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Identifying Representative Financial Ratios of the Indian Tyre Industry: A Principal Component Analysis Approach

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Abstract: *Financial Ratio analysis is a quintessential technique to evaluate financial statements and is widely used to interpret the performance of companies. This paper examines the application of factor analysis to financial ratios. Factor analysis is applied to investigate and find representative ratios based on different business functions and stakeholder perspectives to reduce complexities in analyzing financial performance through ratio analysis due to multiple ratios. Companies from the Indian tire industry listed on the Bombay Stock Exchange (BSE) have been selected for the study. A form of factor analysis is Principal component Analysis (PCA). From an initial set of fifty-three ratios, nine factors were generated, of which the ratios based on the highest factor loading were identified and selected as the representative ratios. Multiple regression analysis was carried out to eliminate statistically insignificant variables, which helped eliminate twenty ratios. Once again, factor analysis was deployed on the remaining variables, which generated seven factors as the outcome. Factors were named, and representative ratios were identified. Cluster analysis was performed to validate the results of factor analysis. The study shows that it is not essential to compute multiple ratios to assess the financial performance of companies.*

Keywords: *Financial Ratio, Factor Analysis, Multiple Regression analysis, Cluster Analysis*

Abstrak *— Analisis Rasio Keuangan adalah teknik klasik untuk mengevaluasi laporan keuangan dan banyak digunakan untuk menginterpretasikan kinerja perusahaan. Paper ini mengkaji penerapan analisis faktor pada rasio keuangan. Untuk mengurangi kompleksitas dalam menganalisis kinerja keuangan melalui analisis rasio karena beberapa rasio, pendekatan komponen utama diterapkan untuk menyelidiki dan menemukan rasio yang representatif berdasarkan fungsi bisnis dan perspektif pemangku kepentingan yang berbeda. Perusahaan dari industri ban India yang terdaftar di Bombay Stock Exchange (BSE) telah dipilih untuk penelitian ini. Salah satu bentuk analisis faktor adalah Principal component Analysis (PCA). Dari set awal lima puluh tiga rasio, sembilan faktor dihasilkan, di mana rasio berdasarkan pemuatan faktor tertinggi diidentifikasi dan dipilih sebagai rasio representatif. Analisis regresi berganda dilakukan untuk menghilangkan variabel yang tidak signifikan secara statistik, yang membantu menghilangkan dua puluh rasio. Sekali lagi, analisis faktor diterapkan pada variabel yang tersisa, yang menghasilkan tujuh*

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faktor sebagai hasilnya. Faktor diberi nama dan rasio representatif diidentifikasi. Analisis klaster dilakukan untuk memvalidasi hasil analisis faktor. Studi ini menunjukkan bahwa tidak penting untuk menghitung beberapa rasio untuk menilai kinerja keuangan perusahaan.

Kata Kunci: *Rasio Keuangan, Analisis Faktor, Analisis Regresi Berganda, Analisis Cluster*

1. Introduction

India is expected to be the third-largest economy in the world by 2031 (rbi.org.in). In 2021, India's Gross Domestic Product (GDP) stood at 14.771 million (pib.gov.in). The Automobile sector is a key sector in the economy. The auto industry is often considered a key contributor to the growth of an economy. India's automobile industry (including component manufacturing like tires and spare parts) is the fifth largest globally (ibef.org). The tire is a key component for any vehicle. As per a report by Automotive Tyre Manufacturers' Association (atmaindia.org.in), tire production grew by twenty-two percent in 2021 compared to the previous year. Hence, analyzing the tire sector's performance is essential for investors, creating investment, portfolio, and wealth-creation opportunities in the auto and tire sectors. Evaluating the financial performance of companies in this area and listed on the Indian stock exchanges will enable investors to aim for a risk-return trade-off. The literature review indicates the absence of studies where the application of factor and cluster analysis on the Auto sector and its allied industries was undertaken. Hence, the study aims to fill this gap.

Further, analyzing one representative industry can be informative and interesting as it can alleviate cross-industry confounding factors, allows for more contextualized interpretations with industry-specific knowledge beyond what is already known in a broader scope, and offers insights for practitioners (e.g., financial analysts and investors). The study will interest accountants, investment analysts, and other stakeholders as there will be time and cost savings.

Financial ratios are the key indicators for interpreting the performance of companies, and they display a summary of the company's financial position (Muresan & Wolitzer, 2004). A financial ratio compares one value with another value or group of values from the components of financial statements so that the investor and other stakeholders gain perspective on the financial performance of the companies (Chong et al., 2013). Analyzing financial reports provides perceptions of the multidimensional performance of a company as well as undertaking peer analysis and contributes to industry analysis to identify areas of scope for improvement and development (De et al., 2010). Ratios also track a company's financial trend over time, which indicates whether the companies are in the growth stage, its cash flow position, and its ability to meet its obligations. Additionally, they indicate the areas of a business's financial characteristics, growth, and strength, amongst others. This will also assist organizations in identifying areas of concern and taking corrective measures.

