

Operational Efficiency and the Growth of Credit Cooperatives in Brazil

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Abstract

Objective: To analyze whether the growth of credit unions between 2012 and 2020 was influenced by operational efficiency.

Method: 355 cooperatives linked to the Brazilian Credit Cooperative System (Sicoob) were empirically analyzed. First, an analysis model applied the Data Envelopment Analysis (DEA) to obtain efficiency scores. Next, a two-stage regression analysis with panel data was performed. Controls related to the cooperatives' number of branches, age, capitalization, provisioning, and financial structure were adopted.

Results: A DEA efficiency score with a median of 0.52 was found among the cooperatives, indicating considerable inefficiency among the units analyzed. The regression analysis results show that a Brazilian credit cooperative's level of operational efficiency is positively related to its growth.

Theoretical and practical contributions: The literature presents empirical evidence on efficiency but not the relationship between Brazilian credit cooperatives' operational efficiency and growth. The results of this study can support cooperative managers' decision-making regarding cooperatives' operational efficiency and growth.

Keywords: Credit Cooperatives; Efficiency; Growth and Data Envelopment Analysis.

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1. Introduction

According to McKillop and Wilson (2011), credit unions are financial institutions whose primary purpose is to accept deposits and grant credit to their members. As stated by Goddard et al. (2002), credit unions' strength lies in their philosophy's appeal and objectives that meet the expectations of a large number of people who want to achieve greater self-sufficiency when managing their financial affairs collectively.

Data from the World Council of Credit Unions (WOCCU) reveal that credit cooperatives worldwide achieved between 1999 and 2020 nominal growth of 137.1% of assets under management, from US\$1.353 trillion in 1999 to US\$3.208 trillion in 2020 (WOCCU, 2020).

The analysis of how credit cooperatives evolved in the United States of America (USA), the country with the greatest representation in the segment, also showed significant growth (Wheelock & Wilson, 2013); the average total assets adjusted for inflation between 1985 and 2006 grew by over 600% (Wheelock & Wilson, 2013). In 2020, the participation of credit unions in the USA represented around 10% of deposits in that country, with US\$ 1.87 trillion in total assets and more than 123 million associated members (Nguyen et al., 2022).

A similar movement concerning the main numbers of the National Cooperative Credit System (SNCC) has been observed in Brazil in recent years (Banco Central do Brasil [Bacen], 2020). Brazil has maintained its growth trajectory higher than the average of the other agents in the National Financial System (SFN), even in 2020, a challenging year marked by the COVID-19 pandemic (Bacen, 2020).

Considering 2012 as the starting point of the historical series of SNCC records published by Bacen, a variation of 389.2% found in the total assets of credit cooperatives up to 2020 stands out (Bacen, 2020). The total assets went from R\$76 billion in 2012 to R\$371.8 billion in 2020, a growth mainly represented by the credit portfolio, with a variation of 355.5% in the same period (Bacen, 2020). These numbers indicate a demand in the market for financial institutions. Regarding the number of active credit cooperatives, the opposite movement was found, with a net reduction of 364 units: in 2012, there were 1,211 units, compared to 847 in 2020 (Bacen, 2020). According to Bacen (2020), this downward trend in the number of credit cooperatives results from an incorporation process that occurred a few years ago in the cooperative segment, aimed at economies of scale and greater Operational Efficiency (OE) (Bacen, 2020).

Santos et al. (2021) note that efficiency has been widely measured as a performance indicator for financial institutions. McKillop and Quinn (2017) applied the common frontier methodology to assess the cooperatives' growth patterns, regardless of the characteristics of their business model, in a study on the structural performance of Irish cooperatives.

There is evidence that studies measuring efficiency support the decision-making of corporations, as their findings indicate practical applications for improving management techniques (Bittencourt & Bressan, 2018). Therefore, this study investigates the following problem: Is the growth of credit unions influenced by their efficiency level?

McKillop et al. (2002) found evidence of a considerable degree of scale inefficiency in the United Kingdom due to cooperatives operating within the restrictions established by the government on the portfolio of products and services. Recent Brazilian studies, Vilela et al. (2007), Bressan et al. (2010), and Bittencourt and Bressan (2018), examine the level of efficiency of credit cooperatives with a delimitation of scope, such as geographic region, time series, and association conditions, respectively.

