Examining Asymmetric Volatility Dynamism of Returns in the Infrastructure Sector in India during Covid 19: - A application of GARCH Models

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Abstract

Due to global shut down of economic activities and transportation, the infrastructure sector has to see a halt in operations due to disruptions in supply chain, impacting international investors as they became cautious of their investment position. The study is aimed at modelling the volatility of the returns in the infrastructure sector in India using S&P BSE Infrastructure Index during Covid-19 by applying univariate stipulations of the GARCH family of models such as GARCH (1,1), EGARCH (1,1), MGARCH (1,1). The study found the presence of asymmetric effects indicating that the arrival of Covid 19 news created more turmoil in the market. Also, significant relationship has been observed between the magnitude of variance and returns, meaning thereby the global investors, while making portfolio decisions, should emphasize that high risk implies high returns holds true for Infrastructure sector in India. The study suggests that the investors, while estimating value at risk, should consider that the infrastructure returns depict higher persistence level and the past volatility of the returns in the infrastructure sector has a significant impact on current volatility in case of BRICS economies.

Keywords: Volatility dynamism, Covid -19, Risk, Infrastructure sector, Return, Management

JEL codes: G10, G11, G17, D81, O18

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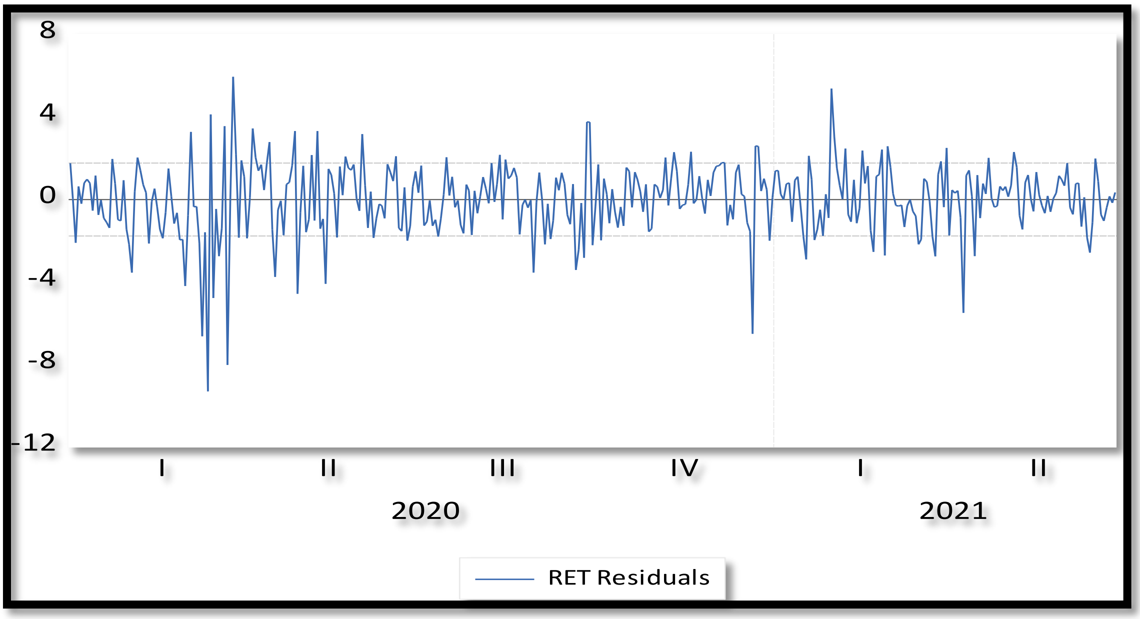
Introduction

The spread of Covid-19 has impacted different sectors of the economy. The wave of the Covid 19 spread has brought both physical and financial impact on the economies. The impacts are seen in the increase in idiosyncratic risk across industries (Baek et al., 2020). Also, the appearance of news of Covid 19 has different repercussions on different sectors (Albuquerque et al., 2020). Owing to the increase in the spread of cases, the Government authorities had to impose a 21days nationwide lockdown on 23rd march 2020 in India. This resulted in a halt in every economic activity of the nation. The infrastructure sector of India, too, noticed a complete shut in the activities such as design & engineering, soil & road construction, maintenance, traffic management, environmental engineering, etc. This adversely impacted the trading of the stock market. Sensex and Nifty plunged to the lowest level due to the rise in the number of cases and the ongoing situation of turmoil everywhere around the world. Even during the second wave of Covid-19 noticed in India and immediate calibrated lockdowns as a measure to curb the further spread, determined by the states, has an impact on the sectors of the nation. Risk and uncertainty are two important considerations hovering over the stock market. In an effort to measure the likely impact of the risk and uncertainty, and understanding the behavior of the volatility of returns generated by the stock market is important. Volatility can be generated by many reasons such as the arrival of any news, information, differences in the opinions and expectations of investors, etc., so the mere understanding of these factors affecting volatility will help the investors to reduce the degree of uncertainty and risk in order to form investment strategies. Since the infrastructure sector has a huge influence on the economic fundamentals of the nations, in order to make investment strategies, an understanding of the specific sectors of the nation is necessary. This study holds significance as the knowledge of the volatility of a particular sector helps the investors to estimate the value at risk while making portfolio decisions. Also, only a few studies have existed so far concerning the influence of Covid-19 on the infrastructure segment in India.

