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Productivity analysis of Sri Lankan cooperative banks: input distance function approach

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Abstract

This study examined how Sri Lankan cooperative banks performed in changing markets and environmental conditions, including the COVID-19 pandemic. We analyzed quarterly financial data for 103 cooperative rural banks (CRBs) between 2016 and 2020 to estimate technical efficiency and total factor productivity (TFP) using the input distance function with multiple outputs. The technical efficiency (TE) of CRBs declined from 99 to 85% over the period and differences in TE between banks increased substantially. TFP decreased substantially, by 38%, so for further analysis, TFP change was separated into a three component-scale change, technical change, and technical efficiency change. According to TFP decomposition, the dominant factor contributing to this decline was the scale change. The loan relief program enacted during the COVID-19 crisis, as well as increased competition in the market, may have reduced the size of operations, thus possibly contributing to this decline. The second component, technical change was overall positive, but minute likely due to the reluctance of cooperative banks' to adopt new technologies. The third component technical efficiency change was negative throughout the period, likely due to increased operating expenses and non-performing loans. These findings suggest the need for a more market-sensitive government intervention, adaptation of modern technology, and comprehensive human resource development to enhance the performance of CRB operations.

Keywords Input distance function · Sri Lankan cooperative banks · Technical efficiency · Total factor productivity · Productivity decomposition

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JEL Classification C33 · D24 · G21

1 Introduction

Cooperative banks are financial institutes functioning under specific cooperative principles and are non-profit-driven.[1] They provide regular banking services as well as credits to their members. The business model of cooperative banks is different from those of traditional commercial banks. While traditional commercial banks are investor-owned, cooperative banks are owned by their members. The working capital of cooperative banks is thus formed by the shares of their members, and every member is entitled to vote to elect the board of directors. They aim to enhance consumer surplus to have maximum benefits for their members (Groeneveld 2012). In 2010, European cooperative banks were holding around 20% of the share of loans and deposits in their domestic markets (Birchall and International Labour Office 2013). Cooperative banks have been resilient to environmental changes (Groeneveld 2012; Roelants et al. 2012). For example, they outperformed traditional investor-owned banks during the global financial crisis, from 2007 to 2010, and have increased their customer base by 14% and assets by nearly 10% (Birchall and International Labour Office 2013). On the other hand, Italian cooperative banks suffered from the recession and over time showed a decline in efficiency (Barra et al. 2013). According to a study by Pasiouras et al. (2007), the technical efficiency of Greek cooperative banks has been negatively affected by GDP per capita and the unemployment rate in the geographical area. Thus, it would be important to examine their recent performance in challenging environmental conditions including the COVID-19 pandemic.

In 2018, the percentage of the population using credit unions is 48.88% in North America, 9.16% in Europe, and only 4.34% in Asia (McKillop et al. 2020). Despite the lower figure in Asia, cooperative banks are prominent in Sri Lanka, the focus of this study. According to the bank division of the Department of Cooperative Development (DCD) of Sri Lanka, more than 30% of the population is using one of the three forms of financial cooperatives in Sri Lanka, namely cooperative rural banks (CRBs), thrift and credit cooperative societies, and other financial services cooperative societies. Among them, CRBs are considered to be more financially stable, as they function under well-established multi-purpose cooperative societies (MPCSs), which are formed by the integration of several business entities such as retail shops, fuel stations, and communications centers. In other words, CRBs are membership-based banking systems, and their operations are restricted to a specific area determined by an MPCS. As stated in the mid-year statistics of DCD in 2020, CRB deposits of over Sri Lankan rupees (LKR) 139 billion were recorded in Sri Lanka, nearly 50% being loaned out to their members. Their prominence stems from the fact that the agriculture sector

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[1] These are open and voluntary membership, democratic member control, members' economic participation, autonomy and independence, education, training, and information, cooperation among cooperatives, and concern for the community (Nilsson 1996).

and small and medium enterprises account for a considerable portion of the credit needs of the population, and traditional commercial banking sectors are not willing to lend such small amounts. In the past decade, CRB operations have been challenged by the increased competition of newly entered microfinance institutions in the market and more recently by the effect of the COVID-19 pandemic.

The current study examines the economic performance of cooperative banks in Sri Lanka, with a focus on CRBs. Studies on the productivity of cooperative banks are relatively scarce in the productivity analysis literature. Most extant productivity analyses have focused on traditional commercial banks and state banks. Their findings are summarized in studies such as Berger and Humphrey (1997), Berger (2007), and Maudos and Pastor (2001). Although several studies focus on cooperative banks, the majority have been carried out in developed countries, mostly in Europe (Lang and Welzel 1996 for Germany; Molyneux and Williams, 2005; Barros et al. 2010; Kontolaimou and Tsekouras 2010; Spulbăr et al. 2015 for Europe; Battaglia et al. 2010 for Italy; Glass et al. 2014; Yamori et al. 2017 for Japan). We identify only a few studies on developing countries, particularly in Asia (Feroze, 2012 for India; Jayamaha and Mula 2011; Jayamaha 2014 for Sri Lanka; Mirasol and Garcia 2020 for the Philippines; Othman et al. 2013 for Malaysia). Most of these studies have used a nonparametric approach with a single performance measure, and none has provided productivity decompositions. Addressing this research gap, the current study contributes to the literature by using stochastic input distance function estimations that handle multiple outputs and allow to decompose productivity of cooperative banks in the emerging economies. Our study would be innovative since to the best of our knowledge, we would be the first to use the input distance function approach with multiple outputs to decompose the productivity of cooperative banks in emerging Asian economies and to empirically examine the effect of government regulations enacted during COVID-19 on their performance.

The objectives of this study are, thus, (1) to empirically examine the performance of Sri Lankan cooperative banks by estimating technical efficiency and TFP, (2) to decompose TFP change to recognize the contribution of each component to the productivity change of cooperative banks and (3) to identify the effect of changing market and environmental conditions on the cooperative banking industry including the COVID-19 pandemic.

To this end, we use a unique set of cooperative banking sector data restructured and compiled from quarterly financial reports of CRBs produced to the Provincial Department of Cooperative Development, Sabaragamuwa Province during the period 2016–2020. This data set contains interest, salary, and other operating expenses as inputs. We also use multiple output measures—interest and other operating revenues. Since we do not have clear price data, we adopt the input distance function method introduced by Shephard (1953), which permits multiple outputs to estimate technical efficiency (TE) while allowing us to decompose total factor productivity (TFP) growth into a scale change (SC), technical change (TC), and technical efficiency change (TEC) without price information.

The remainder of this paper is organized as follows. Section 2 briefly reviews the literature on bank performance studies. The methodology is presented in Sect. 3 and

Sect. 4 describes the data. The empirical results are discussed in Sect. 5, and Sect. 6 concludes.

2 Studies on bank performance

Economists have been analyzing the performance of banking sectors for several decades. These studies have used both parametric and nonparametric approaches and focused on factors that influence efficiencies, such as ownership, size, governance structure, regulatory mechanism, labor laws, market conditions, technology, and service quality.

