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K-Means Clustering Using Principal Component Analysis (PCA) Indonesia Multi-Finance Industry Performance Before and During Covid-19

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Abstract
The cluster analysis within specific industry such as in multi finance industries is designed to be a tool for accelerating investment decisions, such as whether to buy, sell, or hold stocks in a way to construct an optimized portfolio. The purpose of the study was to apply cluster analysis on multi-finance stock data listed on the Indonesia Stock Exchange in the years 2019 and 2021, before and during Covid-19, using the PCA (Principal Component Analysis) K-means algorithm. The objective of this study is to classify stocks based on PCAs in order to assist investors in segmenting a multi-finance stocks cluster. The clustering is done on the 16 stocks registered in ISE using two-time windows: 2019 data where Covid-19 has not yet occurred and 2021 data where Covid-19 is still ongoing, and the firm is still in the recovery stage. The cluster analysis results show 12 companies worth investing in because they performed well. There is finding that company that have unfavorable Covid-19 externalities since this cluster has worsening performance and is thus not advised as a stock investment. Meanwhile, the others company has neutral externalities because it remains in the same cluster in 2019 and 2021.

Keywords
PCA, K-Means, Clustering, Multi-finance, Covid-19, Investment
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Introduction

According to the Indonesia Financial Services Authority (OJK), multi-finance is a financing company that provides money to a debtor to finance his needs in obtaining goods or services purchased through a third party (dealer/showroom/supplier) as a provider of goods or services based on a loan and loan agreement between the financing company and the debtor, which requires the debtor to pay off his debt within a certain period of time along with interest and other fees charged (OJK, 2019).

The multi-finance industry plays a vital part in the financing ecosystem, assisting micro, small, and medium-sized businesses in renting or purchasing equipment or inventory, as well as financing their everyday operations with accounts receivable as security, providing multiple financing services such as credit loans. Despite an increase in financial inclusion from 67.8 percent in 2016 to 76.2 percent in 2019, many Indonesians remain without a bank account, particularly in rural areas. This is an opportunity for multi-finance firms to cover the funding shortfall (Oxfordbusinessgroup, 2021). In April

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2022, there were a total of 218 multi-finance companies in Indonesia, as indicated by the multi-finance institution statistic. However, from 218 companies, only 16 companies are registered in stock exchange. In April 2022, the outstanding loan receivables of multi-finance had reached Rp. 381.16 trillion (OJK, 2022).

In the year 2020, because of the pandemic, fresh financial funding has become more difficult, and COVID-19 has caused some financing to be adjusted. The sluggish nature of the economy required the multi-finance institution to make allocations to their reserves, which had the effect of lowering the efficiency ratio. This is made abundantly evident by the fact that their Operating Expense to Operating Income (BOPO) ratio is projected to rise from its current level of 78.93 percent in 2019 to 91.09 percent in the year 2020. (Kontan, 2020). Certain elements originating from demand and supply have the potential to influence the expansion of loan. On supply side, banks have a tendency to be exceedingly cautious when it comes to the provision of credits in the face of global uncertainty, which may be having an effect on the performance of local corporations including multi-finance funding (Bank Indonesia, 2020b). The Non-Performing Loan (NPL) as one of the credit loan indicators jumped from 2.4 percent to 4.01 percent after having been at 2.4 percent previously (OJK, 2020).

Multiple studies have revealed the impact that COVID-19 has had on a global scale. These include the effect of COVID-19 on Stock Prices (He et al., 2020), the crude oil market and the stock market during the COVID-19 Pandemic (Zhang & Hamori, 2021), the exchange rate volatility response to COVID-19 (Feng et al., 2021), and its effect at the enterprise level (Shen et al., 2020a). To determine whether the multi-finance institution subsector is positively or negatively impacted by the COVID-19 pandemic, Shen (2020a), utilised a quantitative technique to examine the financial performance of multi-finance institutions prior to and during the pandemic. This was done so that the performance of these institutions before and after the epidemic could be compared. According to (SEOJK Number 1 /SEOJK.05/2016, 2016), a financial institution's health in Indonesia can be judged primarily by its capital, loan quality, rentability, and liquidity.

