

# Python-based PCA for Analyzing Financial Performance Changes in the Health Sector's Pharmaceutical Sub-Industry

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## Abstract

*A meticulous examination of the financial status of 11 prominent pharmaceutical corporations was initiated through a comprehensive analytical investigation. Employing 15 pertinent financial metrics, encompassing indicators like the Price-Earnings Ratio (PER) and Net Profit Margin (NPM), allows for a thorough assessment of their financial health. The chosen analytical methodology is the Principal Component Analysis (PCA) technique. Over consecutive years, the analysis reveals that five companies—namely DVL, KLBF, MERK, PEHA, and SOHO—demonstrate consistent performance by exhibiting minimal changes in their operational status. Firms categorized as "moderate" were questioned regarding potential limitations within their existing operational growth model or external hindrances impacting their advancement. Conversely, four companies—KAEF, PYFA, SIDO, and TSPC—exhibit positive trends and amplified performance. Notably, PYFA transitions from the "very poor" category to "fair" within a year, signifying potential strategic adaptations, effective crisis management, or advantageous market circumstances. Further investigation is warranted to delve deeper into directional shifts in strategies for change and distinctive approaches to fostering growth. In stark contrast, SCPI undergoes a significant downturn, marked by a "very poor" performance rating. These significant changes significantly differ from the overall organizational performance trend, indicating possible severe internal challenges or external pressures. This research fundamentally emphasizes the various changes in organizational performance within a single year, showcasing successful and stable organizations alongside those facing declines. Moreover, the findings underscore the imperative for continual self-assessment by organizations and the necessity to adapt strategies in response to internal and external environmental dynamics. This analysis serves as an initial step towards investigating causal factors impacting organizational performance, thereby facilitating the formulation of strategies geared towards future enhancements.*

**Keywords:** *PCA, Financial Performance, Pharmaceutical, Healthcare.*

## Introduction

The health service sector plays a crucial role in community well-being, providing a spectrum of care services crucial from preventive measures to treatment, thereby constituting a significant part of a nation's fabric (Wang et al., 2021). The pharmaceutical sub-sector is pivotal in researching, manufacturing, and disseminating medications to address diverse health conditions within the expansive pharmaceutical industry. Notably, this sub-sector has gained prominence due to its pivotal role in the race to develop medications and vaccines, particularly in combating the COVID-19 pandemic. Consequently, understanding the fluctuations in financial performance within the pharmaceutical sub-sector holds immense importance, impacting various stakeholders, including investors, policymakers, and healthcare administrators.

In recent decades, the worldwide pharmaceutical market has undergone significant expansion, as evidenced by the data provided by Filipe (2023) (see Figure 1). This growth surge is attributed to several factors, including technological advancements, amplified investment in research and development, the demographic shift toward an aging population, and the widening accessibility of healthcare infrastructure (Huateng, 2019). However, amidst this growth, the sector faces challenges, including patent expiration, stringent regulatory frameworks, and pricing pressures. Given the constantly evolving industry dynamics, pharmaceutical entities' financial performance has fluctuations, underscoring the critical need to analyze and comprehend these variations thoroughly.

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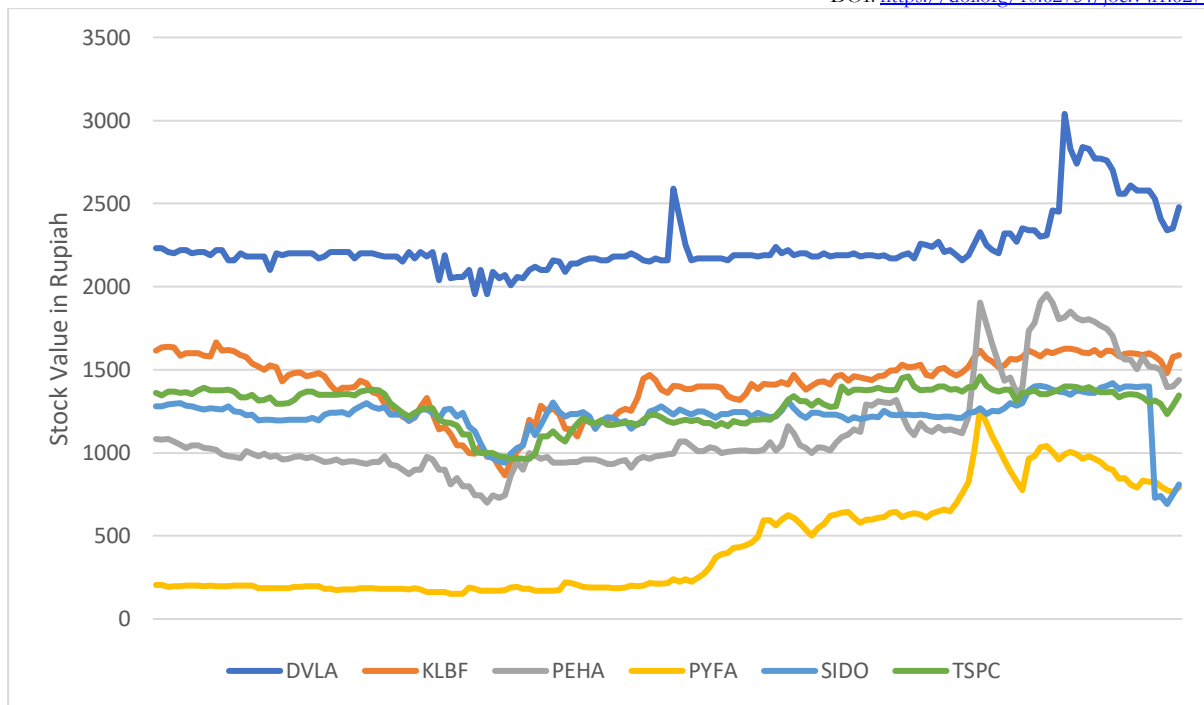


