CREDIT COOPERATIVE ECONOMIC EFFICIENCY WITH TWO-STAGE DATA ENVELOPMENT ANALYSIS (DEA): EVIDENCE FROM THE CENTER-WEST REGION, BRAZIL

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ABSTRACT

Credit cooperatives play an important role in promoting regional development around the world. In this scenario one finds the Sicredi Cooperative, which is located in Brazil's Center- West region, specifically in municipalities of the extreme south of Mato Grosso do Sul state, including the border strip with Paraguay, with a huge lack of information about the economic efficiency of its activities. In this context, the present study aimed to measure and analyze the efficiency border of the Center-South MS Sicredi Cooperative Service Units. The analysis was performed in two stages. We used the product-oriented Data Envelopment Analysis non- parametric model named Variable Returns to Scale and Tobit regression model, as second stage. Sampling involved 24 agencies in the period between 2019 and 2021. We determined efficiency scores from the analysis of the variables personnel, administrative expenses, capital stock, credit operations, and operational spillovers, extracted from agencies' financial statements. Results showed gaps capable of adjustments between pure technique efficiency (obtained by the Variable Returns to Scale border) and scale efficiency (Constant Returns to Scale/Variable Returns to Scale), suggesting margins of adjustment for the improvement of the cooperative's performance. The analysis in second stage showed that personnel expenses and operational spillovers impacted negatively efficiency, while credit operation showed a consistent positive effect. It is worth noting that humanized management and cooperativism are valued even with the limitations found for assessing collaborators' individual performance. Therefore, this trend for the variables should be monitored in future studies.

INTRODUCTION

The economic development of any country normally has to do with the bank sector organization, which involves the efficient use of surplus and deficit units mediated by banks and other financial intermediaries. In this sense, the advance of high quality demands that economic growth carries out efficient capital allocation. Furthermore, efficiency involves evaluation of the work productivity, of the capital productivity, and of the factors' total productivity.

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Brazil's Central Bank (2022) has developed actions aimed at simplifying access to financial markets, comprising small and big users, investors and borrowers. The mentioned body has confirmed the importance of credit cooperatives, which are in many locations where the other financial institutions do not operate. Furthermore, the review of cooperatives' regulatory framework strengthened the class, allowing better expansion conditions, which resulted in considerable growth in this sector, which recorded from September 2019 to September 2022, an increase of 41.12% in the number of associates and of 31.42% in the number of service units. Therefore, these financial institutions significantly contribute to the country's economy and, for this reason, actions for the continuous improvement of processes of those (public or private) institutions must focus on efficiency, which is an indispensable condition for the continuity of the business. The maximum production efficiency demands that goods and services are obtained with the lowest possible cost, that is to say, the lowest use of inputs per production unit for each combination of inputs/products.

In this context, the efficiency border is associated with the ability to maximize benefits to members, which happens from the materialization of credit operations and the activity's net benefits, according to the resources used for obtaining them. In this case, efficiency would be formed by the measurement of the ability that agents and mechanisms have best to hit their aims or to produce a better expected effect.

As for the efficiency estimation calculations, there are several approaches for establishing an efficient border. The parametric and non-parametric categories are those that most stand out. In the strict context of those terminologies, a test considered parametric is characterized by the formulation of suppositions about properties of the underlying distributions for the population of interest, from what data they are found. A non-parametric test does not make use of those suppositions and dispenses with the imposition of prerequisites on the nature of underlying distributions.

Thus, in the light of financial institutions' significant influence in the context of local and regional economic development, there emerges the credit union movement developed by Center-South MS Sicredi Cooperative, which has operated in Brazil's Center-West region, specifically in municipalities comprising the extreme south of Mato Grosso do Sul state including the border strip with Paraguay.

Considering the importance of the work of Center-South MS Sidredi Cooperative, in the context of economic development promotion in municipalities under its jurisdiction and the scarcity of information and analyses on the theme, this study aimed to measure and analyze the Sicredi Cooperative Service Units' efficiency border.

To achieve this aim, we used the Data Envelopment Analysis (DEA) technique, which was preceded by a process of identification of the variables with greater influence on the efficiency rate.

As an innovative contribution to the region, the study emphasizes the preponderance of credit cooperatives in municipalities comprised by the area of operation of the institution under analysis, where more than 80% of those municipalities are in a border region with the Republic of Paraguay, which stresses their importance in the context of local development.