The study will tries to analyse it using K-means clustering with the PCA method. The clustering result is expected to bring an impact on the basic consideration in making financial and investment decisions in multi-finance institutions. The PCA clustering is based on key financial ratios to separate multi-finance stocks and investigate the change in the cluster to determine which stocks are greatly affected by Covid, which stocks are slightly affected by Covid, and which stocks are not affected by Covid. Year 2019 and 2021 were chosen to distinguish the clustering results before and during the pandemic. In a normal market environment, all market players have the potential of being in a safe zone, which tends to have strengthened due to the status of the economy and good company fundamentals. However, in a downward-moving market or during a crisis, the market may move in an unexpected manner, causing investors to merely follow trends or experience losses since the market swung in an adverse direction.

Literature Review

Clustering Method

Clustering is one of the most prominent approaches for unsupervised learning. This method groups data such that the records inside a cluster are most similar to one another and the records between clusters are most distinct (Jafarzadegan et al., 2019). Clustering is used to extract patterns from data for applications like data analysis, pattern classification, grouping, decision making, machine learning, data mining, document retrieval, and image segmentation.

In general, clustering approaches can be classified as either non-hierarchical (flat) or hierarchical (tree) algorithms (Rasmussen, 1992). Flat clustering methods separate data into disjoint groups. K-means is one of the most extensively used techniques in this field (Jain et al., 1999). Hierarchical clustering methods assemble data into hierarchical tree structures called dendrograms (Dash, Liu, Scheuermann & Tan, 2003). The dendrogram's root node holds all the data, each leaf node represents a record, and the intermediate nodes depict the similarity between records. The performance of clustering and classification algorithms is based on the problem and the data, and the best appropriate technique must be chosen for every challenge. Moreover, applying the same strategy to diverse problems provides unreliable results; hence, combinational methods have been developed to overcome this issue. The purpose of first-generation combinational techniques is to combine classification method results (Kuncheva, 2014). Using principal component analysis, a method for merging the results of core hierarchical clustering algorithms is provided (PCA).

PCA (Principal Component Analysis)

In pattern recognition, PCA is a statistical approach used to reduce dimensionality and extract features. PCA has a lower error rate than other dimensional reduction methods; hence, it was selected to integrate the fundamental clusterings. As a dimensionality reduction of the problem, PCA will reduce high-dimensional data into smaller dimensions while maintaining as much information as feasible.

Finding clusters in arbitrarily oriented subspaces is a fundamental data mining task for a vast array of applications. It is most likely impossible to discover clusters in high-dimensional data due to the properties of high-dimensional feature spaces. In contrast, clusters are often positioned in arbitrary subspaces of the original data space. The subspace cluster points are then placed on a shared lower-dimensional hyperplane and exhibit a common correlation between a subset of the attributes. The majority of correlation clustering algorithms employ principal component analysis (PCA) on a selection of points to establish the appropriate orientation and weighting of the converted axis. PCA is a sophisticated technique that enables the production of a large number of similarity measures that capture the local correlation of attributes, hence enabling the identification of arbitrarily oriented subspace clusters.

Methodology

This study will use PCA methodology for dividing the data into groups which are having similar traits that separated with other groups.

PCA Methodology

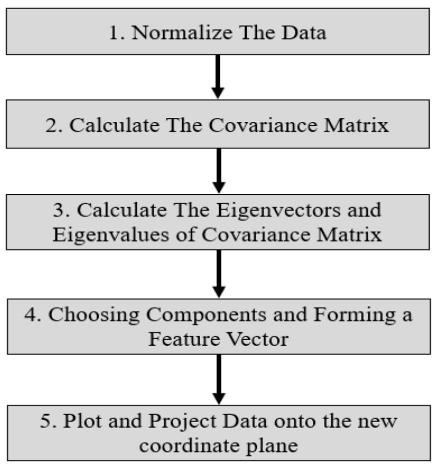

Figure 1. PCA Methodology

Using PCA methodology (figure 1), a new set of dimensions contains principal components of the data. It is often useful to measure data in terms of principal components (underlying the data structure) rather than on a normal X-Y axis. Go through the methodology, the steps can be elaborated in the following:

Step 1. The data input needs to be standardized/normalized first, to calculate centre data over the origin (standard deviation and variance). This will produce a data set whose mean is zero.

Step 2. Calculate The Covariance Matrix

The covariance matrix is the diagonal of a matrix that includes the variance of each variable. Off diagonal includes covariance of each pair of variables.

