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Portfolio Diversification of Nifty50 in Pandemic Situation By Principal Component Analysis

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ABSTRACT
To outperform the NIFTY 50 index of the national stock exchange of India, the present study is devoted for obtaining portfolios using Principal Component Analysis. Portfolio has been constructed on each of the 10 principal components termed at Principal portfolios. A very high number of principal components are used for the identification of linearly correlated stocks and stock selection procedures under the correlation structure. The performance of principal portfolios in covid 19 period is also discussed. The benchmark index NIFTY 50 is observed as an impressive performance.
Keywords*: Portfolio****,*** *NIFTY 50, Principal Component Analysis, covid 19, Diversification Effect.*

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I. INTRODUCTION

Today investors are generally assumed to be at risk for averse wanting to maximize their expected investment return, generally agreed to be the total of income and capital gain over a particular period, for a given level of risk. **Jules Regnault (1860)[9]** laid the basis of modern stochastic models of price behaviour and **Henry Lefever (1870)[3]** discussed with consistent graphs representing financial payoffs under the "canonical" history of financial economics. **Markowitz (1952)[5]** developed model portfolio theory by applying a mean-variance model for the portfolio selection model. **James Tobin (1958)[10]** concluded that investment portfolios differ only in their relative proportions of stocks and bonds. **Markowitz (1991)[6]** introduced a formalized model of portfolio selection combining the statistical definition of risk with the risk averse assumption of investor behavior. The study of **Lowenfeld** in (**1907)[3]** and (**1909)[10]** shows portfolio diversification with practical applications of how to internationally spread portfolio risks. A recent study by **Edlinger and Parent (2014)[1]** has established that similar insights can also be found in France around the same time.

The objective of diversification is to maximize returns and minimize risk by investing in different assets that would each react differently to the same event. For instance, negative news related to the Indian debt crisis generally causes the stock market to move significantly lower. At the same time, the same news has had a general positive impact on the price of certain commodity such as gold. Diversification Effect refers to the relationship between correlations and portfolios. When the correlation between assets is imperfect (positive/negative), the result is the diversification effect. It is an important and effective risk reduction strategy since risk reduction can be achieved without compromising returns and we say the diversification effects in the results if correlation (either positive or negative) between assets is imperfect. Markowitz Efficient Frontier (MEF) is a key concept of MPT represents the best combination of securities those producing the maximum expected return for a given risk level within an investment portfolio.

It describes the relationship between expected portfolio returns and the riskiness or volatility of the portfolio. Portfolios lying on the 'Efficient Frontier' represent the best possible combination of the expected return and investment risk. The relationship between securities within a portfolio is also an important part of the Efficient Frontier. **Partovi and Caputo (2004)[8]** showed that principal component analysis

can be used to extract uncorrelated synthetic portfolios which represent uncorrelated risk sources in the stock market. **Meucci (2009)[7]** stated that maximum diversification is achieved when a portfolio has equal exposure to all uncorrelated risk sources. Principal component Analysis is a statistical method of dimension reduction. The present paper is focused on the potential use of PCA in portfolio management. Portfolio only with stocks has been taken into account under this study. PCA can reduce the complexity of a stock portfolio by transforming the stocks into a new set of uncorrelated principal components that represent .

uncorrelated risk sources and it also allows us to identify the stocks that can be used as a representative of the whole data set and find the number of stocks which is sufficient to diversify a portfolio.

II. DATA AND METHODOLOGY

Data and Descriptive Statistics

The constituents of the NIFTY50 index from MAY 2012 to April 2022 has been retrieved from the Indian stock exchange. Here the NIFTY50 index is a market capitalization weighted index of the50largest shares by capitalization listed on the National Securities Exchange (NSE), that starts from7 May 2012.

For this Index the Following eligibility criteria for a stock has been taken into consideration:

- It considered that an average impact cost of 0.50% or less during the last six months for 90% of the observations, for the basket size of Rs. 100 million.

- Data have been retrieved from the companies having listing history of six months.

- Only those companies have been selected that are allowed to trade in F&O segment.

- In the index company which comes out with an IPO is considered as eligible for inclusion if it fulfills the normal eligibility criteria for the index for a 3-month period instead of a 6 month period.

- Index is re-balanced on semi-annual basis. The cut-off date is January 31 and July 31 of each year, i.e., for semi-annual review of indices, average data for six months ending the cut-off date is considered.

- The three-tier governance structure comprising the Board of Directors of NSE Indices Limited, the Index Advisory Committee (Equity) and the Index Maintenance Sub-Committee is adopted while retrieving data.

