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CREDIT RISK AND PERFORMANCE EVALUATION OF COOPERATIVES IN REGION XI USING DATA ENVELOPMENT ANALYSES (DEA)

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Abstract:
This paper illustrated the methodology that indicates how the Standard and Negative Data Envelopment Analysis (DEA) techniques can be applied to predict likely failures in cooperatives. The general objective of this study is to develop a model that will provide a reasonably accurate means of evaluating the creditworthiness of cooperatives in Region 11 using information obtained from the Financial Statement submitted to the Cooperative Development Authority. The results showed that the Standard DEA could predict cooperatives that are likely to fail in combination with the Negative DEA. The proposed methodologies identify companies with a high risk of going bankrupt by looking at their total financial situation.

JEL: E51; L10; L20

Keywords: cooperatives, standard, and negative Data Envelopment Analysis, efficiency, failure

1. Introduction

Corporate bankruptcies and reorganizations are typical occurrences in today's vulnerable and competitive business climate, affecting businesses of all sizes and industries. As a result, policymakers are becoming more concerned with quantifying the credit risk associated with their lending activities. For instance, the number of bankruptcy filings among cooperatives in the Davao Region has increased dramatically over the years, with

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over 500 bankruptcies among 4,000 cooperatives filed from 2012 to 2016. As a result, the most important priority for the most financial institution is to reduce credit risk.

Corporate failure has tremendous economic consequences, particularly for shareholders in publicly traded businesses. Financial losses of over $1 billion have been recorded. These widely publicized losses, as well as situations such as currency hazards, have piqued the interest of both regulators and private-sector practitioners (Simak, 2013). The financial position of a company is frequently in jeopardy before its failure. As a result, investors, creditors, auditors, and other stakeholders are interested in developing a way to detect corporate financial problems as early as possible. Detecting symptoms of financial distress that could lead to bankruptcy is critical to early intervention and resolution of corporate imbalances while also protecting the interests of all parties involved before the company defaults. Many scholars have studied the challenging task of predicting the signs and symptoms of corporate financial crises, generating various bankruptcy prediction models of varied types and scopes. Credit risk quantification and identification are becoming more crucial in improving the risk management program's efficiency, accuracy, and consistency. Not only does it help with credit approval, but it also helps with credit management, risk-based pricing, loan securitization, and loan portfolio management. Bankruptcy filing, which is not an acceptable indicator for predicting bankruptcy, is the most basic and relevant concept in learning credit risk analysis for enterprises of any size. This is because bankruptcy statutes and legislation, as well as real-world instances, show that a corporation facing bankruptcy might choose to avoid bankruptcy through alternative means. Most of the time, government action to avoid bankruptcy is already too late.

Many organizations producing risk management tools and methodologies have blossomed in response to the increased need for financial institutions to manage their exposure and risk. As researchers and practitioners strive to establish models that allow for early diagnosis of financial trouble, several techniques for measuring company risks have been developed. Although useful in some circumstances, these approaches have several drawbacks when used. Most research frequently employs a statistical or iterative learning technique to construct a prediction model. Almost all distress prediction models use data from the company's financial statements, primarily because they capture a lot of valuable information and secondly because all firms have them.

Introducing rationality and economic efficiency standards into cooperative management has become a top focus to optimize processes by identifying the most important elements. Government and cooperatives are, in fact, implementing efficiency-enhancing techniques. Researchers in cooperative management focus on efficiency management and assessment since the allocation of public resources and their efficient utilization are two closely related aspects. The DEA is generally used for credit risk evaluation and bankruptcy prediction by identifying the worst companies. Expanding and developing approaches lies in Data Envelopment studies, which may combine qualitative and quantitative data into the analysis. As researchers and practitioners strive to establish models that allow for early diagnosis of financial trouble, several approaches for evaluating company risk have been developed. Although useful in some circumstances, these approaches have a number of drawbacks when used (Simak, 2013).

Thus, the general relevance of this study arises from the need to reduce financial difficulties, bankruptcies, and loan losses by assessing the credit risks of cooperatives in Region XI. This is also important in pinpointing key policies that can mitigate loan losses. This kind of undertaking will help support improvements in lending activities locally in particular, and hence, the economy in general. Therefore, this study is expected to assist the government in identifying the worst performers among cooperatives where the most significant improvement potential can be found and determine the credit risks among cooperatives in Region 11 before a cooperative signifies bankruptcy. This study is relevant to banks and other lending institutions in lending-borrowing activities to be aware of the signs of bankruptcy. This comprises companies that have filed for bankruptcy and those with the lowest financial health status among the non-bankrupt companies under consideration. This allows lending institutions to regularly assess the risk that businesses (large and small) pose to their lending activities.

2. Research Objectives

The general objective of this study is to develop a methodology utilizing the capabilities of Data Envelopment Analysis that provides for a reasonably accurate means of evaluating the creditworthiness of cooperatives in Region 11. Specifically, the study aimed to:

a) Present the financial profile of firms included in the analysis;
b) Pick out the cooperatives that are most efficient under ideal conditions and cooperatives that are most efficient at being bad that might get into financial difficulties and/or bankruptcy in the future using DEA models; and,
c) Identify the factors of predicted bankruptcies among cooperative companies.

