Financial performance index for Santander manufacturing companies

Alfredo Enrique Sanabria Ospino [1], William Stive Fajardo-Moreno [2]

1. *Universidad Santo Tomás seccional Bucaramanga*; alfredoenrique.sanabria@ustabuca.edu.co; 0000-0001-8250-0647
2. *Universidad EAN;* wsfajard74913@universidadean.edu.co ; 0000-0003-1819-1629

Abstract: During the last two years the representative indicators of financial and operational performance of the North American market of the manufacturing sector, the S&P Global and the ISM, have shown decreases in their measurement parameters. In this order of ideas and a more local context, in the last manufacturing survey conducted in Colombia, the real production and sales presented decreases of 6.8% and 3.5%, this downward trend of the national metrics was reflected in the Santander regions, represented in the metropolitan area of Bucaramanga and its capital city. The objective of this research is to design a financial composite indicator for the manufacturing sector of Santander using the principal components statistical method that allows weighting the main financial metrics (assets, equity, revenues, and profits) of 2392 companies in the sector under study, using the SPSS, R-studio, and R commander statistical packages. The findings showed that in their respective order, the metrics that contribute most to financial performance are equity, assets, profits, and sales. In addition, it allowed the classification of the companies in the sector according to the financial composite indicator. This will allow decision-makers to generate investment, financing, and market strategies to generate financial sustainability.

Keywords: Financial Sustainability, Financial Performance, Project Management, Manufacturing Sector, Principal Component Analysis

Construcción de un índice de desempeño financiero para las empresas manufactureras de Santander.

Resumen:

Durante los últimos dos años los indicadores representativos de desempeño financiero y operacional del mercado Norte americano del sector manufactura el S&P global y el ISM han presentado descensos en sus parámetros de medición. En este orden de ideas y en un contexto más local en la última encuesta manufacturera realizada en Colombia, la producción y ventas reales presentaron descensos de 6.8% y 3.5%, esta tendencia bajista de las métricas nacionales se reflejó en las regionales santandereanas, representadas en el área metropolitana de Bucaramanga y en su ciudad capital. El objetivo de esta investigación es el de diseñar un indicador compuesto financiero para el sector manufactura de Santander utilizando el método estadístico de componentes principales que permita ponderar las principales métricas financieras (activo, patrimonio, ventas y utilidades) de 2392 empresas del sector objeto de estudio, para esto se utilizó los paquetes estadísticos de las herramientas SPSS, R-studio y R commander. Los hallazgos presentados evidencias que en su respectivo orden las métricas que más

aportan al desempeño financiero son: patrimonio, activo, utilidad y ventas. Además, permitió clasificar las empresas del sector de acuerdo con el indicador compuesto financiero. Lo anterior permitirá a los tomadores de decisiones generar estrategias de inversión, financiación y de mercado con el objetivo de generar sostenibilidad financiera.

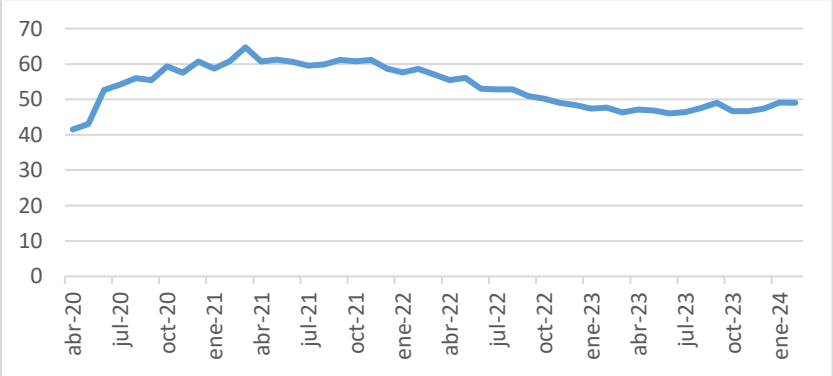
Palabras clave: Sostenibilidad financiera, Desempeño financiero, Gestión de proyectos, Sector manufactura, Análisis de componentes principales.