Let us first review some studies in developed countries that use parametric approaches. Lang and Welzel (1998) used the thicker frontier approach (TFA) to evaluate the technology and efficiency of German banks. They found evidence of scale economies up to a certain level of total assets while finding that non-operating costs caused scale diseconomies. Battaglia et al. (2010) used SFA to analyze the cost and profit efficiency of Italian cooperative banks and found that environmental conditions, such as a larger number of company registrations, higher concentration of cooperative banks than other banks, and concentration of the population close to the main city have a substantial effect on bank branch performances. Using a parametric distance function, Glass et al. (2014) examined the efficiency of Japanese cooperative banks over the study period of 1998–2009 and found that the amalgamation process leads to increasing returns to scale of the sector. Their results further reveal that the pressure from the regulations to reduce non-performing loans would result in negative effects on performance and output. Lu et al. (2019) used SFA to examine the cost and profit efficiency of New Zealand banks for the period from 2002 to 2011 and found that foreign banks were having higher efficiency levels than domestic banks.

Our next focus is on the banking studies in transition and developing economies that use parametric approaches. Using SFA and the distribution-free approach (DFA), Semih Yildirim and Philippatos (2007) analyzed the banking sector efficiency of 12 transition economies in Center and Eastern Europe over the period from 1993 to 2000. The estimation results of both approaches showed that profit efficiency levels were significantly lower than cost efficiencies. Using an input distance function, Kumbhakar and Wang (2007) analyzed the effect of banking reforms in China on efficiency and TFP. Their results indicate that the performance is higher for the banks with joint-equity holdings than the state-owned banks. Aissia and Ellouz (2021) also used SFA to estimate the efficiency of 94 branches of a Tunisian public bank for the period from 2007 to 2019 and found that efficiency levels among branches are rather similar. The annual TFP growth was 4.4% over the period 1993–2002.

We found several studies that have been carried out in the South Asian region using parametric approaches. Das and Kumbhakar (2012) used an input distance function with hedonic aggregator functions to examine the impact of deregulation on the efficiency of the Indian banking sector. According to their findings, state-owned banks in India recorded higher efficiency gains than private banks in the

post-deregulation period from 1996 to 2005. A study by Hassan and Hassan (2018) that examines the performance of the Bangladesh banking sector using the stochastic frontier analysis method finds that the mean cost efficiency of the sector for the period from 2011 to 2015 is 88.5%. Technological progress finds to be low during the period and non-performing loans have been a dominant factor to lower the cost efficiency in the banking sector. Seelanatha (2021) analyzes the change of cost efficiency of Sri Lankan local banks in several political regimes using stochastic frontier analysis (SFA) and found high performance under liberal economic policies than under restrictive ones.

We now turn our attention to the literature that uses nonparametric approaches. Using a slack-based data envelope analysis (DEA) method, Drake et al.(2006) assessed the technical efficiency of the Hong Kong banking system. Results indicated considerable differences in efficiency levels among different banking sectors, and among different size groups. Mostafa (2007) used a DEA method to analyze the relative efficiency of the top 50 Gulf Cooperation Council banks. Results showed that several banks were operating under sub-optimal conditions. The authors suggested reducing resource usage and to increase savings to enhance performance. Ariff and Luc (2008) analyzed the cost and profit efficiency of Chinese banks using a nonparametric DEA method. According to their results, profit efficiency levels were well below the cost efficiency levels while mid-sized banks were high performing than small and large banks. Kontolaimou and Tsekouras (2010) analyzed the performance of European cooperative banks using a nonparametric meta-frontier approach and showed that many cooperative banks were away from the European meta-frontier while performance differences seem rising within cooperative bank types. In a recent study, Mirasol and Garcia (2020) analyzed the efficiency of 23 cooperative banks in the Philippines using a slack-based DEA method and found that the overall mean technical efficiency is 64.1%.

Several banking studies use nonparametric approaches in the South Asian region. Feroze (2012) used a DEA method to analyze the efficiency of District Cooperative Banks in Kerala, India, showing that many banks are inefficient due to their inappropriate size and managerial inefficiency. Asmild et al. (2019) studied the banking behavior of Bangladesh during the global financial crisis accommodating a multidirectional efficiency analysis. Analyzing the inefficiency measures of a set of Bangladesh banks, they found that Islamic banks have outperformed traditional commercial banks during the period from 2011 to 2015. Zhu et al. (2021) used the DEA and the Malmquist productivity index to examine the productivity, operational efficiency, and differences in these indicators among public, private, and international commercial banks in Pakistan, from 2006 to 2017. While foreign banks were having higher mean technical efficiency than domestic banks it was the opposite for mean scale efficiency. Overall, mean total factor productivity shows a decline of 1.9% whereas domestic banks show a decreasing trend and foreign banks show a growing trend. In one of the most recent studies, Shah et al. (2022) employed a DEA Meta-frontier Malmquist productivity index approach to examine the cross-country efficiency and productivity of commercial banks in five South Asian countries. Nepalese

commercial banks are the most efficient and closest to the meta-frontier of the five countries, whereas Sri Lankan commercial banks are ranked fifth. During the study period from 2013 to 2018, the sector's mean total factor productivity fell by 0.8% on average. Despite having the lowest rank in meta-frontier analysis, Sri Lankan commercial banks, along with Nepal and Pakistan, have seen a gain in mean total factor productivity change, while Bangladesh and India have seen a fall.

Some studies have used both parametric and nonparametric approaches to compare the efficiency estimates. Delis et al. (2009) for Greece commercial banks and Wang et al. (2019) for Vietnamese commercial banks used both DEA and SFA methods in efficiency analysis and found that both methods yield similar results.

We found two previous studies conducted to examine the efficiency of CRBs in Sri Lanka that used DEA methods. Jayamaha and Mula (2011) analyzed the financial strength and its impact on CRBs in Sri Lanka and found a strong relationship between some financial practices and efficiency, and considered that good financial practices with a self-regulatory mechanism would enhance efficiency. Jayamaha (2014) showed that CRBs have not operated efficiently in microcredit activities from 2005 to 2010. The author further found substantial efficiency differences among CRBs in different geographical districts. Neither of the above two studies has focused on productivity decomposition. To the best of our knowledge, we are the first to do so. Thus, our research contributes to the literature by decomposing the productivity of cooperative banks using stochastic input distance function estimations with multiple outputs and empirically examining the effect of COVID-19 relief measures on the performances of cooperative banks in emerging economies in the Asian region.

3 Methodology

3.1 Input distance function and technical efficiency

We employ an input distance function for the estimation of the efficiency scores and the decomposition of the total factor productivity growth. Parametric models, such as input distance function estimation, are commonly used to estimate the efficiency of production units in many sectors including agriculture, energy, banking, and transport. The ability to accommodate statistical noise and their readily available statistical tests are the parametric approaches' two main advantages as compared to nonparametric approaches such as DEA.

When efficiency measures are estimated for a production technology with multiple outputs, we need to modify the traditional SFA models. Distance functions (Shephard 1953), input requirement function (Gathon and Perelman 1992), and the ray frontier model (Löthgren 1997) are three main models adopted to allow using multiple inputs and multiple outputs. However, the input requirement function restricts production technology to a single input and the ray frontier model

is a generalized single input model. The distance function approach has no such restrictions.

