---|---|---|---|---|
| SOBs | β-Convergence | – 0.374 | – 0.6096 | – 0.280 | – 0.600 | – 0.807 |
| | σ-Convergence | – 0.267 | – 0.452 | – 0.256 | – 0.434 | – 0.652 |
| POBs | β-Convergence | – 0.054 | – 0.242 | – 0.048 | – 0.254 | – 0.357 |
| | σ-Convergence | – 0.044 | – 0.259 | – 0.034 | – 0.271 | – 0.390 |
| FOBs | β-Convergence | – 0.245 | – 0.466 | – 0.211 | – 0.508 | – 0.616 |
| | σ-Convergence | – 0.243 | – 0.490 | – 0.204 | – 0.530 | – 0.556 |

SOBs, POBs, FOBs refer to state owned, private owned and foreign owned banks respectively

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