Introduction

In the last 25 years, humanity has lived through different types of crises, in health, war, natural disasters, and financial crises [1] in the manufacturing sector the Covid 19 pandemic crisis generated challenges in the industry when production lines were stopped, the relaunching and slowdown of the economy, as a consequence of the blockades and restrictions imposed on international trade negatively affecting the financial situation of companies globally [2], [3], generating significant losses in the global industry [4]. Therefore, it is important to support the manufacturing sector because it helps the welfare of communities [5]. One of the concerns is the high resource consumption of the sector, which currently accounts for 25% of the world's resources [6]. Therefore, decision-makers need to use financial indicators constructed with accounting data to measure financial performance [7]. In the manufacturing sector, the traditional way to measure the impact of practices on competitiveness is indicators related to return on assets (ROA), return on equity (ROE), and return on investment (ROI) [8]. However, these indicators are not appropriate for measuring operating efficiency because they reflect financial leverage [9], [10]. Therefore, there is a need to design more robust indicators to measure the financial performance of the companies in the sector under study, different from the traditional measures used.

In an international context, the ISM is a survey applied to a sample of more than 400 companies belonging to 19 manufacturing sub-sectors, the metric is a scale of 0-100 where values above 50 mean expansions, however, figures below this benchmark inform the stock market about a contraction in the sector's purchases[11]. However, according to data reported on the Investing financial information platform, from June 2022 to February 2024, the indicator is below its cut-off of 50, which means that the financial situation of the sector is not favorable (Figure 1).

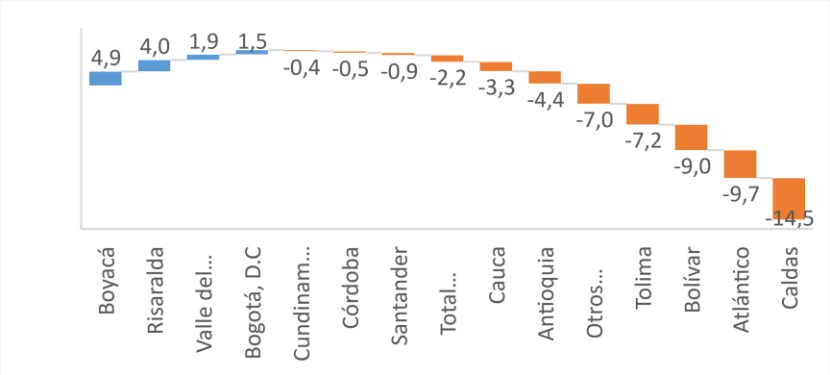
Figure 1. ISM Manufacturing Purchasing Managers Index



Source: Own realization with the data reported in investing.

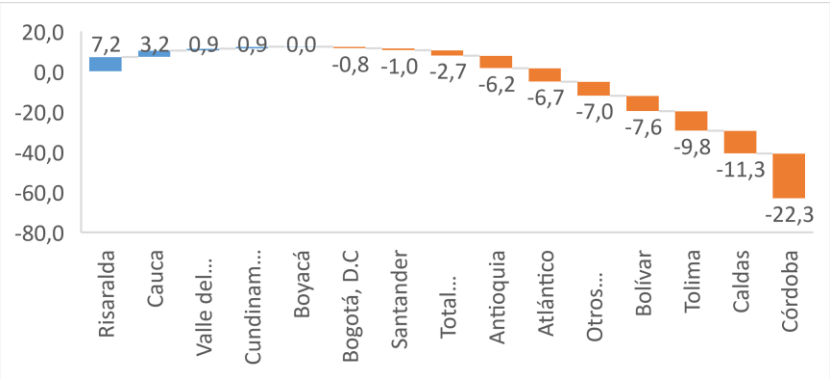
In a more local context and according to the monthly manufacturing survey carried out in Colombia from February 2023 to February 2024 conducted by Dane [12], A cascade effect can be seen in the real production, revenues, and employment metrics, where there were more departments with negative variations than positive ones. Concerning the department of Santander, the variations were all negative, 0.9 1 and 1 respectively, with a contribution of 0 to the total industry (Figure2-4).