Volatility clustering

The returns series shows volatility clustering signifying the behavior of the time-series data to cluster around in a manner that high volatilities are followed by noticeable large changes in the data and small volatilities are followed by evident small changes.

Fig. 1:- Graph showing volatility clustering



The highest volatility clustering has been found in the infrastructure sector during the first quarter of 2020. Beginning from February, the volatility increased due to an increase in fear of the spread of Covid-19 outside chine leading to the biggest fall in the Dow Jones Industrial Average. Also, on 12th March, stock prices fell as WHO declared Covid-19 as a pandemic. Other subsequent reasons adding to volatility in the infrastructure sector include the 21-day nationwide announcement of lockdown restricting the movement of goods and people and activities limiting to bare essentials only in India. Another volatility clustering in the infrastructure sector has been observed on 30th March 2020 owing to the biggest fall in oil prices to lowest 6% due to fall in global oil demand. Thus having impact on Indian infrastructure sector too.

Review of literature

The research world is full of studies conducted on the impacts of an ongoing pandemic on the functioning of different sectors of economies. Some studies focus on examining the possible impacts on the stock markets due to an increase in the number of cases and deaths; some studies examined the impact of sudden announcements such as declaring covid-19 as a pandemic, imposing lockdowns, any big policy changes having a bearing on the economic fundamentals and thereby impacting the financial markets. Some of the past studies conducted in several nations are as follows.

Table 1: Snapshot of studies on the impact of Covid-19 on stock markets of economies

Author(s)	Nation(s)	Sector	Tools	Conclusion
1. Banumathy and Azhagaiah (2015)	India	S&P CNX Nifty Index	GARCH extension models	Presence of Leverage effect, the insignificant relationship between variance and return
2. Baek et al. (2020)	US	Telecom, utilities, automobiles, and business equipment industries	Markov Switching AR model	Negative news impacts volatility more as compared to positive news
3. Albuquerque et al.(2020)	US	Environmental and Social	CAPM	Lowest volatility in the returns from higher-rated Environmental and Social firms
4. Awadhi et al.(2020)	China	Commerce, public utility, finance, conglomerates, industrials, and property.	Panel data regression	Air, water & highway transportation, and beverages showed worse performance, and the returns of IT and medicine performed considerably better than the benchmark.
5. Bildirici et al.(2020)	Russia and Saudi Arabia	Crude oil	GARCH and LSTARGARCH methods	Oil prices exhibit ARCH and GARCH effects
6. Bhatia and Gupta (2020)	India	Banking sector	EGARCH model	The presence of leverage effect is more in case of subprime cases period as compared with Covid period
7. He et al. (2020)	China	Education, transportation, mining, electricity, environment, manufacturing, IT, and healthcare industries	Event study	Adverse impact on mining, transportation, electricity, environment and heating, sectors. Whereas, the positive response has been shown by IT, education, manufacturing, and health industries during pandemic providing a boost up to confidence in the market
8. Ali et al. (2020)	US, China & Europe	Financial markets(Equity, Debt,	EGARCH model	China remained relatively calmed during Covid, whereas European

		Bitcoin, Gold, Oil)		regions faced increased volatility during the pandemic
9. Ozturk et al.(2020)	Europe	Real Estate, Paper, Printing, Wood, IT, Investment, Banking, and Basic Metal sectors	Fixed effect model	Less affected sectors were Food beverage, Real estate, wholesale & retail trade. While banking, basic metal products, sports, machinery, and insurance sectors saw adverse effects in returns
10. Haroon and Rizvi (2020)	US	23 sectoral indices	EGARCH model	The strongest impact has been observed in increasing volatility due to media coverage in the auto, energy, transport, and travel industries
11. Shibila and Jayarajan (2021)	India	Pharma, IT, Auto, Banking, FMCG, metal, energy, Oil & Gas,	Event study	Negative effect on sectors due to increase in fatality cases

Investors keep a watch on the scenario of the infrastructure growth while making investment decisions. No earlier attempt has been made to determine the relationship between volatility and returns in the infrastructure sector in India so far. This study holds importance to understand the comprehensive view of volatility and diagnosing its asymmetric behavior with respect to size and sign effect during the pandemic.