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Credit Cooperatives: Center-South MS Sicredi

The cooperatives play a fundamental role in the promotion and improvement of their members' economic potential and abilities. According to Ribas et al. (2022), they operate within the capitalist market as an organization aiming for its members' prosperity, as well as their mutual contribution to reach common aims, regardless of the economic power that each one has. As highlighted by Mhembwe and Dube (2017), by contributing to economic and social well-being, those institutions exert a significant role in increasing the quality of life of the population. Simultaneously, they strengthen economic framework and sustain the national economy's robustness and resilience. Furthermore, as Sudarmadji, Samryn and Baskoro (2021).

Stress, credit cooperatives promote the development of the economy based on family values, of collective collaboration and centered on economic democracy.

From this perspective, credit cooperatives show their importance by catering to a type of clientele often excluded from the commercial banking sector, be it for its dispersion in remote rural areas or in demand for small loans with few physical assets as collateral, thus promoting free competition.

With the potential of being promoters of the economies where they are present, credit cooperatives provide economic benefits to their members, including fewer costs to the services and products offered, guarantee the distribution of surpluses (spillovers) to members, and even pay for the applied stock capital.

Thus, these institutions have established themselves as access alternatives to financial services and products, showing wide adherence of the Brazilian population in recent years. This is primordially due to their form of operation with distinctive interest rates and bank tariffs, as well as efforts to improve their functioning and technology structures, in search of operational results that, in part, return to the community.

It is in this context that Center-South MS Sicredi figures as an important agent promoter of local/regional development in its area of operation. In total, 38 municipalities are in the region where it operates. An area occupied by 901,474 inhabitants. Founded on 07/05/1989, the cooperative is present in 100% of its area of operation, which comprises those 38 municipalities, 81.57% of which considered border strip municipalities, situated on the border with the Republic of Paraguay. Sicredi operates with 44 physical agencies to serve more than 121,000 members, offering more than 663 work posts.

The Center-South MS Sicredi expansion, which covers all of its area of operation, reinforces its commitment to the community, ratifying the International Labor Organization Recommendation n° 193/2002 that recognizes the importance of cooperatives in creating employment, in mobilizing resources, and in stimulating investment, as well as its contribution for the economy, recognizing that cooperatives, in their different forms, promote the most complete participation of all the population in socioeconomic development.

Efficiency and the Data Envelopment Analysis method

The DEA model's characteristic is to optimize, individually, each decision making unit (DMU). After optimization, DEA presents through its results an efficiency border of the DMUs that express an efficiency ratio between products and inputs, equal to one or 100%. From this perspective when a ratio between input and product is lower than one (outside the efficiency curve) it is understood that for producing a product more than one input will be needed. The

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same interpretation is followed when the ratio between inputs and products is greater than one, indicating that an input produces more than one product.

Among the benefits of using this technique of optimization and benchmarking of DMUs is the dispensable need for a functional relationship between input and product allowing the use of distinct variables, as energy, workforce, raw material, etc., in conjunction with other variables, such as operational result, profit, and quantity of produced units. This makes the application of multiple products and multiple inputs without pre-attributed weights possible.

The suggested model has been widely applied as a tool to measure the banking sector efficiency in Brazil and around the world, be it in the traditional model financial institutions or cooperative models, as demonstrated in Table 1.

Table 1
APPLICATION OF THE DATA ENVELOPMENT ANALYSIS (DEA) MODEL IN TRADITIONAL BANKS AND CREDIT COOPERATIVES IN BRAZIL AND OTHER COUNTRIES

AUTHORS	STUDY LOCATION	DESCRIPTION OF THE STUDY
Alkhathlan and Malik (2010)	Saudi Arabia	Applied the model to evaluate banks' relative efficiency, using annual data from 2003 to 2008.
Othman et al. (2016)	Malaysia	measure efficiency, serving as an early warning of performance and creating conditions for defining improvements in the sector
Anouze and Bou- Hamad (2019)	Middle East and Northern Africa	Assessed the impact of environmental factors on bank performance
Ferreira (2019)	Europe's member states	Considered a sample of 485 banks from member states of the European Union between the periods from 2011 to 2017 indicating managerial inefficiencies, among other factors.
Zhong, Li, and Wang (2021)	China	Identified the efficiency of banking innovation, taking China's rural commercial banks as examples
APPLICATION OF THE MODEL IN CREDIT COOPERATIVES		
Kumar, Swain, and Dash (2019)	China	Carried out research in District Central Cooperative Banks in China
Braz and Gonçalves (2020)	Minas Gerais – Brazil	The study aimed to analyze the efficiency of Minas Gerais' credit cooperatives according to their size, as well as identify efficiency standard indicators
Gautam, Srivastasa, and Jain (2022)	India	Benchmarking assessing the efficiency of 48 Urban Cooperative Banks in India.
Arandara and Takahashi (2023)	Sri Lanka	Analyzed Sri Lanka's cooperative banks aiming to estimate technical efficiency using the VRS model.