Figure 1. 2020 Stock Value

Examining the financial performance within the pharmaceutical sub-industry transcends a mere assessment of profit margins or revenue figures. The study delves into a spectrum of financial indicators, encompassing metrics like ROE, DER, and EBT. Conventional financial methodologies often focus on isolated metrics, potentially overlooking intricate interrelations among diverse financial facets. Consequently, advanced analytical techniques such as Principal Component Analysis (PCA) have emerged to address this limitation. PCA, a statistical procedure, transforms a collection of linearly uncorrelated values from possibly linked variables termed principal components (Fonseca et al., 2023).

Henceforth, Principal Component Analysis (PCA) enables analysts to condense a dataset's dimensionality while retaining crucial information. This technique holds significant value within financial analysis, particularly in navigating the intricate interconnections among various indicators and identifying the pivotal drivers of performance (Jain & Shandliya, 2013). Nevertheless, Wainwright et al. (2020) highlighted that implementing PCA necessitates judicious consideration. Each analytical technique carries its own set of assumptions and constraints. PCA, for instance, assumes a linear structure within the data and presupposes orthogonality among its principal components (McVean, 2009).

Given its pivotal role within global healthcare, the pharmaceutical industry houses a myriad of financial indicators warranting thorough examination. While traditional financial metrics hold value, they often need to catch up in capturing the nuanced interactions between factors influencing overall performance. Principal Component Analysis (PCA) is a promising avenue for comprehending this intricacy. This endeavor relies on Python's capabilities to ensure a robust and insightful analysis, enhancing our understanding of these financial dynamics.

## Literature Review

Kalotra (2014) underscores the pharmaceutical industry's heightened complexity, necessitated by its involvement in developing, producing, and marketing medicinal products. Entities within this sector encounter formidable challenges, including patent expirations, advancements in biotechnology, regulatory shifts, and intense market competition. Moreover, the landscape is further complicated by mergers, acquisitions, joint ventures, and globalization initiatives (Narayana et al., 2014). Principal Component

Analysis (PCA) is a statistical technique utilized to reconfigure original variables in a dataset into a new collection of primary components, which are uncorrelated variables (Kherif & Latypova, 2020). As noted by Sorzano et al. (2014), the primary objective of PCA resides in dimensionality reduction, aiming to retain as much of the original variance as feasible. Financial metrics like sales, profit margins, research and development expenditures, and earnings per share serve as potential variables in financial analysis, as articulated by Martani and Khairurizka (2009). Ferreira and Tobyn (2015) suggest that PCA becomes a valuable tool in this context, enabling analysts to pinpoint significant variables or key combinations thereof (termed "principal components") that exert influence on the financial performance within the pharmaceutical sector.

Although it has shortcomings, PCA retains its significance as an essential resource for analysts and decision-makers in the pharmaceutical sector because of its capacity to simplify complex situations and identify crucial financial elements (Jombart et al., 2010). The trajectory of the financial industry will notably hinge upon the progression of statistical methodologies like PCA and the evolution of computational tools such as Python, signifying their enduring importance in shaping the industry's future landscape.

## Methodology

### Data

This study includes eleven stocks from pharmaceutical sector companies, as outlined in Table 1, and the assessment period spanning from March 2022 to March 2023 involved the utilization of Principal Component Analysis (PCA) to analyze stock trends and patterns. The dataset from these stocks serves as the primary source for subsequent analysis, facilitating an in-depth exploration of the interplay between market dynamics and company-specific attributes impacting stock performance within the industry.