Variance will measure the deviation from the mean for points in one dimension whilst covariance will measure how much each dimension between two dimensions are vary from the mean with respect to each other and to see the relationship between those dimensions. Any covariance for just one dimension and itself is the variance.

$$cov_{x,y} = \frac{\sum(x_i - x)(y_i - y)}{N-1}$$

$cov_{x,y} = covariance\ between\ variable\ x\ and\ y$
$x_i = data\ value\ of\ x$
$y_i = dat\ value\ of\ y$
$x = mean\ of\ x$
$y = mean\ of\ y$
$N = number\ of\ data\ values$

For any three-dimensional data, the covariance calculation, will be counted to measure the covariance between the x and y dimensions, the y and z dimensions, and the x and z dimensions.

The covariance matrix for 3 dimensions will look like this:

$$Matrix\ Covariance = \begin{bmatrix} Var(X) & Cov(X,Y) & Cov(X,Z) \\ Cov(X,Y) & Var(Y) & Cov(Y,Z) \\ Cov(X,Z) & Cov(Y,Z) & Var(Z) \end{bmatrix}$$

Step 3. Calculate the eigenvectors and eigenvalues

Eigenvalues is a special set of scalar values that are associated with the set of linear equations mostly in the matrix equations. The eigenvectors are non-zero vector that can be changed at most by its scalar factor after the application of linear transformations (Characteristic Roots). By finding the eigenvalues and eigenvectors of the covariance matrix, we find that the eigenvectors with the largest eigenvalues correspond to the dimensions (principal components) that represent the highest variance and have the strongest correlation in the dataset. Omitting the smaller eigenvector or value sets removes dimensional redundancies.

Step 4. Choosing components and forming a feature vector

As we order the eigenvalues from largest to smallest, this will give us the order significance of the components thus will reduce the dimensionality.

Step 5. Plot the data into a new coordinate

This step will plot the eigenvector direction with respective eigenvalue magnitude and project the data onto the new coordinate space and plotted onto a 3D graph. The PCA plot makes it possible to visualize strong patterns, such as groups of similar observations, in the original dataset. By having a new dimension of the data set, another algorithm will be used which is K-Means Clustering.

K-Means Clustering

K-Means clustering is an unsupervised clustering algorithm meant to partition the data into a specific number of groupings (called the K). K-Means organizes observations into clusters based on their shared similarities in terms of relevance. K-Means is commonly employed due to its simplicity and ease of implementation. However, the K-Means technique has a number of drawbacks, including its susceptibility to outliers, its sensitivity to data scale and the number of discovered clusters, and its ineffectiveness for clusters with various characteristics (Feng and Zhang, 2020).

One of the distance metrics commonly used in conjunction with K-Means to group data is Euclidean distance. The euclidean is often the default distance used in K-Means clustering to find the K closest point of a particular sample point. The process of K-Means clustering is described in figure 2.

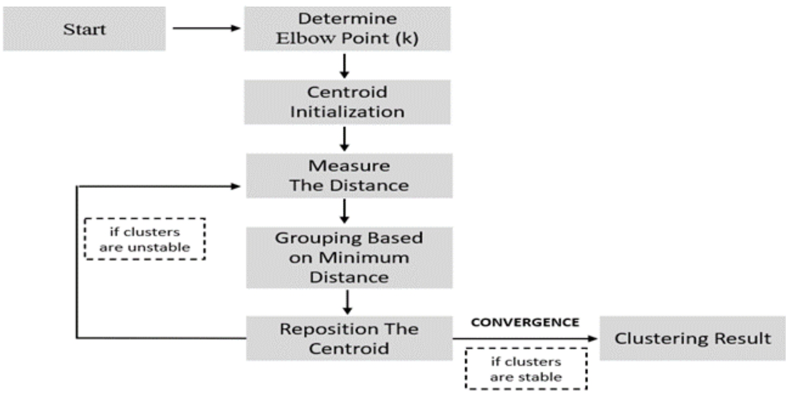

Figure 2. K-Means Clustering Process

Research Methodology

Data stocks will be taken from Indonesia Stock Exchange and the annual report of public companies within the multi-finance industry in Indonesia during years 2019 and 2021 to further evaluate the Covid-19 impact on the financial ratio performance.
From the 17 company's data in 2019, one company (Findo-American Leasing will be taken out) since the company is already bankrupt. Thus, the data observation is total of 16 companies' stocks.

Data will be running and assessed using Kaggle (phyton) programming and the clustering result will be plotted into 3 D data visual for better analysis.

