Economic Systems xxx (xxxx) xxx

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

Risk-adjusted efficiency and innovation: an examination of systematic difference and convergence among BRIC banks

Thanh Nguyen[a,*], Son Nghiem[b], Abhishek Singh Bhati[a,c]

[a] School of Business, James Cook University Australia, Singapore Campus, 149 Sims Drive, 387380, Singapore
[b] Department of Health Economics, Wellbeing and Society, National Centre for Epidemiology and Population Health, ANU College of Health and Medicine, The Australian National University, Canberra, ACT 2600, Australia
[c] James Cook University Australia, Singapore Campus, 149 Sims Drive, 387380, Singapore

ARTICLE INFO

JEL Classification:
G21
G32
O33
O57

Keywords:
Efficiency
Innovation, Risk
Convergence
BRIC

ABSTRACT

We argue that technological progress and technology diffusion is improving innovation the banking industry, leading to a potential steady-state equilibrium in operational efficiency and innovation across banks with similar characteristics. Using the latest meta-frontier method, this study examined BRIC banks during the period from 2000 to 2020. We found that Indian and Brazilian banks are more innovative in reducing costs, whereas Indian and Chinese banks are more cost efficient. Chinese, Russian, Indian, and Brazilian banks rank first to fourth in profit efficiency and profit-making innovation, respectively. Risk-taking boosts group cost and profit efficiencies and profit-making innovation but reduces cost-reducing innovation in each country. BRIC banks diverged in innovation during the analysis period but slowly converged after the 2008 crisis. Reform policies, adoption of production technology, formulating regulations and investing in human capital and technologies are crucial for less efficient and innovative banks to catch-up with frontier banks.

1. Introduction

Brazil, Russia, India, and China (BRIC), accounting for 25% of global GDP, have demonstrated the fastest economic growth rates and emerged as a major driving force in the global economy since the 2000 s (Moudud-Ul-Huq, 2021). Banking systems in these countries have undergone several rounds of regulatory and structural reforms towards deregulation, as manifested in their performance, especially in terms of efficiency and risk (Zhang et al. 2013; Bansal, 2012). Although individual countries in the BRIC region have been analysed for bank efficiency, a comparative study of efficiency and innovation across BRIC banks is yet to be conducted. As cost and profit are fundamental to a bank's economic performance (Maudos et al. 2002), the primary focus of our study is to compare cost and profit efficiencies and investigate cost-reducing and profit-making innovations across BRIC banks.

Our study uses the stochastic meta-frontier (SMF) methodology proposed by Huang et al. (2014) to estimate the meta-cost/profit efficiencies which are comparable among BRIC banks. The SMF approach captures technological variations across countries and differentiates random noise from inefficiency. This approach addresses the limitations of the common frontier method, which assumes identical technology across countries, and the deterministic meta-frontier method of Battese et al. (2004) and O'Donnell et al. (2008)

* Corresponding author.
E-mail addresses: nguyen.thanh@jcu.edu.au (T. Nguyen), son.nghiem@anu.edu.au (S. Nghiem), abhishek.bhati@jcu.edu.au (A.S. Bhati).

https://doi.org/10.1016/j.ecosys.2023.101167
Received 25 January 2023; Received in revised form 4 December 2023; Accepted 5 December 2023
Available online xxxx

Please cite this article as: T. Nguyen, S. Nghiem and A.S. Bhati, Risk-adjusted efficiency and innovation: an examination of systematic difference and convergence among BRIC banks, Economic Systems, https://doi.org/10.1016/j.ecosys.2023.101167

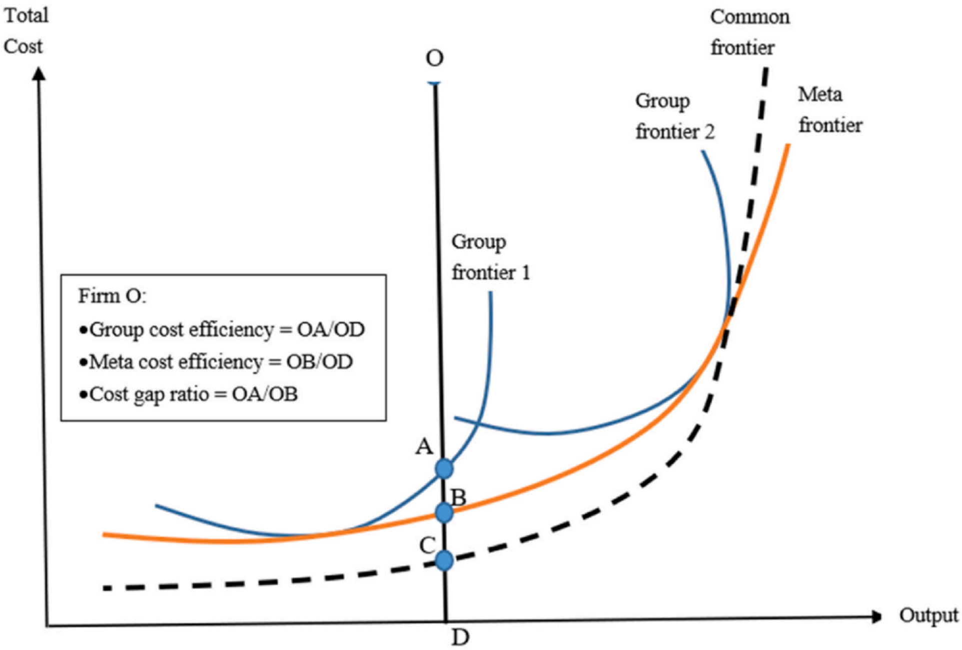

Fig. 1. Group, common, and meta-cost frontiers; group and meta-cost efficiencies and cost-gap ratio.

that attributes all deviations to inefficiency. A bank's meta cost/profit efficiency measures the distance between its actual cost/profit and cost/profit meta-frontier and is determined by the group cost/profit efficiency and the cost/profit gap ratio. Group cost/profit efficiency shows the distance between the bank's actual cost/profit and cost/profit group-specific frontier. The cost/profit gap ratio represents the relative difference between the cost/profit group frontier and the cost/profit meta-frontier. The meta-frontier method encompasses all group frontiers and shows the best available production technology in the group. Therefore, the cost/profit gap ratio serves as a proxy for cost-reducing/profit-making innovation. Fig. 1 is a graphical representation of the various cost frontiers, including group, common, and meta-frontiers. Additionally, it shows different cost efficiencies, such as group cost efficiency, meta-cost efficiency, and the cost-gap ratio of firm O, using the distance function.

In our study, production technology refers to the decision to choose optimal input and output quantities to minimise total costs or maximise profits. That is, bank efficiency and innovation are determined by inputs, outputs, and their respective prices. According to the intermediation approach of Sealey and Lindley (1977), bank outputs include loans, other earning assets, and services, while bank inputs comprise funds, physical capital, and personnel. However, risk-taking activities, such as credit, liquidity, operational, and insolvency risks, also affect bank inputs, outputs, and their prices (Dietrich et al. 2014; Adesina, 2019; Mutarindwa et al. 2020b), thereby impacting bank efficiency and innovation. Previous studies examined the impact of risk-taking on bank efficiency using either a two-stage approach (estimating efficiency in the first stage and the impact of risks on efficiency risks in the second stage) (Saeed et al. 2020; Sakouvogui and Shaik, 2020) or including risks as environmental variables in the frontier models (Lee and Huang, 2019; Le et al. 2020). They only considered a few of the four major risks that are interdependent (Mutarindwa et al. 2020b; Hassan et al. 2019). Only a few studies, such as Matousek et al. (2015) and Qayyum and Riaz (2018), capture the efficiency impact of credit risk through its effect on bank inputs, outputs, and prices by including it as one of the variables used to construct the frontier; that is, the estimated efficiency is adjusted by credit risk. Therefore, our second investigation includes all four major risks in the frontier construction to estimate the risk-adjusted efficiency and innovation of banks in the BRIC region. This allows us to compare the efficiency and innovation of banks in the BRIC region under risk-adjusted and risk-unadjusted cases, providing evidence about the impact of risk-taking on bank efficiency and innovation through its impact on bank inputs, outputs, and prices.

We also argue that technological progress in online banking and business intelligence drives profitability and promotes efficiency and innovation in the banking industry. Consequently, it is plausible that a common steady-state equilibrium in operational efficiency and innovation (i.e. a scenario wherein BRIC banks operate at similar levels of operational efficiency and innovation) can eventually be achieved among banking sectors that share common characteristics. Competitive changes have facilitated technological diffusion, including the increased presence of foreign banks and financial integration. In recent decades, rapid technological diffusion, particularly in core banking solutions, has increased similarities among banking products, reduced price differentials for the same product, and lowered cross-border transaction costs. That is, technological diffusion may foster banks with low levels of efficiency and innovation to catch up with better banks. Viewed from another perspective, with technology diffusion, small banks can innovate and offer products and services tailored to their customers, creating new outputs. However, we believe that these innovations (i.e. creating new tailored outputs), ultimately serve as the means to reach the end (i.e. the bottom line) of banks (or any other business), which aim to increase profits, reduce costs, or both. Thus, we focus on the view that technological diffusion leads to convergence in cost or profit efficiency in the banking sector. Cost-effective innovations, such as new products provided by technological advancements, help banks to allocate resources effectively, leading to improved efficiency. Therefore, our study aims to assess if there is convergence in efficiency and innovation among BRIC banks. Considering the significant changes in competitive banking conditions after the 2008 global financial crisis (GFC), our study examines both the entire analysis period (2000–2020) and the post-GFC period. To evaluate potential convergence, we employed two widely used convergence tests, Barro and Sala-i-Martin's (1992) beta and sigma and the recent gamma (log-t) test proposed by Phillips and Sul (2007).

Using data on BRIC banks from 2000 to 2020, our study finds that Indian and Brazilian banks are more innovative in reducing costs, while Indian and Chinese banks are more cost efficient. The Chinese, Russian, Indian, and Brazilian banks rank first to fourth in profit efficiency and profit-making innovation, respectively. Risk-taking boosts group cost and profit efficiencies, and profit-making innovation but reduces cost-reducing innovation in each country. Banks in the BRIC region diverged in innovation over the analysis period but slowly converged after the 2008 crisis.