Therefore, this study is intended to fill this gap in the literature, at least partially, expanding the scope of research on the efficiency of credit cooperatives and seeking an explanatory variable for credit cooperatives' growth (GROW). In this context, the objective of this study was to analyze whether the growth of credit unions between 2012 and 2020 was influenced by operational efficiency.

Regarding the research methodology, Data Envelopment Analysis (DEA) was used to determine the cooperatives' efficiency level. Next, the Two-Stage Least Squares (2SLS) Regression technique was applied to determine the statistical significance between the efficiency level and the cooperatives' growth. The period from 2012 to 2020 was analyzed. The results suggest that the level of the cooperatives' operational efficiency presents a positive and statistically significant relationship, possibly explaining the growth of cooperatives in the period.

This study contributes to the Brazilian literature on credit cooperatives, with practical application in the following: (i) providing support to studies on management based on the relationship between efficiency and growth that can benefit managers in the cooperative segment and (ii) providing inputs to research funding agencies linked to the cooperative segment to promote research on credit cooperative management.

This paper is organized as follows: The next section provides an overview of credit cooperatives in the world and Brazil, emphasizing the representativeness and studies on the efficiency of cooperatives. Next, the empirical methodology and econometric modeling are discussed, followed by a summary of the variables' definitions, data sources, and descriptive statistics. Finally, the empirical results are presented and discussed, along with practical implications.

2 Literature Review

2.1 The Growth of Credit Cooperatives

Qualitative records concerning 2020 from the World Council of Credit Unions (WOCCU) show that credit unions were present in 118 countries, distributed in 86,451 units, and had 375.1 million associated members, a contingent that represented 12.1% of the economically active population at that time (WOCCU, 2020). Regarding the number of cooperatives on a global scale in 2020, the consolidation of savings through deposits was US\$2.7 trillion (WOCCU, 2020). In turn, the loan portfolio held US\$2 trillion and total assets of US\$3.2 trillion (WOCCU, 2020).

By 2013, 136.3 million associated members were linked to 5,655 cooperatives in the USA, the country with the largest share of credit unions in the world (WOCCU, 2020). At the time, the country had a membership rate of 50.4% of the population considered economically active (WOCCU, 2020). According to Wheelock and Wilson (2013), the assets of USA credit unions practically doubled between 1985 and 2009, going from 3.3% to 6.0% of their share among depository institutions. The authors also highlight that membership/association grew faster than the country's population, from 52 million members in 1985 to 93 million in 2009 (Wheelock & Wilson, 2013).

According to Bacen, with a historical series starting in 2012, the total assets of credit unions grew from R\$76 billion in 2012 to R\$371.8 billion in 2020 in Brazil, a variation of 389.2% in eight years (Bacen, 2020). The records also show continuous member growth, from 6 million in 2012 to 11.9 million in 2020 (Bacen, 2020). The growth of cooperatives is explained by the appeal of their philosophy and objectives that meet the expectations of a wide range of people who wish to achieve self-sufficiency in financial management collectively (Goddard et al., 2002). Therefore, Brazilian credit cooperatives have shown consistent growth over the last eight years, measured by total assets, representing an average annual growth of 48.6%. Note that the growth in 2020 was higher than the average of other agents in the National Financial System (SFN), even during the COVID-19 pandemic (Bacen, 2020).

2.2 Studies on the Efficiency of Credit Unions

Farrell's (1957) is a seminal study on productive efficiency. It exposes a model that considers, in addition to other characteristics, the relationship of multiple inputs and products and exogenous variables, such as the benchmarking approach and efficient frontier based on the study's data.

A limited-scope approach was adopted in the study above, as only the analysis of financial ratios was applied to characterize whether USA cooperatives presented an increasing return to scale (McKillop & Wilson, 2011). The literature on the efficiency of financial institutions comprises a large volume of research on the structural performance of the banking segment; however, the literature on credit cooperatives is scarce (Worthington, 2010).

In this context, McKillop and Quinn (2017) emphasize that studies on credit cooperatives are more widespread in countries with more accessible data and greater representation of credit cooperatives, such as the United States, Canada, and Australia.