**Table 1. Each Indicator Value from Eleven Companies from March 2022 to March 2023**

March 2022	Darya-Varia Laboratoria Tbk	Indofarma Tbk	Kimia Farma Tbk	Kalbe Farma Tbk	Merck Tbk	Pharos Tbk	Pyridam Farma Tbk	Organon Pharma Indonesia	Industri Jamu Dan Farmasi Sido Muncul Tbk	Soho Global Health Tbk	Tempo Scan Pacific Tbk
Assets	2188.4	1926.56	17924.83	26861.58	10667.8	1978.79	1243.73	1438.43	4289.63	4512.68	10390.73
Liabilities	673.86	1469.43	10681.72	4915.6	313.84	1232.2	1074.13	410.02	1199.73	2159.72	3226.1
Equity	1514.54	457.13	7243.11	21945.98	752.94	746.59	169.6	1028.41	3089.91	2352.96	7164.63
Sales	646.25	339.03	2260.5	7015.71	301.57	269.26	172.44	435.99	880.49	1838.99	2972.44
Earnings Before Tax	177.5	-46.86	2.5	1092.25	81.04	7.57	3.26	61.45	377.2	184.52	354.93
Profit	137.02	-51.18	2.59	852.66	62.61	5.61	2.49	55.86	295.04	144.67	291.08
Dividend	137.02	-51.18	5.77	834.88	62.61	5.6	2.5	55.86	295.04	144.4	270.52

Earnings Per Share	181.09	-29.23	52.35	70.44	314.64	11.33	-5.38	40897.33	42.9	444.09	179.02
Book to Value	1352.27	147.5	1304.13	468.18	1680.67	888.8	316.95	285669.61	103	1853.94	1588.66
Price Earning Ratio	14.36	-34.39	25.41	23.57	12.97	82.98	-191.55	0.71	23.31	13.96	7.82
Price to Book Value	1.92	6.81	1.02	3.55	2.43	1.06	3.25	0.1	9.71	3.34	0.88
Debt to Equity Ratio	0.44	3.21	1.47	0.22	0.42	1.65	6.33	0.4	0.39	0.92	0.45
Return On Asset	0.09	-0.05	0.02	0.12	0.13	0	0	0.1	0.3	0.12	0.08
Return On Equity	0.13	-0.2	0.04	0.15	0.19	0.01	-0.02	0.14	0.42	0.24	0.11
Net Profit Margin	0.31	-0.27	0.13	0.47	0.47	0.04	-0.02	0.34	1.46	0.31	0.27
<b>March 2023</b>	<b>Darya-Varia Laboratoria Tbk</b>	<b>Indofarma Tbk</b>	<b>Kimia Farma Tbk</b>	<b>Kalbe Farma Tbk</b>	<b>Merck Tbk</b>	<b>Pharos Tbk</b>	<b>Pyridam Farma Tbk</b>	<b>Organon Pharma Indonesia</b>	<b>Industri Jamu Dan Farmasi Sido Muncul Tbk</b>	<b>Soho Global Health Tbk</b>	<b>Tempo Scan Pacific Tbk</b>
Assets	2053.33	1576.2	20197.16	28239.68	1038.64	1790.56	1488.16	1417.69	4219.88	4592.58	11521.01
Liabilities	595.74	1551.7	10594.47	5318.49	235.09	1012.75	1058.13	359	1102.79	2107.84	3404.83
Equity	1457.59	24.55	9602.69	22921.19	803.55	777.81	430.04	1058.7	3117.09	2484.74	8116.18
Sales	513.16	169.8	2303.67	7869.16	261.13	260.97	164.86	581.07	907.3	2057.26	3233.7
Earnings Before Tax	79.42	-63.72	10.73	1095.96	59.78	6.18	-12.98	87.93	380.22	77.26	698.67

Profit	60.91	-61.8	24.63	853.87	46.31	4.55	-12.32	73.36	300.28	57.18	572.91
Dividend	60.91	-61.8	0.39	855.72	46.31	4.71	-12.31	73.36	300.28	57.18	568.77
Earnings Per Share	65.42	-141.67	-31.54	72.6	365.03	32.36	486.72	53412	37	212.36	288.23
Book to Value	1301.42	7.92	1726.36	488.98	1793.64	925.96	803.69	294082	103.9	1957.77	1799.65
Price Earnings Ratio	30.11	-4.45	-24.73	28.24	12.88	20.71	1.71	0.54	19.73	23.12	5.69
Price to Book Value	1.51	79.53	0.45	4.19	2.62	0.72	1.03	0.1	7.03	2.51	0.91
Debt to Equity Ratio	0.41	63.2	1.1	0.23	0.29	1.3	2.46	0.34	0.35	0.85	0.42
Return On Asset	0.04	-0.28	-0.01	0.12	0.16	0.02	0.18	0.14	0.26	0.06	0.11
Return On Equity	0.05	-17.88	-0.02	0.15	0.2	0.03	0.61	0.18	0.36	0.11	0.16
Net Profit Margin	0.14	-2.59	-0.08	0.43	0.63	0.1	1.58	0.33	1.22	0.13	0.4

### Data Analysis

An intricate analysis was conducted in March 2022 and 2023 to discern performance variations across eleven prominent companies. This analytical approach combines advanced statistical techniques, specifically Principal Component Analysis (PCA), and traditional manual methods renowned for their reliability. PCA was selected due to its capability to convert multivariate correlated data into a manageable collection of uncorrelated variables known as principle components. In this study, PCA is tactically employed with the Python programming language. The selection of the Python environment stems from its adaptability and efficacy in managing diverse data analysis tasks, notably those associated with PCA.