3. Scope and Limitations

This study evaluates the credit risk among cooperatives in Region 11 and identifies those with high chances of facing bankruptcy. The variables used were based on the available information obtained from the Financial Statements of the cooperatives submitted at the Cooperative Development Authority XI from 2014 to 2016. The results, however, cannot be used to validate cooperatives that already went bankrupt in the past because the data are simply not available. The cooperatives in the financial sector were chosen for this investigation. This restriction was imposed since the results are predicted to vary by industry, and cooperatives are the sector with the most documented public failures, projected to be around 500 throughout its 4,000 member cooperatives based only on the information accessible at the CDA. The analysis centered only on financial variables available to all cooperatives as reflected in their Financial Statements and did not include variables about mismanagement.

4. Review of Related Literature

4.1 Bankruptcy Prediction

Financial ratios have long been the most popular performance indicators among analysts since they allow quick comparisons between companies, usually within the same industry. Financial ratios were first used to analyze business failure in the 1930s, when Fik-Patrick, Winakor, and Smith and several subsequent research found that failed enterprises have considerably different ratio readings than continuing entities (Simak, 2000).

Beaver conducted the first current investigation on distress prediction in 1967. His univariate analysis of distress markers paved the way for future multivariate failure prediction methodologies. He calculated 30 ratios for 79 unsuccessful businesses for every five years leading up to bankruptcy and discovered cut-off thresholds that reduced the number of inaccurate forecasts. His most important discovery was that financial ratios, or more broadly accounting statistics, can predict failure at least five years in advance. He noted that not all ratios forecast with the same accuracy and that certain ratios are better at predicting failure than others.

The study of predicting bankruptcy dates back to the early 1930s. Univariate (single factor/ratio) analysis was the center of research until the mid-1960s. Beaver's study is the most well-known univariate study (1967). Altman published the first multivariate study in 1968, and it is still widely used in the literature today. Aziz et al. (2006) conducted a comprehensive review and divided the techniques into statistical, artificially intelligent expert systems, and theoretical models.

Altman's multivariate study, published in 1968, expanded on Beaver’s findings by employing many discriminant analyses to combine multiple means into a prediction model. His research led to creating the "Z score," a linear combination of five important financial variables that provides compelling evidence that financial distress can be predicted.

4.2 Data Envelopment Analysis in Bankruptcy Prediction

Using data from the Shanghai Stock Exchange, Xu et al. (2009) conducted a study predicting financial insolvency and used the efficiency score as a predictive variable. The results of Data Envelopment Analysis (DEA) were utilized to predict company failure, and efficiency rating was a good predictor variable.

In a study on financial hardship prediction, Mousavi et al. (2008) employed efficiency rating as predictive variables. They initially constructed a model that used these variables and then used a comparison pattern based on Multiple Discriminant Analysis models to interpret the data appropriately. The study evaluated the predictability of this model with two Binary Dependent (Logit and Probit) approaches to forecasting the likelihood of manufacturing enterprises going bankrupt. The study's findings revealed that standard DEA estimation is less effective in forecasting bankruptcy than the two logit and probit techniques.

Khalili et al. (2012) compared the predictive power of Data Envelopment Analysis to Logit and Probit models in another study. From 2000 to 2010, the study sample included all manufacturing enterprises listed on the Tehran Stock Exchange. The results showed that when applying DEA approaches, the accuracy of the DEA model is 72 percent, and the predictability of the logit and probit models is 81 percent, respectively. The DEA model was also a valuable tool for predicting the likelihood of a manufacturing firm's insolvency. Still, it performed less well than the Logit and Probit models.

Simak (1997) used Data Envelopment Analysis to predict publicly-traded companies' bankruptcy using non-ratio inputs and outputs. The analysis results compared favorably with the popular Z score model results and outperformed it in many cases. The original model successfully predicted bankruptcy among over 75% of the firms that eventually went bankrupt and correctly classified 56% of the firms that did not. This combined for a 63% classification accuracy over the three years analyzed.

Thore et al. (1994) applied DEA to companies' financial statements in the US computer industry found that a few of the successful corporations were able to maintain their efficient standing throughout the period investigated. However, other successful companies received inefficient ratings, which seemed to indicate that sub-efficiency sometimes goes together with rapid growth.

As a result of the growing number of bank failures in the United States, there has been an increasing interest in predicting bank failures. According to bank failure prediction research, the quality and efficiency of a bank's management are frequently the major factors of failure. Barr, Seiford, and Siens (1993) developed two models from publicly available information that they believe do the best job quantifying a bank's managerial quality. Up to three years before failure, their research found significant variations in average management quality scores between failed and non-failed banks. They compared the DEA method to three well-known bank failure prediction methods in the literature, using Probit or Logit regression as a statistical classification tool. Barr et al. (1993) concluded that DEA models are an effective tool for quantifying management quality as they showed superior results to leading published approaches.

4.3 Negative DEA in Bankruptcy Prediction

Simak (2000) developed a methodology that utilized the capability of Data Envelopment Analysis (DEA) by evaluating the creditworthiness of corporations. He popularized the notion of Negative DEA, which involves placing the weakest performers on the efficient frontier to identify them. Using Negative DEA, a layering method was developed that does not rely on an idea cut-off point yet gives correct classification results.

