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Identifying Homogeneity of Small-Cap Stocks in Indian Market: A Data Mining Approach

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Abstract

Investors in equity shares look for two basic aspects while investing i.e. consistently rising returns with a decreasing or at least stabilized level of risk involved. Amidst the numerous stocks available in the market which differ widely on the basis of different aspects i.e. segment, sector, industry, market capitalization etc. it becomes a challenge for the investor to form a diversified portfolio where heterogeneity of the constituent stocks is the main criterion. Thus it is imperative that the basis be finalized on which the heterogeneity of the stocks shall be determined. Traditionally portfolios have been constituted on the basis of low coefficient of correlation of returns from the constituent stocks. The dissimilarity of co-movement of returns from stocks has traditionally been attempted to be maximized in portfolios. Another method of grouping similar stocks by using data mining approach is fast gaining popularity. This approach uses clustering technique to group homogeneous stocks on the basis of a set of selected criteria. These criteria can be financial ratios, indices or any other related matrices. Advanced versions of this technique can group homogeneous time series data as well. This paper attempts to identify homogeneous clusters of companies in the Indian small-cap segment based on valuation ratios. Valuation ratios have been selected to be the grouping criteria as these were not been used in earlier studies by researchers and scholars. The small cap companies in India have been chosen for this study for its better resilience and recovering potential compared to mid cap and large cap companies. The companies constituting the CNX NIFTY Small Cap 50 Index have been considered in the study.

Keywords: Cluster Analysis, Valuation Ratios, Small Cap Sector, CNX NIFTY Mid Cap 50 Index

Introduction

A system of categorization of stock market would be useful to investors and financial analysts, providing them with the opportunity to predict the stock price changes of a company vis-a-vis other companies. In recent years, clustering companies in the stock markets based on their similarities on different aspects has increasingly become a common practice. However stock price data are high-dimensional in nature and the changes in the stock price usually occur with shift, which makes the categorization a complex issue. Clustering Method is an adaptive procedure in which homogeneous objects are clustered or grouped together, based on the principle of maximizing the intra-class similarity and minimizing the inter-class similarity. It is essentially a data mining technique in which similar data are automatically placed into related groups without advanced knowledge of the group definitions. Clustering of companies in the stock market is very useful for managers, investors and policy makers. There are numerous companies listed in the Indian market which vary widely based on a host of aspects i.e. the industry, size, capitalization, business models etc. However, the investors have only two aspects to consider i.e. consistently increase returns with a cap on risk involved. Earlier studies have used financial ratios as clustering factors. To capture the market price of the stocks, which is of prime importance to the investors,

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into the clustering factors, this paper uses valuation ratios as the grouping factors because valuation ratios link the market prices of stocks with the performance financials of the companies. The small cap companies have been chosen for certain reasons. While CNX Nifty has returned 4 per cent over the past one year, mid-cap and small-cap indices have returned 15 per cent and 24 per cent. Between January 2018 and February 2019, midcap and smallcap indices have seen deeper corrections compared with the largecap index despite registering higher profit growth. The BSE Smallcap index, which fell 32 per cent between January 15, 2018 and February 18, 2019, has recovered 10 per cent since then. Similarly, the BSE Midcap index gained 7.32 per cent since February 2 after sliding 25 per cent between January 9, 2018, and February 18, 2019. The obvious expectation of the market is that the tide is about to turn and the small and mid-cap sector is poised to outperform the large-cap sector. Among small cap and mid cap stocks, the former have exhibited greater resilience and higher recovering potential. Small companies can begin to rebound in growing economies faster than larger companies. Decisions about new products and services and how to bring them to market can also be made and implemented faster with small companies because they have fewer committees, fewer layers of management, and fewer potential obstructions of the kind that exist in the typical large and mid cap companies. When the economy begins to emerge from recession and starts growing again, small-cap stocks can respond to the positive environment quicker and potentially grow faster than large-cap stocks. Small cap companies typically raise most of their capital from investors through the equity route. Larger companies raise capital substantially through debt route which raises their financial leverage positions. Hence this paper focuses on the small cap companies and attempts to identify homogeneity across industries among the companies using valuation ratios as the clustering factors.