The initial phase of the analysis involves a compilation of 15 indicators. To condense this information without compromising its authenticity or comprehensiveness, the pivotal role of scalers in Python becomes evident. Employing this function facilitates the standardization of data, a crucial step prerequisite for various statistical and machine learning techniques, including PCA.

The concluding phase of this analytical procedure involves the visualization of data. Elaborate graphical representations are invaluable tools for elucidating perspectives and uncovering patterns that might remain opaque within tabulated datasets. Therefore, Python's functionalities encompassing cluster and k-means are

deployed. Leveraging clustering methodologies like k-means enables categorizing data points based on their similarity levels, offering enhanced comprehension of underlying structures or patterns within the dataset. In essence, this comprehensive data analysis has yielded significant insights into the performance trajectories of eleven companies over a defined period, incorporating various methodologies spanning from conventional approaches to advanced techniques like PCA.

## Results and Discussion

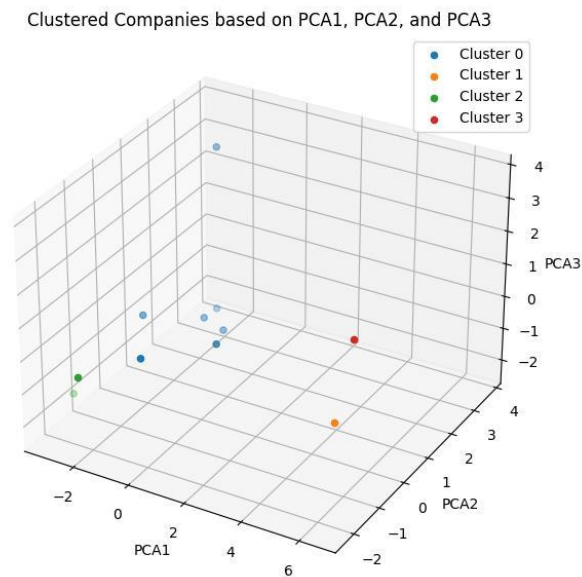
### *PCA Analysis*

A common strategy for managing the dimensionality of extensive datasets, enhancing comprehension, and facilitating visualization involves the utilization of Principal Component Analysis (PCA) (Metsalu & Vilo, 2015). These principal components effectively encapsulate the most substantial variations within the data, being mutually orthogonal. Table 2 presents outcomes derived from financial or performance data transformation via Principal Component Analysis (PCA) about various organizations denoted by distinct codes. PCA, an acronym for Principal Component Analysis, serves as a methodology frequently employed to condense dataset dimensions while endeavoring to preserve a maximum amount of information encapsulated within the variations in the data.

**Table 2. PCA Result Based on 2022 Data**

Code	PCA1	PCA2	PCA3	Cluster
Darya-Varia Laboratoria Tbk	-0,47	0,63	-0,12	0
Indofarma Tbk	-2,87	-1,63	-1,00	2
Kimia Farma Tbk	0,12	-2,27	0,80	0
Kalbe Farma Tbk	6,53	-2,02	0,40	1
Merck Tbk	-0,70	1,36	-0,40	0
Phapros Tbk	-1,70	-0,39	0,34	0
Pyridam Farma Tbk	-3,10	-1,60	-1,58	2
Organon Pharma Indonesia	-1,46	2,19	3,84	0
Industri Jamu Dan Farmasi Sido Muncul Tbk	2,21	3,75	-2,30	3
Soho Global Health Tbk	0,18	0,68	-0,38	0
Tempo Scan Pacific Tbk	1,25	-0,70	0,41	0

Based on the ratings assigned to three main components, each firm, identified by its code, has been placed in a unique three-dimensional geographical context: PCAs 1, 2, and 3. For instance, the company 'DVLA' exhibits specific coordinates within this spatial realm, with scores of -0.47, 0.63, and -0.12 for PCA1, PCA2, and PCA3, respectively. A notable observation gleaned from this dataset involves distinct placements of certain companies. Notably, 'KLBF' stands out with an exceptionally high PCA1 score, registering at 6.53, thus setting it apart from other companies. These notable deviations in scores suggest the presence of unique characteristics or patterns inherent in the original data specific to 'KLBF' (refer to Figure 2).