Objectives of the study

1. To analyze the volatility of returns with respect to conditional, persistence, and news sensitivity during in infrastructure sector Covid-19.
2. To examine the asymmetric volatility with respect to size effect and sign effect of returns in infrastructure sector during Covid-19.
3. To understand the risk and return relationship between the returns in infrastructure sector during Covid-19.

Research Methodology

In order to apply ARCH, which is a univariate model, the returns values have been computed after the conversion into Inlog series. The S&P BSE infra index returns has been used as a proxy for market returns of infrastructure companies. The Index has been designed, including the top 30 Indian infrastructure companies by BSE in 2014. The daily returns from 1st January 2020 to 30th June 2021 have been taken for the study since the World Bank declared the first Covid case on 31st December 2019. After validating the presence of the ARCH effect, the study has employed the Generalized Autoregressive Conditional Heteroscedasticity GARCH(1,1), Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH), and Multivariate MGARCH(1,1) model in order to understand the nature of volatility with respect to persistence, shock or news, the presence of asymmetric volatility and risk-return relationship in returns during Covid19.

Methodology of modeling volatility

ARCH (1, 1) model

The ARCH model has been developed by Engel in the year 1982 in order to forecast the volatility of the return, which is based on past volatility. The ARCH model is premised on the fact that series has a variance, which is time-varying (heteroscedasticity) conditional on lagged values (autocorrelation). The term volatility has been explained as a function of errors. These errors represent any sudden shocks or news. ARCH model is concerned about modeling the volatility of the variance of the returns series. The variance is time-varying. Conditional variance is dependent on its past variance.

$$\mathbf{Y_t = k + u_t \ldots\ldots (1)}$$

$$\mathbf{u_t \sim iid\ N(0, S_t{}^2) \ldots..(2)}$$

$$\mathbf{S_t{}^2 = b0 \ldots\ldots. (3)}$$

Eq. (1) is a mean equation, Where Y_t is represented as the mean (k) of the series and adding an error term, u_t. Eq. (2) u_t is normally distributed with k= 0 and variance $S_t{}^2$. Eq. (3) $S_t{}^2$ is variance which is constant as b_0, and the t denotes that variance changes with time. The ARCH model proposes certain adjustments as follows;-

Let the error variance be time-variant, i.e., heteroskedastic as h_t

$$\mathbf{S_t{}^2 = h_t}$$

so the basic ARCH(1,1) process and variance equation will be

$$\mathbf{h_t = b_0 + b_1\, u_t{}^2{}_{-1} + u_t}$$

h_t is time variance and represented as a function of a beta term which is constant, and $b_1\, u_t{}^2{}_{-1}$, which is squared error of the previous term, one lagged period, implying that due to shock in the previous day, the likely value of u_t will also be large. And when $u_t{}^2{}_{-1}$ is small/big, the variance of the next period u_t will also be small/big. The coefficient of b_0 and b_1 should be positive in order to ensure a positive variance. B_1 should be less than one; otherwise, h_t will continue to rise. Also, b_1 should be positive as the squared error term contains a positive serial correlation. b_1=0 implies that the volatility is not time-variant, while b<1 signifies time-varying variance.

GARCH (1, 1) model

The extension of the ARCH model is the GARCH model, propounded by his student Bollerslev in 1986. They were of the view that the volatility of the stock market data is time-variant and tends to be clustered. The simplest specification of the GARCH (1,1) model is

$$h_t = b_0 + b_1 u^2_{t-1} + b_2 u_{t-1} \ldots\ldots\ldots\ldots (4)$$

The above GARCH eq. (4) is defined as the summation of squared residuals of past series and the lagged variance conditional on past series.

EGARCH (1, 1) model

The exponential GARCH Model was developed by Nelson(1991) based on the fact that GARCH suffers from underlying weakness as it assumes that the volatility is symmetric in nature, denoting equal impact of both positive and negative news on conditional variance (Ekong & Onye, 2017; Magweva & Sibanda, 2020). Along with measuring the asymmetry, EGARCH accommodates for the examination of leverage which states that negative shocks give impetus to volatility more as compared with positive news. With bad news, the asset leans towards the state of turmoil, subsequently ensuing in increasing the volatility. And with the arrival of good news, the asset tends to enter in the position of tranquillity and thereby reducing the volatility. EGARCH will be used to study the leverage effects and to confirm the asymmetric impacts of positive and negative news in the infrastructure sector of the Indian economy.