The Analysis and Result

The financial ratios data are taken from all multi-finance Indonesia (2019 and 2021). For the purpose of this research, we took 10 financial ratios that consist of the following (figure 3).

NO	FINANCIAL RATIOS	ADIRA		BUANA FINANCE		BFI		Batavia		Clipan		Danasupra		Fuji Finance Indonesia		Radana Finance	
		2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021
1	ROA	8.7%	6.3%	1.2%	0.8%	5.7%	9.6%	5.04%	5.37%	4.08%	0.46%	12.54%	-6.32%	3%	6%	-16.64%	2.72%
2	ROE	29.1%	14.7%	5.0%	2.3%	11.6%	16.1%	11.76%	11.21%	0.96%	7.98%	12.71%	-6.39%	3%	6%	-33.35%	5.53%
3	NPM	18.6%	14%	7.1%	5.2%	13.6%	27.4%	15.61%	16.72%	16.70%	3.14%	16%	-198%	30%	20%	-75%	-22.40%
4	NPL	1.8%	2.3%	2.20%	2.63%	0.85%	1.25%	2.00%	3.00%	1.07%	1.61%	0.00%	0.00%	0%	0%	2.10%	0.12%
5	DER	2.80	1.20	3.08	1.77	1.90	1.00	1.00	0.40	1.48	0.41	0.00	0.00	0.00	0.00	0.84	0.87
6	FAR	85.20%	85.30%	89.00%	85.00%	91.40%	87.51%	78.00%	68.00%	93.11	83.4	43.60%	37.30%	54%	53%	42.2%	76.6%
7	Liabilities to Equity Ratio	3.30	1.70	3.27	3.27	2.10	1.10	1.34	1.09	1.58	0.48	1.38	1.06	1.00	3.00	1.79	1.71
8	Liability to Asset Ratio	0.80	0.60	0.76	0.65	0.70	0.50	0.57	0.52	0.61	0.33	1.36	1.06	1.00	3.00	0.97	0.51
9	Price Earning Ratio	5.50	7.98	11	37	6.15	19	30	62	3.36	17	91.00	145.00	17	108	-7.04	-55
10	Price to Book Value	1.40	0.93	0.56	0.50	1.38	2.61	2.92	2.85	0.25	0.21	15.00	8.64	0.90	4.61	5.43	2.54

NO	FINANCIAL RATIOS	Intan Baruprana		Indomobil Multi Jasa		Mandala Multifinance		Pool Advista Finance		Tifa Finance		Trust Finance		Verena Multi Finance		Wahana Ottomitra Multiartha	
		2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021
1	ROA	-11%	-1%	0.18%	-0.33%	0.80%	0.60%	-12.34%	-13%	3.21%	2.61%	6.58%	0.08%	0.08%	-0.33%	2.54%	0.02%
2	ROE	-77%	-6%	1.33%	-2.11%	1.70%	0.12%	-14.83%	-13%	9.22%	3.82%	7.24%	0.08%	0.38%	-1.24%	16.30%	0.06%
3	NPM	-51%	-79%	1.10%	-1.99%	1.30%	0.25%	-0.30%	-5.47%	2.30%	1.40%	5.74%	0.74%	0.53%	-2.56%	10.90%	0.08%
4	NPL	12.96%	3.71%	1.50%	3.50%	0.45%	1.11%	2%	2.13%	1.76%	2.02%	1%	2%	2%	3.47%	0.65%	0.59%
5	DER	3.7	-1.87	7.06	5.48	0.94	0.69	0.07	0.01	1.82	0.27	0.03	0.03	2.87	2.6	4.19	2.31
6	FAR	62.30%	50.70%	70%	74%	93.15%	82.04%	70%	70%	75%	75.00%	86%	60%	80%	80%	87.11%	85.72%
7	Liabilities to Equity Ratio	-3.7	-2.1	6.4	5.49	1.09	0.9	0.08	0.03	2.5	0.41	0.10	0.08	3.29	2.54	5.43	2.74
8	Liability to Asset Ratio	1.2	1.88	0.86	0.85	0.5	0.47	0.07	0.03	0.71	0.29	0.09	0.07	0.77	0.72	0.84	0.73
9	Price Earning Ratio	21	-0.13	15.00	1.190	9.34	9.14	-15	-13	7.47	192	11	13	-20	33	4.63	11
10	Price to Book Value	0.90	-0.21	0.50	0.95	1.56	1.11	2.00	1.76	0.71	2.14	0.80	1.04	1.25	1.30	0.76	0.66

Figure 3. Financial Ratios

The data is then being normalized by using a standard scaller and defining the number of PCA. As the intended plot is using 3D thus the PCA components are defined as 3.