**Figure 2. 2020 Data Clustering**

Moreover, the 'Cluster' column illustrates the categorization of companies predicated on specific resemblances discerned within their PCA-transformed data. Businesses like DVLA, KAEF, and MERK are included in Cluster 0 because their data exhibits common patterns or traits. On the other hand, entities such as 'INAF' and 'PYFA' combine inside Cluster 2, confirming possible parallels. On the other hand, 'KLBF' and 'INDUSTRI JAMU DAN FARMASI SIDO MUNCUL TBK' exhibit distinct placements within Clusters 1 and 3, respectively, signifying their individual uniqueness within this categorization.

In Table 3, the "Code" column serves as a distinctive code for every organization, including entities like "DVLA," "INAF," and "KAEF." The scores associated with each of the columns designated "PCA1," "PCA2," and "PCA3" are. For instance, 'DVLA' exhibits coordinates of -0.65, -0.96, and -1.19 for PCA1, PCA2, and PCA3, respectively. These values are simplified representations of the original data associated with 'DVLA,' functioning as coordinates within this transformed space.

**Table 3. PCA Result Based On 2023 Data**

Code	PCA1	PCA2	PCA3	Cluster
Darya-Varia Laboratoria Tbk	-0,65	-0,96	-1,19	0
Indofarma Tbk	-5,26	4,52	0,075	1
Kimia Farma Tbk	0,38	1,39	1,41	2
Kalbe Farma Tbk	5,83	2,75	0,26	2
Merck Tbk	-0,67	-1,47	-0,89	0
Phapros Tbk	-1,05	-0,93	-0,95	0
Pyridam Farma Tbk	-0,71	-1,83	-0,67	0
Organon Pharma Indonesia	-1,00	-2,47	3,73	3
Industri Jamu Dan Farmasi Sido Muncul Tbk	0,97	-1,20	-0,98	0
Soho Global Health Tbk	-0,26	-0,55	-0,79	0



Tempo Scan Pacific Tbk	2,43	0,75	0	2
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Moreover, proximity within the PCA space serves as an indicator of similarity. Essentially, companies exhibiting similarity in the original dataset tend to cluster within the PCA analysis, whereas those with disparate patterns tend to maintain greater distance. The "Cluster" column introduces a probable classification derived from applying a clustering algorithm to the PCA outcomes. This algorithm segregates data into distinct groups based on shared attributes or characteristics. Certain companies like 'DVLA,' 'MERCK TBK,' and 'PEHA' are grouped under Cluster 0 due to resemblances in their data transformations. Conversely, entities such as 'INAF' and 'KLBF' are allocated to distinct clusters (Cluster 1 and 2, respectively), signifying unique attributes distinguishing them from Cluster 0 (refer to Figure 3). An intriguing observation arises from the distinct positioning of 'SCPI' within Cluster 3, implying exclusive characteristics specific to this entity.

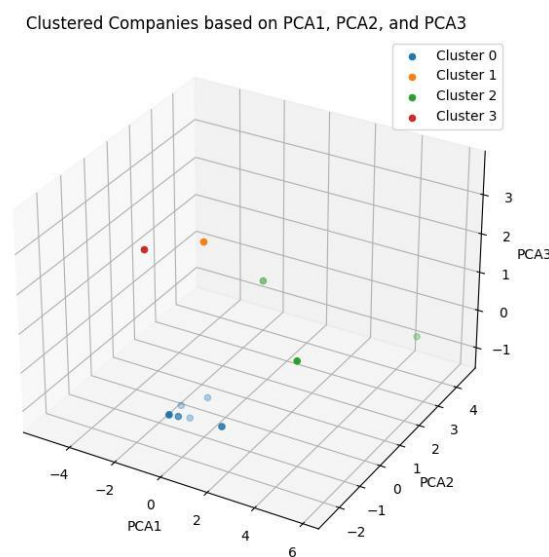


Figure 3. 2023 Data Clustering

### 2022 Clustering

The cluster analysis employed financial ratios extracted from fifteen distinct variables is detailed in Table 1. Entities were categorized into four distinct groups: A (representing good financial condition), B (moderate), C (bad financial), and D (very bad financial condition) (Table 4). This classification serves as a valuable tool for the comparative evaluation of the financial well-being of various companies. These classifications furnish essential insights into each entity's financial status and performance for 2022 and 2023.