The conditional variance equation for EGARCH can be specified as

$$\text{Log}(h_t) = \mu_0 + \mu_1 \left| \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}} \right| + \mu_2 \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}} + \mu_3 \log(h_{t-1}) \ldots\ldots\ldots\ldots\ldots (5)$$

The eq. (5) consists of Log (h_t) is the conditional variance of the index returns in logarithmic form, which is exponential hence ensuring that the estimates are positive. $\dot{\varepsilon}_t$ is the disturbance term. μ_0 represents the constant coefficient of volatility. The μ_1 is ARCH effects. $\mu_2 \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}}$ It is representing the asymmetric effect of volatility. $\mu_2 \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}}$ Indicates the impact of the arrival of news on the volatility. Negative μ_2 is indicative of the presence of leverage effect and the positive μ_2 indicates the reverse volatility asymmetry. The effect is symmetric if the $\mu_2 = 0$. The impact of the news (bad or good) can be measured in terms of magnitude and sign. $\mu_1 \left| \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}} \right| + \mu_2 \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}}$ together constitute the influence of the shock on the volatility in the infrastructure sector returns, whereby, $\mu_1 \left| \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}} \right.$ is indicative of the size effect of the news and $\mu_2 \frac{\dot{\varepsilon}_{t-1}}{\sqrt{h_{t-1}}}$ Is indicative of the significant effect of the news.

M GARCH (1,1) model

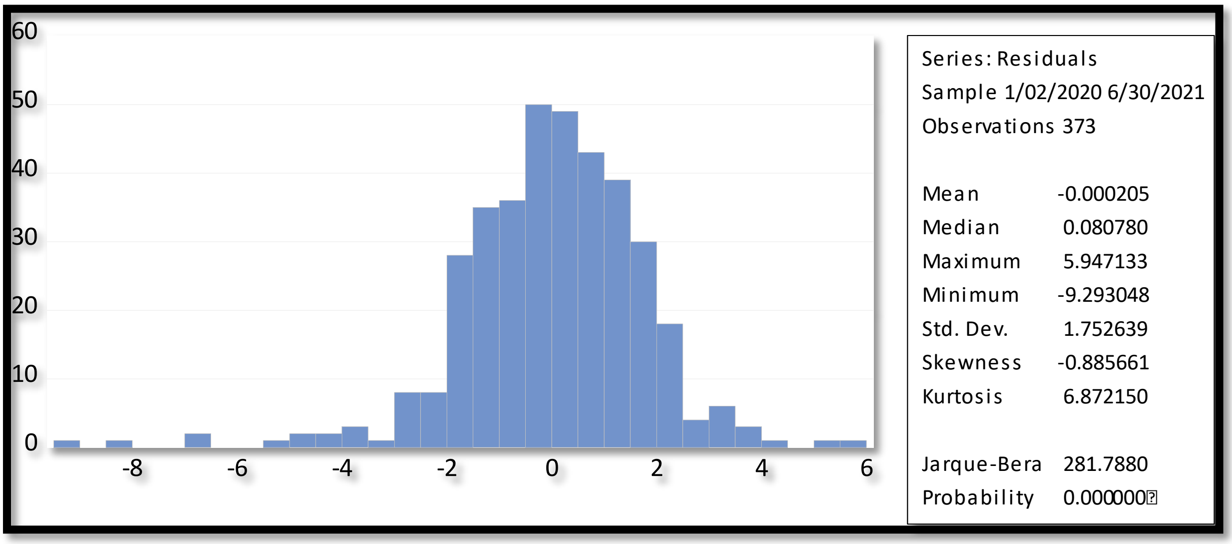
According to Bollerserve (1990), MGARCH model can be used to estimate time-varying coefficients of beta**.** In financial econometrics, high returns are the consequence of taking high risks. M GARCH model has been developed to find the relationship between volatility and returns. The equation estimating the MGARCH (1, 1) can be defined as:

$$R_p = \alpha + \beta_1 Y_{t-1} + \beta_2 u_{t-1} + \beta_3 S^2_{t-1}$$

Rp is the return from the portfolio. β_3 is the impact of variance on the returns.