Broadly, across countries, banks operate within unique frontiers influenced by factors such as technology, regulation, competition, available resources, and input prices. It is, therefore, essential to estimate the efficiency scores of banks in each country by benchmarking them against their own country's frontier. These distinctive frontiers make it difficult to directly compare the efficiency scores of banks across different countries. However, the development of meta frontiers by Battese et al. (2004), O'Donnell et al. (2008), and Huang et al. (2014) has facilitated the estimation of comparable cross-country efficiencies, with the latter framework addressing the limitations of the former ones. Several studies have utilised the meta-frontier approaches proposed by these researchers to compare bank efficiency across countries. For example, Bos and Schmiedel (2007), Huang et al. (2010), Chen and Yang (2011), Huang and Fu (2013), and Abid et al. (2019) have employed the meta-frontier approach of Battese et al. (2004). Kontolaimou et al. (2012), Nguyen (2018), and Chaffai and Hassan (2019) used the meta-frontier approach developed by O'Donnell et al. (2008). Furthermore, Nguyen et al. (2016), Fontin and Lin (2019), Chaffai and Hassan (2019), and Chaffai and Coccorese (2019) applied the meta frontier approach proposed by Huang et al. (2014). Our study contributes to the literature by employing the latest framework in meta-frontier analysis, that is, the meta-frontier technique introduced by Huang et al. (2014). This allows us to compare bank efficiency across the BRIC countries, representing the first contribution of our research.

Previous comparative studies on bank efficiency focuses on Europe and the MENA region, highlighting the lack of similar research on BRIC banks. Notably, BRICS established the New Development Bank in 2014 for the purpose of mobilising resources for infrastructure and sustainable development projects. Additionally, Russia, China, and India are members of the Shanghai Cooperation Organization, which promotes cooperation across various sectors, while Brazil participates as an observer. In 2015, the BRICS Contingent Reserve Arrangement was formed to provide support during the balance-of-payment pressure. Furthermore, BRICS trade fairs and exhibitions have been organised to strengthen economic ties among the member nations. Bilateral trade agreements have also been signed between the BRIC countries, potentially paving the way for a common BRIC market, and necessitating the adaptation of their financial systems to global market trends. Reforms within the BRIC financial systems are aimed at enhancing bank efficiency and profitability. Our study makes a valuable contribution by estimating the comparative efficiency scores of BRIC banks. This analysis provides benchmarks for less efficient banks to learn from, as they can look to banks with high scores as examples of best practices. Ultimately, this facilitates integration into regional and global financial markets.

Additionally, this study accounts for the spillover effects of the four major risks on efficiency and innovation. Finding the optimal levels of risk and an optimal combination of inputs and outputs could enhance efficiency and innovation in BRIC countries. Moreover, this is the first study to examine if rapid technological progress and diffusion can converge economic efficiency and financial innovation during the 2000–2020 and post-GFC periods. The finding of convergence after 2008 suggests that less efficient and innovative banks can benefit from technology diffusion to reduce the divergence phase.

The remainder of this paper is organised as follows: Section 2 provides a review of the relevant literature and develops the hypotheses. Section 3 provides an overview of our methodology and data. Section 4 discusses the results, and Section 5 presents the conclusions.

2. Literature review and hypothesis development

2.1. Bank efficiency

The two most widely used techniques for estimating bank efficiency are the Stochastic Frontier Analysis (SFA) introduced by Aigner et al. (1977), and Data Envelopment Analysis (DEA) developed by Charnes et al. (1978). The DEA attributes any deviation of the actual observation from the frontier to inefficiency, whereas the SFA attributes the deviation to noise and inefficiency. However, studies employing these techniques to estimate bank efficiency in the BRIC region mainly focused on single countries, with the Brazilian and Russian banks receiving less attention compared to Indian and Chinese banks. Moreover, these efficiency scores cannot be used to compare the efficiency of different banking systems because they are derived from different frontiers.

To address this issue, Weill (2009), Zhang et al. (2013), Matousek et al. (2015), Bitar et al. (2018), Bitar et al. (2020) and others constructed a common frontier when conducting comparative studies across countries. However, only Zhang et al. (2013) focus on banks in the BRIC region and find that Chinese and Brazilian banks outperform Indian and Russian banks in terms of income efficiency. The construction of a common frontier assumes that banks in different countries have the same production technology and can accept the production technology provided by the common frontier without any constraints. These assumptions are difficult to hold because BRIC countries, despite offering similar traditional banking products, such as mobilizing funds through deposits and utilizing funds primarily through loans[1](Kaur et al. 2013; Wahab et al. 2022), have different banking models, technologies, regulatory structures, and environmental factors, which may prevent inefficient banks from accessing the common frontier technology due to regulatory constraints.

Battese et al. (2004), O'Donnell et al. (2008), and Huang et al. (2014) developed non-parametric and stochastic meta-frontiers to encompass all group frontiers, allowing for differences in production technology across countries through the decomposition of meta-efficiency into group efficiency and technology gap. However, only a few studies have employed this meta-frontier framework to compare bank efficiency across countries, such as those comparing low-income countries (Fontin and Lin, 2019), Islamic and conventional banks in the MENA region (Chaffai and Hassan, 2019), MENA countries (Chaffai and Coccorese, 2019), Taiwan and China (Huang and Fu, 2013), and China, India, and Vietnam (Nguyen et al. 2016). Among these studies, only the last is related to the two BRIC countries and focuses on cost efficiency over the period 1995–2011. The findings show that Indian banks are more cost-efficient and innovative than Chinese banks in reducing costs. This result, along with that of Zhang et al. (2013), provides evidence that bank efficiency scores vary across the BRIC countries.

In the BRIC countries, state-owned banks play a crucial role in financing state-led development and deficits. They are more dominant in India and China, whereas foreign banks are prevalent in Brazil and Russia (Zhang et al. 2013). China and Brazil have the highest industry concentrations,[2] while Russia has the highest bank penetration, followed by Brazil.[3] This suggests that banks' market power over inputs and outputs varies across BRIC countries. The banking sector is more developed in China, followed by Brazil, reflecting the differences in loan portfolios across these systems. Although banks in the BRIC region have undergone significant reforms, they are at different stages of development, resulting in variations in competitive and regulatory changes and ongoing regulatory compliance costs. Revenue diversification is the highest in Russian banks and the lowest in Chinese banks,[4] indicating that the structures of bank inputs, outputs, costs, and profits vary across BRIC countries. Additionally, the stock market has developed rapidly in China, followed by India,[5] enabling firms in these countries to raise more capital, which can affect banks' input structures and prices. The macroeconomic and institutional environments in BRIC countries also differ, leading to differences in banks' input–output mix and prices. Therefore, we hypothesised the following:

H_1. Cost and profit efficiencies, and cost-reducing and profit-making innovations vary across BRIC banks.

2.2. Bank risk-taking and efficiency

The growth of credit risk can impede future loan growth if banks tighten lending standards in response to deteriorating loan quality (Foos et al. 2010), but it can enhance loan growth if banks prioritise expanding loans without considering creditworthiness (Malede, 2014). Credit risk assessment aids in determining appropriate credit risk costs, which impact banks' pricing behaviour (Behr and Guettler, 2007). Holding a high volume of liquid assets may lead to a lower lending volume for economic projects, whereas holding a low volume of liquid assets may result in depositors withdrawing their funds if the quality of the lending portfolio deteriorates (Diamond and Rajan, 2005). However, banks with a lower liquidity risk may have lower borrowing costs (Dietrich et al. 2014), greater market power over loans (Tan and Floros, 2018), and higher lending volumes (Mutarindwa et al. 2020b). Banks with greater stability may have more market power over deposits and loans (Kasman and Carvallo, 2014). Liquidity risk is positively correlated with credit and insolvency risks; banks with low liquidity risk may lend less, whereas those with low insolvency risk may lend more (Mutarindwa et al. 2020a). This suggests that banks' risk taking, including credit, liquidity, operational, and insolvency risks, can impact both input and output volumes either separately or in combination.

Several studies have investigated the impact of risk taking on bank efficiency, either through a two-stage approach (Saeed et al. 2020; Sakouvogui and Shaik, 2020) or by including risks as environmental variables in frontier models (Lee and Huang, 2019; Le et al. 2020). However, these approaches may not completely capture the spillover effects of risk taking on bank efficiency through their impact on bank inputs, outputs, and prices. While some studies, such as Matousek et al. (2015) and Qayyum and Riaz (2018), have included credit risk in the frontier construction, credit, liquidity, operational, and insolvency risks are interconnected (Mutarindwa et al. 2020b; Hassan et al. 2019; Ghenimi et al. 2017; Imbierowicz and Rauch, 2014), and our dataset shows differences in these risks across BRIC banks.[6] Therefore, we argue that banks' production decisions involve not only selecting the optimal levels of inputs and outputs but also choosing the optimal risk levels. As risk-adjusted cost or profit efficiency is different from risk-unadjusted cost or profit efficiency, we hypothesise the following:

H2. Risk-taking affects cost and profit efficiencies and cost-reducing and profit-making innovations of BRIC banks.

[1] The authors' calculation from the dataset reveals that the average ratios of deposits to total funding in the BRIC countries are 81.26%, 75.29%, 92.30%, and 95.50%, respectively while the average ratios of loans to earning assets are 59.5%. 74.02%, 64.62%, and 54.44%, respectively.

[2] The average industry concentration in BRIC i 70.54%, 41.03%, 46.58%, and 69.01%, respectively.

[3] The average bank branches per 100,000 adults in BRIC are 19.93%, 31.63%, 12.88%, and 8.44%, respectively.

[4] The average bank non-interest income to total income in BRIC are 37.29%, 59.57%, 31.73%, and 16.93%, respectively.

[5] The average stock market total value traded to GDP (%) in BRIC are 31.84%, 25.51%, 55.77%, and 131.42%, respectively.

Data sources for footnotes 2–5 are authors' calculations based on data obtained from the World Bank's Global Financial Development.

[6] Please see Section 3.2.

2.3. Convergence

Barro and Sala-i-Martin (1992) pioneered the literature on economic convergence by introducing two tests: beta and sigma convergence. In the context of bank services, beta convergence refers to the process by which individual banks with a low initial level of service grow faster than those with high initial levels, thereby catching up. Sigma convergence does not focus on catching-up processes instead emphasises the reduction of dispersion among banks over time. Although beta convergence is necessary, it is insufficient for sigma convergence to occur. The existing literature shows that several studies have employed these convergence tests on bank efficiency, such as Weill (2009) and Andrieş and Căpraru (2014) for European banks' cost efficiency, Carvallo and Kasman (2017) for Latin American banks' cost and profit efficiencies, and Kumar and Gulati (2009) for Indian public banks' cost efficiency. All these studies support beta and sigma convergence in bank efficiency. However, there is a noticeable lack of convergence tests for bank efficiency in the BRIC region.

The beta- and sigma-convergence tests are based on the restrictive assumption that all banks follow the same growth path. To address this limitation, Phillips and Sul (2007) developed the gamma (log t) test that enables different transition paths across banks. This test represents the state of the art in convergence testing and can overcome the drawbacks of beta and sigma tests. Efficiency and innovation in banking are based on the production function concept, which considers two groups of factors that contribute to group efficiency and innovation: common factors (such as the technology shared by all banks) and bank- and country-specific factors (such as managerial ability, institutional and regulatory environments, and government intervention). Gamma convergence occurs when the contribution of common factors becomes substantially larger than that of bank- and country-specific individual factors. Although a few studies have employed the log t-convergence test for bank efficiency, most of them reject overall convergence, and none are specific to the BRIC. For instance, Matousek et al. (2015) reject log t-convergence in technical efficiency for banks in 15 European countries, while Carvallo and Kasman (2017) reject it for cost and profit efficiency for Latin American banks.