Table 4. Financial Clustering 2022

Cluster	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Category	B	A	D	C
Assets	5642,95	26861,58	1585,14	4289,63
Liabilities	2671,06	4915,60	1271,78	1199,73
Equity	2971,88	21945,98	313,36	3089,91
Sales	1246,42	7015,71	255,73	880,49
Earnings Before Tax	124,21	1092,25	3,26	377,20
Profit	99,92	852,66	2,49	295,04



<b>Dividend</b>	97,39	834,88	2,50	295,04
<b>Earning Per Share</b>	6011,40	70,44	-29,23	42,90
<b>Book to Value</b>	42048,29	468,18	232,22	103
<b>Price Earning Ratio</b>	22,60	23,57	-34,39	23,31
<b>Price to Book Value</b>	1,53	3,55	5,03	9,71
<b>Debt to Equity Ratio</b>	0,82	0,22	4,77	0,39
<b>Return On Asset</b>	0,07	0,12	-0,02	0,3
<b>Return On Equity</b>	0,12	0,15	-0,20	0,2
<b>Net Profit Margin</b>	0,26	0,47	-0,27	1,46

Cluster 1, with a rating of "A" or "Good" emerged as a standout performer in this analysis, showcasing exceptional economic prowess relative to other clusters under examination with economic indicators within the dataset:

The strong pre-tax profitability was highlighted by the Group Earnings Before Tax (EBT), which came in at \$1,092.25.

The cluster exhibited substantial profitability, accumulating \$852.66, indicative of its capacity to generate substantial income. Additionally, Cluster 1 attained impressive sales figures, totaling \$7,015.71, highlighting its adeptness in generating substantial revenue.

Notably, Group 1 achieved a commendable Return on Assets (ROA) at 3.55%, signifying efficient asset utilization for production purposes.

The Return on Equity (ROE) standing at 0.15 highlights profitability for shareholders within Cluster 1. Furthermore, this cluster has a 15% Net Profit Margin (NPM), demonstrating its ability to keep a sizeable amount of income as profit. In addition, the price-to-earnings ratio (PER) for this cluster is 23.57, which indicates that investors find it attractive because of its strong income and a favorable market perception. Finally, Cluster 1 boasts a price-to-book value (PBV) ratio of 3.55, aligning it with the "Good" category. This ratio underscores a consistent market valuation of its book value, signaling investor perception of this cluster as an appealing investment opportunity.

Cluster 0, classified as "moderate" within category "B," exhibits commendable financial performance, slightly trailing behind Cluster 1. Despite this distinction, the cluster portrays a positive financial picture based on crucial economic indicators. The EBT recorded at \$124.21 indicate robust pre-tax profitability, with significant profits of \$99.92 showcasing revenue generation alongside positive financial performance. Although Cluster 0 demonstrates a lower ROE at 0.08 compared to Cluster 1, it still yields favorable returns for shareholders. A Return on Assets (ROA) of 1.53% demonstrates efficient asset utilization for profit generation.

Additionally, boasting a robust NPM of 12.29%, Cluster 0 effectively retains a substantial portion of revenue as profit. The PER of 22.60 underscores positive market perception and potential investor appeal owing to its substantial income. Despite the PBV ratio of 1.54, indicating a fair book value in the market, it falls slightly short compared to Cluster 1.

Cluster 3, categorized as "bad" or "C," exhibits notably poorer financial performance than Clusters 1 and 0. An assessment of critical financial data unveils an overall less favorable economic outlook within this group. With EBT at \$377.20, considerably lower than Clusters 1 and 0, profitability remains evident, albeit less robust. At \$295.04, the cluster's profitability is reasonable but falls short compared to higher-ranked clusters. The ROA of 0.39% indicates a need for more efficient asset utilization to generate profits compared to Clusters 0 and 1.

Similarly, the ROE of 1.46 demonstrates inferior shareholder returns compared to higher-ranked clusters. Despite these disparities, Cluster 3 displays a relatively high NPM at 30%, showcasing its ability to retain a significant portion of turnover as profits. The PER of 23.31, classifying it within the "good" category, implies a positive market outlook, potentially attracting investors due to reasonable income returns. However, the high PBV ratio of 9.71 suggests potential overvaluation of the cluster's book value, potentially reducing profitability for potential investors.

Due to its noticeably worse financial performance than other clusters, Cluster 2 most definitely qualifies as a "highly unfavorable" cluster. A detailed analysis of important economic indicators, taken as a whole, paints a dismal picture of Cluster 2's economic future and supports this classification. Interestingly, Cluster 2 has an Earnings Before Tax (EBT) of just \$3.26, which indicates the lowest possible earning potential prior to tax receipts. Moreover, the profit from this cluster stands at a meager \$2.49, representing a substantial shortfall in financial outcomes. Exhibiting a Return on Assets (ROA) at -2.50%, this cluster operates where losses surpass its capacity to utilize assets effectively. Additionally, the Return on Equity (ROE) of -0.20 underscores the incapability of the cluster to generate profits for its shareholders, having a negative equity position.

Net profit margin (NPM) for Cluster 2 was alarmingly low at -27%, reflecting substantial losses surpassing total revenue. Moreover, a highly negative price-to-earnings ratio (PER) of -34.39 signifies an unfavorable market outlook, potentially deterring investors due to potentially significant losses. Despite a price-to-book value (PBV) ratio 5.03, indicating a market value exceeding the book value, this fails to offset the overwhelmingly negative financial performance evident in other indicators. Based on these economic metrics and an inclusive evaluation, the following clusters are ranked from best to worst: cluster 1, cluster 0, cluster 4, and cluster 2, with the last denoting extremely unfavorable and unproductive financial performance.