Survey of Literature and Identification of Research Gap

The survey of concerned literature has been done with the objective of probing into the results of the past researches on clustering companies with focus on three aspects i.e. the method used, the grouping factors used and the results obtained. Tufan and Hamarat (2003) opined that a combination of clustering methods and fuzzy logic methods provided better results in clustering financial ratios of listed companies. Da Costa (2005) successfully applied cluster analysis on companies in North & South America to classify stocks in spot markets according to a risk-return criterion. Lemos et al. (2005) used K-Means clustering analysis technique along with Data Envelopment Analysis method and was successful in reducing the numbers of variables, improving the visualization of variables and making a coherent and a homogeneous comparison. Silva and De Costa (2005) showed how investors in North & South America can take better investment decisions using cluster analysis to select stocks. Wang and Lee (2008), in their research, modified the K-Means clustering method to leverage on its strengths and avoid its weaknesses in classifying companies based on financial ratios. Setty (2010) found encouraging results by using clustering methods to classify NIFTY 50 companies based on financial ratios over the period of two consecutive years of 2008-09 & 2009-10. Li and Sun (2011) used two-step clustering methods and was able to predict business failures successfully. Babu (2012), in their research, proved that Hierarchical clustering algorithm with reverse K means method and Hierarchical Agglomerative Clustering method yielded better results than K-Means clustering methods. Setyaningsih (2012) used cluster analysis to analyze performance of successful entrepreneurs in Indonesia. Temouri (2012) also used cluster analysis techniques while analyzing the performance of 80 selected enterprises across two observation periods i.e. pre-recession (2005-2007) and recession (2007-2009), on through six indicators: i) share of firms aged below 5 years (entrepreneurialism); ii) employment growth; iii) turnover growth; iv) profitability growth; v) liquidity ratio growth; vi) solvency ratio growth and was able to identify the top performing enterprises in the pre-recession as well as in the recession periods. Aghabozorgi and Teh (2014) worked on companies listed in the Kualalampur Stock Exchange. They used time series clustering methods to identify homogeneous movements in returns of stocks in three phases i.e. pre-clustering, purifying and merging. The algorithm developed by them yielded satisfactory results. Gruener (2015) performed clustering technique in risk clustering based on operating leverage. Marvin (2015) proposed an algorithm based on clustering techniques to create diversified Portfolios with S&P 500 companies. Momeni et al. (2015) worked on companies from cement, metal and automobile companies listed in Tehran Stock Exchange. They used K-Means clustering to identify homogeneous stocks across the clusters using five financial ratios i.e. Return on Assets, Return on Equity, Earnings per share, Profit to Sales and Operating Profit Margins.

Their research provided good results. Szucs (2015) worked on the Hungarian Automotive Industry and was able to identify clusters of homogeneous companies based on index numbers and data from the financial statements of the respective companies. Cai et al. (2016) showed that density-based clustering does not suit financial dataset. Dias (2016) used financial ratios to identify clusters which in turned effectively filtered out potential tax-evading companies. Hou (2016) worked on companies listed in the Shanghai Stock Exchange and could satisfactorily predict financial distress by using K-Means Clustering method with 87.50% accuracy. Goudarzi (2017), in his research on companies listed in Tehran Stock Exchange, proved that clustering method can be used to optimize portfolios. Perisa (2017) worked on companies in the Croatian Market and successfully used clustering methods using profitability indicators. Banerjee and Hofmann (2018) used clustering methods to identify firms that were unable to cover debt servicing costs from current profits over an extended period. Ferrando (2018) utilized clustering technique on the basis of five distinct business models to identify access to finance and innovative activity of companies in the European Union. Fodor (2018) was able to form stock groups using cluster analysis of common size statements and was also able to identify homogeneous co-movement of stock returns. Alexandra Horobet et al. (2019) analyzed financial performances of companies from four Central and Eastern European countries covering five industries i.e. financial services, food and beverages, chemicals, energy and pharmaceuticals. They identified natural groups of companies depending on corporate performance. They came to the conclusion that no clear-cut evidence on their grouping according to industries and/or countries can be identified.