As can be observed, performance efficiency – be it in traditional banking institutions or cooperative credit models – refers to the measure of capacity that agents or mechanisms have best to achieve their aims, to produce the effect expected from them, Table 1.

Application of the Data Envelopment Analysis

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Materials and methods

We highlight that the analyzed cooperative operates in 38 municipalities comprising the center-south region of Mato Grosso do Sul state. Of these, 31 are considered municipalities situated on the border with the Republic of Paraguay, according to data from IBGE (2022).

Currently, the cooperative operates with 44 agencies. More units should be created in some municipalities given the local population density.

In this context, to ensure conformity with requisites of the model of analysis in question, we excluded from the evaluation agencies whose accounting statements showed indicators (used in the model as input/output variables) with negative values. This approach is aligned with the restriction defined by Cooper, Seiford, and Tone (2000), which allows considering only non-negative values. The analysis comprises the period from 2019 to 2021, and therefore includes a total of 24 service units, representing 54.55% of the agencies in operation, while the others that were discarded did not meet the previously mentioned prerequisites.

The input and output variables employed in the study were collected in their respective financial statements, service unit's Balance Sheet and Surplus and Loss Statement.

Several scientific articles that used similar variables applying the Data Envelopment Analysis models are contained in Table 2.

Table 2
STUDIES WITH THE APPLICATION OF INPUT AND OUTPUT VARIABLES – DEA MODELING

Type	Variables	Authors
	Personnel expenses* – comprehends all expense items related to a company's personnel.	Ferreira, Gonçalves, and Braga (2007); Ureña and Úbeda (2008); Ureña (2012); Maia et al. (2020) .
		Mckillop, Glass, and Ferguson (2002); Ferreira, Gonçalves, and Braga (2007); Vilela, et al. (2007); Souza and Staub (2007); Glass, Mckillop, and Rasaratnam (2010); Bittencourt and Bressan (2018) ; Maia et al. (2020).
Inputs	Administrative expenses – a company's overall spending that is not directly linked to production. Capital stock – is the sum of all	Höher, Souza, and Fochezatto (2019).
	quotas-parts of the cooperative's members. Credit operations – represented mainly by loans, funding, and advances granted.	Mckillop, Glass, and Ferguson (2002); Ferreira, Gonçalves, and Braga (2007); Vilela et al. (2007); Ureña and Úbeda (2008); Wheelock and Wilson (2013); Maia et al. (2020). Ferreira, Gonçalves, and Braga (2007);

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Outputs	Operational spillovers - when the cooperative records revenue higher than its expenses - operational profit.	Vilela et al. (2007); Bittencourt and Bressan (2018); Maia et al. (2020).

* The volume of resources expressed in the “personnel expenses” account was dissociated from the “administrative expenses” account to avoid double entries.

It is relevant to note that the configuration of variables (composed of three inputs and two outputs) conforms with the rule established by Banker et al. (1989) for its use in DEA models. According to this rule, the number of decision making units must be at least three times the total sum of variables used. The proposed efficiency indicator was obtained via the Data Envelopment Analysis method application, using product-oriented CRS and VRS models, an approach that aims to maximize the proportional increase in production levels (y), keeping the number of inputs constant (x).

However, scores obtained by the CRS modeling were not analyzed with depth. This model was applied to determine DMUs’ global technical efficiency, subsequently decomposed into pure technical efficiency (obtained by the VRS border) and scale efficiency (CRS/VRS).

The calculation of efficiency scores through DEA, using the product-oriented CRS and VRS models, was carried out according to the equations below:

Equation 1: CRS Model:

Where: $h0$ = efficiency of the DMU0 under analysis; η = inverse of efficiency (1/ $h0$); λk = participation of the DMUk in the goal of the DMU under analysis; xik = quantity of input i of the DMUk; yik = quantity of output j of the DMUk; $xi0$ = quantity of input i of the DMU under analysis; $yj0$ = quantity of output of the DMU under analysis; vi = weight attributed to the input i; uj = weight attributed to the output j; $u*$ = scale factor; j=1 = convexity constraint; s = number of outputs; and r = number of inputs.