Paradi (2001) applied Negative DEA with the combination of normal DEA for credit risk evaluation. He advocated using a layering technique rather than the standard cut-off point approach to incorporate risk attitudes and risk-based pricing. The method is validated by an empirical application on credit risk evaluation. In the calibration data set, the optimal combination of layered standard and Negative DEA models produced

100 percent bankruptcy and 78 percent non-bankruptcy prediction accuracy, as well as equally compelling 100 percent and 67 percent out-of-sample classification accuracies.

In summary, the literature showed that Negative DEA is far better than the normal DEA in terms of efficacy in credit risk evaluation. But very few studies have been made since Negative DEA was developed and introduced.

5. Methodologies

5.1 Theoretical Framework

The proposed research explored using two (2) Data Envelopment Analysis methodologies as a multi-dimensional and multi-criteria tool for evaluating the credit performance of the different cooperatives in Region XI. The value of this assessment is anchored on the dynamic resource-based view (RBV) of strategic management. Under the dynamic RBV, the firms are evaluated for the characteristics to identify the resources or assets with specific characteristics that may provide firms with a sustainable competitive advantage (Maijoor and van Witteloostujn, 1996; Black and Boal; 1994). On the other hand, this approach views the nature of the firm's resources and how these resources are combined into capabilities.

The foundation of the RBV is to search for those resources that create a competitive advantage for the future. Internationalization does not only consist of one step but involves learning, capability building, and experience (Pisano and Shuen, 1994). The RBV combines a company's internal analysis, external analysis, and competitive market analysis. It compensates for resources that are frequently overlooked by other strategies due to their narrower emphasis. The ability of RBV to explain why some organizations are more profitable than their competitors and its ability to build smart diversified strategies are two of its assets.

The purpose of this study is to pick out the cooperatives that might get into financial difficulties in the future. Two (2) Data Envelopment Analysis (DEA) methods were used: the Standard DEA and the Negative DEA. Figures 1 and 2 present the conceptual framework of the study.

The input and output variables employed in this study were based on some of the literature's inputs and outputs variables (Simak, 2013). The other variables used in the previous studies were not used because they are not available in the FS obtained from the CDA.

The traditional DEA was used to determine the best performers from among the different cooperatives, while the Negative DEA was used to determine the decision-making units that are furthest away from this best practice frontier. This approach aims to set up DEA models that will place the bad cooperatives on or close to the empirical frontier. This is achieved by defining variables as outputs that unhealthy cooperatives are good at maximizing and as inputs those variables of which they do not have enough. In a sense, the production models are rewarding cooperatives that are efficient at being bad; that is, the variables that go into such models are chosen to make the distressed cooperatives look as efficient as possible.

5.2 Standard DEA

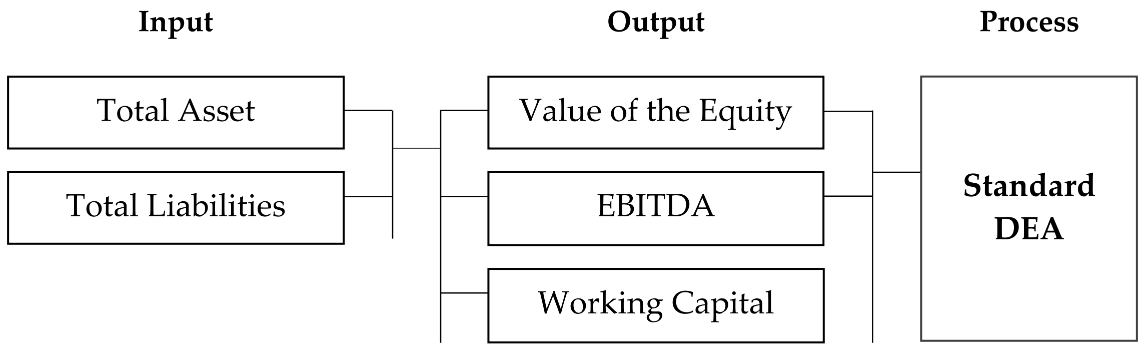

Figure 1: Input and Output Variables Used for the Standard or Normal DEA Analysis

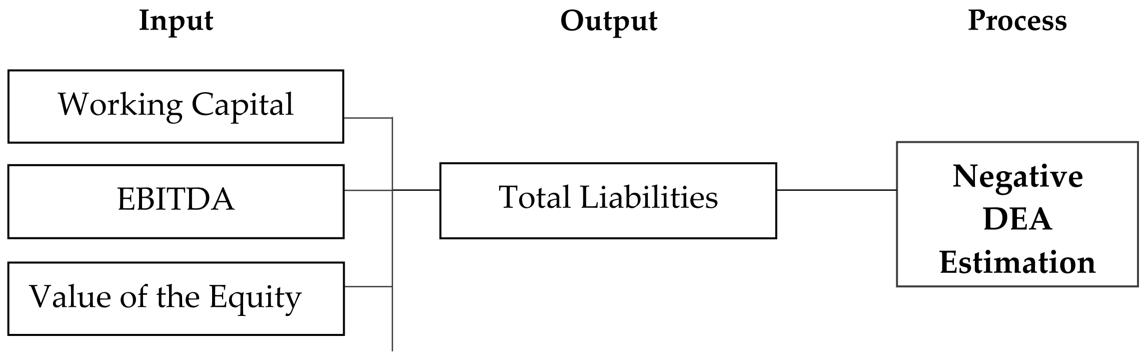

Figure 2: Input and Output Variables Used for the Negative DEA Analysis

It is important to note that there are two approaches to developing models for predicting financial distress within the DEA context. First, we can use it to evaluate the competency of management. In some studies, the incompetence of management is cited as the number one cause of bankruptcy. Managers are faced with a multitude of decisions to operate the business, and DEA can be used to evaluate how well they manage the transformation of resources to desired products and services with the least amount of waste and expense. A DEA model can capture the quality of the manufacturing company's management. The inputs are the company's resources, such as labor, materials, machinery, and facilities. The latter two inputs focus primarily on management control decisions on the company's degree of leverage and the resulting possible financial difficulties. Using the company's resources, the management's goal is to maximize earnings, ensure that there is enough liquidity to meet obligations as they come up; and, maximize the company's value.