Fig 1: NIFTY50 from 2012-2022

The weight percent from various sector have been considered as follows

Table 1: Sector Representation:

Sector	Weight (%)	Sector	Weight (%)
Financial Services	35.66	Metals & Mining	2.76
Information Technology	15.89	Construction	2.75
Oil, Gas & Consumable Fuels	14.26	Telecommunication	2.28
Fast Moving Consumer Goods	8.25	Power	2.12
Automobile and Auto Components	5.64	Construction Materials	2.11

Healthcare	3.91	Service	0.73
Consumer Durables	3.05	Chemicals	0.59

Table 2: Constituents by Weightage: The following companies/industries have been taken into consideration under different sectors with the weights as under noted

S. No.	Constituent	Industry	Weightage (%)
1	Reliance Industries Ltd.	Oil and Gas	12.86
2	HDFC Bank Ltd.	Financial Service	8.10
3	Infosys Ltd.	IT	7.66
4	ICICI Bank Ltd.	Financial Service	6.90
5	HDFC Ltd.	Financial Service	5.39
6	TCS Ltd.	IT	4.91
7	Kotak Mahindra Bank Ltd.	Financial Service	3.51
8	ITC Ltd.	FMCG	3.03
9	Larsen & Toubro Ltd.	Construction	2.74
10	Hindustan Unilever Ltd.	FMCG	2.67
11	Axis Bank Ltd.	Financial Service	2.57
12	State Bank of India	Financial Service	2.54
13	Bajaj Finance Ltd.	Financial Service	2.37
14	Bharti Airtel Ltd.	Telecom	2.33
15	Asian Paints	Consumer Durables	1.95
16	HCL Technologies Ltd.	IT	1.53
17	Titan	Consumer Durables	1.37
18	Tata Steel Ltd.	Metals & Mining	1.37
19	Maruti Suzuki India Ltd.	Automobile	1.37
20	Sun Pharmaceutical Industries Ltd.	Healthcare	1.34
21	Bajaj Finserv Ltd.	Financial Service	1.20
22	Mahindra & Mahindra Ltd.	Automobile	1.18
23	Tech Mahindra Ltd.	IT	1.05
24	Tata Motors Ltd.	Automobile	1.05
25	Power Grid Corporation of India Ltd.	Power	1.04

26	Ultratech cement Ltd.	Construction Materials	1.02
27	Wipro Ltd.	IT	1.01
28	NTPC Ltd.	Power	0.99
29	Hindalco Industries Ltd.	Metals and Mining	0.94
30	JSW Steel Ltd.	Metals and Mining	0.94
31	Nestle India Ltd.	FMCG	0.87
32	Grasim Industries Ltd.	Construction Materials	0.85
33	IndusInd Bank Ltd.	Financial Service	0.85
34	Adani Ports Ltd.	Services	0.82
35	ONGC Ltd.	Oil and Gas	0.78
36	Divi’s Laboratories Ltd.	Healthcare	0.77
37	HDFC Life Insurance Co.	Financial Service	0.72
38	Cipla Ltd.	Healthcare	0.68
39	Dr. Reddy’s Laboratories Ltd.	Healthcare	0.67
40	Tata Consumer Products Ltd.	FMCG	0.66
41	SBI Life Insurance Co.	Financial Service	0.65
42	Bajaj Auto Ltd.	Automobile	0.65
43	Apollo Hospital	Healthcare	0.61
44	UPL Ltd.	Chemicals	0.60
45	Britannia Industries Ltd.	FMCG	0.52
46	Coal India Ltd.	Oil and Gas	0.51
47	Eicher Motors Ltd.	Automobile	0.49
48	Bharat Petroleum Corp. Ltd.	Oil and Gas	0.46
49	Shree Cement Ltd.	Construction Materials	0.46
50	Hero MotoCorp Ltd.	Automobile	0.43