Factor analysis is a statistical approach that helps in identifying such latent variables through the mix of these variables into a lesser number or a singular variable. It is a multivariate tool of statistics that enables data reduction and summarisation (Hair et al., 2016). According to Gorsuch (2013), factor analysis is used to analyze and interpret relationships within a large number of variables and to explain these variables through a common underline factor with a minimum loss of information and conceptualization (Foster, 2007).

Computation of all ratios is not cost-effective and is time-consuming, hence the need to identify a representative set of ratios, minimizing the impact of relationships among the ratios. Initially, ratios are grouped into eight categories covering various business functions. Factor analysis is then deployed to identify latent variables and at least one representative ratio for each group of variables (ratios). The sample consists of listed companies, covering a market capitalization of 97.40%, from the Tyre sector in India for the current study. Fifty-three ratios were computed initially, and factor analysis yielded forty-six ratios in nine factors as the outcomes. Multiple regression was then carried out, leading to twenty-six ratios grouped into seven factors. Subsequently, factor analysis was conducted again to improve the results. The results were then validated using cluster analysis.

In the Indian context, limited research was found on the iron and steel, cement, and information technology sectors. The application of factor and cluster analysis was undertaken on financial ratios. The Indian tire industry has not been covered yet by any study. The current study covers the Tyre sector as a whole. It aims to extract the representative ratios (variables), which help to analyze a company's historical performance and enables the prediction of liquidity, earnings and profitability, capital structure, leverage, and other aspects of the Indian tire sector.

The study's objective is a reduction in the number of ratios required for analyzing the performance of selected companies from the tire sector, which would act as representatives of the original classification of ratios. This saves time for financial statement analysis and assists in understanding the financial position of tire companies in India. A review of past Studies indicated a lack of a study on the tire sector. The present paper aims to reduce the gap by undertaking a similar study on the tire sector. The contribution of this paper is to add value to existing literature relating to the tire sector, which will help in-stock selection for investors, and fund managers, amongst others, for a better risk-reward on investments.

The first part of the paper is the introduction. The remaining parts of the research paper are structured as follows: Section two reviews the literature relating to the study, followed by the research methodology in Section three, and statistical Procedures and methodology about the tire industry in section four. Section five deliberates on findings and discussion. The conclusion is presented in Section six.

2. Theoretical Framework

Financial ratios aid in the evaluation of financial statements and the performance of businesses. However, a large number of ratios exist, which are sometimes difficult to comprehend as their application and interpretations vary from industry to industry. Hence, a need arises to reduce the number of ratios to simplify the analysis and identify any latent variables that would reflect the company's qualitative aspects.

Pinches (1973), who first provided the application of factor analysis on financial ratios, stated that factor analysis is one such tool that helps to identify key ratios for a set of observed variables from a bigger basket of ratios as variables and further clusters can be used to classify them. It means tagging a large number of variables (ratios) into sets so that the variables within the groups are relatively similar.

Pal and Bhattacharya (2011) studied the impact of various financial ratios based on leverage ratios, liquidity ratios, and activity ratios on the profitability of the selected steel sector companies in India; Their study was based on a twenty-year horizon. Applying factor analysis, cluster analysis, and multiple regression, their findings indicated that the overall profitability was impacted primarily by Interest coverage ratios, which have a positive impact, and the fixed asset turnover ratio, which impacted sales. Subsequently, De et al. (2010) examined the financial statements of one hundred and thirty Indian cement companies for ten years from 1999-2000 to 2008-2009 using Factor analysis, Cluster analysis, and multiple regression. The outcome of their research indicated eight significant categories of ratios for the sector, including return on capital employed, solvency position, sources of capital, asset efficiency and material management, short-term liquidity position, dividend policy, and short-term application of funds which can be considered as relevant for the analysis of the Indian Cement sector.

Kountur and Aprilia (2020) studied the various dimensions of financial ratios using exploratory and confirmatory factor analysis of one hundred and twenty listed Indonesian companies on the IDX exchange. Their findings indicated that four groups could be formed to cover twenty essential indicators of the financial health of the company relating to operations, return generated for owners, turnover ratios for assets, and capital structure as the key ratios for analyzing the Indonesian Companies. In the study undertaken by Murphy et al. (1996), they analyzed corporate performance based on eight financial indicators, namely efficient use of the assets employed, profitability on sales, the growth rate of profit, short-term liquidity, market share, and others. Non-financial indicators like the satisfaction of consumers, the reputation of the company, and corporate social responsibility was lacking, as per their findings.

A study by Banerjee and Bandyopadhyay (2016) aimed to identify sample liquidity and profitability ratios for thirty-five IPOs from 2011 to 2013 to measure the solvency and returns, which would refer to investors' forecast of the financial health of the issuing company based on fifteen profitability and liquidity ratios by applying factor and regression analysis, which were used to identify the predictive ability of the representative financial ratios. The profitability ratio and Interest coverage ratio were found to be significant.