Wheelock and Wilson (2013) investigated how the productivity and efficiency of credit unions evolved in the USA between 1989 and 2006 and found evidence of a decreased average cost-productivity among the cooperatives they analyzed, especially in the smaller ones (Wheelock & Wilson, 2013). The findings of the previously mentioned study also indicate decreased efficiency, which was less pronounced among the largest cooperatives (Wheelock & Wilson, 2013).

Pille and Paradi (2002) conducted a study to examine the efficiency of cooperatives in Ontario (Canada), and DEA modeling was adopted to identify potential failures that can be predicted before the bankruptcy of cooperatives.

Credit unions in the UK were classified as having a considerable degree of scale inefficiency, with over 50% of inefficient credit unions subject to diminishing returns to scale (McKillop et al., 2002). The study above highlights that the problem for credit unions in the UK is that they operate within strict limits set by the government, for example, in terms of the type and range of products they can offer their members (McKillop et al., 2002). Therefore, larger cooperatives invest heavily in facilities, personnel, and technology; hence, it is not surprising that they are subject to diminishing returns to scale (McKillop et al., 2002).

In Australia, the cooperatives' age (AGE) factor was decisive for efficiency, as older cooperatives were classified as more efficient on average (Esho, 2001), considering restrictions common to other cooperatives, which had high ratios of capital with the provision of services charging lower rates on loans and paying higher rates on deposits (Esho, 2001).

According to the World Council of Credit Unions, data from Europe show that, despite Ireland's prominent participation in the credit cooperative segment on that continent, McKillop and Quinn (2017) assert that only three studies – i.e., Quinn and McKillop (2009), Glass et al. (2010), and Glass et al. (2014) – investigated the structural performance of credit unions in that country.

In Brazil, Bressan et al. (2010) investigated cost efficiency and economies of scale in mutual credit cooperatives in the State of Minas Gerais, Brazil. They found that the average cost efficiency score was 15%, which indicates cost inefficiency. The authors above found a weak correlation between the cooperatives' size and the cost efficiency score; i.e., a cooperative's size would not interfere with the efficiency metrics (Bressan et al., 2010).

Bittencourt and Bressan (2018) expanded the sample of Brazilian credit cooperatives by analyzing 130 credit cooperatives linked to the Sicoob, Sicredi, and Unicred Systems. Thus, they found an average efficiency score of 70.38%, in which credit operations were the leading determinant of efficiency score (Bittencourt & Bressan, 2018).

In a study on scale efficiency and technological change in cooperatives, Bittencourt et al. (2016) analyzed 130 cooperatives from 2009 to 2013. The results suggest that institutions that allocated a more significant portion of volumes to credit assets in the total composition of resources showed increased scale efficiency (Bittencourt et al., 2016).

Finally, we highlight the results of a recent study by Santos et al. (2021) addressing the relationship between credit risk and technical efficiency in Brazilian credit cooperatives. They draw attention to decreased efficiency scores due to an increase in the number of branches and the positive contribution of the diversification of the portfolio of products and services to the gain in efficiency scores (Santos et al., 2021).

Therefore, relevant literature uses different approaches to investigate the efficiency of the cooperative credit system at a global and local level; however, no studies were found identifying the relationship between the efficiency and growth of credit cooperatives, whether at the global or national level. Therefore, the existing gap supports the hypothesis proposed here.

In this context, aiming to find evidence that explains the growth in the total assets of Brazilian credit unions and verify how such variation influences this growth in operational efficiency, Equation 1 expresses the logical foundation of this purpose:

$$P(\textit{Growth}|\textit{Efficiency}) = \frac{P(\textit{Growth} \cap \textit{Efficiency})}{P(\textit{Efficiency})} \quad (1)$$

Equation 1 shows how growth and efficiency events behave conditionally; i.e., if there is efficiency, how this affects the probability of growth in the number of credit unions. The numerator shows the intersection between the two events, i.e., the mutual occurrence of both.

Therefore, assuming a dependency relationship between growth and Operational Efficiency (OE), by controlling all factors, such as the variation in OE, it is possible to explain the variation in the growth of credit cooperatives over time. Hence, Hypothesis 1 (H1) is proposed:

H1: The OE positively influenced the growth of total assets of Brazilian credit unions.