### 2023 Clustering

Cluster analysis was conducted on the 2023 dataset utilizing a consistent methodology involving a spectrum of economic indicators pertinent to each factor. This methodical technique allows data points to be systematically categorized and clustered based on their financial characteristics (see Table 5). Through analytical calculations of financial parameters, the dataset is divided into separate groups or categories, improving the structure and segmentation of the 2023 data. Subsequently, this aids in enabling comprehensive research and comprehension of the financial performance exhibited by the respective companies. Notably, this method facilitates a comprehensive evaluation of the economic landscape, ensuring coherence and compatibility with preceding cluster analyses.

**Table 5. Financial Clustering 2023**

Cluster	Cluster 0	Cluster 1	Cluster 2	Cluster 3
<b>Category</b>	B	C	A	D
<b>Assets</b>	2530,52	1576,2	19985,95	1417,69
<b>Liabilities</b>	1018,72	1551,7	6439,26	359
<b>Equity</b>	1511,80	24,55	13546,68	1058,7
<b>Sales</b>	694,11	169,8	4468,84	581,07
<b>Earnings Before Tax</b>	98,31	-63,72	601,78	87,93
<b>Profit</b>	76,15	-61,8	483,80	73,36
<b>Dividend</b>	76,18	-61,8	474,96	73,36
<b>Earning Per Share</b>	199,81	-141,67	109,76	53412,00
<b>Book to Value</b>	1147,73	7,92	1338,33	294082,00
<b>Price Earning Ratio</b>	18,04	-4,45	3,06	0,54

<b>Price to Book Value</b>	2,57	79,53	1,85	0,1
<b>Debt to Equity Ratio</b>	0,94	63,2	0,58	0,34
<b>Return On Asset</b>	0,12	-0,28	0,07	0,14
<b>Return On Equity</b>	0,22	-17,88	0,09	0,18
<b>Net Profit Margin</b>	0,63	-2,59	0,25	0,33

Cluster 2, referred to as "Cluster A" or "Good," has exhibited commendable performance across various financial aspects, suggesting stability and prospects for sustained profitability and expansion. An analysis of financial indicators paints an intriguing picture of the financial health and operational effectiveness of this cluster. With a balance sheet volume of 19,985.95, it possesses the most significant asset base among its competitors, signifying a robust financial foundation. This extensive asset base offers a competitive advantage by mitigating risks and facilitating investment and expansion opportunities. Moreover, the accumulated equity of 13,546.69 portrays a well-capitalized entity, emphasizing financial flexibility and reduced reliance on external funding. This substantial equity base safeguards against economic downturns, ensuring investor confidence.

Cluster 2 exhibits robust turnover with sales at 4468.84, reflecting effective marketing strategies and a strong market presence crucial for sustainability and market dominance. Moreover, the Return on Assets (ROA) stands at 7.33%, signifying adept asset management and profitable resource utilization. Additionally, the Return on Equity (ROE) of 9.67% assures investors of promising returns on their investments, attracting and retaining investor interest. The NPM of 25.00% reflects efficient sales-to-profit conversion, vital for operational and cost efficiency. With a low Price-to-Earnings Ratio (PER) at 3.07, the cluster's shares might be undervalued providing room for long-term expansion. A balanced perspective of the market and book value is ensured by the Price-to-Book Value (PBV) ratio of 1.85, fostering sustainable shareholder growth. Moreover, the Debt-to-Equity Ratio (DER) of 0.58 indicates a balanced capital structure, minimizing financial risks.

Cluster 0, categorized as a 'moderate' or 'B' ranking, represents a critical evaluation of its financial measures. It highlights regions of relative weakness in comparison to higher-performing clusters like cluster 2, even as it has strengths in some aspects. With a balance sheet volume of 2530.53, though high, it signifies a relatively constrained economy compared to top-ranked clusters yet denotes a robust economic base. The equity of 1511.80 suggests adequate capital, yet it may not be as resilient as leading companies amid potential market volatility. Despite a decrease in sales to 694.11, commendable profits highlight effective marketing strategies and competitive offerings within this cluster.

Despite a moderate overall rating, the cluster exhibits remarkable efficiency and profitability. ROA at 6.67% and ROE at 22.67% signify effective utilization of assets and equity, showcasing proficient resource allocation and management within the cluster. The NPM of 22.67% underscores healthy profitability, reflecting adept cost and revenue management. The cluster offers a reasonable market value and a balanced opportunity for potential investors, with a PER of 18.04 and PBV of 2.57. Even though the DER is comparatively low at 0.94, it signifies acceptable leverage, minimizing financial risks while allowing room for potential growth. Although not as robust as cluster 2, cluster 0 maintains a sturdy and steady financial performance, suggesting characteristics and strategies that, if optimized further, could enhance its future positioning.