The Scree Plot for the years 2019 and 2021 (figure 4).

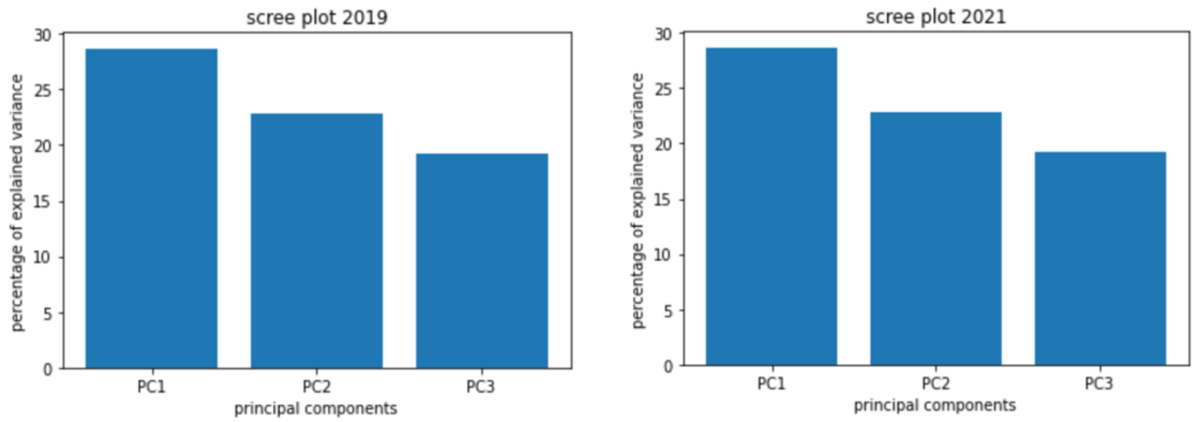

Figure 4. Scree Plot of PCA

Principal components analysis (PCA) is a technique that can be used to simplify a dataset, thus from 10 dimensions, using PCA the dimension can be reduced to three (PCA1, PCA2, and PCA3). The detail of PCA is displayed in figure 5.

Company Name		YEAR 2019			YEAR 2021		
		PC1	PC2	PC3	PC1	PC2	PC3
1	ADIRA	-1.736.156	-0.239719	0.65776	1.250.809	-1.496.510	0.28367
2	BUANA FINANCE	-0.657879	-0.736736	0.724557	1.131.085	0.25865	-0.426539
3	BFI	-1.239.722	-0.463023	-0.153992	0.984036	-2.016.245	1.175.766
4	Batavia	-0.832144	0.57303	-0.748004	0.618236	-1.182.448	0.128866
5	Clipan	-0.956098	-0.856651	-0.562241	0.065602	-1.901.422	-1.428.330
6	Danasupra	-0.588198	5.974.154	0.016809	-3.856.599	2.582.975	2.151.416
7	Fuji Finance Indonesia	-0.408866	1.159.678	-0.658155	-0.149919	-0.498596	3.389.642
8	Radana Bhaskara Finance	3.720.852	0.475914	-0.00995	-0.36858	-0.58001	0.965051
9	Intan Baruprana	5.932.012	-0.175923	0.715887	-2.314.687	-0.251983	-1.511.679
10	Indomobil Multi Jasa	-0.587623	-0.674277	3.113.238	3.983.277	3.772.207	-0.025075
11	Mandala Multifinance	-0.594714	-0.673338	-1.041.127	-0.31859	-0.321293	-0.325418
12	Pool Advista Finance	1.103.686	-1.437.092	-2.226.540	-1.960.855	1.482.964	-2.377.749
13	Tifa Finance	-0.50864	-0.271438	0.03318	-0.056168	-0.479682	-0.320637
14	Trust Finance Indonesia	-0.969096	-0.732351	-2.127.601	-0.542713	-0.519482	-1.120.555
15	Verena Multi Finance	-0.199413	-1.138.431	0.602987	0.974373	0.808448	-0.804076
16	Wahana Ottomitra Multiartha	-1.477.999	-0.783797	1.663.194	0.560694	0.342427	0.245647

Figure 5. PCA Model

A hybrid model will be used in this study by combining the PCA and K-Means Clustering.