5.3 Measurement of Efficiency

Decision-makers are increasingly confronted with balancing the rising demand for service with limited resources. Economists say that maximizing efficiency from limited resources should be a significant criterion for prioritization. Efficiency assesses whether resources are being utilized in the most efficient manner possible. Efficiency is concerned with the relation between resource inputs and intermediate outputs or outcomes. The efficiency of decision-making units with many inputs and outputs is defined as follows in its most basic form;

$$\text{Efficiency} = \frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}}$$

A DMU's efficiency is divided into two categories: technical efficiency and allocative efficiency. Technical efficiency refers to a company's ability to create the most output with the least resources. Alternatively, DMUs can create a particular output level with the least inputs (Coelli, 1996). The physical relationship between resources (capital and labor) and the outcome is referred to as this. A technically efficient position is achieved when a collection of resources inputs yields the greatest potential improvement in output. The intervention is technically inefficient if the same (or better) results could be achieved with less of one input type.

5.4 Negative DEA Estimation

Consider n production units or Decision-Making Units (DMUs) that are to be evaluated using the same m inputs to produce s different outputs. Let X_j be the input consumption vector for DMU_j where X_j= $(x_{1j},\ldots,x_{mj})$T, and Y_j the output production vector, Y_j = $(y_{1j},\ldots,y_{sj})$T. The DEA output efficiency score under a variable returns to scale assumption for DMU', θ,' is given by

$$\theta' = \max_{\theta,\lambda} \theta$$

s.t.

$$X' \geq \sum_{j=1} \lambda_j X_j$$

$$\theta Y' \leq \sum_{j=1}^{n} \lambda_j Y_j$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

Units on the frontier are classified as efficient, whereas units outside the boundary are classified as inefficient. However, the companies that are most efficient at being bad are on the envelopment surface or best practice frontier because the negative DEA technique was used. Companies that are inefficient at being bad are the farthest from the frontier.

6. Results and Discussion

6.1 Profile of the Cooperatives in the Davao Region

As of 2016, there were 892 registered cooperatives in the Davao Region. This is quite a large number. The actual number is more than these figures. Only those with complete information in the Financial Statements were used in the analysis. Out of the total 892, only 630 cooperatives were used in the analysis because of incomplete data.

By type, most of the cooperatives are multipurpose cooperatives comprising more than 60% of the total cooperatives considered in the study. Cooperatives engaged in production accounted for only about 2% of the sampled cooperatives. Table 1 shows the distribution of these cooperatives by type as of 2016.

Table 1: The number of cooperatives in the Davao Region, by type, as of 2016

Type	2016	
	Number	**% to total**
Credit	46	7.30
Consumer	29	4.60
Producer	11	1.74
Marketing	18	2.86
Service	16	2.54
Multipurpose	470	74.60
Others	40	6.36
Total	630	100

About 1/3 of the cooperatives are found in Davao City, while Davao Province, Compostela Valley, and Davao del Sur contribute around 20% each to the total cooperatives operating in Region XI (Table 2).

Table 2: Number of cooperatives in the Davao Region, by province, 2016

Province	2016	
	Number	**% to total**
Compostela Valley	128	20.32
Davao City	220	34.92
Davao Del Norte	125	19.84
Davao Del Sur	115	18.25
Davao Occidental	4	0.63
Davao Oriental	38	6.03
Total	630	100

In terms of assets, more than half of the total cooperatives are classified as micro industries, and only 4 percent are classified as large (Table 3). The following categories were used to classify cooperatives in terms of total assets: micro if their assets are less than PhP3 million, small if PhP3,000,001 to Php15 million, medium if PhP15,000,001 to PhP100,000,000, and large if PhP100,000,001. One cooperative reported the lowest declared assets at PhP2,486.18, while one cooperative has declared more than PhP2 billion in 2014. In 2015, the lowest assets recorded was PhP12,506.12, while three (3) declared more than PhP900 million of assets in 2016.

Table 3: A number of cooperatives in the Davao Region, by assets, 2016

Asset Classification	2016	
	Number	% to total
Micro	339	53.81
Small	173	27.46
Medium	89	14.13
Large	29	4.60
Total	630	100.00

In terms of declared liabilities, more than ¾ of the total cooperatives have liabilities less than PhP5M, while 3% have liabilities over PhP100M. Around 2% of the cooperatives did not declare any liability (Table 4). Some 23 cooperatives have liabilities greater than PhP100M in 2014; 21 cooperatives in 2015. 24 cooperatives in 2016.