Another advantage of the input distance function approach is that it does not require the assumption of perfectly competitive markets like cost minimization or profit maximization. Moreover, unlike in the cost functions, the efficiency estimation of the input distance function does not suffer from the issue of inconsistency even having input misallocations (Kumbhakar 2012).

Readily available decomposition is another attractive feature of the input distance function. Färe et al. (1986) developed a method to obtain the scale effect using the estimated input distance function. Atkinson and Cornwell (1998) introduced a method to compute the technical change using the input distance function, where the method relies on the duality of the input distance function with the cost function. Karagiannis et al. (2004) applied the above methods to decompose the total factor productivity growth into scale change, technical change, and technical efficiency change.

Given the aforementioned advantages, the input distance function has been used widely in banking efficiency studies that often need to incorporate multiple outputs (Kumbhakar and Wang 2007; Li et al. 2009; Das and Kumbhakar 2012; Fernández et al. 2020). Our study also needs to incorporate multiple outputs. There would be misallocations of operational inputs of CRBs that can be handled by the input distance function. Moreover, CRBs are unlikely to satisfy the assumption of perfect competition since the new entry into the cooperative banking business is strictly regulated by the government. Considering these facts, we have chosen the input distance function as our preferred method. Our data come from quarterly financial reports obtained from CRBs. We have two output variables, direct interest revenues, and other operating revenues. Our input variables are interest expenses, salary, and other operating expenses.

The input distance function measures the maximum amount by which the input vector could be radially reduced to produce a given vector of outputs. Mathematically, it can be expressed as:

$$D_I(y,\, x,\, t) = \max\{\lambda :\ x/\lambda \in L(y)\},$$

where x denotes the input vector, y the output vector, and $L(y) = \{x: D_I(y,\, x,\, t) \geq 1\}$. Parameter λ takes the value 1 or above. If $\lambda = 1$, the inputs cannot be reduced at all to produce a given amount of output and, thus, the firm is as efficient as possible. If $\lambda > 1$, the firm can reduce input to produce a given amount of output and, therefore, there is some inefficiency in its production process.

For the empirical estimation of the distance function, Coelli and Perelman (1999) define the translog input distance function of K inputs and M outputs as:

$$
\begin{aligned}
\ln D_I(y, x, t) = {} & \alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_k + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \alpha_{kl} \ln x_k \ln x_l \\
& + \sum_{m=1}^{M} \beta_m \ln y_m + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \beta_{mn} \ln y_m \ln y_n \\
& + \sum_{k=1}^{K} \sum_{m=1}^{M} \gamma_{km} \ln x_k \ln y_m + \delta_t t + \frac{1}{2} \delta_{tt} t^2 + \sum_{k=1}^{K} \zeta_{kt} t \ln x_k \\
& + \sum_{m=1}^{M} \eta_{mt} t \ln y_m.
\end{aligned}
\tag{1}
$$

The restrictions required for homogeneity of degree one are:

$$
\sum_{k=1}^{K} \alpha_k = 1,
\tag{1a}
$$

$$
\sum_{l=1}^{K} \alpha_{kl} = 0, \quad k = 1, 2, \dots, K,
\tag{1b}
$$

$$
\sum_{k=1}^{K} \gamma_{km} = 0, \quad m = 1, 2, \dots, M.
\tag{1c}
$$

Some further restrictions required to hold symmetry are:

$$
\alpha_{lk,} = \alpha_{lk}, \quad k, l = 1, 2, \dots, K,
\tag{1d}
$$

$$
\beta_{mn} = \beta_{nm} \quad m, n = 1, 2, \dots, M.
\tag{1e}
$$

Equation (1) can be transformed into an estimable form as follows (Coelli and Perelman 1999; Karagiannis et al. 2004). First, the input distance function is a homogeneity of degree + 1, and this restriction can be imposed by dividing the left-hand side and all the inputs of the right-hand side by one input, such as x_1:

$$
\ln \left(D_I / x_1 \right) = \ln D_I - \ln x_1 = \alpha_0 + \sum_{k=2}^{K} \alpha_k \ln \left(\frac{x_k}{x_1} \right)
$$

$$
+ \frac{1}{2} \sum_{k=2}^{K} \sum_{l=2}^{K} \alpha_{kl} \ln \left(\frac{x_k}{x_1} \right) \ln \left(\frac{x_l}{x_1} \right) + \sum_{m=1}^{M} \beta_m \ln y_m
$$

$$
+ \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \beta_{mn} \ln y_m \ln y_n + \sum_{k=2}^{K} \sum_{m=1}^{M} \gamma_{km} \ln \left(\frac{x_k}{x_1} \right) \ln y_m + \delta_t t \qquad (2)
$$

$$
+ \frac{1}{2} \delta_{tt} t^2 + \sum_{k=2}^{K} \zeta_{kt} t \ln \left(\frac{x_k}{x_1} \right) + \sum_{m=1}^{M} \eta_{mt} t \ln y_m .
$$

Now, using a shorthand notation for the right-hand side of the above equation, TL $(x_k/x_1, y, t)$, we can express it more concisely as:

$$
-\ln x_{1it} = \text{TL} \left(x_{kit} / x_{1it}, y, t \right) - \ln(D_{Iit}). \qquad (3)
$$

Note that we also introduce subscripts i and t, where i denotes the decision-making unit and t the time. Following Aigner et al. (1977), we assume $\ln (D_{Iit}) = u_{it}$, where u_{it} follows a half-normal distribution: $u_{it} \sim \text{i.i.d. } N^+(0, \sigma_u^2)$. By further adding a random error term, $v_{it} \sim \text{i.i.d. } N (0, \sigma_v^2)$, we obtain an estimable model of the stochastic input distance function:

$$
-\ln x_{1it} = \text{TL} \left(x_{kit} / x_{1it}, y, t \right) + v_{it} - u_{it}. \qquad (4)
$$

This is a typical stochastic production frontier estimation. The actual likelihood function can be found in Kumbhakar and Lovell (2000). We estimate Eq. (4) using maximum likelihood estimation (MLE).

The relationship between TE and the distance function is:

$$
\text{TE}_{it} = 1/D_i = \exp[\ln(1/D_{it})] = \exp\left[-\ln(D_{it}) \right] = \exp(-u_{it}).
$$

While we do not know the true value of u_{it}, we can compute its expected value, given the estimated error term $\varepsilon_i = -u_{it} + v_{it}$. Thus, following Battese and Coelli (1988) and Kumbhakar and Lovell (2000) we define technical efficiency as:

$$
\text{TE}_{it} = E[\exp(-u_{it} | \varepsilon_{it})]. \qquad (5)
$$

3.2 Total factor productivity decomposition

Let us briefly discuss the TFP decomposition we utilize. As noted by Karagiannis et al. (2004) in a multiple inputs and outputs model, TFP change can be mathematically expressed as:

$$
\dot{\text{TFP}} = \sum m R_m \dot{y}_m - \sum k S_k \dot{x}_k, \qquad (6)
$$

where the dots above denote the rate of change and $R_m = p_m y_m / R$. p is the output price, and R is the observed total revenue. Similarly, $S_k = w_k x_k / C$, and w is the input price. C is the observed total cost. Therefore, this definition of the decomposition requires output as well as input price information. However, Karagiannis et al. (2004) show that R_m and S_k can be expressed as:

$$R_m = \frac{\partial \ln DI / \partial \ln ym}{\sum m \partial \ln DI / \partial \ln ym} \text{ and } S_k = \frac{\partial \ln DI / \partial \ln xk}{\sum k \partial \ln DI / \partial \ln xk} = \partial \ln DI / \partial \ln xk.$$

Therefore, the input distance function estimation allows us to compute TFP change without price information.