China is at the forefront of building closer trade and investment relations in the BRIC region, and this has increased the demand for international banking services and promoted technology spillovers among the best technologies. Over time, BRIC countries have reduced regulatory barriers to cross-border banking (Matthews and Zhang, 2010), which has fostered efficient and low-cost banking and reduced price differentials for the same products (Berger and Smith, 2003). The increased presence of international banks and gradual deregulation have also facilitated the transmission of global banking products and production technologies. Therefore, competition, deregulation, cross-border transactions, and globalisation are believed to have accelerated technological diffusion in the BRIC region. Adopting new production technology is critical for a long-term growth, as it helps less efficient and innovative banks access new customers and funding sources, diversify their earnings, assets, and liabilities, and improve risk management. This enables them to catch up with better-performing banks. Furthermore, diffusion of technological advancements requires banks that are less efficient and innovative to re-evaluate their banking business and adapt their production technology, as this will narrow disparities in both efficiency and innovation.

However, banking institutions in the BRIC region vary in their capacity to absorb new technologies, as this is subject to banking regulations in each country. While technological progress and diffusion have created a common platform among BRIC banks, it may not be sufficient to equalise the cost and profit structures of these banks owing to country- and bank-specific structural differences. Nevertheless, the gradual adoption of the Basel standards for bank capital adequacy, stress testing, and liquidity across BRIC banks after the GFC may have reduced these differences, shortening the divergence period, particularly for banks operating in the same country. Considering these factors, we propose the following hypotheses:

H3a. BRIC banks vary in cost-reducing and profit-making innovations during the period 2000–2020, but converged after the GFC.

H3b. Banks in each BRIC country converge in terms of efficiency and innovation.

3. Methodology and data

3.1. Methodology

3.1.1. Efficiency estimation

To model cost and profit efficiency and innovation across BRIC banks, this study employs SFA and SMF, given that banking data in BRIC are prone to errors in collection, measurement, and accounting.

3.1.1.1. Cost gap ratio and meta-cost efficiency. The first step involves estimating the cost-group-specific frontiers for all bank groups using the dataset for each country. Let C_{it}^{j} denote the total actual cost, which is the sum of interest and non-interest expenses of bank i in year t in group j; X_{it}^{j} denote a vector of outputs and input prices of bank i in year t in group j; and $v_{it}^{j}$and u_{it}^{j} denote the two components random noise and non-negative efficiency, respectively, of the error term. The stochastic frontier of bank i in year t in group j is modelled as follows:

$$C_{it}^{j} = f_{t}^{j}(X_{it}^{j})e^{v_{it}^{j}+u_{it}^{j}} \tag{1}$$

The group cost efficiency (group CE) of bank i in year t in group j with respect to the group j frontier is the ratio of the cost group frontier $f_{t}^{j}(X_{it}^{j})$ adjusted by random noise $e^{v_{it}^{j}}$ and the actual cost C_{it}^{j} as follows:

$$Group \quad CE_{it}^{j} = \frac{f_t^j(X_{it}^j)e^{v_{it}^j}}{C_{it}^j} = e^{-u_{it}^j} \tag{2}$$

In the second step, we conduct a likelihood ratio (LR) test for the null hypothesis that these bank groups have the same technology.[7] If the null hypothesis is rejected, the third step involves estimating the stochastic cost meta-frontier that envelops all the cost group frontiers (Fig. 2) using the following equation:

$$\hat{C}_{it}^{j} = f_t^{M}(X_{it})e^{v_{it}^{*}+u_{it}^{*}} \tag{3}$$

Here, $\hat{C}_{it}^{j} = f_t^j(X_{it}^j)$ is the estimated cost at the group frontier for bank i in year t from Eq. 1; u_{it}^{*} and v_{it}^{*} denote the cost gap ratio and random noise, respectively. The estimated cost $\hat{C}_{it}^{j}$ is the optimal cost incurred if a bank is as efficient as the best-practice bank within its group.

The cost gap ratio for bank i in year t (CGR_{it}) represents the relative difference between the cost meta-frontier $f_t^M(X_{it})$ and the cost group frontier and is calculated as

$$CGR_{it} = \frac{f_t^M(X_{it})}{f_t^j(X_{it}^j)} = e^{-u_{it}^{*}} \tag{4}$$

Similarly, meta-cost efficiency (meta-CE) measures the efficiency of bank i during year t in group j relative to the cost meta-frontier. It is calculated by adjusting the cost meta-frontier using the group frontier noise[8] and dividing it by the actual cost C_{it}^j as follows:

$$Meta \quad CE_{it}^{j} = \frac{f_t^M(X_{it})e^{v_{it}^j}}{C_{it}^j} = \frac{f_t^M(X_{it})}{f_t^j(X_{it}^j)} * \frac{f_t^j(X_{it}^j)e^{v_{it}^j}}{C_{it}^j} = CGR_{it}*Group \quad CE_{it}^{j} \tag{5}$$

3.1.1.2. Profit gap ratio and meta-profit efficiency. We utilise an alternative profit frontier model to estimate the group profit efficiency (group PE) of BRIC banks. This model expresses profit before tax P_{it}^j as a function of output and input prices, and replaces negative profits with $P_{it}^j + \pi$, where $\pi = P_{itmin}^j + 1$, to avoid taking the logarithm of negative profits. The stochastic alternative profit frontier model for the j^{th} group is expressed as

$$P_{it}^{j} = f_t^j(X_{it}^j)e^{v_{it}^j - u_{it}^j} \tag{6}$$

The group PE of bank i in year t in group j is calculated as the ratio of the actual profit P_{it}^j to the group frontier profit $f_t^j(X_{it}^j)$ adjusted by the statistical noise $e^{v_{it}^j}$ as

$$Group \quad PE_{it}^{j} = \frac{P_{it}^j}{f_t^j(X_{it}^j)e^{v_{it}^j}} = e^{-u_{it}^j} \tag{7}$$

If the null hypothesis that all bank groups have identical technology is rejected in the LR test, we estimate the profit meta-frontier which envelops the profit group frontiers (see Fig. 3) using

$$\hat{P}_{it}^{j} = f_t^{M}(X_{it})e^{v_{it}^{*}-u_{it}^{*}} \tag{8}$$

where $\hat{P}_{it}^{j} = f_t^j(X_{it}^j)$ is the predicted profit at the group frontier for bank i in year t from Eq. 6.

The profit gap ratio of bank i in year t (PGR_{it}), which shows the relative gap between the profit meta-frontier $f_t^M(X_{it})$ and the profit group frontier, is

$$PGR_{it} = \frac{f_t^j(X_{it}^j)}{f_t^M(X_{it})} = e^{-u_{it}^{*}} \tag{9}$$

Similar to group PE, meta-profit efficiency (meta-PE) reflects the relative distance between actual profit P_{it}^j and profit meta-frontier, adjusted by the group frontier noise as

$$Meta \quad PE_{it}^{j} = \frac{P_{it}^j}{f_t^M(X_{it})e^{v_{it}^j}} = \frac{P_{it}^j}{f_t^j(X_{it}^j)e^{v_{it}^j}} * \frac{f_t^j(X_{it}^j)}{f_t^M(X_{it})} = PGR_{it}*Group \quad PE_{it}^{j} \tag{10}$$

The risk-adjusted frontier models incorporate the risk measures of bank i in year t within group j. The estimation process for the risk-adjusted groups CE/PE, CGR/PGR, and meta-CE/PE is similar to that for the risk-unadjusted efficiency.

[7] The statistic $LR_s = 2[L(H_a) - L(H_o)]$, where $L(H_o)$ is the value of the log-likelihood function for the common frontier for all groups, and $L(H_a)$ is the sum of the values of log-likelihood from individual cost frontiers.

[8] Please see Huang et al. (2014) for a decomposition of meta CE.

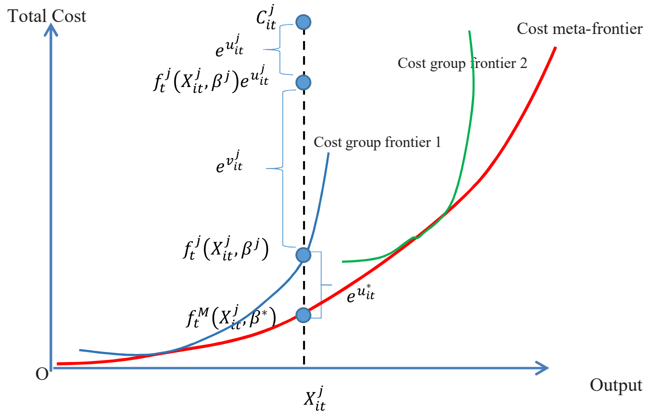

Fig. 2. Cost meta-frontier model.

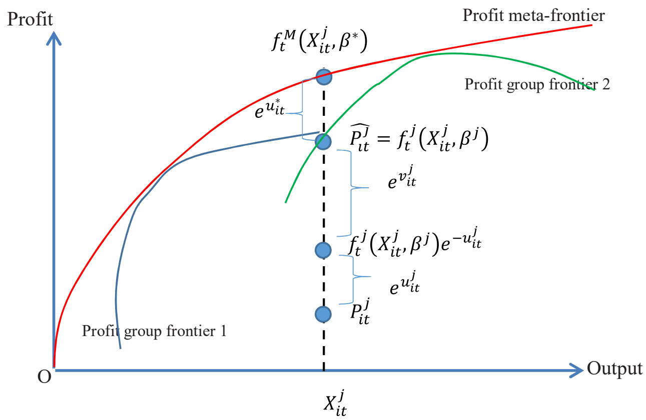

Fig. 3. Profit meta-frontier model.