The application of these models allows identifying efficient DMUs and building, through calculations, a production border with units that reach maximum productivity, giving shape to the benchmarks for quality.

The results understanding demands the comprehension of concepts of efficiency addressed by the DEA methodology that clarify the difference between the CRS and VRS models. Thus, one understands by:

Productive Efficiency (EP): as being the ability to avoid waste, producing as much result as the used resources allow for or otherwise, using the least possible resources. This efficiency is traditionally decomposed into scale efficiency (SE) and technical efficiency (TE).

Technique Efficiency (TE): the component of productive efficiency resulting from the separation of the scale efficiency effects. One associates this efficiency with the managerial ability of the manager of the DMU under analysis.

Scale Efficiency (SE): a component of productive efficiency associated with the productivity variations that derive from changes in the operation scale.

Therefore, the scores obtained by the VRS efficiency tend to be equal to or higher than those obtained through the CRS model. This is due to the composition of the DEA/CRS measure, which incorporates both the VRS efficiency measure and the scale efficiency. This approach

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enables a description of technical efficiency in two specific components: scale efficiency and "pure" technical efficiency. Notably, the VRS model imposes less strict constraints when compared to the CRS model, as highlighted by Banker and Thrall (1992).

Thus, considering DMUs' efficiency scores, the scale inefficiency is demonstrated when there are differences for results between those two models.

In this context, it is worthwhile to stress that:

The CRS/output model measures Technical Efficiency (TE) on the assumption of constant returns to scale (CRS), being also known by global productivity measure or productive efficiency, and

The VRS/output model shows the Technical Efficiency (TE) measure on the assumption of variable returns to scale (VRS).

Thus, scale efficiency is the result obtained from the ratio between TE on the assumption of CRS and TE on the assumption of VRS. This relationship is demonstrated in the equation below.

Where $Te\ CRS\ (Xk\ , Yk)$ is the technical or productive efficiency (CRS); and $Te\ VRS\ (Xk\ , Yk)$ is the technical efficiency (VRS); and $Se\ (Xk\ , Yk)$ is the scale efficiency.

Subsequently, one applies the Tobit econometric model, which allows investigating the factors that most contribute to explain efficiency scores obtained in previous calculations and that denote the efficiency achieved for the analyzed DMUs.

The Tobit model is given by:

$$y^* = X_i\, \beta + \varepsilon_i, \qquad (4)$$

In which y^* represents a latent variable; X_i represents explanatory variables; and β, the parameters to be estimated, assuming that the probable errors are normally distributed, with zero average and σ^2, $\varepsilon \sim N(0, \sigma^2)$ variance.

In this way, the Tobit regression is regarded as the second stage of data envelopment analysis due to the efficiency variable truncated characteristic.

The applied model and its respective dependent variables are described in Equation.

Equation (5): Economic Efficiency (EE)

$$EE = \beta 0 + \beta 1\, X1 + \beta 2\, X2 + \beta 3\, X3 + \beta 4\, X4 + \beta 5\, X5 + \varepsilon \qquad (5)$$

Where:

Economic efficiency (EE) (dependent variable) = economic efficiency indicators, calculated from the use of the inputs and products variables; $\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$ = are the regression estimated coefficients; $X1$ = personnel expenses; $X\ 2$ = administrative expenses; $X\ 3$ = capital stock; $X\,4$ = credit operations; $X\,5$ = operational spillovers; ε = error factor of the regression.

In the present study the dependent variable (Y) was constituted of efficiency scores

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obtained through the VRS model, where every DMU will have a positive efficiency classification.

RESULTS AND DISCUSSION

Correlations of the Operational Model

The analysis of correlations between the input and output variables is an essential initial step in quantitative research. This occurs because one wants to investigate the relationships between the variables under study, they are formulated at the beginning of the process. These questions are directly related to the target population, dependent and independent variables, as well as the research design Table 3 shows the correlations between the selected variables.

Table 3
CORRELATION BETWEEN THE INPUT AND OUTPUT VARIABLES SELECTED FOR THE MODEL

		INPUT			OUTPUT	
	Variables	Personnel Expenses	Administrative Expenses	Capital Stock	Credit Operations	Operational Spillovers
	Personnel Expenses	1				
Input	Administrative Expenses	0.99	1			
	Capital Stock	0.95	0.92	1		
	Credit Operations	0.97	0.95	0.96	1	
Output	Operational Spillovers	0.97	0.96	0.95	0.98	1

The correlation between variables is found to be “strong and positive” Table 3 as indicated by Hopkins (2006), who establishes that correlations with these magnitudes must be between 0.9 and 1.0.