The survey of literature revealed that across the globe, past researches have used only financial ratios and indices as clustering factors and have obtained, on an overall basis, satisfactory results. This identified gap in earlier research works prompted the use of valuation ratios as clustering factors in this study.

Objective of the Study

The main objective of this study is to identify homogeneous clusters of companies from the constituent companies of the CNX NIFTY Small Cap 50 Index by using selected valuation ratios as clustering factors. The ancillary objective of this study is to whether the cluster constituents are industry specific.

Methodology of the Study

The constituent companies of the CNX NIFTY Small Cap 50 index have been selected for the study. The index represents top 50 companies selected based on average daily turnover from the top 100 companies selected based on full market capitalization in NIFTY small cap 250 index. The main objective of the NIFTY small cap 50 Index is to capture the movement of the small cap segment of the market. In India, small cap is a term used to classify companies with a relatively small market capitalization i.e. normally below INR 5,000 crores.

Valuation ratios link the market price of an equity shares of a company with the financials of that company for a particular financial year.

Table 1: Ratios Used in Identifying the Significant Financial Ratios & Their Abbreviations

Ratio	*Abbreviation*	*Method of calculation*
Price – Equity ratio	ADPE	Dividing the current market price of the share by the current earnings per share
Price to Book Value	PTBV	Dividing the current market price of the share by the book value per share
Dividend Yield	DIVY	Dividing total annual dividend payments by market capitalization, assuming the number of outstanding equity shares is constant
Enterprise Value to Net Sales	EVNS	Dividing the current enterprise value of the company by its current net sales
Enterprise Value to Capital Employed	EVCE	Dividing the current enterprise value of the company by its current capital employed
Market Capitalization to Total Sales	MCTS	Dividing the current market capitalization of the company by its current total sales
Price to Cash Flow	PTCF	Dividing the current market price per share of the company by its current cash flow per share
Price to Free Cash Flow	PFCF	Dividing the current market price per share of the company by its current free cash flow per share
Free Cash Flow Yield	FCFY	Dividing the free cash flow per share by the current share price

Source: authors' own assignment of abbreviations

The values of the selected nine valuation ratios were collected for three consecutive financial years i.e. 2015-16, 2016-17 and 2017-18 from Ace Equity ® Data Product. The outliers of the ratios were identified and those companies were excluded from the data set. The values of the ratios were then standardized by using the formula $s_{tandardized} = (x -) / \sigma$.

To have an idea about the number of clusters, hierarchical cluster analysis has been done using the nine valuation ratios as the categorizing factors. Based on the outcome of the hierarchical cluster analysis, the K-Means Cluster Analysis has been done to get the final cluster constitutions. The statistical processes have been carried out on R Studio Platform version 3.5.1. The R codes have been appended as an Annexure after the references.

The Financial Year 2015-16

The results of the hierarchical cluster analysis yielded showed that there are two optimum clusters with 5 & 7 members respectively.