3.1.1.3. Model specification. This study adopts the intermediation approach of Sealey and Lindley (1977), which considers banks' primary function as the transfer of funds between surplus and deficit units. This approach identifies three inputs, namely funds, fixed assets, and personnel that banks use to generate three outputs: loans (y_1), other earning assets (y_2), and non-interest operating income (y_3). The prices of these inputs are determined by the ratio of interest expense to total funding (w_1) for funds, the ratio of other operating expenses to fixed assets (w_2) for physical capital, and the ratio of personnel expenses to total assets (w_3) for labour. To account for the technical progress that affects both the cost/profit group and meta-frontiers over time, a time trend (t) is included in the function, where t = 1 represents 2000, t = 2 represents 2001, until t = 21 represents 2020. To ensure homogeneity in input prices, the total cost C_{it}^j or profit before tax P_{it}^j, and the prices of funds (w_1) and physical capital (w_2) are divided by the price of labour (w_3). The final specification for the stochastic risk-unadjusted cost group frontier model in Eq. 1 is

$$\ln\left(\frac{C}{W_3}\right) = \alpha_0 + \sum_{m=1}^{3}\alpha_m \ln\ y_m + \frac{1}{2}\sum_{m=1}^{3}\sum_{k=1}^{3}\alpha_{mk}\ln\ y_m \ln\ y_k + \sum_{n=1}^{2}\beta_n \ln\left(\frac{w_n}{w_3}\right) + \frac{1}{2}\sum_{n=1}^{2}\sum_{l=1}^{2}\beta_{nl}\ln(w_n/w_3)\ln\ (w_l/w_3) + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{2}\delta_{mn}\ln y_m \ln(w_n/w_3) + \gamma_1 t + \sum_{m=1}^{3}\gamma_{1+m} t \ln y_m + \sum_{n=1}^{2}\gamma_{3+n} t \ln(w_n/w_3) + v + u \tag{11}$$

To define the stochastic risk-adjusted cost group frontier model, we modify Eq. 11 as follows:

$$\ln\left(\frac{C}{W_3}\right) = \alpha_0 + \sum_{m=1}^{3}\alpha_m \ln y_m + \frac{1}{2}\sum_{m=1}^{3}\sum_{k=1}^{3}\alpha_{mk}\ln y_m \ln y_k + \sum_{n=1}^{2}\beta_n \ln\left(\frac{w_n}{w_3}\right) + \frac{1}{2}\sum_{n=1}^{2}\sum_{l=1}^{2}\beta_{nl}\ln(w_n/w_3)\ln(w_l/w_3) + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{2}\delta_{mn}\ln y_m \ln(w_n/w_3) + \gamma_1 t + \sum_{m=1}^{3}\gamma_{1+m} t\ln y_m + \sum_{n=1}^{2}\gamma_{3+n} t\ln(w_n/w_3) + \sum_{g=1}^{4}\alpha_g \ln r_g + \frac{1}{2}\sum_{g=1}^{4}\sum_{k=1}^{4}\alpha_{gk}\ln r_g \ln r_k + \frac{1}{2}\sum_{g=1}^{4}\sum_{m=1}^{3}\alpha_{gm}\ln r_g \ln y_m + \frac{1}{2}\sum_{g=1}^{4}\sum_{n=1}^{2}\delta_{gn}\ln r_g \ln(w_n/w_3) + v + u \tag{12}$$

where r_1, r_2, r_3, and r_4 represent credit risk (measured by the ratio of loan loss provisions to gross loans), liquidity risk (measured by the ratio of liquid assets to deposits and short-term funding), operational risk (measured by the inverse of the standard deviation of return on assets (ROA) over a three-year period), and insolvency risk (measured by the inverse of the ratio of ROA plus the equity-to-assets ratio to operational risk) of bank i in year t within group j.

By replacing C with P in Eqs. 11 and 12, we obtain the translog specifications for the stochastic risk-unadjusted and risk-adjusted profit group frontiers in Eq. 6, referred to as Eqs. 13 and 14, respectively: Additionally, by replacing the dependent variable in Eq. 11–14 with the predicted cost/profit from the cost/profit group frontiers, we obtain the translog specifications for the stochastic risk-unadjusted and risk-adjusted cost/profit meta-frontiers, denoted as Eq. 15–18. The translog cost and profit functions are estimated using the procedure described by Battese and Coelli (1995).

3.1.2. Gamma (Log t) club convergence

As innovation levels (CGR and PGR) are estimated from the same meta-frontier, while group efficiencies are derived from different group frontiers, we test for convergence in innovation levels (CGR and PGR) among banks in the BRIC region, and convergence in innovation and group efficiency for banks in individual countries. We use a log t-convergence test because it has shown superiority over the beta and sigma convergence tests described in Section 2.3. The following tests were conducted:

The relative transition parameter h_{it}, which describes the transition path for each bank relative to the cross-sectional average in each year, is defined as the ratio of the growth rate of a bank to the average rate for efficiency measure y as follows:

$$h_{it} = \frac{y_{it}}{1/n\sum_{i=1}^{n} y_{it}} \tag{13}$$

Overall, convergence is achieved in the sample when $h_{it} \rightarrow 1$ for all i as $t \rightarrow \infty$. This convergence condition can be expressed as

$$H_t = \frac{1}{n}\sum_{i=1}^{N}(h_{it} - 1)^2 \tag{14}$$

Convergence is documented if $H_t \rightarrow 0$ as $t \rightarrow \infty$. We assume that *log (t)* is a decay function, where γ is the parameter of *log (t)* that indicates the adjustment speed, and e_t is the error term. According to Phillips and Sul (2009), the overall convergence test can be simplified to a one-sided t-test for γ to be non-negative in the following function:

$$\ln\left(\frac{H_1}{H_t}\right) - 2\log(\log(t+1)) = \theta + \gamma \log t + e_t \tag{15}$$

The null hypothesis of convergence is rejected if $t_\gamma < -1.65$. We implemented log t regressions with the Christiano-Fitzgerald filter and discarded the first 30% of the data.

3.2. Data

The dataset comprised131 Chinese banks, 45 Indian banks, 64 Brazilian banks, and 153 Russian banks from 2000 to 2020. Our sample includes domestic commercial banks with complete data for at least five consecutive years. The included banks are categorised as state-owned, privately owned, and city commercial banks for China; public and private sector banks for India; public and private banks for Brazil; and universal banks for Russia. We consider matching the sample based on the bank size or profits that are unnecessary in efficiency studies because the focus is on evaluating resource utilisation and identifying areas for improvement. Primarily, efficiency studies in the banking sector analyse how effectively banks employ their inputs, such as funds, physical capital, and labour, to generate outputs, such as loans, earning assets, and services, and outcomes, such as costs, revenue, and net profit. The objective is to identify opportunities for enhancement and best practices that can optimise the overall efficiency. Therefore, these studies focused on evaluating resource utilisation rather than strictly matching the sample based on bank size or profits.

This dataset was compiled from various sources, including Fitch-IBCA, Bloomberg, and bank websites. During the data collection process for Indian banks, we observed missing data on other earning assets and non-interest income, exclusively for five private-sector banks for the year 2020. To address this, we obtained financial statements directly from the websites of respective banks websites to fill the gaps in the data. The conversion from Indian rupee to US dollars was based on an exchange rate consistent with that used in Bloomberg.

Table 1
Descriptive statistics of variables used for estimating cost and profit efficiency frontiers.

Variable names	Variable notations	Unit measurement	**Chinese banks**		**Indian banks**		**Brazilian banks**		**Russian banks**	
			Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Part A: Dependent variables										
Total cost	TC	Million $	4902.36	13,189.67	1958.12	3249.81	2286.94	7141.64	776.91	2844.76
Pre-tax profit	P	Million $	2367.26	7645.06	276.23	612.84	431.48	1488.14	138.61	1005.42
Part B: Output quantities										
Gross loans	y1	Million $	95,486.63	293,155.91	17,212.32	29,468.27	11,101.29	36,992.90	5466.95	28,649.22
Other earning assets	y2	Million $	61,296.92	162,037.50	8584.09	14,393.99	8601.79	29,250.99	1355.91	5926.58
Total non-interest income	y3	Million $	1102.47	3672.86	411.73	1008.33	530.53	1991.15	376.38	1624.72
Part C: Input prices										
Price of fund	w1	Ratio	0.024	0.018	0.062	0.024	0.126	0.112	0.055	0.025
Price of physical capital	w2	Ratio	0.841	1.171	1.307	1.343	20.529	87.439	19.564	99.973
Price of labour	w3	Ratio	0.005	0.002	0.012	0.008	0.022	0.017	0.023	0.013
Part D: Risk measures										
Credit risk	r1	%	1.074	0.720	1.363	1.423	3.738	4.472	2.360	2.510
Liquidity risk	r2	%	22.519	10.553	475.176	10,584.718	59.413	235.886	48.367	41.836
Operational risk	r3	%	2.949	8.751	21.009	175.638	90.678	245.807	112.312	386.662
Insolvency risk	r4	%	11.437	30.199	12.671	29.004	8.141	17.284	7.240	16.255

Table 1 presents the descriptive statistics of pre-tax profit, total cost, output quantities, input prices, and risk measures which are used to calculate efficiency scores. The gross loan output indicates that Chinese banks are the largest on average, followed by Indian, Brazilian, and Russian. Funding prices are highest for Brazilian banks at an average of 12.6 cents per US$1 of funding, followed by Indian banks at 6.2 cents, Russian banks at 5.5 cents, and Chinese banks at 2.4 cents. Risk measures show that Brazilian banks have the highest credit risk, Chinese banks have the highest liquidity risk, Russian banks have the greatest operational risk, and Indian banks have the highest insolvency risk exposure. These differences in output and input price and risk-taking indicate the need for further research on optimizing banks' costs and profits in the BRIC region.

4. Empirical results

First, we estimate the cost/profit group frontier models (Eq. 11–14) and present the results in Tables A1 (risk-unadjusted) and A2 (risk-adjusted) in the Appendix. Columns 1–4 and 6–9 show the coefficients of outputs, input prices, and time trends, respectively, which are significant when they are single or when interacted with other variables. This indicates the contribution of these factors to the construction of the translog risk-unadjusted/-adjusted cost/profit group frontiers for the Chinese, Indian, Brazilian, and Russian groups. In Table A2, the significance of the risk variables, either alone or while interacted with other variables, justifies their inclusion in the cost/profit group-frontier models. Additionally, the significance of parameters γ confirms the existence of operating cost/profit inefficiency in the error term of these models.

The results of the LR tests in Table A3 in the Appendix show that banks in Brazil, Russia, India, and China operate under four different technologies. Thus, a cost/profit meta-frontier should be employed to compare cost/profit efficiencies across BRIC banks. We estimate the parameters of the translog cost–profit meta-frontier (Eq. 15–18), which are presented in columns 5 and 10 of Tables A1 (risk-unadjusted) and A2 (risk-adjusted). Most parameter estimates are significant, indicating that the cost/profit meta-frontier effectively envelops the four cost/profit group frontiers. Significant parameters γ confirm the existence of technology gaps across BRIC banks. We now discuss the group CE/PE, CGR/PGR, and meta-CE/PE.

4.1. Cost efficiency and cost-reducing innovation and the impact of risk-taking

4.1.1. Cost efficiency and cost-reducing innovation

In this section, we present the results of the risk-unadjusted cost efficiency measures. According to Table 2, Chinese banks have an average group CE of 0.9390, Indian banks 0.9317, Brazilian banks 0.8119, and Russian banks 0.8438 over the period 2000–2020. This suggests that, on average, a typical bank in China (India/Brazil/Russia) could reduce its costs by 6.1% (6.83%/18.81%/15.62%, respectively) by learning from the best-practice banks within the country. However, as these efficiency scores are derived from different group frontiers, they cannot determine which banking system is more cost-efficient.