Following Karagiannis et al. (2004) we can further decompose TFP change as follows:

$$\dot{\text{TFP}} = \left(1 - \text{RTS}^{-1}\right) \sum m R_m \dot{y}_m + \frac{\partial \ln DI}{\partial t} - \frac{\partial u}{\partial t} + \sum j I_j \dot{Z}_j, \qquad (7)$$

where RTS represents the return to scale and $\text{RTS}^{-1} = \sum_{m=1}^{M} 1 \frac{\partial \ln DI(y,x,t)}{\partial \ln ym}$. Note that, when RTS > 1, scale economies are positive, and they are negative if RTS < 1. If RTS = 1, the technology exhibits constant returns to scale. $I_j = I_j = \frac{\partial \ln e^{-u}}{\partial \ln Z_j} = -\frac{\partial u}{\partial Z_j} Z_j$. Accordingly, the components of $\dot{\text{TFP}}$ are:

SC: scale change $(1 - \text{RTS}^{-1}) \sum m \, _{Rm\dot{y}m}$;
TC: technical change $\left(\frac{\partial \ln DI}{\partial t} \right)$;
TEC: pure (neutral) technical efficiency change $\left(\frac{-\partial u}{\partial t} \right)$; and.
TEC$_z$: non-neutral technical efficiency change $\left(\sum j I_j \dot{Z}_j \right)$.

Based on these, (8) can be written as:

$$\dot{\text{TFP}} = \text{SC} + \text{TC} + \text{TEC} + \text{TEC}_z. \qquad (8)$$

In Eq. (8), SC refers to the scale change related to RTS. The second term TC is technical change. A positive TC refers to an outward shift of the production frontier. The third component, TEC, is neutral technical efficiency change. It defines the change in the rate of efficiently used inputs over the period. The last term TEC$_z$ refers to non-neutral technical efficiency change due to exogenous forces such as bank-specific characteristics and environmental factors (Kumbhakar and Wang 2007). CRBs have been continuing their operations in the same business model without change of ownership, bank size, and location over the period. Therefore, in our estimation, we assume those factors (the z variables) as time-invariant, i.e., TEC$_z$ = 0.

We compute the TFP index considering the fourth quarter of 2016 (2016: q4) as the base to get the cumulative TFP change as:

$$\text{TFP}_{t+1} = \left(1 + \dot{\text{TFP}}_{t+1}\right) \text{TFP}_t \quad t = 1, 2 \dots, T \text{ and } \text{TFP}_1(2016 : \text{q4}) = 100. \quad (9)$$

Table 1 Descriptive statistics of all variables

Variable	Observations	Mean	SD	Min	Max
Interest expenditure (x_1)	1644	326,477	285,876	7270	2,138,600
Salary expenditure (x_2)	1644	127,616	60,110	180	1,190,710
Other operating expenditure (x_3)	1644	161,074	148,832	8650	1,570,227
Interest revenue (y_1)	1644	576,551	410,409	20,255	3,829,457
Other operating revenue (y_2)	1644	243,079	300,753	615	2,045,790
Non-performance loan ratio (NPLR)	1644	14.6	10.8	0.0	81.2

The table presents the observations and descriptive statistics of all variables. All monetary variables are in LKR, deflated by the consumer price index (2010 = 100)
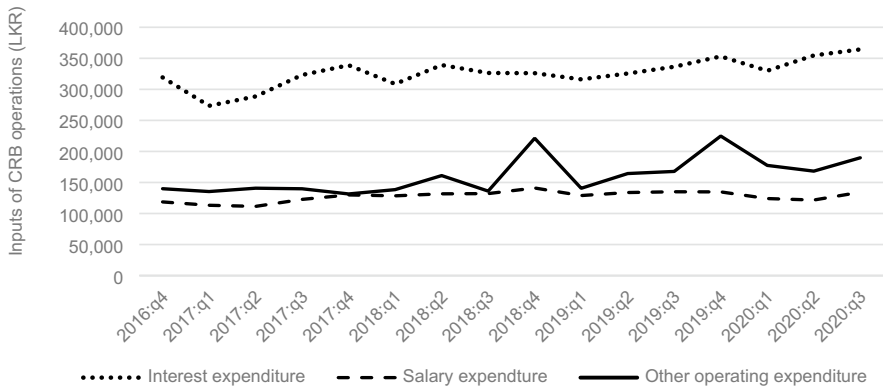
Fig. 1 Inputs of cooperative rural bank operations from the fourth quarter of 2016 to the third quarter of 2020. Values are in Sri Lankan rupees (LKR)

4 Data, variables, and descriptive statistics

We use a quarterly panel data set of 103 CRBs between 2016 and 2020 from the Kegalle District of Sri Lanka, which is compiled using the quarterly financial reports submitted to the Provincial Department of Cooperative Development, Sabaragamuwa province. The dataset comprises 16 quarters, from the fourth quarter of 2016 to the third quarter of 2020. We believe that the Kegalle District provides a fairly good representation of the nation since it includes communities from the three major economic environments in Sri Lanka (urban, rural, and plantation).

There are two main approaches in the literature in defining inputs and outputs of the banking process, the production approach and the intermediation approach. The production approach (Benston 1965) counts physical variables such as labor, premises, and material as inputs and the outputs are the number of accounts in operation, the number of deposits, and so on. This approach does not include interest expenses. The intermediation approach considers the bank's role as an intermediation service that collects deposits and invests them in loans and other investments. This approach uses interest costs and operating costs as inputs and
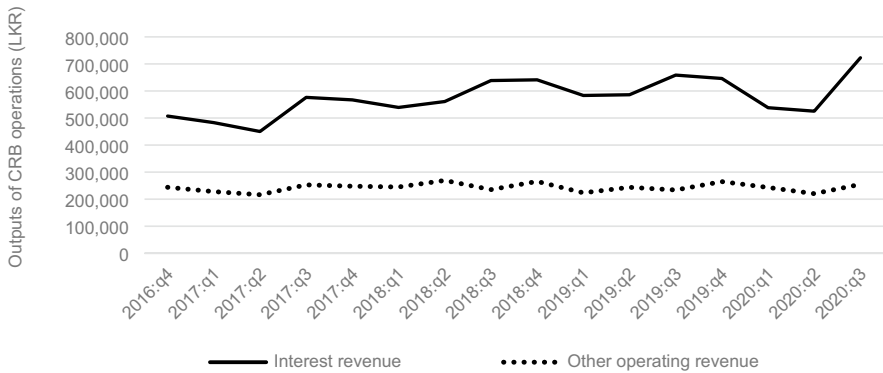
Fig. 2 Outputs of cooperative rural bank operations from the fourth quarter of 2016 to the third quarter of 2020. Values are in Sri Lankan rupees (LKR)
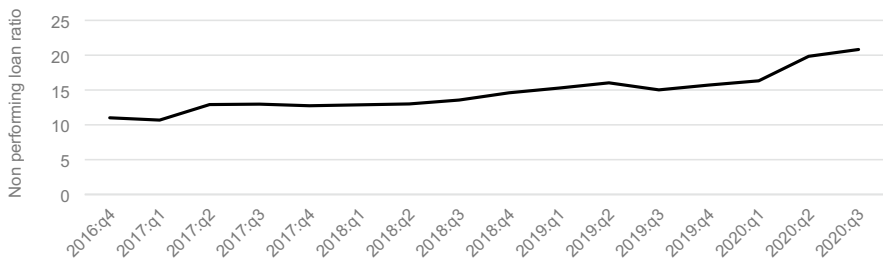
Fig. 3 Change of non-performing loan ratio of cooperative rural banks from the fourth quarter of 2016 to the third quarter of 2020