Coding of Dmus and Descriptive Statistics of Variables

The present has estimated efficiency scores of the respective analyzed Service Units and it dealt with specific data of the SUs, then we opted for keeping those units confidential. The criteria adopted for coding are exemplified in Table 4.

Table 4
AMOUNT OF FINANCIAL RESOURCES, CONSIDERING THE RESPECTIVE INPUT AND OUTPUT VARIABLES IN THE PERIOD BETWEEN 2019 AND 2021

Year/ Reference	Personnel Expenses	Administrative Expenses	Capital Stock	Credit Operations	Operational Spillovers
2019	91,75,882.63	1,25,41,502.37	45,94,83,382.68	4,25,13,624.37	2,16,17,726.73
2020	96,77,164.72	1,22,03,587.36	53,02,39,128.66	4,22,62,478.54	2,21,71,892.71
2021	1,08,25,636.34	1,42,67,255.95	59,51,37,421.22	5,08,55,061.92	2,93,85,844.62

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* Values expressed in American currency (US$).
** The currency conversion (from Real to Dollar) was carried out on 10/25/2023 through the website of the Central Bank of Brazil (BACEN).

The set of 24 service units, which includes agencies from different sizes (II, III, and IV), administers a specific volume of resources. This set demonstrates in a dynamic way how the total values are allocated to each specific variable during the periods worked. It is noticeable that the organization directs a substantial amount to areas such as personnel expenses, administrative expenses, and capital stock to achieve its aims. These values were relatively proportional from 2019 to 2020. A significant increase is observed in all those categories in 2021.

Calculation of efficiency scores from the DEA CRS/VRS models

From the application of the variables listed in the previous section to the proposed model, we have the following results:

Table 5
DESCRIPTIVE STATISTICS OF SUS' EFFICIENCY - PRODUCT-ORIENTED CRS AND VRS MODEL – PERIOD FROM 2019 TO 2021

Year	Qty. DMUs	Model	Average	SDev*	Minimum	Maximum	% Efficient DMUs
		CRS	0.8188	0.1817	0.4237	1	25%
2019	24	VRS	0.8782	0.1475	0.584	1	41.67%
		CRS	0.7642	0.2017	0.3578	1	25%
2020	24	VRS	0.8475	0.1806	0.444	1	45.83%
		CRS	0.7258	0.2196	0.3191	1	20.83%
2021	24	VRS	0.8186	0.1942	0.4664	1	37.50%

*** SDev = Standard deviation.**

In Table 5, we see that while efficiency averages show results higher than 70% for CRS and VRS models, there is a notable reduction in DMUs operating under the technical efficiency border (CRS). Considering the averages, this decline was from 81.88% in 2019 to 72.58% in 2021, representing a reduction of 9.30%, which can be related to the emergence of the Covid-19 pandemic, in Brazil officially declared in March 2020, which was accompanied by public health preservation instructions, such as isolation, quarantine, social distancing, and community containment measures, as described by Wilder-Smith and Freedman (2020). These measures probably impacted the cooperative's operations, leading to a downturn in the volume of Credit Operations and compromising Operational Spillovers in 2020 (Table 5).

On the other hand, this period brought uncertainty to many investors, evidencing the need for caution in decisions for future investments. This directly affected the increase in cash and time deposits, with implications for the institution's accounts at the resumption of 2021 (Table 5).

Technical Efficiency (TE) versus Scale Efficiency (SE). The descriptive analysis contained in Table 6 demonstrates that the cooperative reached better scores for DMUs operating under the efficiency border, as those 11 SUs in 2020 that got 100% efficiency, representing

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45.83% of the sample, even considering the circumstantial difficulties mentioned previously. Thus, the calculation of scale efficiency is important, pointing out possible operational adjustment margins. Table 6 shows obtained efficiency scores.