The dendogram below gives a visual representation of the clusters

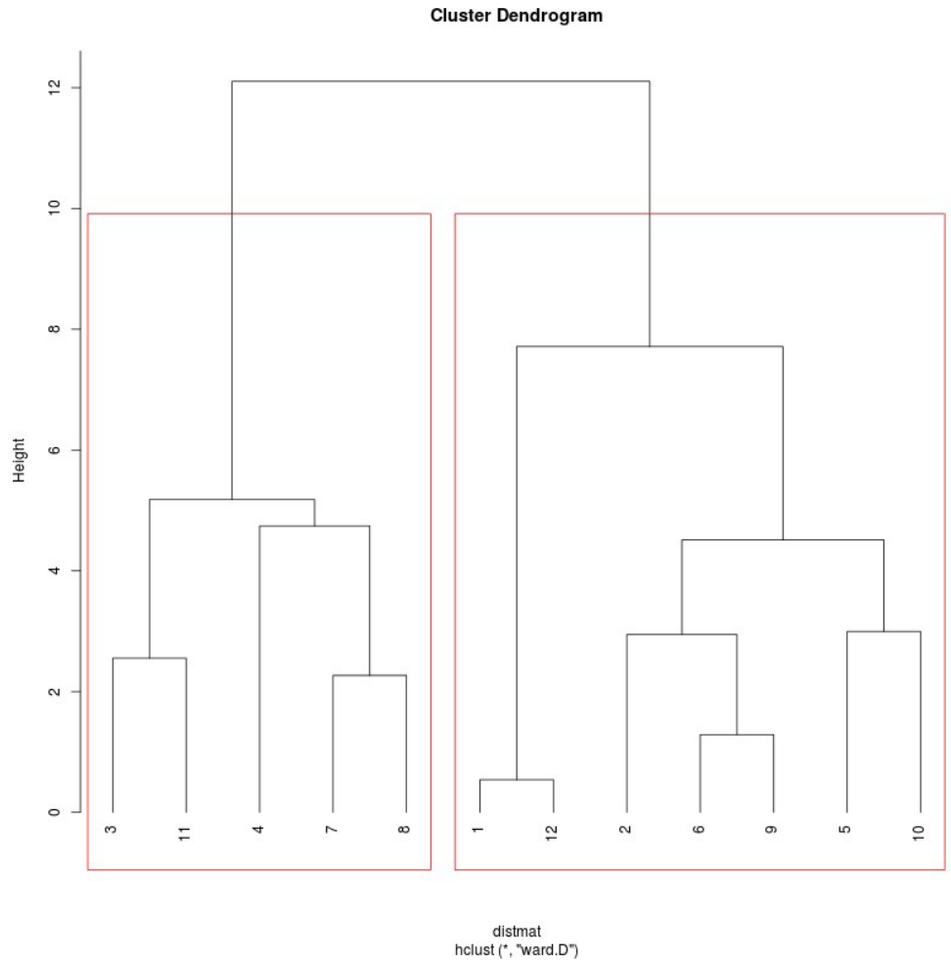


Chart 1: Dendogram – 2015-16

Now K-Means Clustering Analysis is applied taking the number of clusters to be 2. The results are appended below.

Table 2: Cluster Means – 2015-16

	adpe	*ptbv*	*divy*	*evns*	*Evce*	*mcts*	*ptcf*	*pfcf*	*fcfy*
1	-0.58474447	-0.51590575	0.15602953	-0.23982172	-0.4961136	-0.73436711	-0.70395625	0.68174415	0.26749964
2	0.81864226	0.72226805	-0.21844134	0.33575041	0.69455904	1.02811395	0.98553875	-0.95444181	-0.3744995

Table 3: K-Means Clustering with 2 Clusters – 2015-16

Within-Cluster Sum of Squares	
	values
1	36.81984735
2	29.05828865

Sum of Squares		
Total Sum of Squares	*Total Within Cluster Sum of Squares*	*Between Cluster Sum of Squares*
110.91666667	65.878136	45.03853067

Cluster Distribution size	
1	5
2	7

The Financial Year 2016-17

The results of the hierarchical cluster analysis yielded showed that there are two optimum clusters with 2 & 3 members respectively.