revenue to measure inputs and outputs. Inputs are typically interest cost, cost of borrowed capital, salary, and operational expenses. Outputs are typically loans and other revenues (Berger and Humphrey 1992; Bhattacharyya and Pal 2013). We use the intermediation approach since our data set mainly consists of revenue and costs.

Our inputs are (1) interest expenses (x_1), that is, interest paid for deposits and borrowings; (2) salaries (x_2), which include monthly wage as well as monthly allowances; and (3) other operating expenditures (x_3), such as premises, depreciation, repairs, renewals, equipment, transports, postal, and taxes.

The outputs are (1) direct interest revenue (y_1), including interest gained from loans including pawning, and (2) other operating revenue (y_2), including the interest of investments, interest for shared capital, and revenue from billing and similar operations. All the monetary figures are deflated using the consumer price index with 2010 as the base year. Table 1 provides the summary statistics of all variables.

Figure 1 presents the average of inputs over the 16 quarters. The interest expenditure is the largest and is the main input in the production process, showing

Table 2 Parameter estimates of input distance function estimation

Variable	Parameter	Estimate	SE	z-value
$\ln(x_2/x_1)$	α_2	− 0.976***	0.205	− 4.76
$\ln(x_3/x_1)$	α_3	0.651***	0.163	3.99
$\ln(x_2/x_1)^2$	α_{22}	0.152***	0.009	16.22
$\ln(x_2/x_1)\ln(x_3/x_1)$	α_{23}	0.057***	0.011	5.24
$\ln(x_3/x_1)^2$	α_{33}	− 0.067***	0.016	− 4.22
$\ln y_1$	β_1	− 0.041	0.195	− 0.21
$\ln y_2$	β_2	− 0.636***	0.105	− 6.08
$\ln(y_1)^2$	β_{11}	− 0.113***	0.019	− 6.02
$\ln y_1 \ln y_2$	β_{12}	0.094***	0.008	11.25
$\ln(y_2)^2$	β_{22}	− 0.062***	0.005	− 11.57
$\ln(x_2/x_1)\ln y_1$	γ_{21}	0.079***	0.017	4.71
$\ln(x_2/x_1)\ln y_2$	γ_{22}	0.057***	0.009	5.98
$\ln(x_3/x_1)\ln y_1$	γ_{31}	− 0.032*	0.013	− 2.47
$\ln(x_3/x_1)\ln y_2$	γ_{32}	− 0.006	0.007	− 0.82
t	δ_t	0.087***	0.024	3.54
t^2	δ_{tt}	0.003***	0.001	3.70
$\ln(x_2/x_1)\,t$	ζ_{2t}	− 0.002	0.002	− 0.99
$\ln(x_3/x_1)\,t$	ζ_{3t}	− 0.002	0.002	− 0.89
$\ln y_1\,t$	η_{1t}	− 0.006***	0.002	− 3.32
$\ln y_2\,t$	η_{2t}	− 0.002	0.001	− 1.63
Sigma_u_square	σ_u^2	0.395***	0.116	3.40

The table presents parameter estimates of input distance function estimation which refers to Eq. (4). Number of observations: 1644; ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively

a slight increase over time. The other operating expenditures also show a minor increase over the period, except for two rapid increases in the quarters of 2018 and 2019, when the two phases of banking software updates in CRBs took place. The salary expenditure seems to exhibit much smaller fluctuations, as the size of a CRB is usually fixed to between two and four staff members.

Figure 2 shows the trends for the output variables. The mean interest revenue has generally had an increasing trend with substantial fluctuations, though a substantial decrease in interest revenue was recorded in the first and second quarters of 2020. When the COVID-19 pandemic hit the country in early March of 2020, the Central Bank of Sri Lanka announced a 2–6 months debt and interest freeze period for debtors (debt moratorium) including personal loans, leasing, and small-scale businesses.[2] This government intervention seems to have resulted in a noteworthy

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[2] Under the instructions of the government, Monetary Board of the Central Bank of Sri Lanka (2021a) issued a special circular numbered 04/2020 on 24.03.2020 named "Relief measures to assist COVID-19 affected businesses and individuals". Under this, circular banks and financial institutions were instructed to implement a debt moratorium on lease, personal loans and affected SMEs and related logistics service providers from two to six months. https://www.cbsl.gov.lk/sites/default/files/cbslweb_documents/laws/cdg/mb_circular_no_4_of_2020_e.pdf.

reduction in the interest revenue of CRBs in the first two quarters of 2020. CRBs lost debtor installments primarily in March, April, and May of 2020 as a result of the implementation of the above Central bank instructions. Following the end of this period, from June 2020, they began to collect outstanding loans, including the arrears, and hence could see an increase in interest revenue in the third quarter of 2020.

Figure 3 shows the trend of the non-performing loan ratio (NPLR). The effect of the COVID-19 crisis is also apparent in this figure, as NPLR increased more sharply after March 2020 (quarter 14 and afterward). However, as CRBs started the recollection of loans from the end of June 2020, compared to the first two quarters the rate of increasing NPLR appears to be lower in the third quarter of 2020.

5 Empirical results

The estimated parameters for our model, as specified in Eq. (4), are presented in Table 2. Before moving to TFP estimation first, based on the Kodde and Palm chi-square statistic, we can reject the null hypothesis that $\sigma_u^2 = 0$ at the 1% significant level.[3] Therefore, this industry exhibits some inefficiency. As another model specification test, we conduct LR test for time-invariant technical change by imposing $\delta_t = 0$, $\delta_{tt} = 0$, $\zeta_{kt} = 0$, and $\eta_{mt} = 0$. The null hypothesis, that the CRBs exhibit zero technical change is rejected at the 1% significance level.[4]

Based on the estimated model, we compute our key efficiency and productivity measurements, as shown in Table 3. Figures 4, 5, 6, 7, and 8 plot these measurements.

5.1 Technical efficiency (TE)

Let us first look at the plot for the mean TE for each quarter in Fig. 4a and the figures in column (2) of Table 3. The efficiency mostly shows a declining trend during this period, starting from a high efficiency of 0.99 and declining to 0.85 in the second quarter of 2020. The mean TE over the period is 0.945, which means that there was a potential to save the cost of production by 5.5%. Interestingly, the TE, which had been trending lower over time, is trending upward in the third quarter of 2020. This shift is most likely attributable to starting the fall in outstanding loans as the debt moratorium implementation period for most debtors came to an end. As a result, CRBs began to boost their outputs as interest revenue increased, allowing them to become more technically efficient in their operations. This growing trend gives vital direction to CRBs, indicating that taking innovative steps to reduce non-performing loans would be a viable approach to running their operations efficiently.