Table 6
TECHNICAL AND SCALE EFFICIENCY SCORES OF THE CENTER-SOUTH MS SICREDI COOPERATIVE BETWEEN 2019 AND 2021

Year	DMUs	Model	Average	Standard Deviation	Min.	Max.	Variation coefficient	Efficient DMUs (qty)	Efficient DMUs (%)
2019	24	Pure technical efficiency (VRS)	0.8782	0.1475	0.584	1	0.1679	10	41.67%
		Scale efficiency (CRS/VRS)	0.9324	0.1075	0.5867	1	0.1153	6	25%
2020	24	Pure technical efficiency (VRS)	0.8475	0.1806	0.444	1	0.2131	11	45.83%
		Scale efficiency (CRS/VRS)	0.9018	0.1761	0.3578	1	0.1952	6	25%
2021	24	Pure technical efficiency (VRS)	0.8186	0.1942	0.4664	1	0.2372	9	37.50%
		Scale efficiency (CRS/VRS)	0.8867	0.1799	0.3379	1	0.2029	5	20.83%

The VRS scores indicating pure technical efficiency are based on the use of inputs considered in counterpoint to their capacity of generating more products for a same level of input. In this way, the VRS reflects the deviations from the border pointing out the managerial inefficiency and has been utilized as a performance index.

The results for pure technical (VRS) and scale (CRA/VRS) efficiency averages had a lower variation, as shown by the variation coefficient Table 7, indicating that those measures do not have significant differences relative to the accounting variables used (inputs and products). In this way, efficiency estimates obtained by the DEA model indicate that most SUs share similar

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characteristics. Moreover, they suggest that a significant number of agencies can improve significantly their results and operations at the same proportion of inputs currently used, on the basis of the product-oriented model.

Results show a significant fall in pure technical efficiency (VRS) throughout the three years, which may be related to failure in more efficient utilization of resources. Furthermore, we observe that while the results obtained in the VRS model show a higher number of DMUs operating above the efficiency border (10, 11, and 9), the averages of all units analyzed are lower (0.8782, 0.8475, and 0.8186) when compared to scale efficiency (0.9324, 0.9018, and 0.8867). This suggests the need for measures to improve the performance of managers of the DMUs operating below the desired level of efficiency. The adoption of this practice may help increase the number of DMUs operating on the efficiency border. Similar results were obtained by Souza, Braga, and Ferreira (2011) in credit cooperatives of Minas Gerais state (Brazil), and for 29 Chinese provinces in the study from Dong and Featherstone (2006).

Scale efficiency estimates (CRS/VRS) indicate a positive variation in the performance improvement for the DMUs analyzed. Such results are similar to the scale efficiency scores observed in the study elaborated by Marwa and Aziakpono (2016), who analyzed 103 audited financial statements, belonging to savings and credit cooperatives in Tanzania.

Thus, the SUs' degree of inefficiency for every year can be measured by using indicators. In this case the pure technical efficiency average (VRS/output) of each analyzed period is defined a score, with the following formula being applied: $(1-1)\,x100$. The results are $score$ contained in Table 7.

Table 7
INEFFICIENCIES FOR THE PERIODS FROM 2019 TO 2021

Periods	Efficiency average (VRS)	Inefficiencies
2019	0.8782	13.87%
2020	0.8475	17.99%
2021	0.8186	22.16%

The results indicate the importance of qualitative guidance in the DMUs under analysis, which would imply an improvement of up to 22.16% in 2021. This can be reached by implementing measures to improve the firms' level of efficiency through the maximization of results or operational capacity improvement.

Ranking of efficiency scores – VRS/output model (2019 to 2021)

Table 8 shows the efficiency border scores for the 24 DMUs as per DEA/VRS model, for the periods under analysis, followed by respective benchmark pairs.

Table 8
RANKING OF EFFICIENCY SCORES OBTAINED IN THE (OUTPUT-ORIENTED) DEA/VRS MODEL IN THE PERIOD FROM 2019 TO 2021, AND RESPECTIVE BENCHMARKS