Using factor analysis, Han and Ren (2020) aimed to develop a financial risk assessment model for one hundred and twenty real estate companies in China based on the impact of solvency, operating ratios, ability to obtain cash flow, development ability, and profitability ratios to form an index weight for the period 2017 to 2019. Their findings indicated that seventy-one companies of the selected sample had negative factor values indicating higher financial risks for these companies. Leano (2004) studied the financial ratios of eighty US bankrupt manufacturing firms from 1995 to 2003 merged or acquired during the same period. The study examined the quantum of financial distress, analyzed the stationarity of data, and the impact of correlation on the accuracy of the variable classification. The findings based on Factor Analysis (FA), Discriminant Analysis (DA), and Linear Regression Analysis (LRA) suggested an increased impact of correlation in classification accuracy and understanding of economic indicators. It differentiated between financially distressed bankrupt firms and stable nonbankrupt firms in the manufacturing industry from 1995 to 2003. Szucs (2015), in their study, applied factor analysis within the principal component analysis based on the multicollinearity between financial ratios as the variables extracted from the automotive industry in Hungary. Their findings indicated that the automobile industry in Hungary consistently had shown growth momentum and that the Liabilities based financial ratios were not significant.

Further, Cluster analysis indicated that foreign ownership is significant for large companies with higher net revenues. Other Factor analysis applications include Feranecová and Krigovská's (2016) work. They studied financial statement analysis of sixty-seven world universities derived from the QS World ranking from 2010 to 2014. Post the elimination of low correlations, they applied factor and cluster analysis. University categories were created using Cluster analysis based on similar financial positions, akin to their rankings and criteria.

Guohua and Wenxing (2020) examined the financial risk of the Iron and Steel industry of the Chinese economy with a focus on financial risk assessment based on five different areas, namely, cash flows, solvency, profitability, growth ability, and operation ability. Through the factor analysis technique, their findings indicated the presence of complex capital structures, weakness in managing costs and resources, and poor implementation of available cash flow in the steel industry, which increased financial risk for selected companies.

Additionally, Filatov (2021) investigated the financial performance of the construction industry of the Russian Federation in adverse economic scenarios by developing ten methods of factor analysis. The findings indicate that these factor analysis methods enable simple conclusions in representative indicators. De et al. (2010) analyzed the forty-four ratios of thirty-eight corporates from the steel and iron sector. These were listed on India's top two stock exchanges from 1999-2000 to 2008-2009. For factor analysis, financial ratios were grouped into seven segments. The findings indicated that financial health is discussed for the industry on eight factors out of forty-four, i.e., ratios. Further, by applying cluster analysis to the factor analysis results, the representative ratios were identified in the study for each group of financial ratios.

Studies by Ugurlu and Aksoy (2006), Chen and Shimerda (1981), Taffler (1982), Ganesalingam and Kumar, (2001) and Koh and Killough (1990) suggest that many ratios need not be computed to analyze financial performance and that factor analysis can be adopted to identify factors that help expound various ratios through a smaller group of ratios.

3. Research Method

3.1 Sample Size

This study analyzed the tire sector for ten years (2011-12 to 2020-21). Sixteen companies in the tire sector (see Table 1 below) are listed on India's Bombay Stock Exchange (BSE). Of these sixteen companies, 97.40% of the total market capitalization of the tire sector has been taken, represented by seven companies as of March 31, 2021 (bseindia.com). The remaining companies were excluded as either they were suspended by the regulator or were listed for less than ten years. The collated panel data comprises fifty-three ratios, ten years, and seven companies.

The Audited financial statements were extracted from the Capitaline database. Financial ratios were computed in Ms-Excel, which were the inputs for Factor and Cluster analysis. The analysis was conducted using IBM SPSS Statistics 25.

Table 1
Market capitalization as per BSE as on 31/03/2021

Sr. No	BSE_ Scrip Code	Company Name	Market Cap (Rs Cr.)	Cumulative Market Cap (Rs Cr.)	Market Cap (%)	Cumulative Market Cap (%)
1	500290	MRF LTD.	34.870,13	34.870,13	36,07%	36,07%
2	502355	BALKRISHNA INDUSTRIES LTD.	32.679,30	67.549,43	33,80%	69,86%
3	500877	APOLLO TYRES LTD.	14.210,38	81.759,81	14,70%	84,56%
4	500878	CEAT LTD.	6.315,27	88.075,08	6,53%	91,09%
5	530007	JK TYRE & INDUSTRIES LTD.	2.680,22	90.755,30	2,77%	93,87%
6	500168	GOODYEAR INDIA LTD.	2.056,26	92.811,56	2,13%	95,99%
7	509243	TVS SRICHAKRA LTD.	1.360,08	94.171,64	1,41%	97,40%
8	542932	BIRLA TYRES LIMITED	324,39	94.496,03	0,34%	97,73%
9	1670	INNOVATIVE TYRES AND TUBES LTD.	1529,28	96.025,31	1,58%	99,32%
10	509162	INDAG RUBBER LTD.	235,99	96.261,30	0,24%	99,56%
11	500890	MODI RUBBER LTD.	233,88	96.495,18	0,24%	99,80%
12	509152	GRP LTD.	05,87	96.601,05	0,11%	99,91%