Table 4: Distribution of cooperatives in the Davao Region, by liability classification, by year

Liability Classification	2014		2015		2016	
	Number	% to total	Number	% to total	Number	% to total
≤ 0	12	1.9	10	1.6	2	0.3
< 5,000,000	478	75.9	477	75.7	483	76.7
5,000,001 – 10 M	48	7.6	47	7.5	43	6.8
10,000,001 – 20 M	28	4.4	31	4.9	36	5.7
20,000,001 – 50 M	30	4.8	32	5.1	30	4.8
50,000,001 – 100 M	11	1.7	12	1.9	11	1.7
>100,000,000	23	3.7	21	3.3	25	4.0
Total	630	100.0	630	100.0	630	100.0

Table 5 shows the distribution of the working capital of cooperatives. Working capital, often known as net working capital, is a liquidity statistic used in corporate finance to determine how efficient a company's operations are. It's the difference between a business's current obligations and current assets (Investopedia.com). Working capital indicates that a corporation has more than enough liquid funds to meet its short-term obligations. In terms of working capital, nearly 60% (on average) of the total cooperatives have working capital less than PhP5M while nearly 30% (on average) have not declared any working capital, but the number of cooperatives that did not declare working capital significantly decreased to less than 10% in 2016. About 2 percent of the cooperatives have more than PhP100 million as their working capital. Five cooperatives have working capitals of less than 1,000, while one cooperative has a declared working capital amounting to PhP1 Billion in 2014. In 2015, 5 cooperatives declared a working capital of less than PhP1,000, while 9 cooperatives declared a working capital of more than PhP100 million in 2015. Two cooperatives, 360 and 513, have working capitals of less than PhP1,000, with one cooperative having more thanPhP300 million working capital in 2016.

Table 5: Distribution of cooperatives in the Davao Region,
by working capital classification, by year

Working Capital Classification	2014		2015		2016	
	Number	% to total	Number	% to total	Number	% to total
≤ 0	260	41.3	235	37.3	55	8.7
1 - 5 M	328	52.1	351	55.7	437	69.4
5,000,001 – 10 M	12	1.9	17	2.7	54	8.6
10,000,001 – 20 M	8	1.3	6	1.0	38	6.0
20,000,001 – 50 M	6	1.0	7	1.1	27	4.3
50,000,001 – 100 M	6	1.0	5	.8	8	1.3
>100 M	10	1.6	9	1.4	11	1.7
Total	630	100.0	630	100.0	630	100.0

Table 6 shows the distribution of the cooperatives when classified according to EBITDA. EBITDA is simply net income after deducting interest, taxes, depreciation, and amortization. EBITDA is a metric that may be used to assess and compare profitability across businesses and industries. It is frequently used to compare ratios to enterprise value and revenue since it eliminates the implications of financing and accounting decisions (www.investopia.com). EBITDA tells an investor how much money a have company would have made if it did not pay interest expenses on its debt, taxes, or take depreciation and amortization charges (www.thebalance). Nearly ¾ of the sampled cooperatives have values less than 5M. This means that the cooperatives have less productive resources in making incomes. In 2014, 4 cooperatives had an EBITDA of less than PhP1,000, while 1 cooperative declared an EBITDA, amounting to PhP400 million in 2014. In 2015, 3 cooperatives declared an EBITDA of less than PhP1,000, while 7 cooperatives declared an EBITDA of more than PhP100 million in 2015. In 2016, 5 cooperatives declared EBITDA of less than PhP1,000, while 1 cooperative declared an EBITDA amounting to PhP67 million in 2016.

Table 6: Distribution of cooperatives in the Davao Region, by EBITDA classification, by year

EBITDA Classification	2014		2015		2016	
	Number	% to total	Number	% to total	Number	% to total
≤ 0	108	17.1	81	12.9	122	19.4
1 – 5 M	485	77.0	433	68.7	474	75.2
5,000,001 – 10 M	15	2.4	43	6.8	15	2.4
10,000,001 – 20 M	10	1.6	33	5.2	10	1.6
20,000,001 – 50 M	10	1.6	20	3.2	7	1.1
50,000,001 – 100 M	2	0.3	13	2.1	2	0.3
>100 M	0	0.0	7	1.1	0	0.0
Total	630	100.0	630	100.0	630	100.0

Table 7 shows the distribution of the cooperatives when classified according to the owner's equity. The Owner's ownership (equity) in the company, or the amount of the company's assets owned by the owner. It's the amount of money the owner has put into the company. It is the amount the owner has invested in the business. Nearly ¾ of the sample cooperatives have equity between PhP1 to PhP5 Million. One cooperative has equity of PhP13,226 only, while 2 cooperatives declared owner's equity at more than PhP1 billion in 2014. In 2015, 3 cooperatives declared an owner's equity of less than PhP10,000, while 1 cooperative declared an owner's equity is amounting to PhP435 million in 2015. In 2016, 1 cooperative declared equity amounting to PhP513.33 only, while another cooperative declared an owner's equity is amounting to PhP490 Million in 2016.