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[3] The estimated mixed χ^2 value of LR test is 18.11. Kodde and Palm (1986), the critical value at 1% is 5.412.

[4] The estimated mixed χ^2 value of LR test is 56.68 with a degree of freedom of 6.

Table 3 Efficiency and productivity measurements

| Quarter	TE	RTS	TFṖ	TFP index	SC	Cum. SC	TC	Cum. TC	TEC	Cum. TEC
2016:q4	0.991	1.684		100.000		1.000	−0.006	1.000		1.000
2017:q1	0.989	1.678	−0.024	97.598	−0.016	0.984	−0.005	0.995	−0.002	0.998
2017:q2	0.986	1.621	0.001	97.019	0.007	0.983	−0.003	0.991	−0.003	0.995
2017:q3	0.984	1.619	−0.097	87.617	−0.090	0.895	−0.004	0.988	−0.003	0.992
2017:q4	0.980	1.617	−0.012	86.582	−0.005	0.890	−0.002	0.985	−0.004	0.988
2018:q1	0.976	1.613	−0.011	85.588	−0.005	0.886	−0.001	0.984	−0.005	0.983
2018:q2	0.970	1.553	−0.040	82.127	−0.034	0.856	−0.001	0.983	−0.006	0.977
2018:q3	0.965	1.540	−0.037	79.088	−0.030	0.831	0.000	0.983	−0.007	0.970
2018:q4	0.956	1.541	−0.036	76.260	−0.027	0.808	0.000	0.983	−0.009	0.961
2019:q1	0.949	1.512	0.007	76.815	0.016	0.821	0.002	0.985	−0.011	0.951
2019:q2	0.935	1.488	−0.031	74.398	−0.021	0.803	0.003	0.988	−0.013	0.938
2019:q3	0.927	1.464	−0.049	70.740	−0.037	0.774	0.003	0.992	−0.016	0.923
2019:q4	0.905	1.423	−0.023	69.147	−0.008	0.768	0.005	0.996	−0.020	0.905
2020:q1	0.887	1.416	0.015	70.171	0.031	0.792	0.007	1.003	−0.024	0.884
2020:q2	0.854	1.373	−0.015	69.112	0.004	0.796	0.009	1.013	−0.029	0.858
2020:q3	0.868	1.382	−0.109	61.737	−0.081	0.733	0.007	1.020	−0.035	0.828
All quarters	0.945	1.533	−0.031	80.250	−0.020	0.851	0.001	0.993	−0.012	0.947

The table presents the mean values of key efficiency and productivity measurements in each quarter. TE indicates the technical efficiency which describes the rate of efficient use of inputs and RTS indicates the return to scale. TFP indicates the change in total factor productivity. TFP change over time is indicated by the TFP index which is calculated using formula (9) considering 2016:q4 as the base. Decomposition of TFṖ is shown with SC, TC, and TEC. SC is the scale change related to RTS on TFP change. The shift of production frontier over time is indicated by TC, i.e., technical change. TEC is a technical efficiency change that defines the change of the rate of efficiently used inputs over the period. Cumulative changes of SC, TC, and TEC have also been calculated following formula (9) considering 2016:q4 as the base
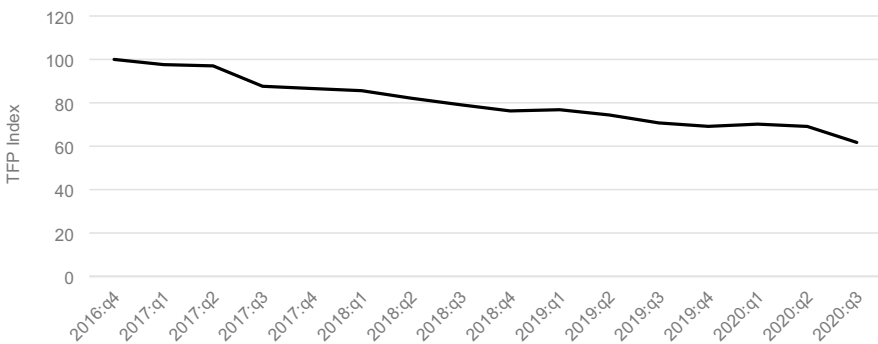
a

b
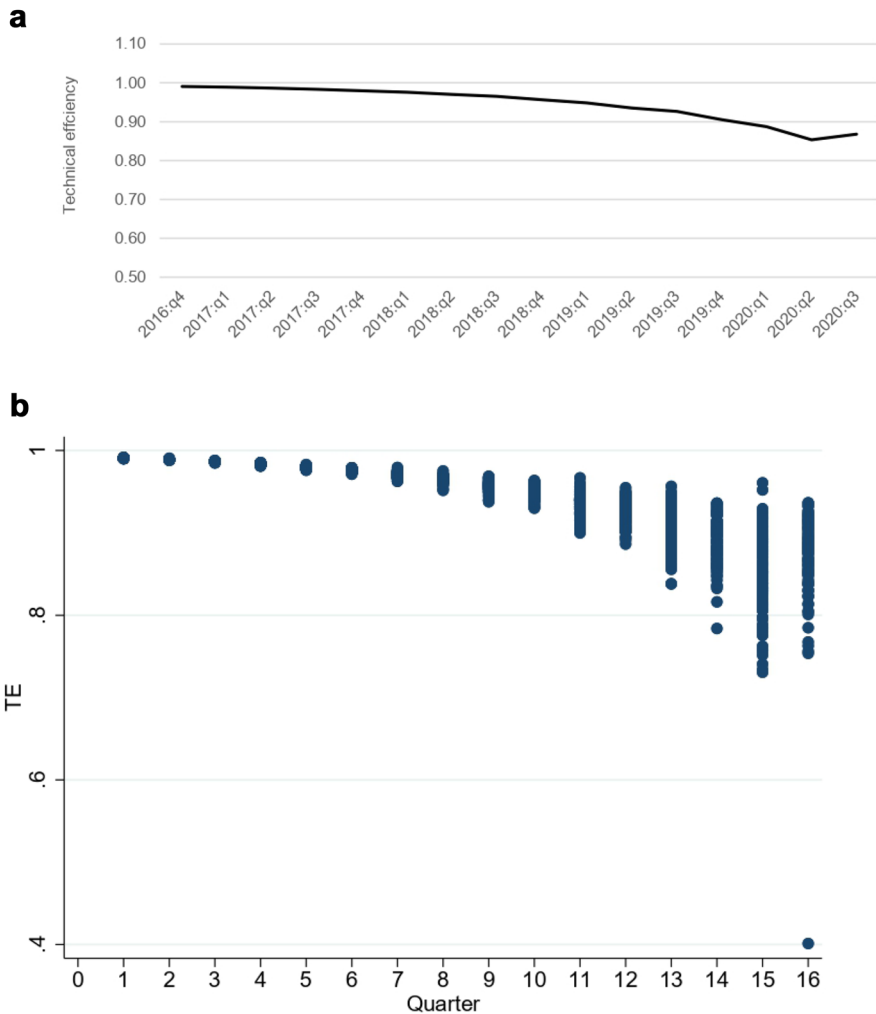
Figure 4 **a** Change of mean technical efficiency of cooperative rural banks from the fourth quarter of 2016 to the third quarter of 2020. **b** Change of technical efficiency of cooperative rural banks from the fourth quarter of 2016 to the third quarter of 2020.