Table 2 shows that the average CGR for banks in China (India/Brazil/Russia) is 0.9181 (0.9386/0.9368/0.9239, respectively). This implies that a typical bank in China (India/Brazil/Russia) could push its cost group frontier downwards by 8.19% (6.14%/6.32%/7.61%, respectively) by learning from banks in the cost meta-frontier. The t-test results for the equality of CGR across BRIC banks (Table 3) indicate that Indian banks employ cost-reducing techniques that are as advanced as Brazilian banks but slightly better compared to Chinese and Russian banks.

Meta-CE, which is the product of group CE and CGR, is 0.8622 (0.8744/0.7610/0.7797) for a typical bank in China (India/Brazil/Russia), respectively. The results of the t-tests for equal meta CE between countries (Table 3) confirm the differences in meta CE across BRIC banks. Indian banks are the most cost-efficient, driven by the employment of the most innovative cost-reducing technology, closely followed by Chinese banks, which mainly result from the high group CE. Owing to their lower group CE, Russian and Brazilian banks ranked third and fourth, respectively. This finding aligns with Nguyen et al. (2016) study of the comparative cost efficiency and cost-reducing innovation between India and China.

In addition, Fig. 4 shows that Indian and Brazilian banks have consistently higher CGRs than Chinese and Russian banks during most years in the 2000–2020 period, while Fig. 5 demonstrates that Indian and Chinese banks have persistently higher meta-CE than their counterparts. The CGR values for Chinese and Russian banks show a slightly decreasing trend (-0.03% and -0.07% per year, respectively), whereas Indian and Brazilian banks show a slightly improving trend (0.04% and 0.11% per year, respectively) over the same period (Table 2). The meta-CE for Indian and Russian banks show a slightly decreasing trend (0.08% and 0.09% per year, respectively), whereas the trend for Chinese and Brazilian banks is unclear. The sharp decline in the CGR and meta-CE of Russian banks in 2009 and 2015 reflects the adverse impact of the 2008–2009 GFC and the 2015 Russian financial crisis on the cost efficiency of Russian banks. The impact of the GFCon the CGR and meta-CE of the remaining three countries are mild, consistent with the findings of Zhang et al. (2013).

Fig. 6 illustrates that Brazilian banks have the most concentrated range of CGRs closest to the cost meta-frontier, followed by Indian, Russian, and Chinese banks. In contrast, Fig. 7 shows that Indian banks have the highest density of meta CE closest to 1, followed by Chinese banks, and then Russian and Brazilian banks. The Kolmogorov-Smirnov tests (Table 3) support these results indicating different distributions of CGR and meta-CE across BRIC banks.

Overall, the tests confirm the statistically significant differences in meta-CE (cost efficiency) and CGR (a measure of cost-reducing innovation) levels, along with their statistically significant differences in distributions across the BRIC countries. These results offer compelling evidence in support of Hypothesis 1, indicating that both cost efficiency and cost-reducing innovation vary among banks in BRIC nations.

Table 2
Summary statistics of risk-unadjusted group CE, CGR, and meta CE.

	Chinese banks				Indian banks				Brazilian banks				Russian banks			
	Mean	SD	Trend	p value	Mean	SD	Trend	p value	Mean	SD	Trend	p value	Mean	SD	Trend	p value
risk-unadj group CE	0.9390	0.0435	0.0006	$<$ 0.01	0.9317	0.0675	-0.0013	$<$ 0.01	0.8119	0.1260	-0.0012	0.1065	0.8438	0.1007	-0.0003	0.5261
risk-unadj CGR	0.9181	0.0329	-0.0003	0.0887	0.9386	0.0140	0.0004	$<$ 0.01	0.9368	0.0503	0.0011	$<$ 0.01	0.9239	0.0273	-0.0007	$<$ 0.01
risk-unadj meta CE	0.8622	0.0514	0.0003	0.2961	0.8744	0.0634	-0.0008	0.0292	0.7610	0.1259	-0.0001	0.8580	0.7797	0.0971	-0.0009	0.0821

Table 3
Tests of equal means and equal distributions of risk-unadjusted CGR and meta CE across BRIC.

Variable	Dist (CN) = Dist (IN)	Dist (CN) = Dist (BZ)	Dist (CN) = Dist (RS)	Dist (IN) = Dist (BZ)	Dist (IN) = Dist (RS)	Dist (BZ) = Dist (RS)
Part A: p value for Ho: the equality of variable means (t tests)						
risk-unadj CGR	< 0.01	< 0.01	< 0.01	0.2893	< 0.01	< 0.01
risk-unadj meta CE	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Part B: p value for Ho: the equality of variable distributions (Kolmogorov-Smirnov tests)						
risk-unadj CGR	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
risk-unadj meta CE	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.0006

CN: China; IN: India; BZ: Brazil; RS: Russia

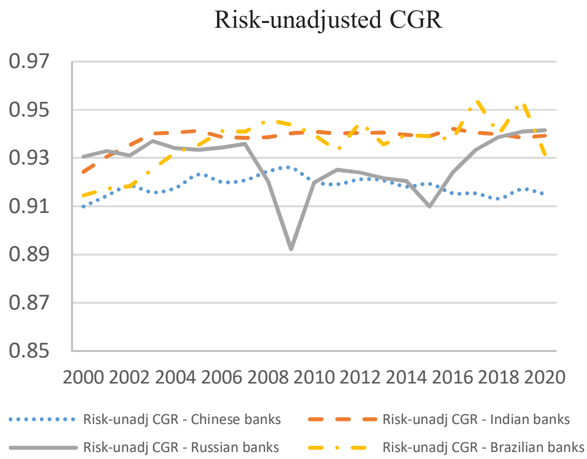

Fig. 4. Risk-unadjusted CGR.

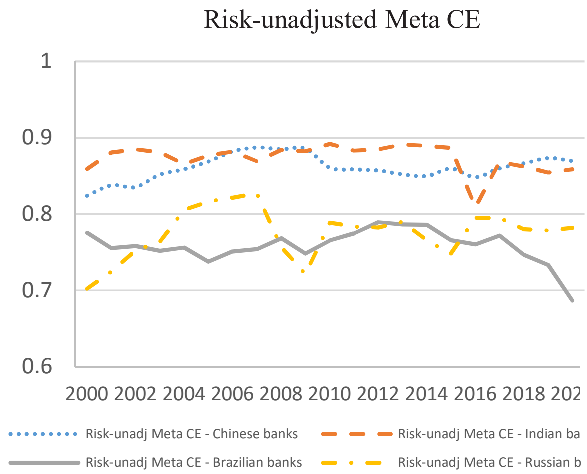

Fig. 5. Risk-unadjusted Meta CE.

4.1.2. *The effects of risk-taking*

After adjusting for risk, the scores in Table 4 confirm that Indian and Brazilian banks are more innovative in reducing costs than Chinese and Russian banks, and that Indian banks are the most cost-efficient, followed closely by Chinese banks. In the risk-adjusted models, Russian banks are the least cost-efficient, whereas Brazilian banks hold this rank in the risk-unadjusted models. The results of the t-tests reject the null hypothesis that the risk-unadjusted and risk-adjusted scores are equal in each country (Table 5), indicating the impact of risk taking on bank efficiency for all measures and confirming Hypothesis 2. In particular, the group CE improves slightly, whereas the CGR deteriorates slightly in BRIC banks after incorporating risks into the frontier models. This implies that under the pressure of risk exposure, BRIC banks may have controlled their costs closer to the cost group frontier, but differences in

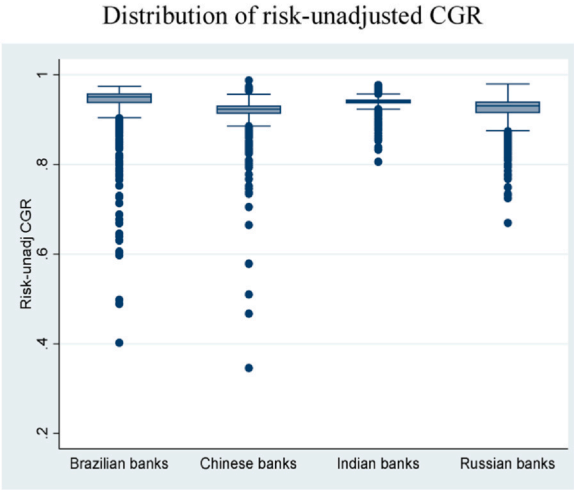

Fig. 6. Distribution of risk-unadjusted CGR.

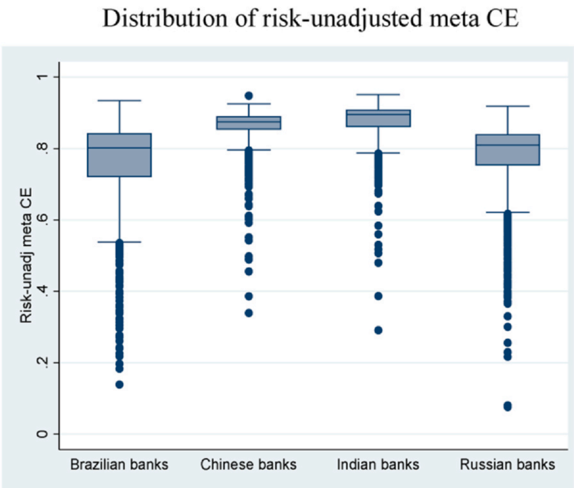

Fig. 7. Distribution of risk-unadjusted meta CE.

their cost-control abilities may have pushed their cost group frontiers slightly further away from the cost meta-frontier. The combined effects of risk-taking on group CE and CGR result in a slight decrease in meta-CE in Chinese and Indian banks (−0.58% and −0.44%, respectively), but a slight increase in meta CE in Brazilian and Russian banks (3.27% and 0.45%, respectively).

4.2. Profit efficiency and profit-making innovation and the impact of risk-taking

4.2.1. Profit efficiency and profit-making innovation

If risks are not accounted for, the average group PE for Chinese (Indian/Brazilian/Russian) banks during the analysis period is 0.8527 (0.8540/0.7769/0.8154) (Table 6). This suggests that a typical Chinese (Indian/Brazilian/Russian) bank could increase its profits by 14.73% (15.60%/22.31%/18.46%) by learning about production technology from banks on its group profit frontier. The average PGR is 0.8724 (0.7639/0.7242/0.8579) for Chinese (Indian/Brazilian/Russian) banks, indicating that a typical Chinese (Indian/Brazilian/Russian) bank can move its group profit frontier upward by 12.76% (23.61%/27.58%/14.21%) by adopting the production technology of banks on the profit meta-frontier.