Table 7: Distribution of cooperatives in the Davao Region, by equity classification, by year

Equity Classification	2014		2015		2016	
	Number	% to total	Number	% to total	Number	% to total
≤ 0	18	2.9	25	4.0	21	3.3
1 – 5 M	461	73.2	437	69.4	432	68.6
5,000,001 – 10 M	63	10.0	68	10.8	72	11.4
10,000,001 – 20 M	35	5.6	42	6.7	43	6.8
20,000,001 – 50 M	27	4.3	33	5.2	37	5.9
50,000,001 – 100 M	13	2.1	10	1.6	11	1.7
>100 M	13	2.1	15	2.4	14	2.2
Total	630	100.0	630	100.0	630	100.0

6.2 Standard DEA Results

The conventional or traditional DEA is used to identify inefficient companies, with the presumption that they are more likely to fail. It evaluates bank efficiency based on data acquired on the quantities of inputs utilized to achieve the observed level of outputs produced. The usual DEA results are summarized in Table 8. A number of 1 indicates that the DMU is totally functionally efficient, whereas a value of 0 indicates that it is completely inefficient.

The table shows that the number of fully efficient cooperatives accounted for only 3% of the total cooperatives included in the study, and nearly 1% is fully inefficient. Some 18 cooperatives were rated fully efficient in 2014. The number of fully efficient cooperatives rose to 30 in 2015. The number of fully efficient firms went down to 21 in 2016. Four cooperatives were consistently rated fully efficient for at least two years, while 1 cooperative was fully efficient for 3 years. It may be recalled that 2 cooperatives had very high working capital and EBITDA.

Four (4) cooperatives were rated fully inefficient in 2014; two (2) cooperatives in 2015, and five (5) cooperatives in 2016. Of these numbers, two cooperatives were consistently rated fully inefficient for at least two years, while one (1) cooperative was fully inefficient for 3 years. It may be recalled that these cooperatives have very high equity against their working capital.

The average efficiency ranged from 0.26 to 0.72, with a standard deviation ranging from 0.241 to 0.252. The average efficiency of the different cooperatives has been significantly increasing over time. Any manager can increase the cooperative's efficiency by (1) maintaining the same input level while increasing output; (2) maintaining the same output level while decreasing inputs; or (3) a combination of decreasing inputs and increasing output. Of course, the viability of these improvements must be carefully evaluated for each cooperative. According to this analysis, cooperatives must reduce their inputs by roughly 80% in 2014 and 31% in 2016 to become fully efficient. On average, the cooperatives should increase their outputs by 47 percent to become fully efficient.

Table 8: Distribution of cooperatives in the Davao Region, by efficiency level, by year

Efficiency Classification	**2014**		**2015**		**2016**	
	Number	**% to total**	**Number**	**% to total**	**Number**	**% to total**
Fully Efficient (1.0)	29	4.6	43	6.8	35	5.6
Slightly efficient (0.99–0.6)	30	4.8	421	66.8	438	69.5
Moderately efficient (0.59-0.01)	566	89.8	161	25.6	150	23.8
Fully Inefficient (0)	5	0.8	5	0.8	7	1.1
Total	630	100	630	100	630	100
Mean efficiency	0.1932		0.6903		0.7115	
Standard deviation	0.2432		0.2523		0.2456	

Table 9 shows the number of cooperatives that are likely to fail from 2014 to 2016 when grouped according to the type of cooperative. Some 6 cooperatives were bound to fail in 2016. The Cooperative Development Authority (CDA) in Region XI should scrutinize these cooperatives to see how these cooperatives can be assisted before they go bankrupt.

Table 9: Distribution of cooperatives is likely
to fail using the Standard DEA Result, by type, by year

Type	**2014**		**2015**		**2016**	
	Healthy	**Predicted to Fail**	**Healthy**	**Predicted to Fail**	**Healthy**	**Predicted to Fail**
Credit	48	0	48	0	47	1
Consumer	29	0	29	0	29	0
Producer	11	0	10	1	11	0
Marketing	16	1	17	0	16	1
Service	16	0	16	0	15	1
Multipurpose	470	3	473	1	470	3
Others	35	1	32	3	35	1
Total	625	5	625	5	623	7

In addition, some 47 cooperatives should also be monitored given the relatively low technical efficiency scores with less than or equal to 10 percent; 10 cooperatives in 2014; 23 cooperatives in 2015; and 14 cooperatives in 2016.

6.3 Negative DEA Results

The Negative DEA is a model that is used to assess a DMU's ability to perform poorly. As a result, based on their high model score, it might be utilized to identify distressed enterprises. The purpose of the Negative DEA is to develop a new model that focuses on poor performance and incorporates components that would not be found in a typical DEA model that seeks best practices (Paradi et al., 2001).

Table 10 presents the summary results of the Negative DEA. Annex B provides the detailed Negative DEA results from 2012 to 2016. Under the Negative DEA parlance, a value of one means technically inefficient. Low values mean efficiency. As seen in the table, the number of fully efficient cooperatives has 0.0216 to 0.0502, with a standard deviation ranging from 0.09320 to 0.14675.

Table 10: Distribution of cooperatives in the Davao Region, by inefficiency level, by year

Inefficiency Classification	**2014**		**2015**		**2016**	
	Number	**% to total**	**Number**	**% to total**	**Number**	**% to total**
Fully Inefficient (1.00)	10	1.6	6	1.0	2	0.3
Highly Inefficient (0.99 – 0.60)	3	0.5	2	0.3	4	0.6
Moderately Inefficient (0.59 – 0.01)	581	92.2	522	82.9	351	55.7
Fully efficient (0.00)	36	5.7	100	15.9	273	43.3
Total	230	100	630	100	630	100
Mean inefficiency	0.0512		0.0389		0.0201	
Standard deviation	0.14675		0.12599		0.09320	

There were 10 fully inefficient cooperatives in 2014, 6 cooperatives in 2015; and, 2 cooperatives in 2016. Three (3) cooperatives have been consistently predicted to fail.

