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Optimizing Stock Market Returns during Global Pandemic Using Regression in the Context of Indian Stock Market

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Abstract: Stock markets around the world experienced a massive collapse during the first wave of COVID-19. Roughly in the month of January 2021, the second wave of COVID-19 struck in India, reaching its peak in May, and by the end of May, the active cases started to decline. A third wave is again predicted by the end of 2021, and as such, the COVID-19 pandemic seems to have become a periodic phenomenon over the last couple of years. Therefore, the study of the behavior of the stock market as well as that of the investors becomes very interesting and crucial in this highly volatile and vulnerable market trend. Motivated by these facts, in the present paper, the researcher develops a model for portfolio management, using curve-fitting techniques and shows that this model can encounter the market volatility efficiently in the context of the Indian stock market. The portfolio is designed based on data taken from the National Stock Exchange (NSE), India, during 1 January 2020 to 31 December 2020. The performance of the portfolio in real-life situation during 1 January 2021 to 21 May 2021 is examined, assuming investments are made according to the proposed model.

Keywords: stock prediction; regression; method of least squares; COVID-19; mutual fund; portfolio management

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1. Introduction

The stock market behavior and its pattern have remained a mystery for mathematicians and scientists for decades. However, there has been a significant amount of successful studies for developing models for short-term prediction in the stock market (see the works of Gottschlich and Hinz (2014); Liao et al. (2012) and the references therein). Altay and Satman (2005) used an artificial neural network and linear regression for stock market forecasting. An interesting survey of stock market prediction was carried out by Atsalakis and Valavanis (2009), and Baralis et al. (2017) developed stock portfolios with the help of weighted frequent item sets.

The first wave of the COVID-19 pandemic ravaged the entire world's economy and hardly any country was prepared to tackle this devastating situation. As a result, the stock markets of each and every country experienced a sudden deep fall and many investors and retailers suffered huge losses. The impact of the COVID-19 pandemic on stock market returns has been and is being studied by scientists all over the world. For some noteworthy research in this vein, we refer to the works of (Al-Awadhi et al. 2020, 2021; Albulescu 2020; Dou et al. 2021; Engelhardt et al. 2020; Erdem 2020; Mazur et al. 2020; Rahman et al. 2021; Takahashi and Yamada 2020; Wilms et al. 2021; Zaremba et al. 2020; Zhang et al. 2020).

Almost after a year, when the pandemic seemed to be in control, the economy started to get back on track. However, then, the second wave of COVID-19 hit and cast a cloud of uncertainty on the stock markets. In such a situation, the investors and retailers are very fearful and confused as to when and where to invest their funds. It therefore becomes very important and essential to develop some mathematical model, which can address these investment queries during a global crisis. The objective is to prepare for the worst case scenario and still stay invested and procure capital gains.

In this paper, we develop a portfolio consisting of five sectors, including pharmaceuticals, petroleum, bank, software (IT) and metal.

This research will help new as well as seasoned investors to manage their own portfolio and generate better returns than mutual funds. Roughly around only 4.5% of the population of India invests directly in the stock market as compared to 54% in the U.S.A. and 10% in China, as of 2020. Such low retail investment in India is partly because of the lack of financial awareness and partly because of the deep risk that stock market investment involves. Our aim is to build a sustainable portfolio consisting of fundamentally strong sectors and companies, which perform well, even in toughest time and minimize the risk of financial loss. At the same time, the retailers can limit their dependence on mutual funds.

2. Methodology

Our main objective in this research is to allocate the total fund into different well-performing sectors and then allocate the sector-wise fund into fundamentally strong companies to maximize returns. In 2003, Rusu and Rusu (2003) suggested some efficient forecasting methods for stock market analysis, whereas a stock market portfolio recommender system was developed by Paranjape-Voditel and Deshpande (2013) in 2013. Recently, Maji et al. (2021) studied a portfolio management method by curve-fitting techniques. The methodology adopted in this research is developed on the basis of works in (Maji et al. 2021; Paranjape-Voditel and Deshpande 2013; Rusu and Rusu 2003).

We develop our model based on data from 1 January 2020 to 31 December 2020. We predict and compare our experimental results with popular mutual funds in the period of 1 January 2021 to 21 May 2021. The main reason for selecting such periods is to study the effect and impact of COVID-19 on stock market behavior and to create a portfolio that can encounter such global hazards and sustain in normal situations as well. In India, the first wave of COVID-19 hit the country in the month of January 2020 and started to decline by the end of the year. Hence, this period is considered to generate our initial data set. The second wave hit in the month of January 2021, reached its peak in April–May 2021 and started to decline at the end of May 2021. Thus, we use the period January–May 2021 for evaluation and comparison.