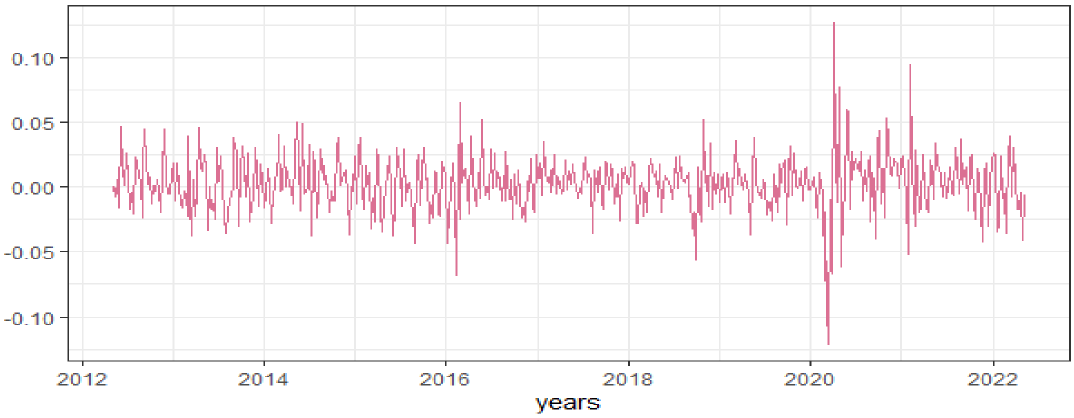


Fig 2*: The daily returns of NIFTY 50 over time*

Note: In our study we use 48 stocks out of given 50 from NIFTY index. We are not using 'HDFC Life Insurance Company' and 'SBI Life Insurance Company' here, as these two constituents of NIFTY50 were listed at Stock Market on Nov 2017 and Oct, 2017 respectively and we used past 10 year's data in this study from May 2012 to April 2022. We have taken here weekly data and done analysis with 523 data points or weeks.

The box polt and Q-Q plots of NIFTY 50 returns can be viewed as

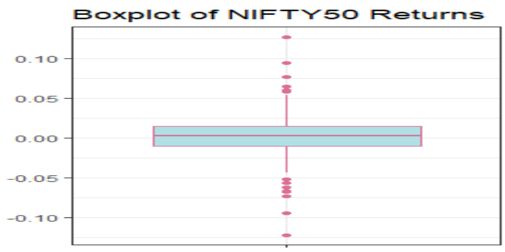


Fig 3.1: *box polt of NIFTY 50 returns*

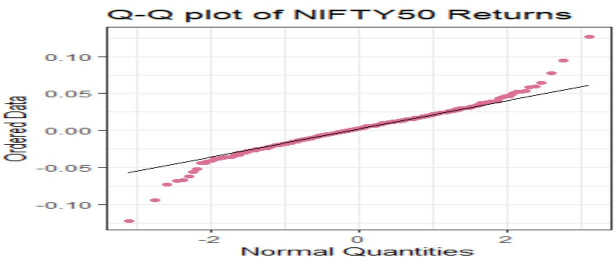


Fig 3.2: *box polt of NIFTY 50 returns*

METHODS

Kaiser-Meyer-Olkin (KMO): KMO measure of sampling adequacy to test the shortest length of sliding window that a PCA could be efficiently applied to. The KMO statistic compares the value of correlations between stocks to those of the partial correlations. If the investigated stocks share more common variation, the KMO will be close to 1. On the other hand, a KMO near 0 indicates the PCA will not extract much useful information.

Bartlett's test of Sphericity: Bartlett's test is used to test the null hypothesis that the correlation matrix is an identity matrix

Principal Component Analysis:

Principal component analysis on the correlation matrix of the return series taking into consideration that dividends are negligible as compared to returns. Formula for applying the PCA using returns of the stocks is given by:

$$R_i(t) = \frac{Price_i(t+1) - Price_i(t)}{Price_i(t)}$$

here t denotes time (in week).

The PCA is aimed to determine the threshold for cutting off the random part of stock price fluctuation and preserve the major risk sources in the data set. There is not a fixed number of principal components to retain. Many rules can be applied to determine the number of principal components to retain.

The data set we used in this study was the 48 stocks with complete price for the sample period of 10 years. We applied PCA to the correlation matrix of the 156 stocks and used three rules

The three rules together with bi-plots of the coefficients in each principal component to determine the threshold for cutting off rather irrelevant principal components may be considered as define below

A. The First rule in determining the number of components to retain is deciding the cumulative variance desired. The actual amount of variation explained by any given principal component is given by

$$Variance\ Explained\ by\ Component\ j = \frac{\lambda_j}{\sum_{i=1}^{n} \lambda_i} \times 100$$

Where,

$$\lambda_i = Eigenvalue\ of\ component\ i$$

The cumulative percentage variance explained by the first m components is given by

$$Cumulative\ Variance = \sum_{k=1}^{m} Variance\ explained\ by\ component\ k$$

The number of components to retain is then the smallest number, m, which exceeds the desired percentage variance explained.

B. Kaiser's rule **(Kaiser, 1960)[11]**, retaining principal components that have an eigenvalue greater than 1. The idea behind this rule is that if all the stocks were uncorrelated, then the principal components are the same as the original stocks and all have unit variance in the case of a correlation matrix. So any principal components with eigenvalue less than 1 contains less information than one of the original variables and so is not worth retaining.

C. Scree graph introduced by **Cattell (1966)[12]**, and log-eigenvalue diagram (LEV diagram) introduced by **Farmer, (1971)[13].** The scree graph is a plot of eigenvalue against component number. The log-eigenvalue diagram is an alternative to the scree graph and plots the log of the eigenvalue rather than eigenvalue against the component number. The decision is made based on finding the point in the graph where the slopes of lines joining the plotted points are 'steep' to the left and have a linear decay to the right.