As shown in Fig. 4b, CRB branches seem to have a similar level of TE at the beginning of the period but it starts to vary over the period. This variation is increasing largely in the last three quarters of 2020. This is the period that the COVID-19 pandemic arose. The crisis affected the daily life of people largely and made many challenges for banking operations mainly in loan recoveries. Therefore, the noteworthy differences in TE among CRB branches in this period might be due to the managerial inefficiency of branch managers in decision-making. Thus, this would be important evidence for bank management to plan for more thorough
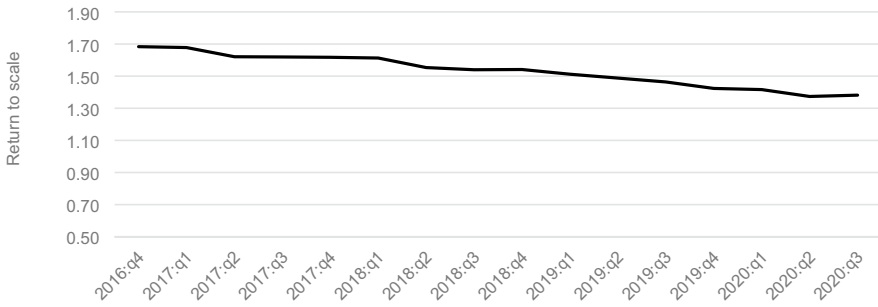
Fig. 5 Change of return to scale of cooperative rural bank operations from the fourth quarter of 2016 to the third quarter of 2020

Fig. 6 Change of TFP index of cooperative rural banks from the fourth quarter of 2016 to the third quarter of 2020

capacity-building programs for CRB managers and staff to make effective business decisions in changing market conditions.

5.2 Return to scale (RTS)

We first conduct the LR test to check for constant return to scale under restrictions $\sum \beta_m = 1$, $\sum \beta_{mn} = 0$, $\sum \gamma_{km} = 0$ and $\sum \eta_{mt} = 0$. The null hypothesis that the cooperative banking sector exhibits a constant return to scale is rejected at the 1% significance level.[5] Figure 5 plots the RTS over the period, and the actual figures are in Table 3, column (3). The technology exhibits increasing returns to scale throughout the sample period, although RTS diminished over time. In the fourth quarter of 2016, the average RTS was 1.68 and gradually reduced to 1.38 at the end of our sample period.

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[5] The test statistic is 9884.06 with a degree of freedom of 8.

a

b
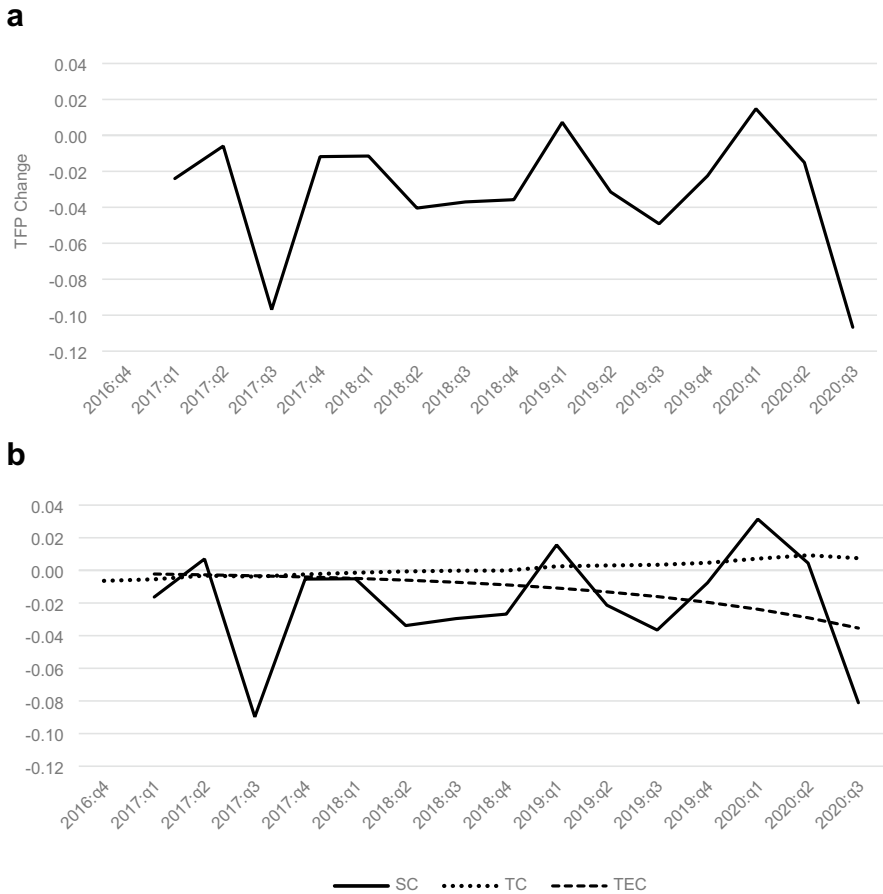
Figure 7 a Dynamics of TFP change of cooperative rural banks from the fourth quarter of 2016 to the third quarter of 2020. **b** Dynamics of decomposed components of TFP change of cooperative banks from the fourth quarter of 2016 to the third quarter of 2020

5.3 Productivity change

Figure 6 plots the cumulative TFP index. The TFP index decreases continuously throughout the period (i.e., from 100 to 61.7 by the end of the sample period, with a mean of 80.2).

Figure 7a shows the quarterly average TFP change (TḞP) over the analyzed period, with a rather large quarter-to-quarter fluctuation that is almost negative in all quarters. Although it started to increase from the third quarter of 2019, it again showed a drastic drop in the first three quarters of 2020. To further analyze the causes of the drop in TFP, we now look at the productivity decomposition, where TFP change is decomposed into SC, TC, and TEC. Figure 7b plots the decomposed factors, and their cumulative effects are represented in Fig. 8.
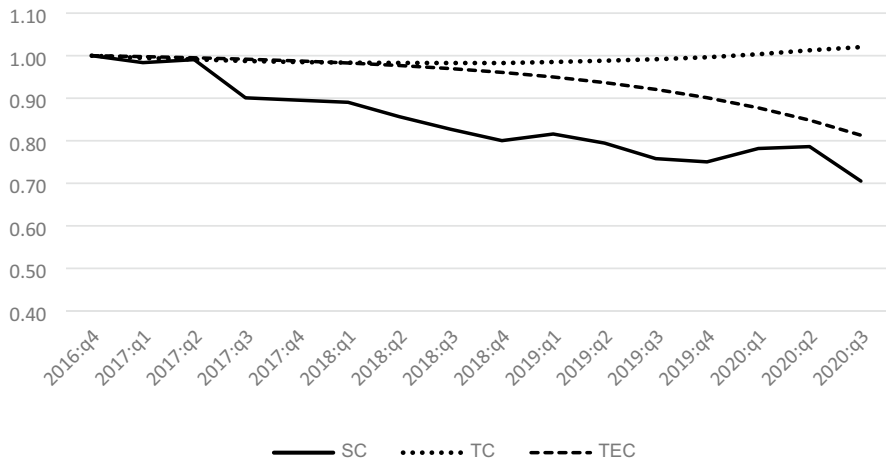
Fig. 8 Cumulative change of decomposed components of TFP change of cooperative rural banks from the fourth quarter of 2016 to the third quarter of 2020