The dendogram below gives a visual representation of the clusters

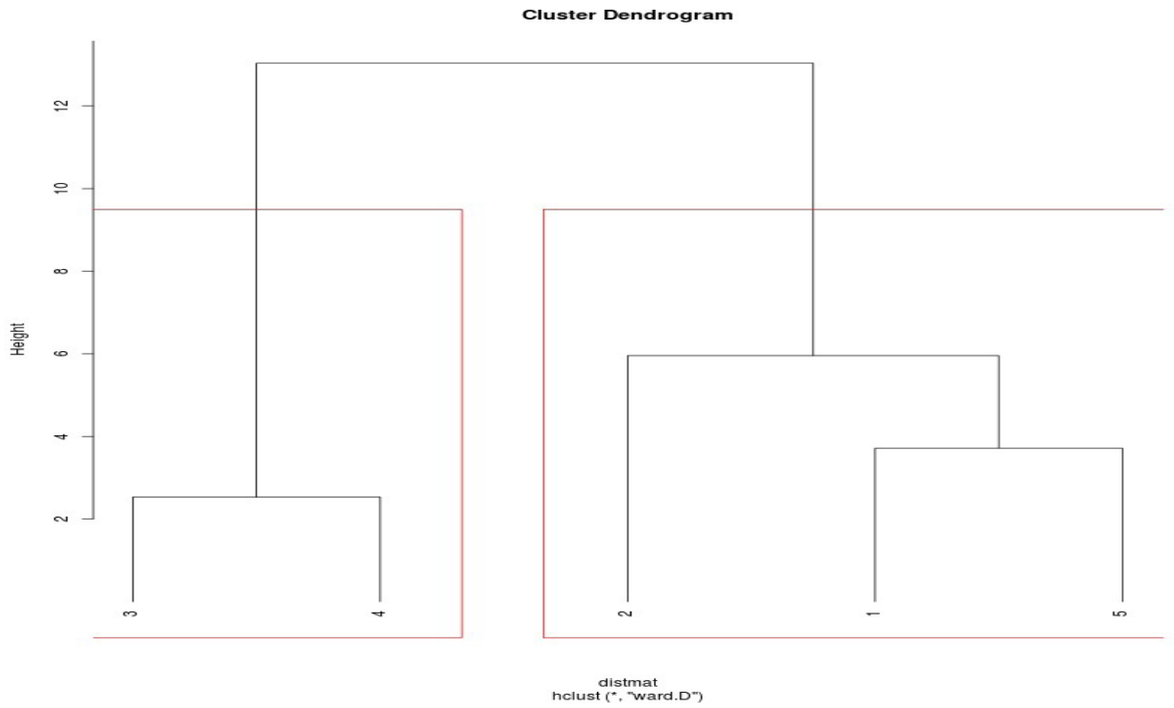


Chart 2: Dendogram – 2016-17

Now K-Means Clustering Analysis is applied taking the number of clusters to be 2. The results are appended below.

Table 4: Cluster Means – Hierarchical Means – 2016-17

Cluster Means									
Cluster	*adpe*	*ptbv*	*divy*	*evns*	*evce*	*mcts*	*ptcf*	*pfcf*	*fcfy*
1	3.0579256	0.58836698	-0.49222891	0.39294344	0.79214206	0.21452671	0.52546139	9.53984275	-0.77878315
2	1.52434337	-0.88255046	0.73834336	-0.58941516	-1.18821309	-0.32179007	-0.78819208	3.65234275	1.16817472

Table 5: K-Means Clustering with 2 Clusters – 2016-17

Within-Cluster Sum of Squares	
	values
1	2.84600579
2	19.93690175

Sum of Squares		
Total Sum of Squares	*Total Within Cluster Sum of Squares*	*Between Cluster Sum of Squares*
81.42422599	22.78290754	58.64131845

Cluster Distribution	
	size
1	2
2	3

The Financial Year 2017-18

The results of the hierarchical cluster analysis yielded showed that there are two optimum clusters with 8 & 6 members respectively.