Constructing Principal Portfolios

1. Apply PCA and get the coefficients of the principal components.

2. A positive coefficient indicates a long position while a negative coefficient indicates a short position. The weights of investment in each stock are the stock coefficient divided by the sum of all positive coefficients (if it is positive) or divided the absolute value of sum of all negative coefficients (if it is negative). This gives a set of weights in which both the long positions sum to 1 and the short positions sum to −1 respectively. The portion of short positions is the ratio of the sum of all negative coefficients to the sum of all positive coefficients. The funds obtained from the short positions are assumed to be invested in an average risk-free rate over the last 10 years.

3. The PPs returns are then the sum of the weighted returns of each stock plus the product of risk-free rate and the ratio of the short position.

The relative performances $= \frac{PP_n(t) - NIFTY50(t)}{NIFTY50(t)}$,

Where $PP_n(t)$ is the principal portfolio n value at time t, $NIFTY50(t)$ is the index value at time t and t is in units of one trading week.

ANALYSIS AND RESULTS

The "psych" package of R software is used to analyze the data set given in section 3.2, the codes for the analysis has been designed as:

Data imported in R:

```
#overall structure of 'portfolio'
> str(portfolio)
tibble [523 x 49] (S3: tbl_df/tbl/data.frame)
 $ Date        : POSIXct[1:523], format: "2012-05-07" "2012-05-14" ...
 $ ADANIPORTS : num [1:523] 122 112 114 125 125 ...
 $ APOLLOHOSP : num [1:523] 646 626 636 641 665 ...
 $ ASIANPAINTS: num [1:523] 362 370 377 378 383 ...
 $ AXISBANK   : num [1:523] 200 190 200 193 210 ...
 $ BAJAJ-AUTO : num [1:523] 1558 1528 1493 1499 1527 ...

#convert 'Date' column from factor to character and then into date
> portfolio$Date<- as.Date(as.character(portfolio$Date),format = "%Y-%m-%d")

#we check new structure of 'portfolio'
> str(portfolio)
tibble [523 x 49] (S3: tbl_df/tbl/data.frame)
 $ Date        : Date[1:523], format: "2012-05-07" "2012-05-14" ...
 $ ADANIPORTS : num [1:523] 122 112 114 125 125 ...
 $ APOLLOHOSP : num [1:523] 646 626 636 641 665 ...
 $ ASIANPAINTS: num [1:523] 362 370 377 378 383 ...
 $ AXISBANK   : num [1:523] 200 190 200 193 210 ...
 $ BAJAJ-AUTO : num [1:523] 1558 1528 1493 1499 1527 ...
```

Correlation matrix:

```
#for correlation among return of stocks
> Corrr<- cor(returns)

#fisrt few elements of 'corrr'
> head(Corrr)
            ADANIPORTS APOLLOHOSP ASIANPAINTS  AXISBANK BAJAJ-AUTO BAJAJFINSV
ADANIPORTS   1.0000000  0.2204354   0.1877745 0.3771480  0.3174892  0.3073605
APOLLOHOSP   0.2204354  1.0000000   0.1471340 0.2283409  0.1848807  0.1909396
ASIANPAINTS  0.1877745  0.1471340   1.0000000 0.2720770  0.3141444  0.2487680
AXISBANK     0.3771480  0.2283409   0.2720770 1.0000000  0.3919462  0.4162017
BAJAJ-AUTO   0.3174892  0.1848807   0.3141444 0.3919462  1.0000000  0.3190993
BAJAJFINSV   0.3073605  0.1909396   0.2487680 0.4162017  0.3190993  1.0000000
```

KMO statistics:

```
#for PCA we load package 'psych'
> library(psych)

#for KMO test on 'returns'
> KMO(returns)
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = returns)
Overall MSA =  0.94
```

We calculated KMO statistic in window of 10 years for all 48 stocks. A window size of 10 years had KMO value 0.94 which is quite enough for factor analysis to commence. This indicates that the degree of information among the variable overlap greatly, i.e., the presence of a strong partial correlation. Hence it is plausible to conduct Principal Component Analysis.

Bartlett's test of Sphericity

```
#for bartlett test on variance-covariance matrix 'corrr'
> cortest.bartlett(Corrr)
$chisq
[1] 1872.867

$p.value
[1] 7.051802e-40

$df
[1] 1128
```

We have value of test statistic 1872.867 with 1128 degrees of freedom and p-value 7.051×10^{-40}. A significant statistical test shows that the correlation matrix is indeed not an identity matrix as we reject null hypothesis here.