Table 7 shows that Chinese banks employ the most advanced profit-making techniques, followed by Russian, Indian, and Brazilian banks. The average meta PE of 0.7435 (0.6540/0.5619/0.6996) for Chinese (Indian/Brazilian/Russian) banks and the results of the t-tests in Table 7 indicate that Chinese banks are most profit-efficient, followed by Russian, Indian, and Brazilian banks. As meta-profit efficiency depends on group PE and PGR, which are partly influenced by group CE and CGR, banks (i.e. those with low meta PE) can improve their meta PE by enhancing their group PE, PGR, group CE, and CGR, as stated above.

Figs. 8 and 9 demonstrate that Chinese and Russian banks consistently exhibit higher PGR and meta-PE than their counterparts in most years during the analysis period. Additionally, PGR displays a slightly decreasing trend in Chinese, Indian, and Russian banks

Table 4
Summary statistics of risk-adjusted group CE, CGR, and meta CE.

Country	China				India				Brazil				Russia			
	Mean	SD	Trend	pvalue	Mean	SD	Trend	pvalue	Mean	SD	Trend	pvalue	Mean	SD	Trend	pvalue
risk-adj group CE	0.9547	0.0330	0.0002	0.2620	0.9425	0.0611	-0.0005	0.2145	0.8667	0.0897	0.0004	0.5568	0.8675	0.0886	-0.0002	0.6580
risk-adj CGR	0.9034	0.0430	0.0003	0.1589	0.9246	0.0427	-0.0003	0.3585	0.9164	0.0817	0.0011	0.0492	0.9022	0.0566	-0.0015	0.0000
risk-adj meta CE	0.8624	0.0505	0.0005	0.0727	0.8714	0.0698	-0.0008	0.1131	0.7946	0.1092	0.0014	0.0696	0.7829	0.0952	-0.0015	0.0152

Table 5
t-tests on the equality of risk-unadjusted scores and risk-adjusted scores.

	Ho: Equality between risk-unadjusted scores and risk-adjusted scores							
	Chinese banks		Indian banks		Brazilian banks		Russian banks	
	Risk-adj – Risk-unadj	p value	Risk-adj – Risk-unadj	p value	Risk-adj – Risk-unadj	p value	Risk-adj – Risk-unadj	p value
Group CE	0.0109	< 0.01	0.0102	< 0.01	0.0554	< 0.01	0.0238	< 0.01
CGR	-0.0165	< 0.01	-0.0150	< 0.01	-0.0221	< 0.01	-0.0202	< 0.01
Meta CE	-0.0058	< 0.01	-0.0044	< 0.01	0.0327	< 0.01	0.0045	< 0.01

Risk-adj – Risk-unadj: risk-adjusted score minus risk-unadjusted score

(0.06%, 0.97%, and 0.08% per year, respectively), and a slightly increasing trend in Brazilian banks (0.19% per year). For meta-PE, Indian banks show a slightly declining trend (0.97% per year), whereas Brazilian banks present a slightly improving trend (0.14% per year), with unclear trends observed in Chinese and Russian banks (Table 6). The Kolmogorov-Smirnov test results in Table 7 confirm the different distributions of PGRs and meta-PEs across the four bank groups. Moreover, the Kernel density plots of PGR and meta-PE in Figs. 7 and 8 consistently indicate that Chinese banks have the most concentrated range of PGR and meta-PE, closest to 1, followed by Russian, Indian, and Brazilian banks. These findings support Hypothesis 1.

4.2.2. *The effect of risk-taking*

After controlling for risks, the results support the ranking of Chinese, Russian, Indian, and Brazilian banks as first, second, third, and fourth, respectively, in terms of PGR and meta-PE (Table 8). Referring to the comparative findings of CGR and meta-CE in Section 4.1.1, we can observe that the superior performance of Chinese and Russian banks in PGR and meta-PE may result from better revenue-generating innovation and efficiency, which can be attributed to the greater emphasis these banks place on traditional lending, the primary source of a bank's income. The t-test results in Table 9 indicate that except for Brazilian banks' PGRs, the three risk-adjusted profit efficiency measures are higher than the risk-unadjusted ones, implying the positive effect of risk-taking on the profit efficiency and innovation of BRIC banks (Hypothesis 2). This can be attributed to the likelihood of BRIC banks undertaking risks for higher returns.

4.3. *Convergence*

Part A of Table 10 presents the results of the log-t convergence tests. The first set of tests examines convergence in innovations, namely cost-reducing innovation (CGR) and profit-making innovation (PGR), across 393 banks in the BRIC region between 2000 and 2020. The t-statistics values are below -1.65 (-1.76 and -3.48, column 1), rejecting the null hypothesis of convergence and supporting the alternative hypothesis of divergence in both types of innovation across all 393 banks at a 5% significance level.

However, when the subsample of the post-GFC period is analysed separately, banks converged in cost-reducing and profit-making innovations, but at a slow pace, as the log-t coefficients are not statistically different from zero (column 6). This finding supports Hypothesis 3a.

Convergence tests are conducted for banks operating in the same market environment. Convergence in innovations is detected in Russian banks, with a faster pace in the post-crisis period (columns 5 and 10). The tests also reveal convergence in cost efficiency among Chinese banks (columns 2 and 7) and profit efficiency among Brazilian banks (columns 4 and 9), with a faster pace of convergence after the GFC. Convergence in both cost and profit efficiencies is observed among Russian banks (column 10) and cost efficiency among Indian banks (column 8) only after the GFC, providing evidence for Hypothesis 3b.

Most of these convergences occurred at a faster pace during the post-crisis period, attributable to the extensive regulatory reforms that boosted bank capital and liquidity, thereby pushing laggard banks towards the mean. When risks are adjusted, these convergences are confirmed, as shown in Part B of Table 10. The findings on log-t convergences are robust with the Hodrick-Prescott filter and are confirmed when using beta and sigma convergence tests (Tables A4–A7 in the Appendix).

4.4. *Further investigation*

We conducted an extensive study to identify factors affecting both risk-adjusted and risk-unadjusted meta-efficiency scores. Based on a review of the existing literature, we categorise the determinants of bank efficiency into three groups: bank-specific factors, industry-specific factors, and the macroeconomic environment. Our analysis includes various potential determinants such as bank size (measured by the logarithm of total assets), revenue diversification (ratio of non-interest income to non-interest and interest income), industry competition (concentration ratio of the three largest banks), economic growth, and economic policy uncertainty (EPU). Table 11 shows the results of the Tobit regression analysis, examining the relationship between these determinants and meta-efficiency.

The analysis reveals that larger banks demonstrate higher levels of meta-cost efficiency in both risk-adjusted and unadjusted scenarios. This finding can be attributed to the superior cost-saving technology that larger banks possess, as suggested by previous

Table 6
Summary statistics of risk-unadjusted group PE, PGR, and meta PE.

	Chinese banks				Indian banks				Brazilian banks				Russian banks			
	Mean	SD	Trend	p value	Mean	SD	Trend	p value	Mean	SD	Trend	p value	Mean	SD	Trend	p value
risk-unadj group PE	0.8527	0.0979	0.0012	0.0112	0.8540	0.0926	-0.0023	< 0.01	0.7769	0.1104	-0.0002	0.7424	0.8154	0.1013	- < 0.01	0.9263
risk-unadj PGR	0.8724	0.0394	-0.0006	0.0009	0.7639	0.1091	-0.0097	< 0.01	0.7242	0.1008	0.0019	0.0015	0.8579	0.0438	-0.0008	0.0004
risk-unadj meta PE	0.7435	0.0903	0.0005	0.2662	0.6540	0.1207	-0.0097	< 0.01	0.5619	0.1110	0.0014	0.0366	0.6996	0.0948	-0.0007	0.1522

Table 7
Tests of equal means and distributions for risk-unadjusted PGR and meta PE across BRIC banks.

Variable	Dist (CN) = Dist (IN)	Dist (CN) = Dist (BZ)	Dist (CN) = Dist (RS)	Dist (IN) = Dist (BZ)	Dist (IN) = Dist (RS)	Dist (BZ) = Dist (RS)
Part A: p value for Ho: the equality of variable means (t tests)						
risk-unadj PGR	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
risk-unadj meta PE	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Part B: p value for Ho: the equality of variable distributions (Kolmogorov-Smirnov tests)						
risk-unadj PGR	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
risk-unadj meta PE	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

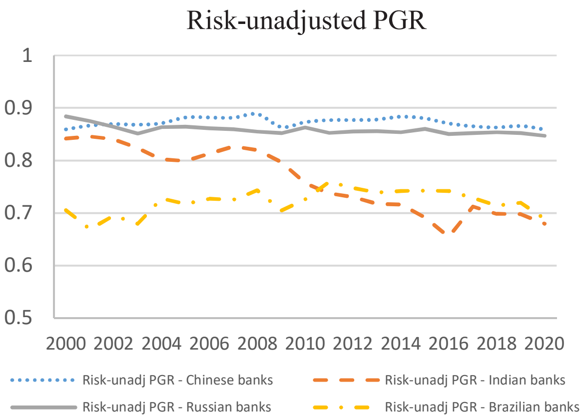

Fig. 8. Risk-unadjusted PGR.

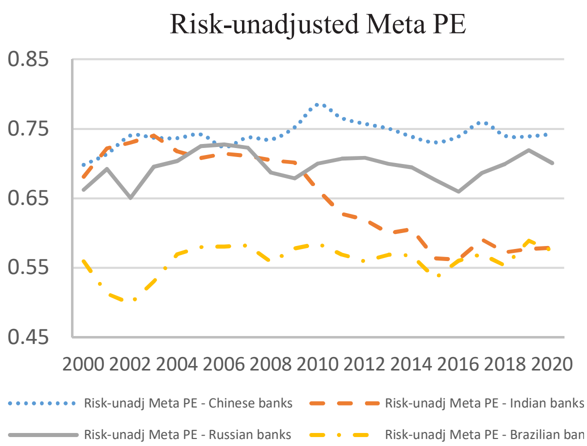

Fig. 9. Risk-unadjusted Meta PE.

studies (Huang and Fu, 2013; Nguyen et al. 2016). Regarding meta-profit efficiency, the positive impact of bank size is statistically insignificant when risk is not considered. However, this became significant when adjusted for risks, and this suggests that banks strive to control costs and enhance their revenue when faced with increased risks. Furthermore, although there is no significant correlation between revenue diversification and meta-cost efficiency, there is a significant and positive association with both risk-adjusted and risk-unadjusted meta-profit efficiency. This finding shows that diversified banks are more effective in generating revenues, contributing to their higher levels of meta-profit efficiency.