The dendogram below gives a visual representation of the clusters

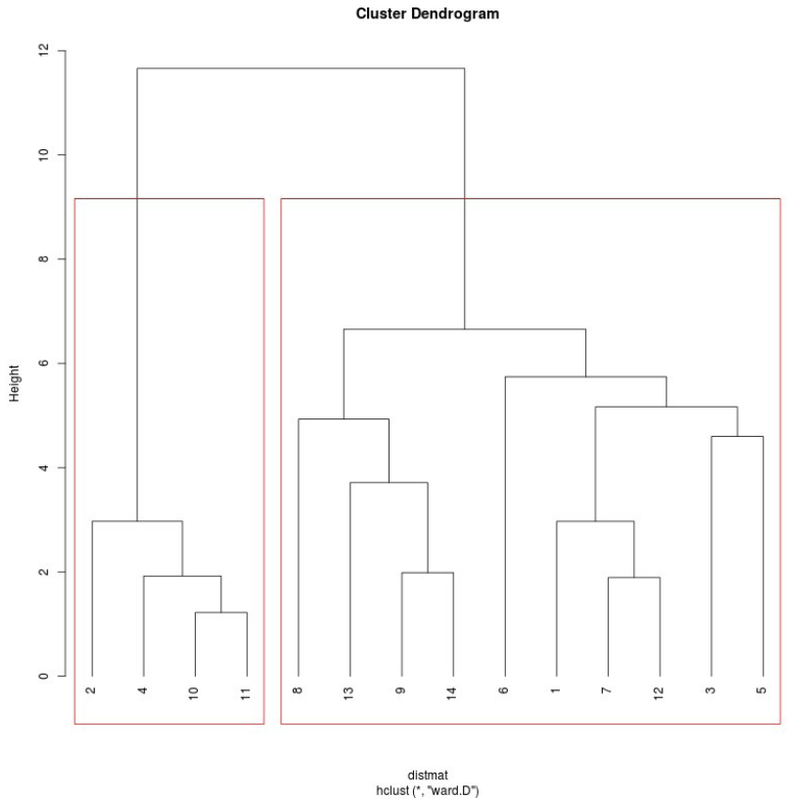
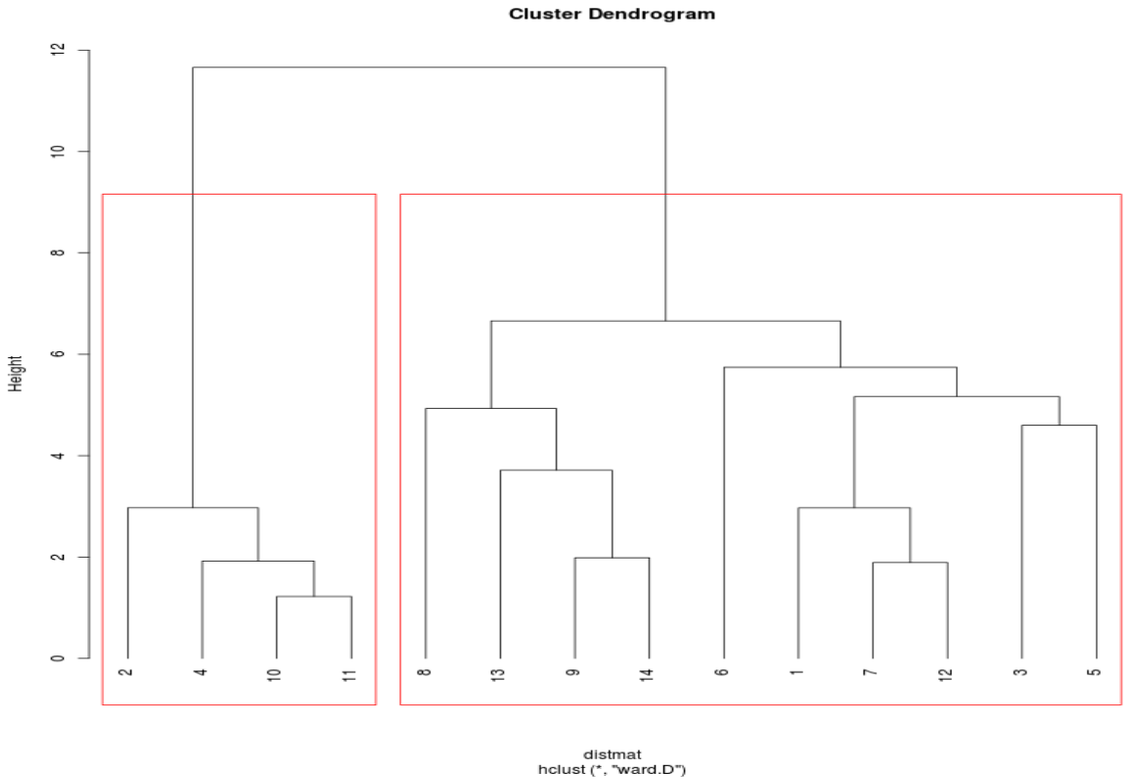