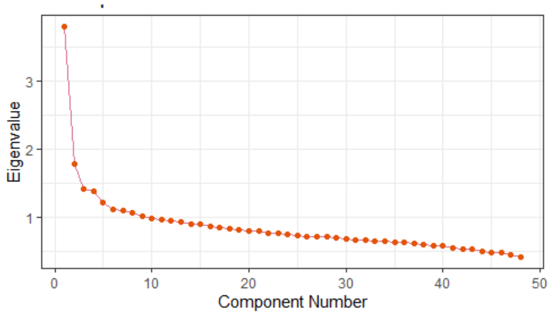
Principal Component Analysis:

```
#we apply pricipal component analysis on 'returns'
> pc<- prcomp(returns,center = T,scale. = T)

#for attributes of 'pc'
> attributes(pc)
$names
[1] "sdev"     "rotation" "center"   "scale"    "x"

$class
[1] "prcomp"

#for summary of principal component analysis
> summary(pc)
Importance of components:
                          PC1     PC2     PC3     PC4     PC5     PC6     PC7
Standard deviation     3.7957 1.79140 1.41405 1.38875 1.22252 1.11641 1.10244
Proportion of Variance 0.3001 0.06686 0.04166 0.04018 0.03114 0.02597 0.02532
Cumulative Proportion  0.3001 0.36700 0.40866 0.44884 0.47998 0.50594 0.53126
                           PC8     PC9    PC10    PC11    PC12    PC13    PC14
Standard deviation     1.06632 1.02270 0.98864 0.97634 0.95042 0.93515 0.90805
Proportion of Variance 0.0236 0.02179 0.02036 0.01986 0.01882 0.01822 0.01718
Cumulative Proportion  0.5549 0.57674 0.59710 0.61696 0.63578 0.65400 0.67118
                          PC15    PC16    PC17   PC18    PC19    PC20    PC21
Standard deviation     0.90303 0.87597 0.85634 0.8372 0.81557 0.79930 0.79783
Proportion of Variance 0.01699 0.01599 0.01528 0.0146 0.01386 0.01331 0.01326
Cumulative Proportion  0.68817 0.70415 0.71943 0.7340 0.74789 0.76120 0.77446
                         PC22    PC23    PC24    PC25    PC26    PC27    PC28
Standard deviation     0.7749 0.76466 0.75162 0.74177 0.72415 0.71963 0.71551
Proportion of Variance 0.0125 0.01218 0.01177 0.01146 0.01092 0.01079 0.01067
Cumulative Proportion  0.7869 0.79916 0.81093 0.82239 0.83331 0.84410 0.85477
                          PC29    PC30   PC31    PC32    PC33    PC34    PC35
Standard deviation     0.69934 0.69237 0.6718 0.66384 0.65916 0.65073 0.63704
Proportion of Variance 0.01019 0.00999 0.0094 0.00918 0.00905 0.00882 0.00845
Cumulative Proportion  0.86496 0.87494 0.8843 0.89353 0.90258 0.91140 0.91985
                          PC36    PC37    PC38   PC39    PC40    PC41    PC42
Standard deviation     0.63548 0.62085 0.59834 0.5919 0.58117 0.55113 0.53985
Proportion of Variance 0.00841 0.00803 0.00746 0.0073 0.00704 0.00633 0.00607
Cumulative Proportion  0.92827 0.93630 0.94376 0.9510 0.95809 0.96442 0.97049
                         PC43    PC44    PC45    PC46    PC47    PC48
Standard deviation     0.5368 0.51124 0.49442 0.48527 0.45589 0.42329
Proportion of Variance 0.0060 0.00545 0.00509 0.00491 0.00433 0.00373
Cumulative Proportion  0.9765 0.98194 0.98703 0.99194 0.99627 1.00000
```



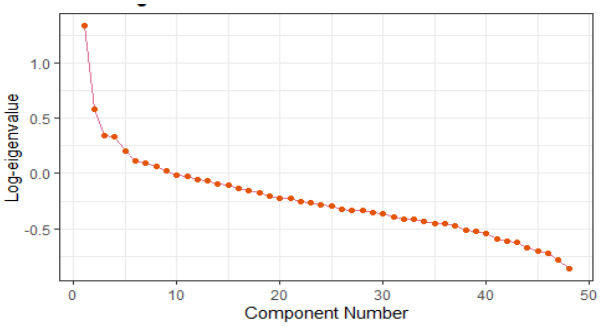


***Fig 4:** Screen plot for correlation matrix of 48 stocks* ***Fig 5:** LEV diagram for correlation matrix of 48 stocks*

From the R-report we can observe each component explains a percentage of the total variance in the data set. In the Cumulative Proportion section, the first principal component explains almost 30% of the total variance. This implies that almost two-fifth of the data in the set of 48 variables can be represented by just the first principal component. The second one explains 06.6% of the total variance.

The cumulative proportion of Comp.1 to Comp.10 explains nearly 60% of the total variance. This means that the ten principal components can accurately represent the data.