Sr. No	BSE_ Scrip Code	Company Name	Market Cap (Rs Cr.)	Cumulative Market Cap (Rs Cr.)	Market Cap (%)	Cumulative Market Cap (%)
13	542013	DOLFIN RUBBERS LTD	34,90	96.635,95	0,04%	99,95%
14	531346	EASTERN TREADS LTD.	28,78	96.664,73	0,03%	99,98%
15	523550	KRYPTON INDUSTRI	13,54	96.678,27	0,01%	99,99%
16	530369	VAMSHI RUBBER LTD.	8,17	96.686,44	0,01%	100,00%
		Total	96.686,44			

Source - bseindia.com

3.2. Identification and Selection of Financial ratios as the Variables

This study uses fifty-three financial ratios representing divergent functions of the business. The ratios were collated from two main sources: Foster (2007) and White et al. (2003). For analysis, categorizations of ratios have been conducted based on different functions of the business as follows: Return and Profitability, Operational Cash Flow, Liquidity, Cash and Cash Equivalent, Long term Solvency, Efficiency and Activity, Expenses, Market Value, total of eight categories (see Appendix 1).

3.3. Statistical Procedures

Initially, it was essential to understand the inter-correlation amongst the ratios (variables) for undertaking factor analysis and cluster analysis. Hence, an intercorrelation matrix was developed. This correlation matrix consists of a correlation coefficient amongst the variables based on 53 x 53 (i.e., n x n, where n = no. of variables). Low inter-correlation between the selected variables reduces the efficacy and reliability of the relation between the variables. Hence, weak correlations were identified from the diagonal of the anti-image correlation matrix, and the correlation coefficients ($r < \pm 0.5$) being considered weak have been excluded (Kountur & Aprilia, 2020). The high correlation between the ratios (variables) leads to 'multicollinearity'. It generates a high variance of the estimated coefficients and becomes sensitive to even minor changes in the estimated model. A reduction in multicollinearity can be achieved using statistical techniques by identifying latent variables, i.e., inherent factors based on financial ratios (De et al., 2011).

The PCA minimizes the data set dimensionality in cases where a substantial number of correlated variables exist. The PCA method has been employed to extract the variables. The PCA aims to retain maximum probable variation by identifying latent variables representing the existing variables. These latent or unobserved variables, known as factors, are uncorrelated with each other and can work as an index of all constituent variables for further analysis of data. (Cross, 2015). As the rotation method, Varimax is applied to improve the data's reliability. It has been observed that the Principal component analysis (PCA) has seen wide application across multiple technical disciplines. The use of PCA has been observed in agriculture (Macours & Swinnen, 2000), Banking and Finance (Panigirtzoglou & Skiadopoulos, 2004; Takahashi & Kurokawa, 1984), Environmental Science (Galloway et al., 2004; Hites 2004).

Cluster analysis can also validate results obtained from the factor analysis (De et al., 2010). Further, Shen (2021) applied cluster analysis using K-means and machine learning techniques in developing consumer credit risk forecasting models. Binary logistic regression was undertaken to develop models indicating the likelihood of default.

Eigenvalues, also known as characteristic roots, describe the variance explained by that specific factor out of total variance. Factors with Eigenvalues of less than one are ignored for deciding factor count for extraction. The cut-off is maintained at 0.30 to identify the factor loading above (Tabachnick & Fidell, 2001).

The Kaiser-Meyer-Olkin (KMO) test was applied to test whether the sample size was adequate. Ideally, the data with a KMO value less than 0.50 is considered reasonable. Bartlett's test of sphericity indicates the presence or absence of an identity matrix. A significant p-value would indicate that the correlation coefficient matrix isn't an identity matrix. (Datar & Garg, 2019). As explained by the extracted factors, the variance in the ratios is known as commonalities. Subsequently, variables with a factor score of less than 0.30 are excluded for further analysis; a factor represents the constituent variables (Judith & Maribel, 2018). A multiple regression analysis has been undertaken to determine the constituent variable's impact on the factor. For this purpose, initially, the factor scores are saved as variables. Further, for the regression analysis, the dependent variable is the factor score across various factors, and the independent variable is the component variables of that factor. Based on the regression results, financial ratios (variable) having absolute t-values < 2, and a confirming p-value> 0.05, are omitted (De et al., 2011). Post the regression, data was re-summarised, and factor analysis was performed again on the remaining variables. This helps in identifying the latent variable from the set of variables. The variable with the highest loading for each factor was identified as the representative of the factor. Subsequently, the factors were named based on representative variables to make the identification easier. The factor analysis identifies the categories of variables which may need further validation. This validation uses cluster analysis on the same variables with a predefined number of clusters, equivalent to several factors identified after the second-factor analysis.