	Scores			Benchmarks		
DMUs	2019	2020	2021	2019	2020	2021

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A402	0.9953	1	1	A418	A412; A418	-
A403	1	1	1	-	-	-
A304	0.9929	0.961	0.9753	A403; A410	A403; A316; A418	A403; A412; A328
A305	0.584	0.608	0.553	A403; A418; A328	A403; A316; A418; A328	A403; A412; A328
A306	1	1	1	-	A328	-
A308	1	0.879	1	A328	A412; A328	-
A209	0.7061	1	1	A319; A328	A319	-
A410	1	0.947	0.866	-	A403; A412	A402; A306; A412
A311	0.6619	0.444	0.4758	A306; A308; A328	A403; A306; A328	A306; A412; A328
A412	1	1	1	-	-	-
A313	0.6922	0.742	0.6628	A403; A418; A328	A403; A306; A328	A403; A306; A328
A314	0.7803	0.77	0.8304	A403; A306	A403; A306	A403; A306
A315	0.9288	0.674	0.7047	A403; A412; A418;	A403; A316; A418; A328	A306; A412; A328
				A328		
A316	1	1	0.8661	-	-	A412; A328
A317	0.6049	0.547	0.4664	A403; A418; A328	A403; A306; A328	A412; A328
A418	1	1	0.9916	-	A412	A402; A412
A319	1	1	1	A306; A328	-	A306
A220	0.7222	1	0.628	A306; A328	-	A209; A323; A328
A321	0.8551	0.673	0.588	A316; A418; A328	A403; A412; A328	A412; A328
A322	0.9225	0.799	0.7698	A403; A306; A410;	A403; A306; A328	A403; A412; A328
				A328		
A323	1	1	1	A328	-	A328
A324	0.7615	0.642	0.6689	A403; A306; A328	A306; A412; A328	A412; A328
A325	0.8689	0.653	0.5991	A316; A418; A328	A403; A316; A418; A328	A403; A306; A328
A328	1	1	1	-	-	-

Technical efficiency scores have maximum values equal to 1 or 100%. Although most SUs part of the analyzed credit cooperative had not achieved the maximum due to inefficiencies, some agencies reached this score and can be considered benchmarks for the other SUs.

Following the DEA/VRS model, the number of agencies used as benchmarks ranged from nine to eleven in the studied period. Agencies' total volume of capital stock (DMU A305) and time of existence (DMU A328) were observed not to significantly influence the classification of efficiency by the DEA model. In other words, the technical efficiency of the Center-South MS Sicredi Cooperative agencies is not related to their time of existence or even volume of capital stock in that agencies with little time of operation received the same maximum classification (score 1) as agencies with more than 30 years of existence (DMUs A328, A323, A402, and A403).

We stress that geographic location also does not exert a determining negative or positive influence on operational efficacy. By way of example, DMU A328, situated in the Bataguassu municipality, consistently demonstrated excellent efficiency performance throughout the analyzed period, and DMU A319, located in the Aral Moreira municipality, while DMU A305, in

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Amambai, did not obtain similar results. This reinforces the finding that an SU's technical efficiency is not limited to its longevity, size, geolocation, or capital stock. In this way, we can infer that the ability to meet associates' demands is primarily associated with the excellence in DMUs' administrative and financial management, to the detriment of their socioeconomic characteristics connected to the respective geographic locations.

Efficiency Determinants in the Center-South MS Sicredi Service Units

The Tobit model applied as analysis modeling in second stage demonstrated a level of significance between 1% and 10% indicating that the variables considered explain levels of efficiency of the credit cooperative's service units, as demonstrated in Table 9 below.

Table 9
RESULTS OF THE TOBIT MODEL FOR THE PERIODS FROM 2019 TO 2021

Variables (2019)	**Estimates**	**Standard Error**	**T value**	**P> |t|**
Personnel expenses	-2.86E-07	1.78E-07	-1.603	0.1088
Administrative expenses	2.04E-08	9.36E-08	0.218	0.8273
Capital stock	-1.99E-09	8.09E-10	-2.455	0.0141*
Credit operations	4.73E-08	1.76E-08	2.692	0.0071**
Operational spillovers	3.45E-08	2.36E-08	1.459	0.1446
Variables (2020)	Estimates	Standard Error	T value	P> |t|
Personnel expenses	-5.42E-07	1.46E-07	-3.72	0.000199***
Administrative expenses	-7.00E-08	8.23E-08	-0.851	0.394948
Capital stock	5.09E-10	1.02E-09	0.501	0.616391
Credit operations	1.29E-07	3.24E-08	3.968	7.25e-05***
Operational spillovers	-4.78E-08	3.66E-08	-1.309	0.190636
Variables (2021)	Estimates Standard Error T value P> |t|			
Personnel expenses -1.057E-07		1.15E-07	-0.922	0.3566
Administrative expenses -1.680E-07		7.52E-08	-2.232	0.0256*
Capital stock -5.486E-10		1.04E-09	-0.529	0.5968
Credit operations 2.273E-08		2.71E-08	0.839	0.4015
Operational spillovers 6.099E-08		4.22E-08	1.445	0.1484
Note: *** significance at the 1% level; ** significance at the 5% level; * significance at the 10% level				

The β coefficients interpretation is not as direct as the interpretation of a conventional linear regression model. This occurs because the changes in the independent variables do not affect only the dependent variable average inside the set interval, but also influence the probability of the variable being inside this interval.