3. Research Methodology

3.1 Sample and Data Collection

The cooperatives' accounting data were extracted from balance sheets collected directly on the publicly accessed Bacen website, the Financial Institutions Accounting Plan (Cosif). The analysis of accounting data was limited to the years from 2012 to 2020 since the first release of consolidated numbers for cooperatives by Bacen was in 2012.

The sample comprised 355 individual credit cooperatives linked to the Brazilian Credit Cooperative System (Sicoob) and distributed throughout the Brazilian territory, resulting in 3,195 observations. The cooperatives were restricted to Sicoob due to its representation in the SNCC during the study period, so its participation in 2020 was equivalent to 43.8% of the total of individual cooperatives, i.e., a relevant sample in terms of the qualitative aspect of national coverage (Bacen, 2020).

Those classified as capital and loan cooperatives were ineligible because they do not collect deposits. Those with missing information, such as cooperatives that failed to report the incorporation event in the period, were also ineligible. Thus, a balanced panel was used.

3.2 Econometric Model and Test of Hypothesis

This topic discusses the econometric model, multicollinearity tests, heteroscedasticity, endogeneity assumptions, Pearson's correlation analysis, and hypothesis testing performed via the two-stage OLS estimator. Equation 2 presents the econometric model for hypothesis testing:

$$Growth_{i,t} = \beta_0 + \beta_1 Operational\ Efficiency_{i,t} + \sum_{k=2}^5 \beta_k Controls_{k,i,t} + \varepsilon_{i,t} \quad (2)$$

Where:

VARIABLE	TYPE	ACRONYM	DESCRIPTION	REFERÊNCIA	FONTE
Growth	Response	GROW	Variation in the logarithm of Total Assets (NL) R\$	McKillop e Quinn (2017) Goddard et al. (2014) Wheelock e Wilson (2013).	Bacen (2020)
Operational Efficiency	Explanatory	OE	Product of the application of the DEA method: as shown in Figure 1.	Mckillop et al. (2002); Esho (2001); Vilela et al. (2007); Freaza et al. (2008); Ferreira et al. (2007); Bitencourt e Bressan (2018)	Bacen (2020)
Branches		BRAN	Number of Branches		
Cooperatives' age		AGE	Age (in years)		
Capitalization	Control	SK	NL of Social Capital (R\$)	Esho (2001); Goddard et al. (2002); Mckillop et al. (2002); e Santos et al. (2021)	Bacen (2020)
Provisioning index		INDP	Provisions for Credit Operations/Credit operations (index)		
Financial Structure		ROA	Return on Assets (Index)		

Source: Developed by the authoro R2.

Figure 1. Variables' characteristics

Regarding the model's response variable, we adopted the variation in total assets logarithmic as a representative measure of the Brazilian cooperatives' growth. It is GROW; previous researchers have predominantly used this indicator for this purpose (Goddard et al., 2002; Goddard et al., 2014). The log of total assets (TA) was used because there are cooperatives with million-dollar TA, and efficiency is a variable estimated through DEA, varying continuously between zero and one. Hence, we use the log of total assets instead of total assets to mitigate the variance in the estimation and reduce the scale effect (Wooldridge, 2023).

The measurement of operational efficiency, also called technical efficiency, has been widely used in the academic milieu to measure the performance of corporations, especially financial institutions (Peña, 2008). According to Bauer (2008), much of the empirical work addressing the efficiency of credit cooperatives uses the DEA model.

Regarding the functional form, DEA modeling is classified as non-parametric since it does not require defining a theoretical functional relationship between the analyzed variables beforehand (Berger & DeYoung, 1997). This model is based on the foundations of microeconomic production theory and reveals itself as the materialization of the practical application of this theory, given its applicability in evaluating the relative performance of production units (Ferreira & Gomes, 2020).

DEA consists of a linear programming methodology whose main application is to measure the technical efficiency of a set of homogeneous units, also called Decision Making Units (DMUs). Technical efficiency, in turn, is associated with the efficient use of inputs. Therefore, when adapting to the cooperatives' environment, the unit (DMU) is efficient by using fewer inputs and producing more products, such as loans, financing, and surpluses (Staub et al., 2010).

In this context, the efficiency frontier was developed using DEA modeling to compare this study's variables. It is known to be a tool with faster analysis processing and less subjectivity (Vilela et al., 2007).