The impact of market power, as measured by CR3, on meta-cost efficiency varies. It is significant and negative without risk adjustment but insignificant when adjusting for risks. However, it has a negative impact on both risk-adjusted and risk-unadjusted meta-profit efficiencies. The concentration of banks in BRIC countries, particularly their strong linkages with the public sector that tends to be less profitable, contribute to this outcome.

BRIC banks exhibit higher levels of meta cost and profit efficiency during periods of robust economic performance. This improvement in efficiency across various dimensions is driven by enhanced resource allocation and favourable market conditions. EPU

Table 8
Summary statistics of risk-adjusted group PE, PGR, and meta PE.

Country	China				India				Brazil				Russia			
	Mean	SD	Trend	pvalue	Mean	SD	Trend	pvalue	Mean	SD	Trend	pvalue	Mean	SD	Trend	pvalue
risk-adj group PE	0.9030	0.0616	0.0001	0.8650	0.9205	0.0538	-0.0004	0.2548	0.8546	0.0457	0.0004	0.2674	0.8617	0.0737	-0.0006	0.1807
risk-adj PGR	0.8832	0.0442	-0.0008	0.0006	0.7992	0.0799	-0.0054	0.0000	0.6979	0.1310	-0.0028	0.0017	0.8663	0.0476	-0.0008	0.0050
risk-adj meta PE	0.7974	0.0658	-0.0007	0.0470	0.7358	0.0855	-0.0052	0.0000	0.5960	0.1156	-0.0022	0.0057	0.7466	0.0765	-0.0013	0.0052

Table 9
t-tests on the equality between risk-unadjusted scores and risk-adjusted scores.

Efficiency	Ho: the equality between risk-unadjusted scores and risk-adjusted scores							
	Chinese banks		Indian banks		Brazilian banks		Russian banks	
	Risk-adj - Risk-unadj	p value	Risk-adj - Risk-unadj	p value	Risk-adj - Risk-unadj	p value	Risk-adj - Risk-unadj	p value
Group PE	0.0443	< 0.01	0.0645	< 0.01	0.0777	< 0.01	0.0449	< 0.01
PGR	0.0157	< 0.01	0.0425	< 0.01	-0.0305	< 0.01	0.0093	< 0.01
Meta PE	0.0526	< 0.01	0.0860	< 0.01	0.0307	< 0.01	0.0465	< 0.01

Risk-adj – Risk-unadj: risk-adjusted score minus the risk-unadjusted score.

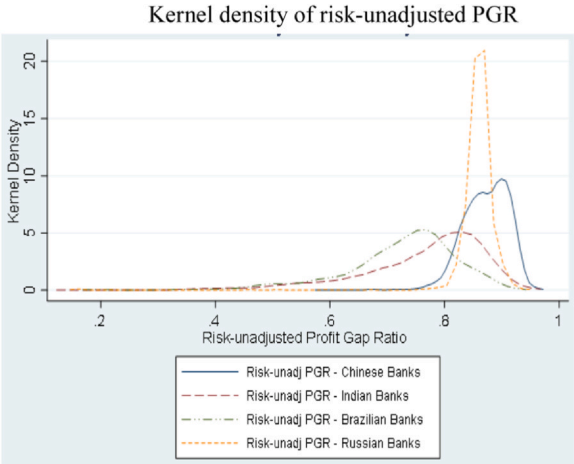

Fig. 10. Kernel density of risk-unadjusted PGR.

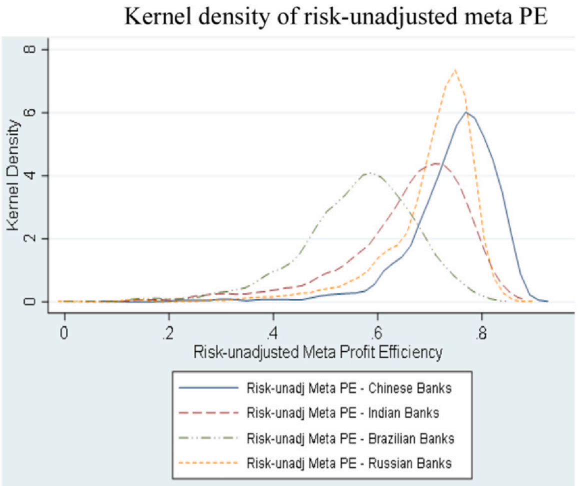

Fig. 11. Kernel density of risk-unadjusted meta PE.

has a positive influence on both risk-adjusted and risk-unadjusted meta-costs and profit efficiencies. One possible explanation is that, during periods of heightened EPU, banks may implement improved cost management strategies (Nguyen et al. 2021), bringing them closer to the meta-cost frontiers. Furthermore, to mitigate potential increases in loan losses as EPU rises (Danisman et al. 2021), banks may adopt more effective profit-making technologies, such as adjusting loan prices (Ashraf and Shen, 2019) and incorporating additional costs into loan contracts (Francis et al. 2014), thereby moving closer to the meta-profit frontier.

The CR3 (concentration ratio of the three largest banks) and GDP Growth data were obtained from the World Bank's Global Financial Development and World Development Indicators, respectively. The data for Economic Policy Uncertainty was collected from the website https://www.policyuncertainty.com/, and the annual mean was used.

Table 10
Gamma (log-t) convergence of CGR, PGR, group CE and group PE.

	Entire period (2000–2020)										**Post GFC crisis (2010–2020)**									
	BRIC		China		India		Brazil		Russia		BRIC		China		India		Brazil		Russia	
	Coef.	t-stat (1)	Coef.	t-stat (2)	Coef.	t-stat (3)	Coef.	t-stat (4)	Coef.	t-stat (5)	Coef.	t-stat (6)	Coef.	t-stat (7)	Coef.	t-stat (8)	Coef.	t-stat (9)	Coef.	t-stat (10)
Part A: Risk-unadjusted																				
Risk-unadj CGR	-1.84	-1.76	-2.99	-5.73	-2.31	-14.11	-3.03	-16.44	**0.39**	**0.20**	**0.65**	**0.66**	-3.06	-5.43	-2.52	-13.51	-1.93	-5.97	**3.21**	**2.74**
Risk-unadj PGR	-1.41	-3.48	-0.87	-4.89	-1.85	-4.92	-1.40	-9.48	**0.22**	**0.14**	**-0.48**	**-1.24**	-1.41	-7.11	-1.31	-12.08	-2.30	-44.15	**3.40**	**3.82**
Risk-unadj group CE			**-0.20**	**-0.40**	-1.05	-2.78	-0.56	-1.98	-2.48	-5.04			**0.23**	**0.52**	**-0.08**	**-0.26**	-2.51	-7.83	**-0.99**	**-1.48**
Risk-unadj group PE			-0.97	-2.41	-2.35	-11.25	**-0.35**	**-0.51**	-1.27	-1.77			-1.72	-19.52	-2.83	-12.39	**0.78**	**2.13**	**1.71**	**2.75**
Part B: Risk-adjusted																				
Risk-adj CGR	-2.75	-3.36	-1.72	-1.89	**0.65**	**0.27**	-1.69	-3.35	-1.64	-1.94	-5.83	-2.91	-3.74	-3.53	**0.20**	**0.26**	-2.99	-3.88	**-0.28**	**-0.52**
Risk-adj PGR	-1.71	-4.98	-2.29	-1.93	**1.78**	**1.38**	**0.73**	**2.60**	**-1.12**	**-1.28**	-2.07	-4.29	-4.75	-3.38	**0.19**	**0.16**	**0.66**	**3.57**	**0.15**	**0.19**
Risk-adj group CE			**-1.14**	**-1.53**	**0.11**	**0.05**	**-0.41**	**-1.22**	-1.47	-1.93			-2.84	-2.88	**0.43**	**0.69**	**-0.39**	**-0.60**	**-0.43**	**-0.69**
Risk-adj group PE			**-1.65**	-1.85	**0.59**	**0.26**	**-0.41**	**-1.35**	**-1.33**	**-1.60**			-3.65	-3.54	**-0.15**	**-0.18**	**-0.63**	**-1.25**	**-0.42**	**-0.64**

Boldfacing indicates that the null hypothesis of the convergence for club merge is not rejected at 5% level of significance.

Table 11
Determinants of meta cost and profit efficiencies.

Dependent variable	Meta CE				Meta PE			
	Risk unadjusted		Risk adjusted		Risk unadjusted		Risk adjusted	
	Coef.	Robust Std Err.	Coef.	Robust Std Err.	Coef.	Robust Std Err.	Coef.	Robust Std Err.
Bank Size	0.0124 * **	(0.0007)	0.0097 * **	(0.0007)	0.0010	(0.0009)	0.0051 * **	(0.0008)
Revenue Diversification	0.0074	(0.0074)	0.0113	(0.0076)	0.0999 * **	(0.0070)	0.0593 * **	(0.0071)
CR3	-0.0004 * **	(0.0001)	0.0001	(0.0001)	-0.0006 * **	(0.0001)	-0.0013 * **	(0.0001)
GDP Growth	0.0072 * **	(0.0004)	0.0065 * **	(0.0004)	0.0111 * **	(0.0006)	0.0092 * **	(0.0005)
Economic Policy Uncertainty	0.0001 * **	(0.0000)	0.0001 * **	(0.0000)	0.0002 * **	(0.0000)	0.0001 * **	(0.0000)
Constant	0.5979 * **	(0.0120)	0.6222 * **	(0.0124)	0.5719 * **	(0.0140)	0.6400 * **	(0.0134)
Observations	5282		4489		5282		4489	

*** and **: 1% and 5% levels of significance, respectively;

5. Conclusion

Our study compares the efficiency and innovation of banks in the BRIC region from 2000 to 2020 using the meta-frontier model proposed by Huang et al. (2014). We also investigate the impact of risk taking on bank efficiency and innovation by including four major risks in the construction of frontiers. We use Phillips and Sul (2007) log t-test to explore the convergence in efficiency and innovation among banks.

Our results indicate that Indian and Brazilian banks are more innovative in reducing costs, whereas Chinese and Indian banks are more cost-efficient. In terms of profit efficiency and profit-making innovation, Chinese, Russian, Indian, and Brazilian banks rank first to fourth, respectively. Risk-taking enhances profit-making innovation (except Brazil), increases group cost and profit efficiencies but reduces cost-reducing innovation in banks in each country. Therefore, risk-taking improves meta-profit efficiency, but it has a mixed effect on meta-cost efficiency (negative in China and India but positive in Brazil and Russia).

BRIC banks vary in cost-reducing and profit-making innovations over the 2000–2020 period but converged after the GFC. Russian banks show convergence during both the analysis and post-crisis periods, with greater speed in the post-crisis period. We observe evidence of convergence in cost efficiency among Chinese banks and profit efficiency among Brazilian banks at a faster pace during the post-crisis period. Convergence seems to have occurred in cost and profit efficiencies among Russian banks and in cost efficiency among Indian banks only after the crisis period.