We filtered out the random part of the stock risks and retain the first 10 principal components that represent the market risk and each risk group. The original set of 48 stocks was transformed to a principal system which included 48 uncorrelated principal components in which the first 10 principal components identify the major risk drivers of stock returns. Essentially, the portfolios constructed based on the principal components were treated as individual investment assets with no correlations.

Investors can choose to hold any principal portfolio to get exposure to a single risk source that is uncorrelated with the other risks in the market. The performances of principal portfolios also provide means of monitoring single risk exposures. The investment universe is simplified in the sense that the choices are among assets with uncorrelated risks. One can decide whether to include an asset solely based on its variance and return without concern about its co-movements with the others in the portfolio. We refer to the 10 PPs that represent the major risk sources.
Principal component one is constructed slightly differently than the others. In our findings all coefficients of PC1 are positive. PCA by design is such that the direction of the principal components has no effect on their variances (the eigenvalues). As a consequence, one can change all negative coefficients to be positive, which is equivalent to rotating the principal component one by 180 degrees.

Fig 6.1: *Graph Year wise Risk-free rate in India*

The following Figures given presents the trajectory of Principal Portfolios against NIFTY50 index value and their relative performance. All the portfolios are assumed to have an initial wealth position equal to INR4928.9.

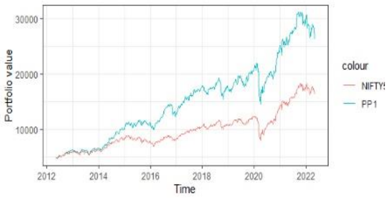


Fig:6.1(a)

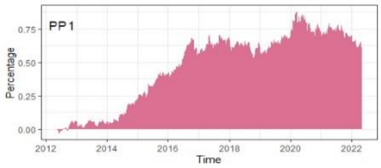


Fig:6.1(b)

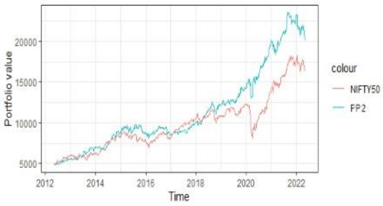
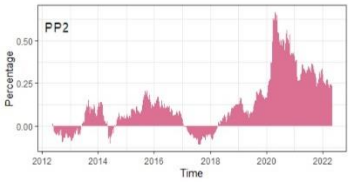


Fig:6.1(c)



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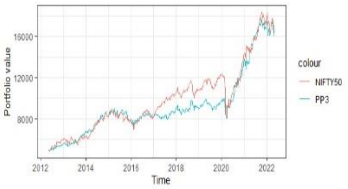

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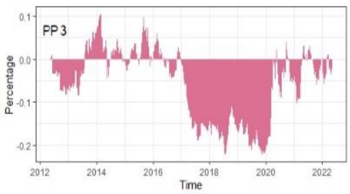
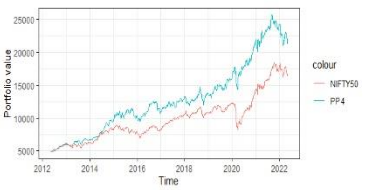


Fig:6.1(f)



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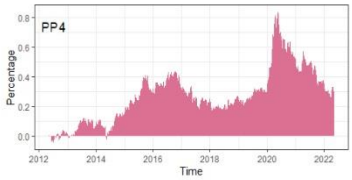

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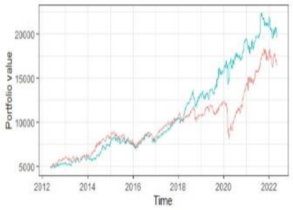
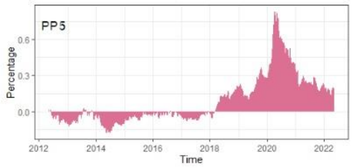


Fig:6.1(i)



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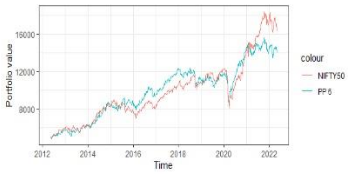

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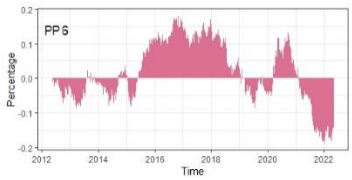

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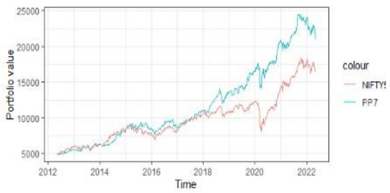


Fig:6.1(m)

Fig:6.1(n)

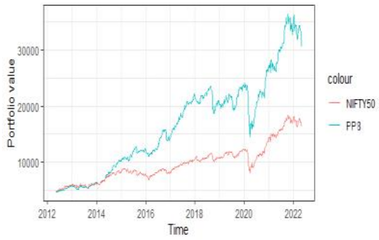


Fig:6.1(o)