As Barros et al. (2020) indicated, the main DEA models are those whose orientation is to minimize inputs and the model with orientation to maximize outputs/products (outputs).

Therefore, the following variables, which consider the standard approach to financial intermediation, were analyzed to measure the efficiency of credit cooperatives, especially technical efficiency. The product orientation specification model (VRS) was applied based on the cooperatives' primary objective: to grant credit (Wheelock & Wilson, 2013; Walke et al., 2018).

Produtos (R\$)	Tipo	Código Conta Contábil (Bacen)	Referência
Operações de Crédito. (y_1)	Output	1.6.0.00.00-1	Santos et al., 2020; Bitencourt e Bressan (2018); Bittencourt et al. (2016); Bressan et al. (2010)
Sobras (y_2)		7.0.0.00.00-9 + 8.0.0.00.00-6	
Depósitos Totais (x_1)	Input	4.1.0.00.00-7	
Despesas de Captação (x_2)		8.1.1.00.00-8	
Despesas Administrativas (x_3)		8.1.7.00.00-6	
Outras despesas operacionais (x_4)		8.1.9.00.00-2	

Source: Official Bacen Website (adapted by the author).

Figure 2. Variables Used – Calculation of Operational Efficiency

The outputs (credit operations and surpluses) were selected as a proxy for the magnitude of services provided by the credit cooperatives, i.e., as a measure of the scale necessary for cooperatives to survive (Wheelock & Wilson, 2013; Goddard et al., 2002). Similarly, the inputs were selected considering their relationship with critical factors for increasing economies of scale, such as expenses with technology, personnel, management practices, and techniques (Bittencourt & Bressan, 2018; Mckillop et al., 2002). These expenses involve the ability of cooperatives to capture the largest volume of resources (fundraising expenses), manage such resources, and put their strategies into practice (administrative costs and other operational costs).

After measuring the cooperatives' efficiency frontier, the operational efficiency variable was calculated and used as the explanatory variable in Equation 2 to test the hypothesis (H_0). Therefore, a positive relationship is expected with Growth (GROW) in the credit cooperatives' operating environment, considering the basic assumption of product-oriented Operational Efficiency (OE), which aims to minimize the relationship between inputs and products (McKillop & Ferguson, 1998; Esho, 2001; Mckillop et al., 2002; Santos et al., 2021).

Regarding the control variables, Santos et al. (2021) found a negative relationship between the number of Branches (BRAN) and the cooperatives' efficiency scores due to a potential compression of margin caused by increased costs. While banks decreased the number of branches during the study mentioned above, in the opposite direction, the cooperatives expanded their service network (Santos et al., 2021).

Esho's (2001) study on Irish cooperatives' age (AGE) showed a positive relationship with the cooperatives' growth. His findings show evidence that cooperatives "learn by doing" and that valuable relationships are built with members over time (Esho, 2001). Goddard et al. (2002) found a positive relationship between the cooperatives' Social Capital (SK) and growth due to the possibility that a solid capital base is necessary to sustain the growth of assets.

A high Provisioning Index (INDP) may indicate a poorly managed cooperative, considering that this index reflects the delay in receiving credits granted, resulting in a negative relationship with growth (Goddard et al., 2002). Finally, the indicator of financial structure (Return on Assets – ROA) showed signs of positive coefficients with the cooperatives' growth, which suggests that high-return credit cooperatives are reinvesting in their assets to ensure sustained growth (Goddard et al. al., 2002).

4. Data Analysis

4.1 Descriptive Statistics Results

4.1.1 DEA Modeling Descriptive Statistics

This topic presents the descriptive statistics of efficiency measured by DEA and inputs and outputs. As shown in Table 1, the DEA efficiency score (explanatory variable) obtained an average of 0.56 and a median of 0.52. According to the model's mathematical structure, this situation indicates a relative predominance of inefficiency in the units analyzed here, i.e., an institution is assumed to be efficient when its score equals 1.

As expected, the maximum score was 1, and the minimum was 0.007. Regarding the dispersion analysis, the standard deviation of 0.24 and the range between minimum and maximum values denote a relevant dispersion in the sample (Table 1). As for the accounting variables that served as inputs for the DEA model, they did not present a constant number of observations. Therefore, missing and/or zero values were disregarded in the model; thus, 3,493 observations remained in the DEA output and efficiency score records (Table 1).