First, we find a curve of best fit for each of the companies by the method of least squares, using the data from 1 January 2020 to 31 December 2020. With the help of this best-fit curve, we predict the stock price closing value at the end of our evaluation and comparison period to justify the validity of our model. However, this prediction is crude, as we do not apply error estimation or correction.

Next, we cluster the top 4 companies within each sector with a positive growth rate in the specified period for diversified fund allocation. We cannot simply allocate all the funds to the top performing company or equally among all the companies. Hence, a mathematical formulation for the allocation is proposed.

Next, the growth rate of each company is calculated. Weights are set for the previous period stock prices. Further, the mean growth rates of the companies are calculated and then the net growth rate of all the sectors are obtained. The idea is to allocate a larger amount of funds to a sector with high growth and a lesser amount to the sectors next to it in terms of growth.

Given below is the step-by-step formulation of our methodology:

- Cluster sector wise:
  - (i) Cluster list companies into different industry sectors manually.
  - (ii) Associate each company to the sector to which it belongs.
- Company growth estimate:
  - (i) Find the estimated growth rate of the company using historical data.
  - (ii) Rank all companies with a positive growth rate.
  - (iii) For each sector, consider the top 4 companies.
- Sector growth estimate:
  - (i) Find the mean growth rate of the top 4 companies in the sector.
  - (ii) Rank all sectors with a positive growth rate.
  - (iii) Top 5 sectors are considered for fund allocation.
- Fund allocation:
  - (i) Fund is allocated among the selected top 5 sectors, proportional to their average growth rate.
  - (ii) Each sector-wise fund is again divided among companies, proportional to their growth rate.

3. Algorithm for Diversified Fund Allocation across Sectors and Companies

In the proposed methodology, the prediction of the current stock price is done on the basis of data from previous s months (in our case, $s = 12$). The month-wise weight (X_i) is used for predicting the stock price. It is to be mentioned that the weighting scheme uses linearly decreasing weights; the highest weight belongs to the last observation, the one preceding the value to be forecast. Then, X_1 with the smallest weight is the oldest observation. For the i-th month, it is calculated as follows:

$$X_i = \frac{2 \times (s - i + 1)}{s \times (s + 1)}. \tag{1}$$

The top performing sectors are identified by analyzing the results of these sectors from NSE web portal in the specified period. Top performing and fundamentally strong companies are then selected within each sector in a similar manner so that all companies are listed in the NIFTY 50 index during this period. All historical data of the stock prices were collected from the NSE (web portal: www.nseindia.com (accessed on 22 May 2021)).

We now present below the algorithm, step by step.

Step 1 Prediction of stock closing prices.

- (a) Identifying the curve of best fit.
  - (i) Collect the historical data of stock closing prices of a company for the specified period of 12 months. This is the initial data set for our model.
  - (ii) Find the curve of best fit using the method of least squares for the collected 12 month data.
  - (iii) The curve of best fit is chosen for which the root mean square error (RMSE) is minimal.
  - (iv) Predict the stock closing price for the end of the comparison period (i.e., when we would be interested in withdrawing the fund—in this case, after 5 months) as decided in the model.
  - (v) Repeat steps (i)–(iv) for each of the selected companies.

Step 2 Selection of companies within sectors.

(a) Choose a company from a particular sector.
(b) Find the percentages of the growth rate of the company of different time periods with respect to the month immediately prior. Suppose the growth rate between the i-th previous month and $(i-1)$-th previous month is p_i, where $i = 1$ to 12. Thus, p_i is the growth rate of the $(i-1)$-th time period with respect to the month immediately prior. Suppose that the growth rates of a company are $p_1, p_2, \ldots, p_{12}$ for the selected period of 12 months.
(c) Calculate company net growth rate (CNGR) by the following formula: $CNGR_l = X_1p_1 + X_2p_2 + \cdots + X_{12}p_{12}$, where $l = 1$ to m (for m number of companies within each sector).
(d) Repeat steps (a)–(c) for each company within the sector.
(e) Consider only the companies having a positive growth rate and discard the ones with a negative growth rate.
(f) Calculate the net growth rate of a particular sector by finding the mean of the growth rates of the companies within the sector.
(g) Repeat all the steps of step 2 for each sector.

Step 3 Allocation of funds.