Chart 3: Dendogram – 2017-18



Now K-Means Clustering Analysis is applied taking the number of clusters to be 2. The results are appended below.

Table 6: Cluster Means – Hierarchical Means – 2017-18

Cluster Means									
	adpe	*ptbv*	*divy*	*evns*	*evce*	*mcts*	*ptcf*	*pfcf*	*fcfy*
1	0.26999943	-0.54773092	-0.27070291	-0.70022314	-0.62337297	-0.73792575	-0.10266131	-0.54036934	-0.52026911
2	-0.26999943	0.54773092	0.27070291	0.70022314	0.62337297	0.73792575	0.10266131	0.54036934	0.52026911

Table 7: K-Means Clustering with 2 Clusters – 2016-17

Within-Cluster Sum of Squares	
	values
1	43.85795107
2	47.94217759

Sum of Squares		
Total Sum of Squares	*Total Within Cluster Sum of Squares*	*Between Cluster Sum of Squares*
126	91.80012866	34.19987134

Cluster Distribution	
	size
1	8
2	6

Findings of the Study

In the year 2015-16, number of companies forming the data set was twelve excluding the companies whose valuation ratios contained outliers. There were no overlapping of industries in the two sectors. Crude Oil, chemicals and banks were included in one cluster indicating homogeneity of valuation ratios among these industries.

Table 8: Constitution of Cluster – 2015-16

Company	*Sector*	*Industry*	*Cluster*
Ceat Ltd.	Automobile & Ancillaries	Tyres & Allied	1
CESC Ltd.	Power	Power Generation/Distribution	1
Jain Irrigation Systems Ltd.	Plastic Products	Plastic Products	1
NCC Ltd.	Infrastructure	Engineering - Construction	1
Raymond Ltd.	Textile	Textile - Weaving	1
Allahabad Bank	Bank	Bank - Public	2
Andhra Bank	Bank	Bank - Public	2
Chennai Petroleum Corporation Ltd.	Crude Oil	Refineries	2
Gujarat Narmada Valley Fertilizers & Chemicals Ltd.	Chemicals	Fertilizers	2
Rain Industries Ltd.	Crude Oil	Petrochemicals	2
Rashtriya Chemicals & Fertilizers Ltd.	Chemicals	Fertilizers	2
Syndicate Bank	Bank	Bank - Public	2

In the year 2016-17, the data set contained only 5 companies as most of the companies had to be dropped from the data set due to outliers in the valuation ratios. The findings for this year exhibited overlapping of IT Sector in the two clusters. The results could not lead to any conclusion for this year.

Table 9: Constitution of Cluster – 2016-17

Company	*Sector*	*Industry*	*Cluster*
Gujarat State Fertilizers & Chemicals Ltd.	Chemicals	Fertilizers	1
NIIT Technologies Ltd.	IT	IT - Software	1
Bajaj Electricals Ltd.	Consumer Durables	Consumer Durables - Domestic Appliances	2
Cyient Ltd.	IT	IT - Software	2
Radico Khaitan Ltd.	Alcohol	Breweries & Distilleries	2

In the year 2017-18, the data set comprised of fourteen companies excluding those whose valuation ratios were outliers. The results showed no overlapping of industries in the two clusters except construction engineering companies in the infrastructure sector. Only two companies from the sector were included in the data set, one each of which were members of the two clusters. Except this exception, a clear demarcation of industries were noticed in the two clusters. Information Technology and Fertilizer companies were distinctly classified in the two clusters.