Table 1

Descriptive Statistics – Inputs and Outputs – DEA Model

Table 1 presents the main descriptive statistics of the variables used in the DEA model, where *Inputs* (R\$) were Total Deposits, Fundraising Administrative and Other Operational Costs, and *Outputs*: Credit and Surplus Operations. Finally, the DEA efficiency score descriptions.

Variáveis	No. observations	Mean	Median	Minimum	Maximum	Desvio-Padrão
Credit operations (R\$)	3.493	103.268.120	39.912.980	4.582	3.885.764.143	231.788.881
Surplus (R\$)	3.493	2.178.357	767.970	-46.074.861	71.489.374	5.463.807
Total Deposits (R\$)	3.446	115.856.623	43.234.589	516	3.964.941.262	243.370.510
Fundraising Expenses (R\$)	3.464	-3.269.296	-1.136.756	-122.843.789	0,00	7.635.581
Administrative Costs (R\$)	3.490	-5.415.847	-3.020.216	-104.379.160	-7.102	7.781.039
Other Operational Costs (R\$)	3.488	-1.585.389	-486.641	-76.624.946	0,00	4.242.109
DEA	3.493	0,56	0,52	0,007	1,00	0,24

Source: developed by the author.

Analysis of the history of the efficiency score per DMU showed that only four cooperatives were efficient with a score of 1.0 throughout the time series: Sicoob Cocred CC, CC Credicitrus, CCM Emp. from Embraer, and CECM Func. Bulk Molding (Table 1). Overall, 372 efficiency scores were equal to 1.0 over the years, representing 10.6% of 3,493 observations. It is an interesting result for the panel data regression due to the variability over time (Table 1).

4.1.2 Descriptive Statistics of the Regression Model's Variables

A balanced panel was determined to apply the regression model, and only institutions that appeared repeatedly over the eight years were included; hence, the study's final sample was composed of 355 cooperatives. The analysis produced 3,195 longitudinal observations. Table 2 shows the main descriptive statistics of central tendency and dispersion of the study's interest and control variables.

Table 2

Descriptive Statistics of the Interest and Control Variables

Table 2 presents the main descriptive statistics of the variables used in the regression model.

Variables	No. observations	Mean	Median	Minimum	Maximum	Standard deviation	Quartile 75%	Quartile 25%
CO	3.195	18,19	18,26	13,10	22,82	1,38	19,14	17,27
EO	3.195	0,56	0,52	0,007	1,00	0,24	0,70	0,38
PA	3.195	6,07	3,00	0,00	116,00	8,51	8,00	1,00
AGE	3.195	13,29	12,51	0,50	52,26	5,65	15,35	9,93
KS	3.195	16,41	16,35	12,65	20,98	1,13	17,11	15,64
INDP	3.195	0,05	0,04	0,00	1,08	0,08	0,07	0,03
ROA	3.195	0,01	0,01	-0,22	0,08	0,02	0,02	0,00

Source: developed by the author.

The dependent variable Growth (GROW), which results from the application of the logarithm of the cooperatives' adjusted total assets, showed a low discrepancy between its minimum and maximum value, in addition to a low dispersion, indicated by the coefficient of variation, of 7.61%. These results are important for the regression model's goodness of fit.

About the number of Branches (BRAN), a median of 3 units per cooperative was found, with a maximum of 116 units. Regarding the cooperatives' age (AGE), measured in years, note that the cooperative with the longest longevity in the analyzed sample is close to 53 years of existence. Another variable with less dispersion in the study, Social Capital (SK), presented a coefficient of variation of 6.86%, with a standard deviation of 1.13, which denotes that these are homogeneous records.

The average Provisioning Index (INDP) calculated throughout the historical series was 5.0%. In comparison, the maximum was 108%, i.e., a given DMU appears in Bacen's records with more than 100% of its credit portfolio provisioned. Still on the segment's provisioning behavior, despite an adverse scenario in 2020 due to the COVID-19 pandemic, SNCC's consolidated provisioning level remained stable, ending the year at 4.8% (Bacen, 2020), very close to the series analyzed between 2012 and 2020.