Based on our comparative efficiency and innovation findings, managers of less efficient and innovative banks should learn and adopt the production technology from the best practices in their country and region. When formulating and implementing bank regulations, regulators of less innovative banking systems (China and Russia for cost-reducing technology, and India, Brazil, and Russia for profit-making technology) should learn from regulators of innovative banking systems. These convergence findings suggest that the continuation of reform policies after the GFC, investment in human capital and technologies that facilitate innovation and deployment of frontier banking technologies, and the formulation of regulations and policies that promote technology diffusion processes are critical for less efficient and/or innovative banks to match with the frontier ones. Further research could examine the possible linkages between innovation, competition, and risk by measuring banks' innovation capacity using a different method.

Declaration of Competing Interest

None.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ecosys.2023.101167.

References

Abid, I., Goaied, M., Ben Ammar, M., 2019. Conventional and Islamic banks' performance in the Gulf cooperation council countries; efficiency and determinants. J. Quant. Econ. 17 (3), 623–665.
Adesina, K.S., 2019. Basel III liquidity rules: the implications for bank lending growth in Africa. Econ. Syst. 43 (2), 100688.
Aigner, D., Lovell, C., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econ. 6 (1), 21–37.
Andrieş, A.M., Căpraru, B., 2014. Convergence of bank efficiency in emerging markets: The experience of Central and Eastern European countries. Emerg. Mark. Financ. Trade 50 (sup4), 9–30.
Ashraf, B.N., Shen, Y., 2019. Economic policy uncertainty and banks' loan pricing. J. Financ. Stab. 44, 100695.
Bansal, S. 2012. An Evaluation of Reforms and comparative perspective on Banking Effeciency in India and China. Management Prudence 3 (1):40.
Barro, R.J., Sala-i-Martin, X., 1992. Convergence. J. Political Econ. 100 (2), 223–251.
Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ. 20 (2), 325–332.
Battese, G.E., Rao, D.P., O'Donnell, C.J., 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J. Product. Anal. 21 (1), 91–103.

Behr, P., Guettler, A., 2007. Credit risk assessment and relationship lending: An empirical analysis of German small and medium-sized enterprises. J. Small Bus. Manag. 45 (2), 194–213.
Berger, A.N., Smith, D.C., 2003. Global integration in the banking industry. Fed. Res. Bull. 89, 451.
Bitar, M., Kabir Hassan, M., Pukthuanthong, K., Walker, T., 2018. The Performance of Islamic Vs. Conventional Banks: Evidence on the Suitability of the Basel Capital Ratios. Open Econ. Rev. 29 (5), 1003–1038.
Bitar, M., Pukthuanthong, K., Walker, T., 2020. Efficiency in Islamic vs. conventional banking: The role of capital and liquidity. Glob. Financ. J. 46, 100487.
Bos, J.W., Schmiedel, H., 2007. Is there a single frontier in a single European banking market? J. Bank. Financ. 31 (7), 2081–2102.
Carvallo, O., Kasman, A., 2017. Convergence in bank performance: evidence from Latin American banking. North Am. J. Econ. Financ. 39, 127–142.
Chaffai, M., Coccorese, P., 2019. How far away is the MENA banking system? Efficiency comparisons with international banks. North Am. J. Econ. Financ. 49, 378–395.
Chaffai, M., Hassan, M.K., 2019. Technology gap and managerial efficiency: a comparison between Islamic and conventional banks in MENA. J. Product. Anal. 51 (1), 39–53.
Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.
Chen, K.-H., Yang, H.-Y., 2011. A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: with application to banking industries in Taiwan and China. J. Product. Anal. 35, 197–212.
Danisman, G.O., Demir, E., Ozili, P., 2021. Loan loss provisioning of US banks: Economic policy uncertainty and discretionary behavior. Int. Rev. Econ. Financ. 71, 923–935.
Diamond, D.W., Rajan, R.G., 2005. Liquidity shortages and banking crises. J. Financ. 60 (2), 615–647.
Dietrich, A., Hess, K., Wanzenried, G., 2014. The good and bad news about the new liquidity rules of Basel III in Western European countries. J. Bank. Financ. 44, 13–25.
Fontin, J.-R., Lin, S.-W., 2019. Comparison of banking innovation in low-income countries: a meta-frontier approach. J. Bus. Res. 97, 198–207.
Foos, D., Norden, L., Weber, M., 2010. Loan growth and riskiness of banks. J. Bank. Financ. 34 (12), 2929–2940.
Francis, B.B., Hasan, I., Zhu, Y., 2014. Political uncertainty and bank loan contracting. J. Empir. Financ. 29, 281–286.
Ghenimi, A., Chaibi, H., Omri, M.A.B., 2017. The effects of liquidity risk and credit risk on bank stability: Evidence from the MENA region. Borsa Istanb. Rev. 17 (4), 238–248.
Hassan, M.K., Khan, A., Paltrinieri, A., 2019. Liquidity risk, credit risk and stability in Islamic and conventional banks. Res. Int. Bus. Financ. 48, 17–31.
Huang, C.J., Huang, T.-H., Liu, N.-H., 2014. A new approach to estimating the metafrontier production function based on a stochastic frontier framework. J. Product. Anal. 42 (3), 241–254.
Huang, M.-Y., Fu, T.-T., 2013. An examination of the cost efficiency of banks in Taiwan and China using the metafrontier cost function. J. Product. Anal. 40 (3), 1–20.
Huang, T.-H., Chiang, L.-C., Chen, K.-C., Chiu, P.-H., 2010. An application of the meta-frontier cost function to the study of bank efficiencies and technology gaps in 16 European countries. Manag. Rev. 29 (1), 25–43.
Imbierowicz, B., Rauch, C., 2014. The relationship between liquidity risk and credit risk in banks. J. Bank. Financ. 40, 242–256.
Kasman, A., Carvallo, O., 2014. Financial stability, competition and efficiency in Latin American and Caribbean banking. J. Appl. Econ. 17 (2), 301–324.
Kaur, M., Yadav, S.S., Gautam, V., 2013. Financial system development and foreign direct investment: A panel data study for BRIC countries. Glob. Bus. Rev. 14 (4), 729–742.
Kontolaimou, A., Kounetas, K., Mourtos, I., Tsekouras, K., 2012. Technology gaps in European banking: Put the blame on inputs or outputs? Econ. Model. 29 (5), 1798–1808.
Kumar, S., Gulati, R., 2009. Did efficiency of Indian public sector banks converge with banking reforms? Int. Rev. Econ. 56 (1), 47.
Le, M., Hoang, V.-N., Wilson, C., Managi, S., 2020. Net stable funding ratio and profit efficiency of commercial banks in the US. Econ. Anal. Policy 67, 55–66.
Lee, C.-C., Huang, T.-H., 2019. What causes the efficiency and the technology gap under different ownership structures in the Chinese banking industry?: what causes the technology gap in Chinese banking? Contemp. Econ. Policy 37 (2), 332–348.
Malede, M., 2014. Determinants of Commercial Banks Lending: Evidence from Ethiopian Commercial Banks. Eur. J. Bus. Manag. 6 (20), 109–117.
Matousek, R., Rughoo, A., Sarantis, N., Assaf, A.G., 2015. Bank performance and convergence during the financial crisis: Evidence from the 'old'European Union and Eurozone. J. Bank. Financ. 52, 208–216.
Matthews, K., Zhang, N., 2010. Bank productivity in China 1997–2007: Measurement and convergence. China Econ. Rev. 21 (4), 617–628.
Maudos, J. n, Pastor, J.M., Perez, F., Quesada, J., 2002. Cost and profit efficiency in European banks. J. Int. Financ. Mark., Inst. Money 12 (1), 33–58.
Moudud-Ul-Huq, S., 2021. Does bank competition matter for performance and risk-taking? empirical evidence from BRICS countries. Int. J. Emerg. Mark. 16 (3), 409–447.
Mutarindwa, S., Schäfer, D., Stephan, A., 2020a. The impact of liquidity and capital requirements on lending and stability of African banks. J. Int. Financ. Mark., Inst. Money 67, 101201.
Mutarindwa, S., Schäfer, D., Stephan, A., 2020b. The impact of liquidity and capital requirements on lending and stability of African banks. *Journal of International Financial Markets*. Inst. Money 67, 101201.
Nguyen, T.P.T., 2018. Comparison of efficiency and technology across the banking systems of Vietnam, China and India: A stochastic cost and revenue meta-frontier approach. Benchmark.: Int. J. 25 (9), 3809–3830.
Nguyen, T.P.T., Nghiem, S., Tripe, D., 2021. Does oil price aggravate the impact of economic policy uncertainty on bank performance in India? Energy Econ. 104, 105529.
Nguyen, T.P.T., Nghiem, S.H., Roca, E., Sharma, P., 2016. Efficiency, innovation and competition: evidence from Vietnam, China and India. Empir. Econ. 51 (3), 1235–1259.
O'Donnell, C.J., Rao, D.P., Battese, G.E., 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empir. Econ. 34 (2), 231–255.
Phillips, P.C.B., Sul, D., 2007. Transition modeling and econometric convergence tests. econometrica 75 (6), 1771–1855.
Phillips, P.C.B., Sul, D., 2009. Economic transition and growth. J. Appl. Econ. 24 (7), 1153–1185.
Qayyum, A., Riaz, K., 2018. Incorporating credit quality in bank efficiency measurements: a directional distance function approach. J. Risk Financ. Manag. 11 (4), 78.
Saeed, M., Izzeldin, M., Hassan, M.K., Pappas, V., 2020. The inter-temporal relationship between risk, capital and efficiency: The case of Islamic and conventional banks. *Pacific-Basin Finance*. Journal 62, 101328.
Sakouvogui, K., Shaik, S., 2020. Impact of financial liquidity and solvency on cost efficiency: evidence from US banking system. Stud. Econ. Financ.
Sealey Jr, C.W., Lindley, J.T., 1977. Inputs, outputs, and a theory of production and cost at depository financial institutions. *J. Financ. (N. Y.)* 32 (4), 1251–1266.
Tan, Y., Floros, C., 2018. Risk, competition and efficiency in banking: Evidence from China. Glob. Financ. J. 35, 223–236.
Wahab, S., Imran, M., Safi, A., Wahab, Z., Kirikkaleli, D., 2022. Role of financial stability, technological innovation, and renewable energy in achieving sustainable development goals in BRICS countries. Environ. Sci. Pollut. Res. 29 (32), 48827–48838.
Weill, L., 2009. Convergence in banking efficiency across European countries. J. Int. Financ. Mark., Inst. Money 19 (5), 818–833.
Zhang, J., Jiang, C., Qu, B., Wang, P., 2013. Market concentration, risk-taking, and bank performance: Evidence from emerging economies. Int. Rev. Financ. Anal. 30, 149–157.