Thus, different behaviors in the variables applied to the model are observed. Notably, the personnel expenses variable, which showed 1% statistical significance in 2020, exerts a negative

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effect on the efficiency score in the three years of analysis. This variable is considered crucial in the context of banking activity because it represents the effort dedicated to the commercialization of products and services. However, it is important to mention the existence of challenges in obtaining an accurate worksheet, which quantifies collaborators' individual performance. Furthermore, it is important to highlight that one of the main virtues of the credit union movement is the humanized management practice. This approach is seen as an element that adds value and as an essential competitive element that contributes to the construction of an institution's prominent position, as discussed by Mackey and Sisodia (2013).

The administrative expenses in 2020 and 2021, with a 10% statistical significance in 2021, are associated with expenses for the carrying out and supervision of management tasks. As regards this variable, some studies indicate that high levels of resources allocated to this category can indicate possible waste.

The econometric model results reveal that social stock exhibited a negative weight in 2019 and 2021, with a 10% significance in 2019. This variable is the main source of resources for cooperatives' development, based on the economic participation principle, with the objective of strengthening the organization's economic structure. In this context, Ferreira, Gonçalves, and Braga (2007) argue that credit cooperatives often deal with capitalization challenges since many members do not face them as an enterprise of their own or as owners of the business. Additionally, because of the non-transactionable nature of those shares in the financial market, partners/members do not see prospects of return on the investment.

The operational spillovers variable showed a negative impact only in 2020. A consequence that may be attributed to operational difficulties faced by cooperatives due to the Covid-19 pandemic and its subsequent effects, in line with what Tanjung and Purnamadewi (2021) emphasized when examining the economic impact of the pandemic on credit cooperatives' performance.

It is particularly noteworthy that credit operation emerges as the only variable showing a consistent positive effect in calculating efficiency in the three consecutive years of analysis, evidencing significance levels of 5% in 2019 and 1% in 2020. This observation is relevant because it concerns products that facilitate access to the credit offered by the cooperative. This variable is of extreme importance since the volume made available reflects the SUs management capacity to attract and maintain financial resources invested by members of a cooperative, be it by savings, cash and time deposits, and/or capitalization.

Results obtained in both indicators indicate possible management technical deficiencies, suggesting the need for specific actions that may minimize administrative expenses or adjustments in the number of collaborators, notwithstanding the offer of personalized services to the cooperative's member, which is part of the essence of the cooperative movement.

CONCLUSION

The study analyzed the economic efficiency of the 24 Service Units (SUs) making up the Center-South MS Sicredi Credit Cooperative, basing itself on data of three years. Results showed that the cooperative's technical efficiency suffered a significant fall due to inefficiency in the use of resources occurring in a pandemic period that impacted credit operations and operational spillovers in the analyzed period.

VRS model suggests margins of adjustment to improve Service Units' (SUs)

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performance. Many of these units operate close to ideal efficiency.

Second stage analysis included the impact of personnel expenses and operational spillovers, which affected efficiency, while credit operations had a consistent positive effect, being important to note that humanized management and cooperativism are essential values for the institution.

The results are of great importance for the cooperatives because they help operate more efficiently under the economic efficiency border on the basis of the model and variables used.

Furthermore, it is fundamental to consider that the marginal effects resulting from the statistics included in the study are conditions necessary for improving the analyzed Service Units' (SUs) performance.

The cooperative operates in municipalities situated on the border strip with Paraguay, which is characterized by cultural, economic, social, and environmental particularities exerting a significant influence on the organization's performance. This, in turn, impacts the desired efficiency. Furthermore, in certain municipalities, the cooperative plays the role of only local financial institution, which results in a specific increase in its responsibilities and commitments to community and regional development.

From the analysis of input and product variables applied to this study, we recommend new scientific studies and managerial actions, among which (i) the carrying out of metric studies on collaborators' efficiency, taking into consideration physical and technological infrastructure available, allocation of collaborators by Service Unit (SU), responsibilities, wage policy, and the local economy potentialities or limitations; (ii) the development of promotional campaigns aiming to strengthen the cooperative's social stock; and (iii) creation of specific products or services (lines of credit), following economic and social specificities of the municipalities where the credit cooperative maintains its operations.

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