The ROA control variable – considering the ratio of surpluses to adjusted assets, i.e., disregarding the “compensation accounts” of the group of assets – was 1.10% on average over the period under analysis. This variable proved heterogeneous with high dispersion, according to a coefficient of variation of 143.5%. In this sense, the highest ROA was 8.0%, and the worst performance was -22.0%.

4.2 Pearson's Analysis of Correlation

Table 3 provides Pearson's linear correlation coefficients of the variables in the model's second stage. Note that Operational Efficiency (OE) and Growth (GROW), considered the core of this study's hypothesis, are positively and significantly correlated with a 99% confidence interval. Despite the positive correlation, these are preliminary results, considering univariate estimation without controls.

As for the control variables, note that only the Provisioning Index (INDP) did not present a statistically significant correlation with the cooperatives' Growth (GROW), indicating a counterpoint to the findings of Goddard et al. (2002). However, its relevance is effectively tested below in the regression model.

Table 3
Pearson's Correlation of Matrix of Variables

Table 3 presents the correlations of the variables in the second stage. Figure 2, "Variables' characteristics," presents the descriptions of the variables.

Variáveis	CA	EO	AGE	KS	INDP	ROA	BR AN
CA	1						
OE	0,232***	1					
AGE	0,118***	0,23***	1				
SK	0,843***	0,354***	0,248***	1			
INDP	0,015	-0,14***	0,035**	0,012	1		
ROA	0,093***	0,157***	-0,074***	-0,015	-0,161***	1	
BRAN	0,663***	0,132***	0,091***	0,588***	0,026	0,018	1

Note: The symbols *** and ** indicate that the correlation is statistically significant at 1% and 5%, respectively.

Source: study's results.

Pearson's correlation indicates a positive and higher correlation in the variables (SK and CA).

4.3 Diagnostic tests for applying the regression model

Diagnostic tests, normality, and serial autocorrelation of residuals were performed with the model to validate the results presented in Table 6. Additionally, the presence of endogeneity in the model was tested. Chow, LM Breusch-Pagan's and Hausman's tests were performed to determine the best model specification; the Hausman test showed that a panel with fixed effects is the most suitable.

The Jarque-Bera test indicated that the residuals did not present a normal distribution. However, according to Wooldridge (2023) and West (1996), under certain conditions, we can assume that the OLS estimators satisfy asymptotic normality; that is, the residuals will present an approximately normal distribution in sufficiently large samples; the residuals must not present heteroscedasticity for this condition (Wooldridge, 2023). This problem was corrected, as the model was estimated with robust White correction. Furthermore, the estimated residuals also statistically presented a close to zero mean. Likewise, Box and Watson (1962) state that the non-normality of the dependent variable may not affect the distribution of test statistics, depending on the choice of model variables.

Finally, the Wooldridge test was performed to test the existence of serial autocorrelation in the residues and endogeneity, indicating a correlation between the residues and the model's explanatory variables. The Two-Stage Least Squares (2SLS) method was used to correct the endogeneity problem. Specifically, the Branches (BRAN) variable was instrumented using the logarithm of Credit Operations as an instrument, which conceptually has a positive covariance with the number of branches and is orthogonal to the disturbance term.

The results of this process are presented in Table 5.

Table 5

Result of the BRAN regression with its instrument NL of Credit Operations

Instrument	Coefficient	Statistics t
NL Credit Operations	3,63***	55,07

Note 1: The symbols ***, **, and * represent the level of significance 1%, 5%, and 10, respectively.

Source: study's results.

As shown in Table 6, the endogenous variable has a positive covariance with its instrumental variable. Endogeneity, strength, and validity tests were applied to the following instruments. The instrument was not invalidated based on the Durbin-Wu-Hausman and Sargan-Hansen tests (GMM).

4.4 Regression Model Results

The two-stage regression model with panel data was used to test the study's hypothesis. It consists of looking for evidence that determines whether the level of operational efficiency influences the growth in total assets of credit unions. Table 6 presents the results of the regression model, applied to the data set, in a panel with fixed and robust effects adjusted to heteroscedasticity.

Table 6

Result of the Two-Stage Fixed Effect Panel Regression: Explained Variable Growth (GROW)

Variables	Coefficients
Operational Efficiency (OE)	0,26***
Cooperatives' age (AGE)	0,09***
Capitalization (SK)	0,03
Provisioning Index (INDP)	-1,11**
Return on assets (ROA)	1,53
Branches (BRAN)	0,25***
Constant	15,24***
Observations	3.195
Wald Test	132916,24***
R ²	0,21

Note 1: The symbols ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively.