By type, the number of cooperatives that are predicted to fail is presented in Table 11.

Table 11: Distribution of cooperatives that are likely
to fail using the Negative DEA Result, by type, by year

Type	**2014**		**2015**		**2016**	
	Healthy	**Predicted to Fail**	**Healthy**	**Predicted to Fail**	**Healthy**	**Predicted to Fail**
Credit	46	2	46	2	48	0
Consumer	29	0	29	0	29	0
Producer	11	0	11	0	11	0
Marketing	16	1	17	0	17	0
Service	16	0	16	0	16	0
Multipurpose	468	6	472	2	473	1
Others	34	1	33	2	34	1
Total	620	10	624	6	628	2

In addition, 4 cooperatives are close to being predicted to fail in 2014, three (3) cooperatives in 2015, and four (4) cooperatives in 2016. These cooperatives should also be monitored very closely as their technical inefficiency is relatively low.

The Negative DEA model is compared to the conventional DEA model in Figures 1a through 1c. Both models used identical DMUs, with the conventional DEA model on the left panel and the Negative DEA model on the right. The DMU is likely a self-identifier, as the values of its variables are such that there aren't many other DMUs with which it may be compared. When compared to other DMUs, a variable can have a very low or very high value; as a result, it is only comparable to itself and seems to be equally efficient in both models. The DEA models can only offer a few predictions about the likelihood of bankruptcy in this situation.

Along with self-identifiers, an agreement between the two models, such as high efficiency in traditional DEA and poor efficiency in Negative DEA, or vice versa, maybe sought to boost confidence in the predictions. Similarly, any conclusion for companies underperformed in both models would have to be reviewed carefully. This level of assurance could be important information in terms of credit pricing. Identify the cooperatives which are fully efficient in both DEA models and which cooperatives are fully inefficient in both models. The highly inefficient cooperatives in both models are predicted to face credit risk or are likely to fail unless competent authorities will guide them before being declared bankrupt or ordered to be closed. These cooperatives include the following: One (1) cooperative scored 0 in normal DEA and 1 in negative DEA. This means that this cooperative is predicted to fail in 2015 and 2016. In addition, some 10 cooperatives are likely to fail, and these cooperatives should be closely monitored.