Figure 2. Annual change in real production in Colombia



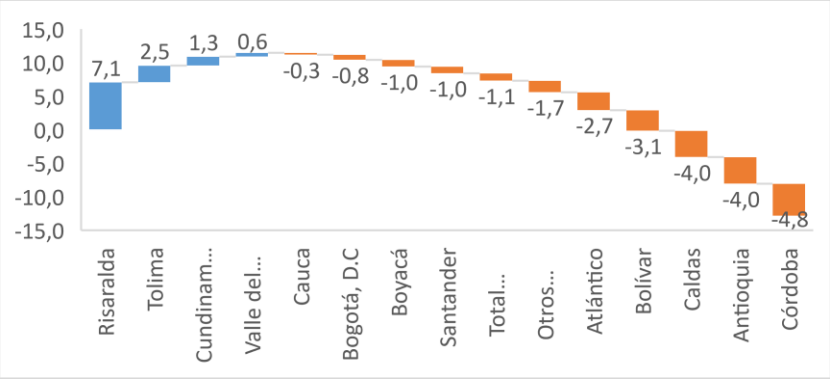
Source: Own realization with the data reported in DANE

Figure 3. Annual change in real revenues in Colombia



Source: Own realization with the data reported in DANE

Figure 4. Annual change employment in Colombia



Source: Own realization with the data reported in DANE

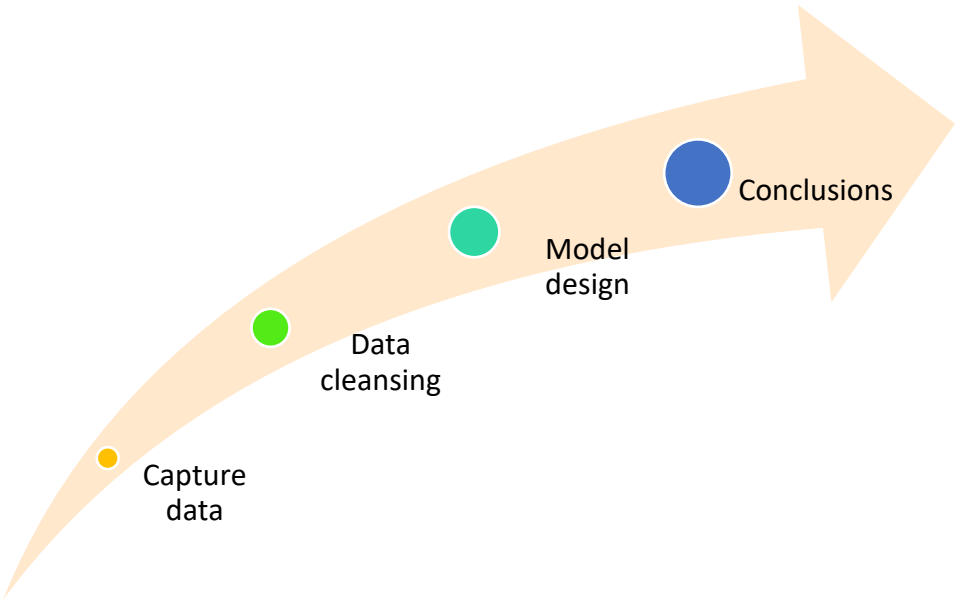
Several studies have contributed to the study of the manufacturing sector in Colombia, Ortega et al. [13] analyzed, the impact of net working capital on the company's profitability, using descriptive statistics. Corrales Liévano et al. studied the link between investment and sales using the e-commerce technology tool, using the linear regression method. Escobar et al. [14] identified the financial situation of the companies in the sector as a barrier to innovation, using the statistical method of correlational analysis. Sanabria Ospino and Fajardo-Moreno [15] investigated and studied the financial behavior of the companies under study in Santander, applying descriptive statistics. How can a composite financial performance index be designed for the Santander manufacturing sector?

Methodology

To perform a Principal component analysis (PCA) prerequisite such as robust correlation between the original variables must be met [16], the PCA successfully reduces the dimensionality of variables while preserving trends and patterns [17], [18]. The Kaiser Myer Olkin (KMO) test is used to assess the relevance of the sample evaluation in the study [19], Indicates the proportion of the variance that could be the effect of underlying factors [20], where values greater than 0.5 indicate that the variables are suitable for the or the PCA method[21], [22], [23], the bartlett's test verifies the robustness of the model to meet the necessary conditions for the PCA, analyzing whether there is redundancy in the variables so that they can be grouped into factors [24], [25], [26], Where P< 0.05 values are adequate for PCA[26], [27], [28], PCA is used to combine variables with the highest maximum variance with few parameters, where values as minima of the total explained variance are accepted [29], [30], [31] also when the communalities largely explain the factors extracted from the variable, values greater than 0.5 are accepted for PCA[29], [32]. To achieve the purpose of the research, the financial information (Assets, Liabilities, Equity, Revenues, Net Income) was analyzed to calculate the metrics leverage level, ROE, ROA, net margin, and the leverage index of 2392 companies in the manufacturing sector of Santander, from the compite 360 database. Secondly, an analysis of outliers was performed to eliminate them. Next, the SPSS software was used to calculate the KMO statistical metrics, Bartlett's test of sphericity, the total accumulated variance, and