Cluster analysis is an exploratory data analysis and a multivariate data mining technique that classifies variables into relatively homogeneous groups based on selected characteristics or attributes, known as Clusters. It sorts different variables so that the degree of correlation is maximum between variables belonging to the same groups or minimum (Gupta & Gupta, 2015).

For the cluster analysis, the standardized values of the variables were computed. The hierarchical clustering approach used Ward's method with a measurement interval based on Squared Euclidean Distance (King, 2015).

Post the cluster analysis, the factor and cluster analysis results were collated so that comparative analysis could be undertaken to identify common variables within relevant factors and clusters, which consist of similar ratios (variables).

4. Results and Discussion

4.1 Results of Correlation

The correlation coefficient expresses how closely interconnected two data chains are and shows the directions of this relationship and the degree of the linear relationship among them (DeFusco et al., 2015). For effective factor analysis, a high correlation is required amongst selected variables.

Initially, Correlation analysis was performed using SPSS on 53 ratios. Inter correlation matrix (53 X 53) was formed to identify the high or low correlation between the variables. Factor analysis requires the existence of a high correlation among the variables (stats.oarc.ucla.edu). Hence variables with a low correlation coefficient (< + 0.5) have been excluded from the study. Seven such variables were identified and collated in Table 2, which were eliminated before the first-factor analysis.

Table 2
Financial ratios (variables) excluded through the correlation matrix process

Sr. No.	Category	Ratio Code	Name of Financial Ratio
1	Cash Flow Ratios	CFO 5	Cash flow from operations to Net Working capital
2	Activity and Efficiency Ratios	TO 2	Fixed Assets Turnover
3	Activity and Efficiency Ratios	TO 7	Working Capital to Fixed Assets
4	Expenses Ratios	EXP 3	Administrative Expenses Ratio
5	Valuation Ratios	VAL 1	Enterprise Value to EBIT
6	Valuation Ratios	VAL 3	Enterprise Value to Cash From Operations
7	Valuation Ratios	VAL 6	Price-Cash Ratio

4.2 First Factor Analysis

Factor analysis was conducted on the remaining forty-six (fifty-three minus seven) variables (ratios), which resulted in nine factors. The KMO and Bartlett's test results are verified before further analysis of factors. The KMO value and Bartlett's test are tabulated in Table 3.

Table 3
KMO & Bartlett's test based on First Factor Analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,560
Bartlett's Test of Sphericity	Approx. Chi-Square	7136,214
	df	1035
	Sig.	0,000

For factor analysis, Bartlett's test was found to be significant (p-value < 0.05), and the KMO, which is a measure of identifying the existence of an adequate sample, has a value of higher than 0.5, which is reasonably good and acceptable and is considered the minimum value for undertaking factor analysis (Chong et al., 2013). Appendix 2 summarises the nine factors from the Rotated component matrix, contributing approximately 89.62% to the total variance, which can be considered a good outcome. Factor names were given based on the constituent variables with the highest factor loading. Table 4 indicates the findings of the Factors post the first Factor Analysis and naming of factors.

Table 4
Naming of factors post First Factor Analysis (Selected Ratios, Factor Loading & Eigen Values)

Factor No	**Ratio Code**	**Name of the Factors**	**Ratio**	**Factor Loading**	**Eigen Value (after Rotation)**
FACT_1	PE2	Profitability	Post-Tax Net Profit Margin	0,9350	9,152
FACT_2	CCE1	Cash & Cash Equvalent Ratio	Cash & Cash Equivalents to Current Liabilites	0,9400	6,538
FACT_3	PE3	Earnings	Return on Equity Ratio	0,8990	6,369
FACT_4	LTS5	Long Term Solvency Ratio	Net Worth to Capital Employed	0,8680	5,915
FACT_5	CFO4	Cash from operations Ratio	Cash flow from operations to Capital Employed	0,9270	5,602
FACT_6	TO5	Turnover Ratio	Debtors Turnover Ratio	0,8540	2,500
FACT_7	VAL8	Valuation Ratio	Price Earnings Ratio	0,6690	1,989
FACT_8	PE9	Profitability	Gross Profit Margin	0,5680	1,851
FACT_9	LTS2	Long Term Solvency Ratio	Degree of Financial Leverage Ratio	0,7940	1,310

4.3 Findings of Multiple Regression Analysis

According to Montgomery et al. (2012), regression analysis is a statistical technique for undertaking an investigation and interpretation of the relationship between and amongst the variables. In this study, factor scores are taken as the dependent variables and variables contributing to the factor are treated as independent variables. A high R2 was obtained (> 0.9) for each of the nine-regression analyses based on the factors. Ratios with a t-value of less than two and corresponding p-value greater than 0.05 have been eliminated by their presence in different factors (De et al, 2011). The number of variables eliminated was twenty based on the same criteria. Table 5, enlists eliminated variables with the assistance of multiple regression analysis.