(a) Sector-wise.
   (i) Find the sector multiplying factor (SMF) as follows: $SMF = \frac{100}{\sum_{i=1}^{n} G_i}$, where G_i is the growth rate of sector S_i, and n is the number of sectors (here $n = 5$).
   (ii) Find the sector-wise fund to be invested by the mathematical formula given by $SP_i = G_i \times SMF$, where SA_i denotes sector-wise % allocation. Thus, the sector-wise allocation is given by $SF_i = F \times SP_i$, where F denotes the total fund.
   (iii) Repeat steps (i)–(ii) for all the selected sectors.
(b) Company-wise: let each sector S_i consist of m number of companies $C_1, C_2, \ldots C_m$ with growth rates of $g_1, g_2, \ldots, g_m$ respectively.
   (i) Determine the company multiplying factor (CMF) by the formula $CMF = \frac{100}{\sum_{i=1}^{m} g_i}$.
   (ii) Find the company-wise fund allocation by the formula $CP_i = g_i \times CMF$ for company C_i, where CP_i denotes company-wise allocation %. Thus, company-wise allocation is given by $CF_i = SF_i \times CP_i$.
   (iii) Repeat step (ii) for all the companies.

4. Results and Discussion

In our experiment, we have collected the historical data of closing stock prices for 20 companies from 5 different sectors (4 companies from each sector). These data were collected from NSE for each of the 20 companies between 1 January 2020 and 31 December 2020. Similar data from 1 January 2021 to 21 May 2021 were used for validation, evaluation and comparison of the proposed portfolio with the performance of other popular mutual funds.

In this research, the currency unit is Indian rupees (INR). For simplified calculations, we have considered our total fund as F = INR 100,000. Such a fund will be useful for a new retail investor. Additionally, for a large fund, suitable scaling of this amount can be very easily done.

In our experiment, first we perform regression on every company's closing stock price from our initial data set and select the curve of best fit.

As an example, in Figure 1, we show the different trend lines fitted with the closing stock prices of Dr. Reddy's Lab (Pharma sector).

Figure 1. Trend lines for Dr. Reddy's Lab (Pharma Sector): January–December 2020.

The equation of the fitted trend line, R-squared error, RMS Error were calculated and are presented in Table 1. The same process was carried out for all the 20 companies, but for the sake of brevity, we display only one.

Table 1. Best fit curve and RMSE for Dr. Reddy's Lab (Pharma sector).

Curve Trend	Equation	R-Squared Error	RMS Error
Linear	$9.9548x + 2828.5$	0.8984	243.5023
Quadratic	$-0.0102x^2 + 12.53x + 2719.5$	0.9024	238.6897
Cubic	$-0.0002x^3 + 0.081x^2 + 3.2879x + 2916.3$	0.9114	334.6979
Logarithmic	$670.11 \ln x + 1042.8$	0.7078	412.9882
Exponential	$2920.1e^{0.0025x}$	0.882	263.5039

Our initial data are based on the closing stock price of all the selected companies from 1 January 2020 to 31 December 2020, which comprises a total of 252 working days in the Indian stock market. Further, our evaluation and comparison period for the experiment is from 1 January 2021 to 21 May 2021, which comprises 94 days. Thus, we find our predicted stock price for the 346th day (252 + 92 = 346) using regression. The best fit curve for each company along with its CNGR and predicted stock price are listed in Table 2.

Table 2. Curve of best fit and CNGR of the companies.

Sl. No.	Sector	Company Name	Curve of Best Fit	CNGR	Predicted Stock Price on 21.05.2120	Actual Stock Price on 21.05.2021
1	Pharma	Dr. Reddy's Lab	Quadratic	4.30124	5833.77	5216.45
2	Pharma	Sun Pharmaceuticals	Cubic	2.6818	497.6	690.4
3	Pharma	Divi's Lab	Exponential	2.1625	4863.2	4079.9
4	Pharma	Cipla	Cubic	3.5268	1021.502	926.9
5	Software	Infosys	Cubic	4.528	2376.92	1354.50
6	Software	TCS	Cubic	2.534	2071.6	3080.5
7	Software	HCL	Quadratic	3.24	2237.98	930.65
8	Software	Wipro	Cubic	4.512	401.52	512.7
9	Petro	Reliance Ind.	Exponential	5.2712	2888.44	2002.55
10	Petro	BPCL	Power	2.1074	359.55	461.05
11	Petro	ONGC	Quadratic	1.9271	151.58	112.75
12	Petro	Indian Oil Corp.	Cubic	1.524	76.65	104.3
13	Bank	HDFC	Exponential	4.109	1329.58	1497.3
14	Bank	ICICI	Exponential	2.1034	556.42	642.45
15	Bank	Kotak Mahindra	Exponential	2.5221	1626.84	1757.65
16	Bank	SBI	Power	4.212	184.66	401.2
17	Metal	Hindalco	Power	2.014	251.2	389.8
18	Metal	SAIL	Quadratic	2.84	59.8	122.0
19	Metal	Tata Steel	Exponential	3.1244	765.32	1113.1
20	Metal	Hindustan Zinc	Exponential	2.0127	251.32	344.55