Using the k-means clustering algorithm, a dataset is separated into k unique clusters. The process is separated into steps. In the first step, the k centroid is determined, and in the second phase, each data point is transferred to the cluster carrying the centroid that is closest to it. Generally, the Euclidean distance is used to compute the distance to the nearest centroid. After grouping is complete, the new centroid of each cluster is recalculated. On the basis of this centroid, a new Euclidean distance is calculated between each center and each data point, and the cluster points with the least Euclidean distance are assigned.

SSE (Sum Squared Error) is calculated using the Elbow Method for a variety of clusters. By using the elbow method, the number of clusters will be defined.

Because we don't want the clusters to be too large, and because the error rate decline decreases after four, we may deduce from figure 6 that four clusters is a suitable number for our circumstance. We run the K-Means model with n cluster or k = 4 and plot the clustering outcome. Elbow graph of year 2019 and 2021 follow the identical pattern.

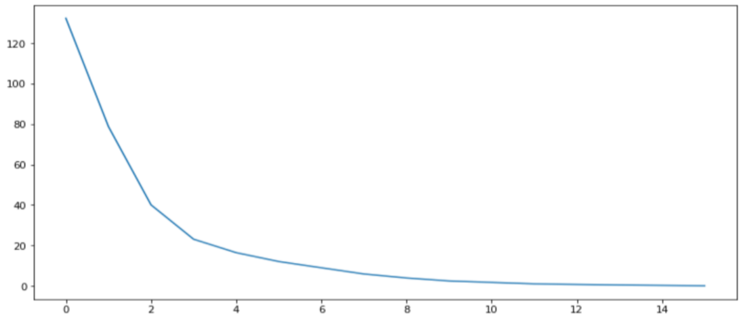

Figure 6. Elbow Model (k)

The Result

Using the 3 D visualisation of clustering method, we are able to separate the different types of clusters and compare the result on year 2019, the condition before the Covid-19 happened versus year 2021 where the Covid-19 still exist but economic recovery is already being underway.

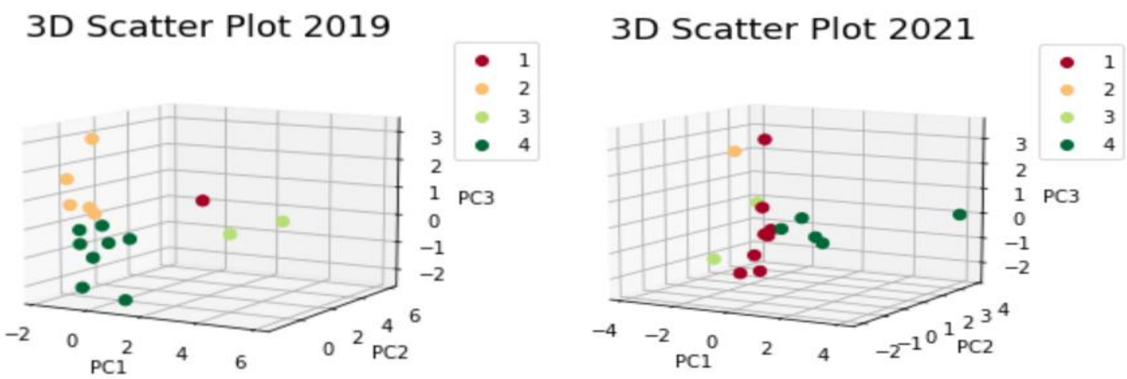

Figure 7. 3D Scatter Plot

	CLUSTER	
Company/Stock Name	**2019**	**2021**
Danasupra	1	4
ADIRA	2	1
BUANA FINANCE	2	1
Indomobil Multi Jasa	2	2
Verena Multi Finance	2	1
Wahana Ottomitra Multiartha	2	1
Intan Baruprana	3	3
Radana Bhaskara Finance	3	1
Batavia	4	1
BFI	4	1
Clipan Finance	4	1
Fuji Finance Indonesia	4	1
Mandala Multifinance	4	1
Pool Advista Finance	4	3
Tifa Finance	4	1
Trust Finance Indonesia	4	1