Table 5
List of Ratios (Variables) not considered based on Multiple Regression Analysis

Ratio Code	**Category**	**Factor**	**Ratio Name**	**t-value**	**p-value**
TO3	Turnover	FACT_1	Average Fixed Assets Turnover	-0,286	0,776
CFO1	Operational Cash Flow	FACT_1	Cash flow from operations to Net Sales	1,015	0,315
LQ1	Liquidity	FACT_1	Current Ratio	0,198	0,844
LQ4	Liquidity	FACT_1	Interest Coverage Ratio	1,109	0,273
PE10	Return & Profitability	FACT_1	Operating Profit Margin	0,097	0,923
PE2	Return & Profitability	FACT_1	Post-Tax Net Profit Margin	1,588	0,118
PE1	Return & Profitability	FACT_1	Pre-Tax Net Profit Margin	1,254	0,216
VAL5	Market Value	FACT_1	Price Sales Ratio	0,805	0,425
CCE2	Cash & Cash Equivalent	FACT_2	Cash & Cash Equivalents to Current Assets	-0,294	0,770
CCE1	Cash & Cash Equivalent	FACT_2	Cash & Cash Equivalents to Current Liabilites	1,136	0,261
LTS6	Long term Solvency	FACT_2	Fixed Assets to Capital Employed	-1,848	0,070
PE5	Return & Profitability	FACT_3	Return on Average Capital Employed Ratio	1,595	0,116
PE6	Return & Profitability	FACT_3	Return on Average Equity Ratio	0,207	0,837

Ratio Code	Category	Factor	Ratio Name	t-value	p-value
LTS8	Long term Solvency	FACT_4	Debt to Total Assets	-0,774	0,442
LTS7	Long term Solvency	FACT_4	Capital Gearing Ratio	-0,498	0,621
LTS3	Long term Solvency	FACT_4	Proprietary Ratio	-0,159	0,874
CFO8	Operational Cash Flow	FACT_5	Cash flow from operations to Average Capital Employed	1,936	0,058
CFO6	Operational Cash Flow	FACT_5	Cash flow from operations to Average Total Assets	-0,905	0,369
CFO4	Operational Cash Flow	FACT_5	Cash flow from operations to Capital Employed	1,798	0,077
CFO2	Operational Cash Flow	FACT_5	Cash flow from operations to Total Assets	0,233	0,816

The outcomes of the regression analysis have been summarised in Appendix 3.

4.4 Second Factor Analysis

Post the regression analysis; twenty-six variables were retained for subsequent analysis. Factor analysis is once again applied to these variables leading to seven factors. The rotated component matrix for the same is presented in Appendix 4. The Working capital turnover ratio has a factor loading of less than 0.30 and hence has been excluded in the subsequent analysis. Therefore, twenty-five variables were the inputs for the second-factor analysis. Further, KMO values were more than 0.5, and Bartlett's test is statistically significant, tabulated in Table 6.

Table 6
KMO & Bartlett’s test based on Second Factor Analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,596
Bartlett's Test of Sphericity	Approx. Chi-Square	2450,373
	df	325
	Sig.	0,000

The total variance was 81.95% for these factors, which can be considered highly significant. Accordingly, factor names were assigned using the highest factor loading based on the component variables. The findings of the factors post the second-factor analysis, along with the factor names, representative ratio, factor loading, and Eigen Values, are collated in Table 7.

Table 7
Findings of Factors post second Factor Analysis

Factor No	**Ratio Code**	**Name of the Factors**	**Representative Ratio**	**Factor Loading**	**Eigen Value (after Rotation)**
FACT_1	LTS3	Long term Solvency	Proprietary Ratio	0,873	4,580
FACT_2	PE3	Return & Profitability	Return on Equity Ratio	0,910	4,272
FACT_3	CCE3	Cash & Cash Equivalent	Cash & Cash Equivalents to Sales Ratio	0,939	3,837
FACT_4	TO6	Turnover	Total Income to Capital Employed	0,862	3,577
FACT_5	TO5	Turnover	Debtors Turnover Ratio	0,850	1,787
FACT_6	EXP4	Expenses	Operating Ratio	0,644	1,641
FACT_7	LQ2	Liquidity	Quick Ratio	0,472	1,615

4.5 Cluster Analysis

Cluster analysis has been performed on the same twenty-five variables to validate the outcomes of factor analysis. The number of clusters was predefined as seven, the same as the number of factors ascertained in the second-factor analysis. The findings of the cluster analysis are produced in Table 8.