As shown in Fig. 7b, scale change is negative for most quarters and often large. As with the change in RTS, the scale of operations has been decreasing over our sample period, which has reduced scale efficiency. We believe that one of the main factors behind this decline is the reduction in cooperative banks' customer base due to private institutions' penetration into micro-financing, which increased rapidly after the year 2000 (Jayamaha and Mula 2011). According to the Central Bank of Sri Lanka, as of December 2021, there were 39 licensed financing companies in Sri Lanka.[6] Using their skillful marketing strategies, private financial institutions, such as Commercial Credit & Finance PLC and People's Leasing & Finance PLC, attracted a considerable number of cooperative members. The competitiveness of Sri Lankan microfinance institutes in the market is evident as they have enhanced their average annual productivity by 2.4% from 2007 to 2012 (Mia and Soltane 2016). Thus, to stay competitive in the market, CRBs must employ innovative and strategic practices to retain existing consumers as well as acquire new ones.

Another factor is the COVID-19 pandemic, which hit the country in early 2020. As the crisis had a severe impact on the economic activities of the general public, the government announced a 2–6-month debt and interest freeze period for lease (debt moratorium), personal loans, and small-scale businesses which led to CRBs losing most of their expected interest revenue and loan installments. This would have resulted in a substantial drop in their scale economies in the third quarter of 2020. Therefore, the largest determinants of the negative TFP change over the sample period are the scale change, as clarified by their cumulative change in Fig. 8. Literature shows similar impacts of debt moratorium on the banking sector (Mehta

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and Kaul 2020). Thus, our findings suggest that government policies in the banking industry should be implemented more proactively rather than haphazardly.

Figures 7b and 8 show that technical change (TC) has been small. The first seven quarters show small negative changes, with a small positive change afterward. This is understandable since the usage of modern computerized systems has been low in the CRBs in Sri Lanka. For example, entering transactions into passbooks and the preparation of daily balances were done manually in all CRBs until 2008. As this was time-consuming and caused mistakes as well as manipulations, simple banking software was introduced in 2009. This system, however, did not support most of the daily operations, and thus, projects to upgrade the system took place in 2018 and 2019. However, as the employees were having lack of motivation in utilizing the new software, its installation did not cause appreciable changes in daily operations. We believe that this resulted in a rather minor effect of TC on productivity growth over the analyzed period. Literature shows that increasing the application of ICT in banking operations enhances the performance of bank branches considerably (Maldeni and Jayasena 2009; Binuyo and Aregbeshola 2014). This is further evident in Sri Lankan commercial banks as they have recorded an increase in total factor productivity growth by 1.37% in the period from 2013 to 2018 mainly due to technological change (Shah et al. 2022). As a result, our findings highlight the significance of taking progressive efforts to improve the use of ICT in CRB operations.

As plotted in Fig. 7b, technical efficiency change (TEC) was negative throughout the sample period. The cumulative change is shown in Fig. 8. Up to the second quarter of 2018, the contribution of TEC to TFP change is small but had a considerable impact afterward. Two factors could have played major roles in the TEC decline. First, the cooperative banks underwent the upgrading of existing banking software, which caused an increase in expenditure during this period. This is in line with the findings of Vu and Turnell (2010) that an increase in cost in business expansions and system upgrades could decrease efficiency. Second, during this period the amount of non-performing loans increased, resulting in a loss of expected revenue. Similarly, Le et al. (2022) indicate that non-performing loans are a dominant cause of inefficiencies.

6 Conclusion

This study examines the economic performance of cooperative banks in Sri Lanka over the period from 2016 to 2020 using an input distance function approach that accommodates multiple outputs. Our output measures are interest revenue and other operating revenue, while our input measures are interest, salary, and other operating expenditures. Using a dataset on 104 CRBs, we find that cumulative TFP decreased rapidly during this period. At the end of this period, productivity had declined by as much as 38%. To better understand the reason for this decline, we decompose the change in TFP into scale change (SC), technical change (TC), and technical efficiency change (TEC). In terms of TC, we observed periods of both positive and negative changes, although the magnitude of the fluctuation was very minor. TEC has been negative throughout the sample period, and the effect

is sizable from the middle of the sampling period. The largest and dominant contributing factor was, however, SC. As the operational scale generally decreased during this period, so did scale economies. This appears to be the result of a combination of two factors. First, private sector financial institutions that entered the market after 2000 could gain continuous productivity growth by attracting customers from CRBs. This resulted in a reduction in the extent of CRB operations, which had a detrimental impact on SC. Second, we believe that the government policy to declare an interest and debt release for 2–6 months in early 2020 had a particularly negative effect on the SC. Specifically, this intervention has resulted in CRBs losing most of their expected interest revenue and loan installments, leading to a considerable drop in their working capital and having a substantial negative effect on businesses. However, we were unable to examine the magnitude of each effect independently due to data limitations on the operations of microfinance institutions in the province.

Our findings show some guidance as to what direction CRBs should take in the future. The almost non-existing technical progress we identified indicates that CRBs should take action to improve their ICT usage as it would enhance the performance of banks considerably. In particular, we believe that the legacy administrative procedures that rely heavily on outdated software can be replaced by modern computerized systems that will connect all branches in a network. More intensive training of branch managers and staff members might be another avenue through which CRBs can increase TE. A modified training plan would replace most existing training modules on regular banking operations with customer care management, market analysis, and managing non-performing loans. The dominant SC means that government policy has to be implemented with more caution. Currently, government policy has been implemented in a rather ad hoc way, without a long-term vision. A recent example is the announcement of an interest and debt freeze period due to the COVID-19 crisis. This seems to have caused a sudden decrease in the scale of operations, which contributed to the drop in productivity. Therefore, to boost the performance level of cooperative banks in Sri Lanka in long run, we recommend implementing a well-planned restructuring of the sector, along with modern technology, comprehensive human resource development, and market-sensitive regulatory mechanisms.

The performance of bank branches varies with their characteristics such as the relationship of the manager with the staff, the effectiveness of employee performance evaluation, the manager's experience, and so on. Since each CRB is operated by a small team, the ability of managers might be a prominent factor in determining its efficiency. Moreover, these performance differences would occur due to spatial effects such as agglomeration economies and the self-selection of productive workers to productive branches. However, due to data limitations on manager-CRB linked data we could not perform further analysis in this regard. Thus, it would be interesting to examine the manager effect and spatial effect in determining performance differences among bank branches in future studies.

Declarations

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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