Next, we perform the allocation of funds into multiple sectors by taking the mean of CNGR computed in Table 2 for each sector. This allocation is presented in Table 3.

Table 3. Sector-wise fund allocation.

Sl. No.	Sector	Sector Growth Rate (G_i)	% of Fund Allocated to a Sector ($SP_i = G_i \times SMF$)	Amount (Approx.) of Fund Allocated to Sector ($SF_i = F \times SP_i$) (in Rs.)
1	Pharma	3.1606	20.6482	20,648
2	Software	3.7035	24.1949	24,195
3	Petro	2.7074	17.687	17,688
4	Bank	3.2367	21.145	21,145
5	Metal	2.4977	16.3174	16,317

In Table 4, we provide the allocation of funds to each company based on their expected returns.

We assume that the allocated funds remain invested throughout the period from 1 January 2021 to 21 May 2021.

We further assume that no stocks were bought or sold during this entire period.

In Table 5, we present the absolute percentage return from each company, which in turn gives us the absolute percentage return from each sector. This table is used for our evaluation and further comparison of performance with popular mutual funds.

Table 4. Allocation of funds within companies.

Sl. No.	Sector	Company Name	Sector Fund	Company Growth Rate (g_i)	CMF	% of Sector Fund Allocated to the Company ($CP_i = g_i \times CMF$)	Amount of Fund (in Rs.) ($SF_i \times CP_i$)
1	Pharma	Dr. Reddy's Lab	20,600	4.30124	7.8911	33.941	6992
2		Sun Pharmaceuticals		2.6818		21.1629	4360
3		Divi's Lab		2.1625		17.0650	3515
4		Cipla		3.5268		27.83	5733
5	Software	Infosys	24,200	4.528	6.7503	30.5653	7397
6		TCS		2.534		17.1052	4134
7		HCL		3.24		21.87	5292
8		Wipro		4.512		30.4573	7371
9	Petro	Reliance Ind.	17,700	5.2712	9.2337	48.6726	8615
10		BPCL		2.1074		19.459	3444
11		ONGC		1.9271		17.795	3150
12		Indian Oil Corp.		1.524		14.0721	2491
13	Bank	HDFC	21,100	4.109	7.7239	31.739	6697
14		ICICI		2.1034		16.2464	3428
15		Kotak Mahindra		2.5221		19.48106	4111
16		SBI		4.212		32.533	6864
17	Metal	Hindalco	16,300	2.014	10.0089	20.1579	3286
18		SAIL		2.84		28.4252	4633
19		Tata Steel		3.1244		31.2718	5097
20		Hindustan Zinc		2.0127		20.1449	3284

Table 5. Absolute % return from 1 January to 21 May 2021.

Sl. No.	Sector	Company Name	Closing Price on 01.01.2021	Closing Price on 21.05.2021	Absolute % Return in This Period	Return from Allocated Fund (in Rs.)	Average Sector Absolute % Return
1	Pharma	Dr. Reddy's Lab	5241.35	5216.45	−0.48	−34	8.36
2		Sun Pharmaceuticals	596.25	690.4	15.79	688	
3		Divi's Lab	3849.05	4079.9	6	211	
4		Cipla	826.6	926.9	12.13	695	
5	Software	Infosys	1260.45	1354.5	7.46	552	10.67
6		TCS	2928.25	3080.5	5.2	215	
7		HCL	950.5	930.65	−2.09	−111	
8		Wipro	388.1	512.7	32.11	2367	
9	Petro	Reliance Ind.	1987.5	2002.55	0.76	65	14.11
10		BPCL	381.95	461.05	20.71	713	
11		ONGC	93.2	112.75	20.98	661	
12		Indian Oil Corp.	91.5	104.3	13.99	348	