Cluster 3, rated as 'C' or 'Poor', shows financial vulnerabilities with a balance sheet volume 1417.69, indicating potential stability issues. Although equity stands at 1,058.70, it remains relatively lower, indicating limited financial buffers in weaker markets. Sales at 581.07 suggest possible competitiveness challenges. Financially mixed, Cluster 3 displays a reasonable ROA of 6.20% and a high NPM of 33.00% but a low ROE of 33.00%. Market valuation is concerning, with a high PER of 79.53 and a low PBV of 0.10, signifying overvaluation and undervaluation, respectively. The moderate DER of 0.34 suggests reliance on debt, posing risks. Overall, uncertainties position Cluster 3 in the 'C' category.

Cluster 1, labeled "very bad" or "D," displays weak financial performance with significantly low total assets at 1576.20, the lowest among clusters, indicating limited financial flexibility. Equity stands at only 24.55, highlighting a lack of capitalization and vulnerability to market fluctuations. Sales figures at 169.80 suggest poor market share and revenue generation capabilities.

The cluster faces severe inefficiency and instability, with a negative ROA of 4.45% and ROE dropping to -17.88%, indicating losses and significant shareholder value decline. A negative NPM of -2.59% emphasizes its unprofitability due to high operational costs. Despite a low PER of -61.80, signifying undervaluation, negative ROE, and NPM deter investors. A misleading PBV of 63.20 amid negative financial indicators amplifies uncertainty. Despite a low DER of 0.28, indicating healthy debt management, numerous negative indicators persist, making Cluster 1 the most financially unstable among peers.

## Summary

A key performance metric involves assessing the relative values of a company's assets and liabilities making it into four categories (Table 6). A significant rise in asset value between March 2022 and 2023 suggests robust financial management. Moreover, high asset value paired with low debt indicates a company's ability to handle its financial commitments effectively. Another essential metric is turnover or sales, signifying market demand for a company's offerings.

**Table 6. Performance Summary for Each Company from March 2022 to March 2023**

No	Code	Financial Performance in March 2022	Category	Financial Performance in March 2023	Category	Financial Performance Changes
1	Darya-Varia Laboratoria Tbk	Moderate	B	Moderate	B	Static
2	Indofarma Tbk	Bad	C	Bad	C	Static
3	Kimia Farma Tbk	Moderate	B	Good	A	↑ Going Up
4	Kalbe Farma Tbk	Good	A	Good	A	Static
5	Merck Tbk	Moderate	B	Moderate	B	Static
6	Phapros Tbk	Moderate	B	Moderate	B	Static
7	Pyridam Farma Tbk	Very Bad	D	Moderate	B	↑ Going Up
8	Organon Pharma Indonesia	Moderate	B	Very Bad	D	↓ Going Down
9	Industri Jamu Dan Farmasi Sido Muncul Tbk	Bad	C	Moderate	B	↑ Going Up
10	Soho Global Health Tbk	Moderate	B	Moderate	B	Static
11	Tempo Scan Pacific Tbk	Moderate	B	Good	A	↑ Going Up

Conversely, NPM, ROA, and ROE are crucial in determining a company's stock appeal to potential investors. A notable decrease in these values within the year warrants a thorough investigation into revenue and production costs. Metrics like equity, dividends, and DER substantially influence the anticipated returns for investors when acquiring company shares. Simultaneously, metrics such as EBT, EPS, BV, PER, and PBV are supplementary benchmarks when evaluating a stock's viability within a specific sector.

## Conclusion

From March 2022 to March 2023, insights into stability, growth, and decline within various organizational units, identified explicitly as TSPC by the DVLA, were discovered. Among the six companies, there was observed stagnation, maintaining their positions from the previous year. This static state, particularly among those showing “moderate” results, signals potential inertia in their strategic or operational initiatives. It implies the necessity for strategic updates to stimulate growth or enhancements. The fluctuating financial performance highlights areas requiring thorough attention, notably potential risks, and challenges that investors should scrutinize meticulously before deciding on investments.

Four companies—Kimia Farma, Pyridam Farma, Sido Muncul Herbal Medicine, Pharmaceutical Industry, and Tempo Scan Pacific—showed growth and efficiency changes. Pyridam Farma notably improved from a "very bad" rating to an average position, signaling a significant turnaround. It suggests successful strategies or adaptability to favorable market conditions, positioning these entities as potential investment opportunities. Conversely, the downgrade of Oragon Pharma Indonesia to "very poor" signifies potential systemic failures, adverse market conditions, or strategic misjudgments impacting performance negatively. Deteriorating financial conditions in these companies highlight operational inefficiencies and reduced profitability, urging investors to conduct thorough long-term prospect evaluations before considering investments. This departure from the upward trend emphasizes the urgency for a strategic review and revision of their operational approach.

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