Table 8
Results of Cluster Analysis

	Cluster Components	
Case	Name of Ratios	7 Clusters
CCE3	Cash & Cash Equivalents to Sales Ratio	3
CCE4	Cash & Cash Equivalents to Total Assets	3
CFO3	Cash flow from operations to Equity	4
CFO7	Cash flow from operations to Average Equity	4
EXP1	Employee Expense Ratio	2

Case	Cluster Components Name of Ratios	7 Clusters
EXP4	Operating Ratio	4
LQ2	Quick Ratio	3
LTS1	Debt/Equity Ratio	4
LTS2	Degree of Financial Leverage Ratio	5
LTS3	Proprietary Ratio	6
LTS5	Net Worth to Capital Employed	6
PE3	Return on Equity Ratio	1
PE4	Return on Assets Ratio	1
PE5	Return on Capital Employed Ratio	1
PE8	Return on Average Assets Ratio	1
PE9	Gross Profit Margin	2
TO1	Inventory Turnover Ratio	7
TO4	Working Capital Turnover	5
TO5	Debtors Turnover Ratio	7
TO6	Total Income to Capital Employed	7
TO8	Total Assets Turnover	7
TO9	Net Working Capital Ratio	3
VAL2	Enterprise Value to Assets	6
VAL7	Price-Book Value Ratio	6
VAL8	Price Earnings Ratio	6

4.6 Comparative analysis of the results of Factor and Cluster analysis

To undertake a comparative study, the findings of both factor and cluster analysis have been collated and organized, facilitating the probable comparison against each other. After the cluster analysis, the cluster and the factors were plotted against each other based on the similar or most similar factor constituent in Table 9.

Table 9
Comparative analysis of the findings of Factor Analysis and Cluster Analysis

Factor	**Ratio**	**Name of Ratio (Variable)**	**No of**	**Cluster**	**Name of Ratio (Variable)**	**No of**
Number	**Code**		**Variables**	**Number**		**Variables**
FAC_01	LTS3	Proprietary Ratio	5	CLUST_06	Proprietary Ratio	**5**
FAC_01	LTS5	Net Worth to Capital Employed		CLUST_06	Net Worth to Capital Employed	

FAC_01	VAL8	Price Earnings Ratio		CLUST_06	Price Earnings Ratio	
FAC_01	VAL2	Enterprise Value to Assets		CLUST_06	Enterprise Value to Assets	
FAC_01	VAL7	Price-Book Value Ratio		CLUST_06	Price-Book Value Ratio	
FAC_02	PE3	Return on Equity Ratio		CLUST_01	Return on Equity Ratio	
FAC_02	PE4	Return on Assets Ratio		CLUST_01	Return on Assets Ratio	
FAC_02	PE5	Return on Capital Employed Ratio	5	CLUST_01	Return on Capital Employed Ratio	**4+1**
FAC_02	PE8	Return on Average Assets Ratio		CLUST_01	Return on Average Assets Ratio	
FAC_02	PE9	Gross Profit Margin		CLUST_02	Gross Profit Margin	
FAC_03	LQ2	Quick Ratio		CLUST_03	Quick Ratio	
FAC_03	TO9	Net Working Capital Ratio		CLUST_03	Net Working Capital Ratio	
FAC_03	CCE3	Cash & Cash Equivalents to Sales Ratio	4	CLUST_03	Cash & Cash Equivalents to Sales Ratio	**4**
FAC_03	CCE4	Cash & Cash Equivalents to Total Assets		CLUST_03	Cash & Cash Equivalents to Total Assets	
FAC_04	TO8	Total Assets Turnover		CLUST_07	Total Assets Turnover	
FAC_04	TO6	Total Income to Capital Employed	3	CLUST_07	Total Income to Capital Employed	
FAC_04	EXP2	Selling & Distribution Expenses Ratio		CLUST_02	Selling & Distribution Expenses Ratio	4+1
FAC_05	TO5	Debtors Turnover Ratio	2	CLUST_07	Debtors Turnover Ratio	
FAC_05	TO1	Inventory Turnover Ratio		CLUST_07	Inventory Turnover Ratio	
FAC_06	CFO3	Cash flow from operations to Equity		CLUST_04	Cash flow from operations to Equity	
FAC_06	CFO7	Cash flow from operations to Average Equity	4	CLUST_04	Cash flow from operations to Average Equity	**3+1**
FAC_06	EXP4	Operating Ratio		CLUST_04	Operating Ratio	
FAC_06	LTS2	Degree of Financial Leverage Ratio		CLUST_05	Degree of Financial Leverage Ratio	
FAC_07	LTS1	Debt/Equity Ratio	2	CLUST_04	Debt/Equity Ratio	1+1
FAC_07	EXP1	Employee Expense Ratio		CLUST_02	Employee Expense Ratio	
			25			**25**

On deep diving into Table 9, it was observed that factors one and three have the same corresponding clusters, namely, clusters six and three. Factor two and cluster five were almost identical except for the gross profit margin (PE nine), which appeared in cluster two. Factor four and cluster seven were similar, excluding the selling and distribution expense ratios (EXP two) which is the constituent of cluster two. The constituent of factor five is identical to cluster seven; however, cluster seven components are like constituents of factors four and five taken together (activity and efficiency ratios) based on domain knowledge. The presence of LTS2 (Degree of financial leverage) is a mismatch in factor six and cluster four. It is the only constituent in cluster five. Factor seven has two variables, namely, Debt/equity ratio (LTS1) and employee expense ratios (EXP1) which are not represented by one single cluster and were reflected in clusters four and two. It can be observed that cluster two has constituent variables associated with three different factors, namely factors two, four, and seven. The findings and the deviations do not significantly challenge factor analysis outcomes when applying subject knowledge. They improve the interpretation of factor analysis. Therefore, we can adopt the seven factors, which have been authenticated via cluster analysis.