Table 5. *Cont.*

Sl. No.	Sector	Company Name	Closing Price on 01.01.2021	Closing Price on 21.05.2021	Absolute % Return in This Period	Return from Allocated Fund (in Rs.)	Average Sector Absolute % Return
13	Bank	HDFC	1425.05	1497.3	5.07	340	14.65
14		ICICI	527.5	642.45	21.79	747	
15		Kotak Mahindra	1994.05	1757.65	−11.86	−488	
16		SBI	279.4	401.2	43.59	2992	
17	Metal	Hindalco	238.35	389.80	63.54	2088	61.12
18		SAIL	74.5	122	63.76	2954	
19		Tata Steel	643.10	1113.10	73.08	3725	
20		Hindustan Zinc	239.05	344.55	44.13	1449	

5. Conclusions

In conclusion, we compared, quantitatively, the performance of our proposed portfolio with some popular mutual funds that have rendered high returns over the years (presented in Table 6 and Figure 2). The performance data of the mutual funds in the said period were collected from their respective web portals. The absolute percentage return by our proposed portfolio was found to be 21.78, which is the average of the 'average sector absolute % return' as given in Table 5.

Table 6. Comparison of the performance of the proposed portfolio with popular mutual funds.

Time Period	Absolute Return by our Proposed Portfolio (%)	Absolute Return by HSBC Large Cap Equity Fund Direct Growth (%)	Absolute Return by ICICI Prudential Technology Direct Growth (%)	Absolute Return by Axis Bluechip Fund Direct Plan Growth (%)	Absolute Return by Tata Digital India Direct Growth (%)	Parag Parikh Flexi Cap Fund Direct Growth (%)
1 January 2021 to 21 May 2021	21.78	6.62	14.31	4.85	14.95	16.22

We can observe that our proposed portfolio performs quite well during the global pandemic and gives much higher returns as compared to many in-demand mutual funds.

The fact that this research does not cover a longer time frame, such as 3 or 5 years, and the performance is evaluated and compared for only 5 months of investment may be contemplated as a limitation. However, our main idea is that, if this model can sustain in this current global pandemic situation, it has a very high plausibility of sustaining when normalcy is restored. Our experimental results indicate that the proposed portfolio generates higher returns than most of the well-established mutual funds. Although this research was carried out in the context of the Indian stock market, such a sector-wise model and methodology is likely to be compatible with the global market as well since stock markets around the world behaved quite uniformly during this pandemic.

Finally, we can conclude that a well-researched and scientifically generated portfolio is capable of surviving the global pandemic situation and provide better returns, even though the market is very sensitive. It is to be noted that the return could further be maximized by the expert investors if they sold certain shares in their peaks and bought the same at dips. In our experiment, we avoided such practices for simplicity. All the details of the calculation are submitted as supplementary materials. Additionally, it is to be noted that in our proposed portfolio, we did not include any company which deals in alcohol or tobacco products. It is observed that the second wave of COVID-19 was not as damaging as the first wave, as the countries were better prepared this time to counter the situation. It will be a very interesting future study to extend this research further by covering a longer time frame to measure the impact of the expected third wave of COVID-19 and also validate this portfolio when normalcy is restored.

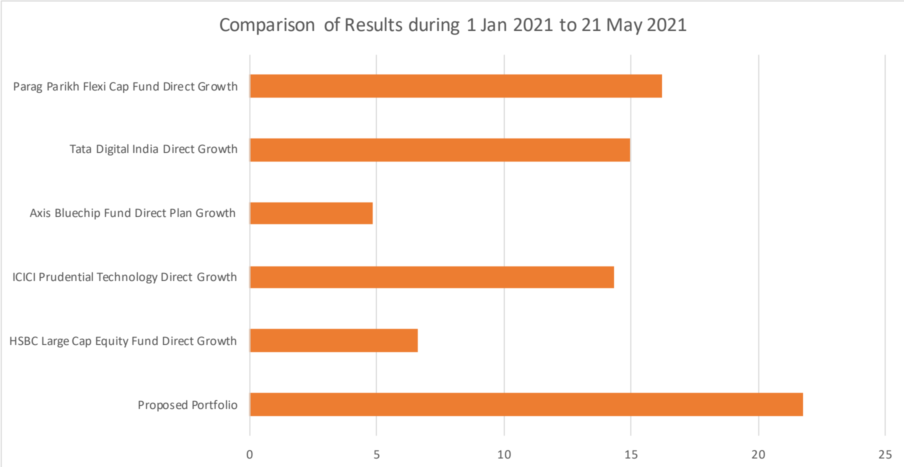

Figure 2. Comparison of the performance of the proposed portfolio with other mutual funds.

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