the communalities. Finally, in the R software with the R commander interface, we proceeded with the grouping of the financial accounts, the calculation of the weights for the design of the indicator, and the classification of the companies. The probabilistic method was used to calculate the sample [33], at a 99% confidence level and 1% error for a segmented population of 2392 for a sample size of 2092. The figure 5 below shows the 4 phases of the investigation.

Figure 5. Methodological phases



Source: Own realization

Results

The results for the KMO were 0.72, Bartlett's test of sphericity presented a value of 10744.876 with a p-value < 0.005 of 0.000, and the total variance explained was 84.57%, the table 1 illustrates the calculation of the extraction of the communalities. After performing these preliminary calculations and according to the references presented above, it is evident that the PCA is feasible for the design of the composite index using this method.

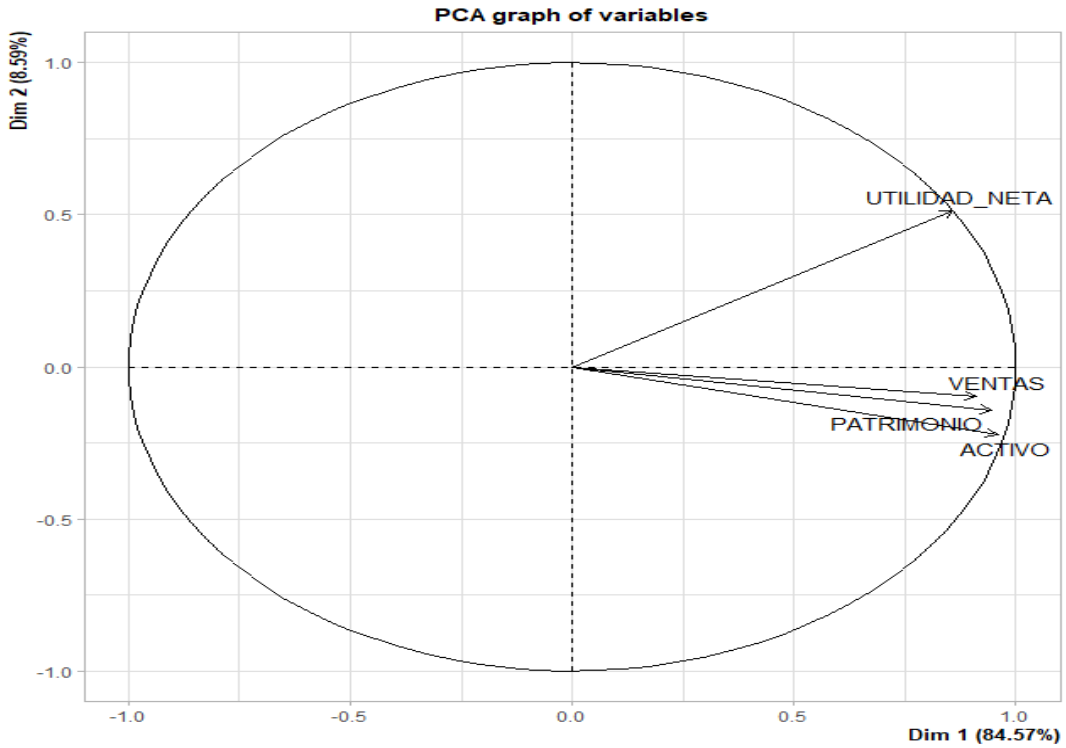
Table 1. Community analysis

Account	Communities' extraction
Asset	0.9
Equity	0.9
Revenues	0.8
Profits	0.7

Source: Own realization in SPSS

Figure 5 illustrates the grouping of the variables in the R commander interface where the total variance explained in the first dimension was 84.57%, Table 2 presents the variables obtained because of the weighting of the information.