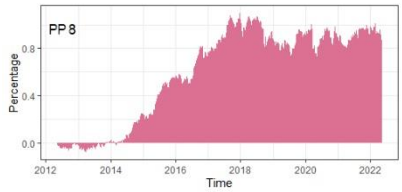


Fig:6.1(p)

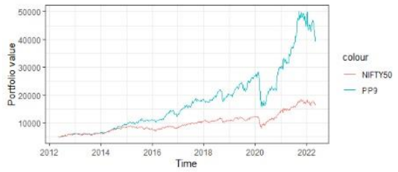


Fig:6.1(q)

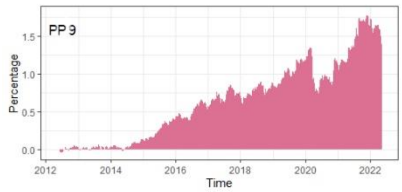


Fig:6.1(r)

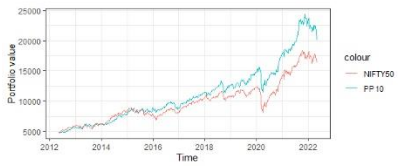


Fig:6.1(r)

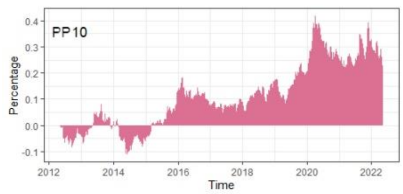


Fig:6.1(r)

The Data set used is the 48 Stocks for the study period of 10 years. The area plot below every PP, shows the relative performance of PPs and index NIFTY.

$Fig6.3: Plot\ of\ all\ 10\ retained\ pricipal\ portfolios\ with\ NIFTY50$

The graph shows PP1, PP4 and PP10 is closely related to Nifty50 index especially after beginning of 2016. PP1 has its special role among all the other PPs. It is a market component that has approximately equal contribution of all stocks and typically all the stocks have same sign of coefficient. This suggests PP1 is essentially an equal weighted portfolio of the underlying stocks. It also shows PP1, PP4, PP8 and PP9 were the only portfolios among all PPs which consistently outperformed the Nifty50 over the full study period. The outperformance of PP1 increased slightly until 2020 and increased gradually after pandemic in 2020.

5.PP's Performance during CoVID-19 situation

The rapid spread of the unprecedented CoVID-19 pandemic has put the world in jeopardy and changed the global outlook unexpectedly. In this situation of pandemic, the financial performance of the stock market is deteriorated due to public fears of declining economic activity, reduced disposable income and investor's negative sentiments. The general market benchmark reflects these effects in the form of reduced liquidity as well as returns. Indian stock market started fall very rapidly in March 2020. If we take Feb17, 2020, as reference point then NIFTY50 fall in next couple of weeks were.

Table 6.1: Change in NIFTY50 during CoVID-19 situation

Date	NIFTY50	% Weekly return	% Change from Feb17,2020
Feb17, 2020	12080.85		
Feb24, 2020	11201.75	-7.27%	-7.27%
Mar02, 2020	10989.45	-1.89%	-9.03%
Mar09, 2020	9955.2	-9.41%	-17.59%
Mar16, 2020	8745.45	-12.1%	-27.60%
Mar23, 2020	8660.25	-0.97%	-28.31%
Mar30, 2020	8083.8	-6.65%	-33.08%

From $Fig6.3$ it is evident that three principal components PP2, PP3 and PP5 are not much affected by CoVID-19 pandemic hence have very less effect of that situation.

Table 6.2: Change in portfolio value of PP2 during pandemic situation with respect to reference point Feb17, 2020 is given by.