Source: study's results.

As shown in Table 6, the p-value of the Wald-Chi2 statistic, which measures the coefficients' overall significance, was 0.0, which is statistically significant at all levels. Therefore, the hypothesis that all model coefficients are equal to zero was rejected. In other words, the model explains the response variable's behavior, i.e., the cooperatives' credit growth (total assets).

The explanatory variable Operational Efficiency (OE) coefficient was statistically significant at 1% and positively influenced the cooperatives' growth. Therefore, the null hypothesis failed to be rejected. Notably, these results corroborate the studies by Wheelock and Wilson (2013), Mckillop et al. (2002), and Goddard et al. (2002), which highlight the importance of cooperatives' economies of scale and efficiency for their survival and growth.

Regarding the control variables, Capitalization (SK) and ROA were not statistically significant. The Cooperatives' age (AGE), Branches (BRAN), and Provisioning (INDP) were statistically significant at 5% (Table 6). In this context, this study corroborates the results of Goddard et al. (2002) and Esho (2001), in which the coefficient of the AGE variable was positive, suggesting that the one-year variation increases the expected variation in the cooperative' total assets (Table 6). In other words, more mature cooperatives and, consequently, with greater market experience tend to show more significant growth.

The INDP variable concerning the cooperatives' default was determined using an index; hence, it is necessary to remove the effect of the unit to interpret its coefficient. In this case, it should be noted that it was negative and significant at 1%, as $-1.11 + 1 = -0.11$; therefore, it suggests that a variation of one unit in this index reduces the growth of cooperatives – a result compatible with the findings of Goddard et al. (2002).

Finally, the number of Branches (BRAN) presented a positive coefficient, in which the variation of one unit in this variable increases the log of expected total assets, thus suggesting that face-to-face relationships established in physical branches may be related to the consumption of the cooperatives' products, according to Esho (2001). Likewise, the greater the service scale of these companies (total number of branches), the greater their growth (Mckillop et al., 2002).

Notably, this study's results show that scale of operations (Branches), technical efficiency (Operational Efficiency), experience with the market (Cooperatives' age), and Provisioning Index are important factors for the growth of credit cooperatives in Brazil. Therefore, in addition to scale efficiency, presented by Mckillop et al. (2002), it is also important to consider the impacts on the cooperatives' operational efficiency (Bittencourt & Bressan, 2018), specifically small-sized ones (Wheelock & Wilson, 2013). Therefore, the scale of operations and the cost of raising and managing these operations are relevant for the cooperatives' growth.

5. Final Considerations

This study's objective was to analyze whether the growth of credit unions between 2012 and 2020 was influenced by operational efficiency. A total of 355 credit cooperatives linked to Sicoob were analyzed, with data collected mainly from Bacen. The DEA efficiency score was used to measure operational efficiency, while the variation in the logarithm of total assets was considered to measure growth.

The calculation of the efficiency score showed that the credit cooperatives addressed here presented relatively low operational efficiency, given the low DEA score (0.52). As highlighted, technical efficiency, including the ability and cost of obtaining credit, besides the volume of operations, is an essential factor for the cooperatives' growth and survival. A low-efficiency score may lead to low growth potential; hence, prioritizing training programs to improve management techniques may be relevant.

The need to improve management techniques and the implementation of practices was also verified, considering operational efficiency's role in the growth of credit cooperatives. Similarly, the size of the operations is important for the cooperatives' growth. In this context, the number of credit cooperatives linked to Sicoob (355) may pose a problem for the group because this number may decrease potential economies of scale necessary for the cooperatives to thrive.

Finally, despite the results presented here, evidence of whether the size of operations (BRAN) and efficiency (Operational Efficiency) impact cooperatives differently was not found. Similarly, the results do not show how a lack of efficiency and scale of operations influence these companies' survival rates. Thus, future studies are suggested to include additional control variables, possibly based on data collected from the cooperative system's internal sources, to identify evidence that confirms the influence on credit cooperatives' growth, consolidation, and survival through gains in scale and/or efficiency.

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