Figure 5. Clustering of variables principal component analysis



Source: Own realization in R commander

Table 2. Example of a table

Account	Dimension 1	Contribution	Cos2
Asset	0.95	27%	0.92
Equity	0.94	27%	0.90
Revenues	0.91	25%	0.83
Profits	0.85	22%	0.73

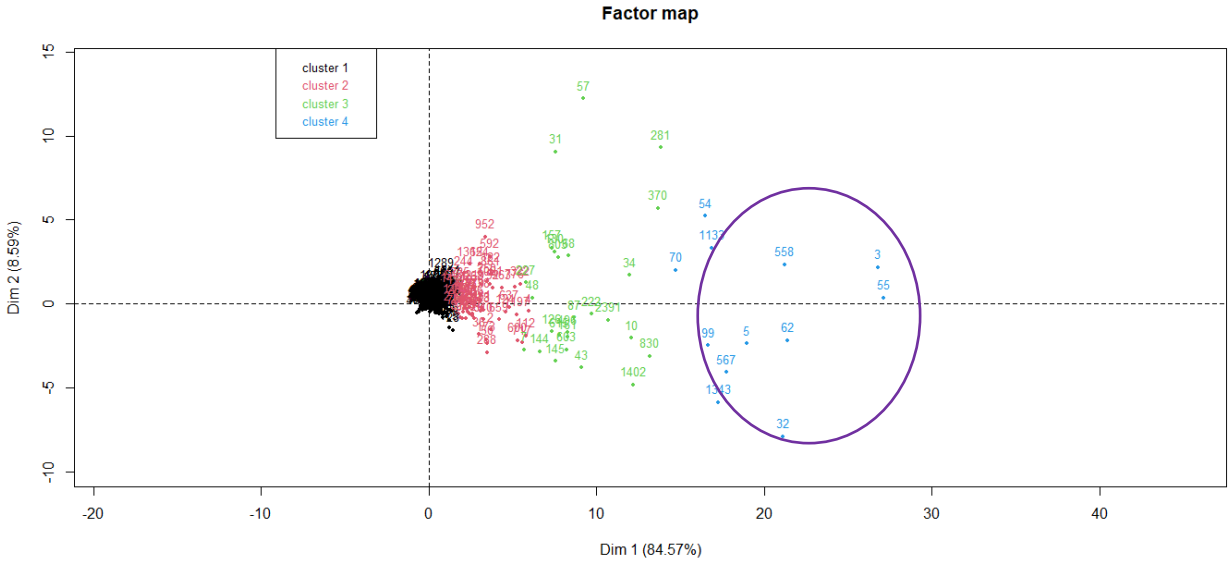
Source: Own realization in R commander

According to the data obtained, the design of the financial performance index for the manufacturing sector in Santander (FPIMS) would be as follows: FPIMS= 0.27* Asset+0.27* Equity+0.24* Revenues+0.22* Profits.

Figure 6 shows the classification of the companies according to their performance. 4 clusters were generated by color. The first cluster is the black cluster where the low-performance companies are located, followed by the red cluster of medium-performance companies, then the green cluster of medium-high-performance companies, and finally the blue cluster of high-performance companies. Therefore, the companies with the highest performance in the manufacturing sector in Santander are the points located in the blue cluster, ranking the first

5: 55, 3, 558, 62, and 32. According to the color density analysis, the majority of companies in the sector are classified as low-performance black cluster, followed by the medium red cluster, in third place medium-high (green) and finally, there are few companies classified as high financial performance (blue cluster).

Figure 6. Performance ranking of Santander's manufacturing companies



Source: Own realization in R commander

Conclusions

There is currently a contraction in the financial and operational performance of the manufacturing sector at an international level, as reflected in the global metrics S&P and ISM. Likewise, according to the last Colombian monthly manufacturing survey, there is a cascade effect in the indicators of the sector under study, production, real revenues, and unemployment, which means that there are more departments with negative and positive variations, among them Santander, with negative values in these metrics of 0.9 and one respectively, with these values the department did not contribute to the national totals. The objective of this work was to design a weighted indicator of financial performance with the principal component statistical method for 2392 companies in the Department of Santander that allows classifying the companies in the low, medium, medium-high- and high-performance categories. The results show that according to the grouping by color, most of the companies in the sector are in the low-medium performance categories. Only 12 companies with high financial performance were identified. Through this model, it is possible to show how international and national problems are reflected in the companies of the sector under study. Future research may corroborate the findings through other statistical methods or case studies.

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