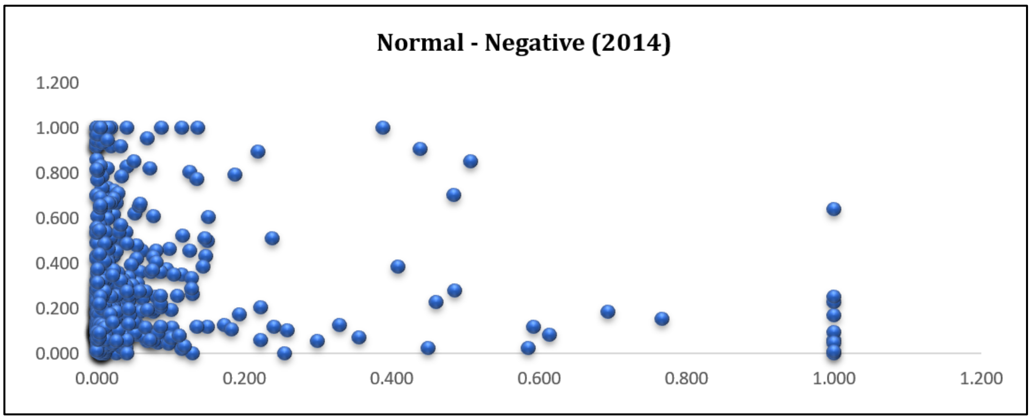

Figure 1a: Relationship between Negative and Standard DEA, 2014

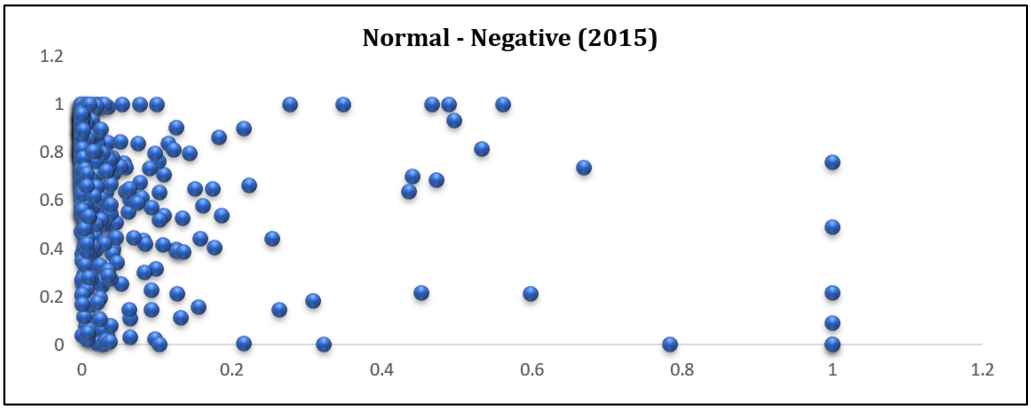

Figure 1b: Relationship between the Standard and Negative DEA, 2015

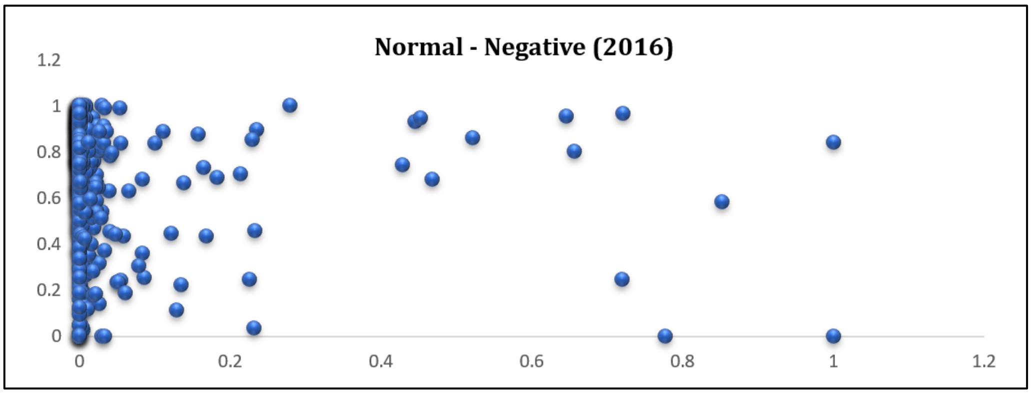

Figure 1c: Relationship between Standard and Negative DEA, 2016

Among the major reasons cited why cooperatives fail in the Philippines are as follows: Incompetent management, a lack of understanding of cooperative principles, practices, true aims, and purposes, improper credit use by borrowers who, rather than using money borrowed for production, spent it on fiestas or luxuries, defective securities, and political interference, particularly in the collection of overdue accounts, a lack of adequate safeguard against unscrupulous officers who took advantage of their position to grant loans to themselves and their compatriots that later proved disastrous to the system, the dominance of the individualistic attitude over the spirit of cooperation among the people, cooperatives' inability to secure adequate capital, their reliance on the government (https://joeam.com/2013/06/19/philippine-agriculture-a-failing-industry).

All of these flaws are weeded out in a corporate structure by the dual imperatives of growth and profitability. The accountability that drives a firm is turned into a must in a cooperative. Individual members of a cooperative are not responsible for anything.

7. Summary, Conclusion, and Recommendations

Failure is a part of the business. Few entrepreneurs ever succeed without first suffering a series of huge setbacks. Bankruptcy is a natural element of an economy's renewal process when outdated businesses exit the market to be replaced by newer, more dynamic businesses. A company's operations are halted when it is unable to make a profit or generate sufficient money to meet its expenses. If a lucrative business does not create enough cash flow to cover its expenses, it will fail. Companies can collapse due to a variety of factors, including wars, recessions, high taxes, high-interest rates, excessive regulations, poor management decisions, insufficient marketing, inability to compete with similar enterprises, or a lack of public interest in the company's goods. Some firms may decide to close their doors before a planned failure. Others may continue to function until they are forced to stop by a court order. Lack of experience, untrustworthy sales representatives, insufficient capital, poor inventory management, over-investment in fixed assets, business finance mismanagement, poor business location, poor credit arrangement management, unexpected growth, and engaging in the wrong business niche are among the additional reasons for small business failure listed by the Small

Business Administration in an article on small business failure. According to research published in 2014 by the Turnaround Management Society, the majority of crises are caused by top management errors.

In this study, the DEA was a suitable model for predicting bankruptcies, especially among cooperatives where they do not have a large asset base. Related to this, it is incumbent upon the regulatory bodies of the government overseeing the cooperatives to examine the Financial Statement variables of the cooperative such as the following: Total assets, total liabilities, the value of equity, working capital, and EBITDA as the major FS indicators to be used to monitor the status and health of the cooperatives' way ahead before bankruptcy and institute reforms to avoid business failure. In this study, DEA was found to have a greater capacity for bankruptcy prediction. Furthermore, there are indications that working capital and total liabilities are the two major indicators that could predict future bankruptcy. The proposed method considers the overall financial situation of firms as well as firms that have already filed for bankruptcy to identify enterprises with a high risk of going bankrupt. The strategy enables government regulators to intervene before bankruptcy is declared. This further emphasizes that simply filing for bankruptcy is insufficient to predict corporate bankruptcy. Because there are various solutions available to a firm facing bankruptcy, its total financial status should be assessed. As a result, losses resulting from a corporation defaulting on a loan will be reduced. The best performers should be recognized, and the worst performers should be constantly monitored because they represent the highest potential savings.

However, if numerous DEA models had been tested, the results could have been close to optimal. Cooperatives are complicated organizations, and managers must be permitted to widen their discussions to include additional aspects. According to the authors, more features that can be regarded as inputs and outputs connected to organizational behavior and performance should be implemented. Several Income Statement and Balance Sheet models should have been built; however, the available data from CDA is far from perfect. Earnings instability, warranty claims, litigation, interest expense, and cash flow from operations are characteristics that could be used to predict bankruptcy. It would have been wonderful if analyses could have been completed three years prior to bankruptcy. The gradual inclusion of non-bankrupt enterprises into the bankrupt group could be a future research topic.

Conflict of Interest Statement

The authors declare no conflicts of interests.

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