Figure 8. List of Company Cluster 2019 and 2021

Recommendation

The clustering outcome illustrates the unique characteristics of each cluster. About 75% percent (12 stocks) have favorable externalities towards Covid-19, indicating that Covid-19 does not have a major impact on the sector and the company has formulated a corporate strategy to defeat Covid-19 financial impact. Among these companies are Adira Finance, Buana Finance, Verena Multifinance, Wahana Multiartha Finance, Radana Bhaskara Finance, BFI, Batavia Finance, Clipan Finance, Fuji Finance, Mandala Finance, Tifa Finance, and Trust Finance. It indicates that they have a rising performance trend and are suggested as an investment. There are two stocks recorded as neutral since they are remaining in the current cluster (Indomobil Finance and Intan Baruprana). Pool Advista Finance is having improvement but still in worsening performance. On contrary, Danasupra Finance is not recommended due to lower profitability, and its performance has not improved throughout the Covid-19 period (the cluster is moving toward bad performance).

2019	2021			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1				Danasupra
Cluster 2	ADIRA			
	Buana Finance			
		Indomobil Multi Jasa		
	Verena Multi Finance			
	Wahana Ottomitra Multiartha			
Cluster 3			Intan Baruprana	
	Radana Bhaskara Finance			
Cluster 4	BFI			
	Batavia			
	Clipan			
	Fuji Finance Indonesia			
	Mandala Multifinance			
			Pool Advista Finance	
	Tifa Finance			
	Trust Finance Indonesia			

Figure 9. Company Stocks Recommendation

During the pandemic, multi-finance industries have adopted a number of activities, including restructuring their financing, increasing collaboration with Fintech, and establishing online processes and digitalizing the process. By establishing an online presence to promote financing solutions, multifinance institutions can collaborate with key partners, such as vehicle showrooms and dealers, to disseminate information regarding their offering. Instead of visiting a showroom, prospective borrowers can choose the product to be financed on the website.

Conclusion

During a presence of Covid-19, the government imposed a lockdown policy to prevent the disease from spreading, which unintentionally pushed individuals and businesses into solvency and liquidity issues (Bartik et al., 2020). During the Covid-19 pandemic, multi-finance is one of the sectors that was also hit with deteriorating performance due to high Non-Performing Loan performance. The NPL percentage has increased as a result of defaulting borrowers, and the majority of lending disbursements have ceased since banks, as one of the funding sources, have slowed credit disbursement channelling. And, because many multi-finance institutions offer auto-financing products, despite falling vehicle demand due to the pandemic, their financial performance is deteriorating. Nonetheless, financial performance in 2021 has slowly improve.
The methodology of PCA and K-means clustering were used in this research to segregate the stocks investment in multi-finance sector. PCA analysis can act as a tool for reducing dimensionality by eliminating the later principal components. Furthermore, PCA has the ability to identify the similarity and difference between the various models created (Yoshino & Taghizadeh-Hesary, 2015). A result showed that 12 out of 16 multi-finance stocks did well during the pandemic. Even with the Covid-19 pandemic, these stocks are deemed to have positive externalities. In addition, the study identified one stock with negative externalities as its cluster declines toward pre and post Covid-19. Three companies were deemed neutral since they remained in the same cluster in 2019 and 2021.

The objective of the cluster analysis may provide more efficient investment choice information on the multi-finance stocks portfolio listed on the Indonesia Stock Exchange, allowing investors to make solid investment trading decisions, particularly regarding financing company stocks.

Notes on Contributors

Sri Mulyaningsih is a MBA graduate of Central Queensland University Australia. Her research interest are Banking, Financial management, Risk Management, Capital market.

Jerry Heikal is Magister Management lecturer at Bakrie University, Jakarta. His research interest are in Financial Data Analytics, Data Modelling, and Digital Marketing.

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LIST OF APPENDIX

Appendix 1. Multi-Finance Financial Ratios

Non Bank Financial Institution	Dec-19	Dec-20	Dec-21	Apr-22
Financial Ratios:				
1. FAR (Financing To Asset Ratio)	87.28%	81.08%	84.10%	84.93%
2. Gearing Ratio	2.61	2.15	1.98	2.01
3. Equity To Paid Up Capital Ratio	271.14%	268.81%	272.10%	283.22%
4. NPF (Non Performing Financing)	2.40%	4.01%	3.53%	2.70%
5. ROA (Return On Asset)	4.79%	1.99%	4.51%	4.89%
6. ROE (Return On Equity)	14.28%	5.27%	11.39%	12.29%
7. Capital Investment Ratio	0.98%	0.99%	1.06%	1.10%
8. Operational Efficiency Ratio	78.93%	91.09%	80.63%	79.62%