5. Conclusion, Implication, and Limitation

5.1 Conclusion

The study's outcome enables the identification of a few relevant ratios, which would provide sufficient interpretation and information on the financial health of the companies in the tire sector. Of the sixteen companies listed on the BSE, seven companies covering a market capitalization of 97.40% were identified. Initially, fifty-three ratios were grouped into eight categories. Inter-correlation matrix was constructed, which eliminated seven ratios. This was followed by the first-factor analysis on forty-six ratios, which created nine (latent variables). The highest factor loading was used to identify the representative ratio. This was followed by multiple regression, which helped to eliminate twenty variables. Subsequently, the second-factor analysis was conducted on the remaining ratios. After the second-factor analysis, seven factors were formed, and the highest loading variables were chosen as representative ratios (see Table 7). The findings were validated using cluster analysis.

Further, a comparative summary was tabulated among the categories of the financial ratios based on the initial groupings and the categories based on the outcome in Table 10.

Table 10
Grouping Comparison of Initial Category & Factor Results

Initial Classification		**Final Outcome of the study**	
Category No.	**Category**	**Factor No.**	**Factor**
CATEG_01	Return & Profitability	FACT_1	Long term Solvency
CATEG_02	Liquidity	FACT_2	Return & Profitability
CATEG_03	Operational Cash Flow	FACT_3	Cash & Cash Equivalent
CATEG_04	Cash & Cash Equivalent	FACT_4	Efficiency
CATEG_05	Long term Solvency	FACT_5	Activity
CATEG_06	Activity & Efficiency	FACT_6	Expenses
CATEG_07	Expenses	FACT_7	Liquidity
CATEG_08	Market Value		

5.2 Implication

The above study indicates that the following seven factors can be considered to understand the financial health of a tire company in India. These include Long term Solvency, Return & Profitability, Cash & Cash Equivalent, Efficiency, Activity, Expenses, and Liquidity. These seven factors are related to the key functions of any business.

Ratios from the market value (CATEG_08) and operational cash flows (CATEG_03) did not find a place in the final results. The final results relating to Efficiency and Activity ratios indicate that Efficiency and Activity are to be analyzed separately, as they formed two separate factors in the results. (FACT_04 and FACT_05), though in the initial classification, both were categorized together (CATEG_06). The remaining categories were reflected in the final factors, except for a few variables, within each category while mapping the same with the constituents of each factor.

After identifying seven factors post the second-factor analysis, seven ratios have been selected to represent diverse functions of business, which are listed in Table 11.

Table 11
Representative Ratios for financial performance analysis of Tyre Sector Companies.

Factor	**Representative Ratio**
FACT_1	Proprietary Ratio
FACT_2	Return on Equity Ratio
FACT_3	Cash & Cash Equivalents to Sales Ratio
FACT_4	Total Income to Capital Employed
FACT_5	Debtors Turnover Ratio
FACT_6	Operating Ratio
FACT_7	Quick Ratio

The ratio of Equity to Total Assets (Proprietary ratio) represents the highest factor loading. This indicates the importance of long-term Equity investment in the company. Thus, companies with high leverage are not suitable for investment in the tire sector. This is further supplemented by the return representing the second-highest factor loading on the Equity ratio. This indicates that since Equity is the preferred source of funds for the tire sector (companies would have a low-interest cost due to low debt), Investors would expect high returns on their investments. The companies in the tire sector with a higher quick ratio and higher Cash and Cash Equivalent to Sales ratio should be preferred as a higher quick ratio indicates efficient short-term solvency, and a higher Cash and Cash Equivalent to income ratio suggests the capacity to generate cash to meet and fund its growth requirements. Total Income to Capital employed and Debtors Turnover ratio indicate long. Short-term efficiency of management in utilizing capital employed effectively to generate higher sales and having an efficient credit policy that helps recover cash from customers quickly. Companies with a high total income to employed capital ratio and a high debtor turnover ratio should be preferred for investing.

These seven factors, identified by our study, will help save resources by analyzing only the seven factors and representative financial ratios identified for different stakeholders. Since the study was based on the substantial time frame of ten years of data covering market capitalization sufficient to represent the industry, the study's implication will help in summarising the industry's performance.

5.3 Limitation

A limitation of this study is that the research relates to a particular sector of a particular country only for a specified period. The findings will be read in the context of the economic and market scenarios relating to the sample period (2012 to 2021).

Future research can be undertaken for other auto ancillary sectors. Additionally, these representative ratios can add value while undertaking the valuation of tire companies, as these are sector-specific. For determining the intrinsic value of the tire companies, the latent variables found in the study can be used as an explanatory variable in different models like Fama-French 3 or 5-factor models, Carhart Model, and similar other models.

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