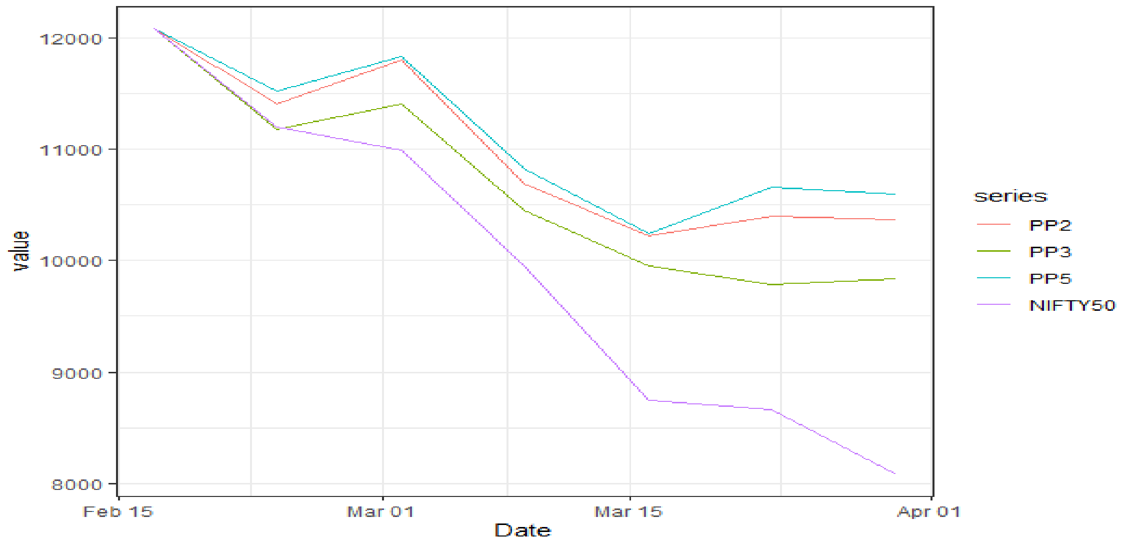
Date	PP2	% Weekly return	% Change from Feb17,2020
Feb17, 2020	15391.91		
Feb24, 2020	14527.08	-5.61%	-5.61%
Mar02, 2020	15041.03	3.53%	-2.28%
Mar09, 2020	13623.98	-9.42%	-11.48%
Mar16, 2020	13024.11	-4.40%	-15.38%
Mar23, 2020	13246.99	1.71%	-13.93%
Mar30, 2020	13205.14	-0.31%	-14.20%

Table 6.3: Change in portfolio value of PP3 during pandemic situation with respect to reference point Feb17, 2020 is given by.

Date	PP3	% Weekly return	% Change from Feb17,2020
Feb17, 2020	9920.98		
Feb24, 2020	9177.52	-7.49%	-7.49%
Mar02, 2020	9364.74	2.04%	-5.60%
Mar09, 2020	8582.73	-8.35%	-13.48%
Mar16, 2020	8173.14	-4.77%	-17.61%
Mar23, 2020	8031.667	-1.73%	-19.04%
Mar30, 2020	8076.098	0.55%	-18.59%

Table 6.4: Change in portfolio value of PP5 during pandemic situation with respect to reference point Feb17, 2020 is given by,

Date	PP5	% Weekly return	% Change from Feb17,2020
Feb17, 2020	16924.44		
Feb24, 2020	16133.97	-4.67%	-4.67%
Mar02, 2020	16574.25	2.72%	-2.06%
Mar09, 2020	15157.75	-8.54%	-10.43%
Mar16, 2020	14346.49	-5.35%	-15.23%
Mar23, 2020	14932.55	4.08%	-11.76%
Mar30, 2020	14848.92	-0.56%	-12.26%



$Fig6.4: Plot\ of\ PP2, PP3, PP5\ and\ NIFTY50\ in\ pandemic\ conditions$

$Table\ 6.1\ to\ 6.4$ Representing downfall of share market in pandemic era. If we take NIFTY50 index from Feb17, 2012, to Mar30, 2020, it decreased very sharply that is -33% in just 6-week time period. If we take our principal portfolios 2, 3 and 5; which were able to tackle these downfalls on an average extent. PP2 decreased by 14.20% in those 6 weeks, PP3 decreased by 18.59% in 6 weeks and PP5 decreased by 12.26%, having significant difference with fall of NIFTY50 Index.

$Fig6.4$ Compares PP2, PP3 and PP5 with NIFTY50 Index for Covid's downfall period from Feb17, 2020, to Mar30, 2020, assuming all portfolios had equal value on Feb17, 2020, as equal to that of NIFTY50, i.e., 12080.85

III. CONCLUSION

A principal portfolio is constructed based on the first component, which is a market component contains the most systematic risk compared to all other components. Before applying PCA applied for KMO test of sampling adequacy and Bartlett's test of spehericity and obtained sufficient results from them to conduct principal component analysis for the week wise data of past 10 years. The graph presented here for portfolio value of each principal portfolio in comparison with NIFTY50 index. More than half of principal portfolio outperforms the NIFTY index in terms of overall returns. Our results also revealed that it is not just any combination of stocks which can used to represent the whole data set. It must be a group of carefully selected stocks using the PCA selection procedure. The variance explained by principal component one was an effective measure of the level of systemic risk and served as a leading indicator of financial crisis. We also found the KMO measure of sampling adequacy was highly correlated with the variance explained by principal component one and hence could be used in the same role. The benchmark index of Indian stock market had heavy downfall during CoVID-19 crisis period. Moreover, we observed that three principal portfolio which had very less downfall as compared to benchmark Index indicating usefulness of those portfolios having greater return as compare to that index as well as ability to tackle the crisis situation present in the market. Thus, it is not only the first ten principal components which have greater returns as compare to market indices but also have important applications in market crisis management.

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