Table 10: Constitution of Cluster – 2017-18

Company	*Sector*	*Industry*	*Cluster*
CESC Ltd.	Power	Power Generation/Distribution	1
Fortis Healthcare Ltd.	Healthcare	Hospital & Healthcare Services	1
Gujarat State Fertilizers & Chemicals Ltd.	Chemicals	Fertilizers	1
Indiabulls Real Estate Ltd.	Realty	Construction - Real Estate	1
Jain Irrigation Systems Ltd.	Plastic Products	Plastic Products	1
NCC Ltd.	Infrastructure	Engineering - Construction	1
Rain Industries Ltd.	Crude Oil	Petrochemicals	1
Rashtriya Chemicals & Fertilizers Ltd.	Chemicals	Fertilizers	1
Cyient Ltd.	IT	IT - Software	2
Godfrey Phillips India Ltd.	FMCG	Cigarettes/Tobacco	2
KEC International Ltd.	Infrastructure	Engineering – Construction	2
NIIT Technologies Ltd.	IT	IT - Software	2
Persistent Systems Ltd.	IT	IT - Software	2
Raymond Ltd.	Textile	Textile - Weaving	2

Conclusion

The findings of the study leads to the conclusion that valuation ratios can be used as categorizing factors in clustering of companies across sectors in the small cap segment of the Indian market. The conclusion has been based on the findings of 2015-16 and 2017-18. The results of 2016-17 has not been considered in forming the conclusion due to very small data set which cannot be used to arrive at a generic conclusion. The results which have been found to hold good in both the years 2015-16 and 2017-18, have identified the following two distinct clusters of industries based on homogeneity of valuation ratios.

Table 11: Clustering of Sectors Based on Homogeneity of Valuation Ratios

Cluster 1	*Cluster 2*
Automobile & Ancillary Units	Bank
Power	Chemicals
Plastic	Crude Oil

Recommendations Based on the Inferences Drawn from the Study

Investors in equity shares may use the information about cluster membership based on valuation ratios in deciding the constitution of their portfolios. Their decision to keep or abstain from keeping the stocks together in a portfolio shall depend on whether the investor wants homogeneity or heterogeneity in valuation ratios of the constituent stocks in the portfolio.

Scope of Future Research

This study can be extended by combining financial ratios and other non-financial factors along with valuation ratios to identify the cluster of companies. This study may also be extended to mid cap companies and large cap companies as well. It may also be extended to sectoral companies. Homogeneity in co-movements of returns of stocks in Indian markets for sectors and segments may also be done by using time series clustering to facilitate construction of better diversified portfolios.

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Appendix

R codes for Hierarchical Clustering

```
dataframe<-data.frame(adpe,ptbv,divy,evns,evce,mcts,ptcf,pfcf,fcfy)
distmat<-dist(dataframe, method="euclidean",diag=FALSE, upper=FALSE)
clust<-hclust(distmat, method="ward.D")
Cluster<-cutree(clust,2)
table(Cluster)
agg<-aggregate(. ~ Cluster,data = dataframe, mean)
dataframe<-cbind(dataframe,Cluster)
rect.hclust(clust,2)
plot(clust,label=,hang=-1)
```

R codes for K-Means Clustering

```
dataframe<-data.frame(adpe,ptbv,divy,evns,evce,mcts,ptcf,pfcf,fcfy,hclust_1)
clust<-kmeans(dataframe, centers=2,iter.max=1,nstart=1, algorithm="Hartigan-Wong", trace=FALSE)
clust$centers
clust$withinss
clust$totss
clust$tot.withinss
clust$betweenss
clust$size
```