Results and interpretation

Fig. 2:- Histogram plot of S&P BSE Infrastructure index returns



The returns data shows the maximum variations in the returns are found on the left side of the data. Hence all the returns are negatively skewed. The jarque Bera test confirms that the returns are not a normal distribution. Also, the value of kurtosis is greater than 1, indicating that that the data is considered nonnormal (Hair et al., 2017). The above parameters satisfy the conditions of financial data.

Table 2: Stationarity check

	t-Stat	Prob.*
ADF test statistic	-5.897627	0.0000

In order to apply and validate the ARCH family of models, the ADF test has been applied in order to check the mean-reverting behavior of data. Since the results confirm the absence of unit root, hence we moved further to estimate the fitness of the conditional mean equation. The conditional mean equation follows the Auto Regressive Moving Average (ARMA) model. $Rt = \beta Rt{-}1 + \varepsilon t + \lambda \varepsilon t{-}1$

Where Rt representing the S&P BSE infrastructure sector returns, and ε is the error, Akaike information criterion (AIC) has been selected to determine the optimal lag length in the above mean equation.

Table 3: Testing for ARCH effects

F-stat	7.399434	Prob. F (1,365)	0.0068
Obs R-squared	7.292149	Prob. Chi-Square (1)	0.0069

The results shown above depict that the time series data contains the presence of the ARCH effect, which measures the volatility clustering; hence we can employ the GARCH extensions model so as to understand the behavior of returns in the Indian Infrastructure sector.

Table 4: Estimating GARCH (1,1), EGARCH (1,1) and MGARCH (1,1)

GARCH(1,1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.241071	0.088842	2.713475	0.0067
AR(1)	0.178660	0.051577	3.463933	0.0005
Variance equation				
C	0.104077	0.066521	1.564585	0.1177
(b1)	0.091550	0.031453	2.910672	0.0036
(b2)	0.864228	0.051599	16.74889	0.0000
EGARCH(1,1)				
C(3)	-0.084033	0.037856	-2.219816	0.0264
C(4) (size effect)	0.144999	0.053743	2.698008	0.0070
C(5)(sign effect)	-0.068536	0.025004	-2.740992	0.0061
C(6)	0.960491	0.020759	46.26868	0.0000
MGARCH(1,1)				
GARCH	0.037691	0.056727	0.664418	0.5064
C	0.094701	0.164656	0.575143	0.5652
AR(1)	0.161444	0.059557	2.710722	0.0067
Variance equation				
C	0.424057	0.160088	2.648892	0.0081
RESID(-1)^2	0.203423	0.053660	3.790997	0.0002
GARCH(-1)	0.667498	0.089941	7.421475	0.0000

The GARCH (1,1) estimates showing the mean equation as:-

S&P BSE Infrastructure index =0.241071+ 0.1787r_AR (1). The mean equation representing the average index returns is positive and significant. Its past value is also significant at the 1% level, indicating that the historical values have the potential to predict the values at present. Based on above table, GARCH model can be written as

$$\mathbf{h_t = 0.104077 + 0.86\ 4_{t-1} + 0.0915\ e^2_{t-1}}$$

The fluctuating volatility contains a constant (0.104077), its historical lagged value (0.86 4_{t-1}), and an element that depends on previous squared errors (0.0915 e^2_{t-1}). All the stability conditions of the coefficients of conditional variance i.e $0<b_1<1$, $0<b_2<1$ and $b_1 + b_2<1$ have been met in the model. So we can say that the volatility is decaying. Also, $b_2 > b_1$ gives us an indication that the persistence level of the shocks in volatility is large, as represented by ($b_1 + b_2$). It signifies that the volatility in the returns is due to persistence; thus, the effect of shock at present-day significantly predicts the variance for a long time in the future. The findings clearly establish the presence of time-varying conditional volatility of the returns of the S&P BSE Infra index.

EGARCH (1,1) model to allow for estimating the asymmetric effect between the stock returns. C(3) is constant. C(4) and C(5) both represent the impact of the shock. The size effect of the news represented by C(4) is 0.1449, and the significant effect of the news represented by C(5) is -0.068536. in exponential terms, C(5)= $\mu_2 = e^{-0.068536} = 0.9337$. C(6) representing GARCH term is 0.960491. The shock has a significant impact on the volatility. C(5) representing that the negative news breed more volatility than the positive news in the infrastructure sector returns. A similar conclusion has been obtained by Baek et al. (2020). It also tells sign effect representing the inverse relationship between the error term and volatility. So if there is positive news, it has a decreasing impact on the volatility. It further states that positive information will decrease volatility. The GARCH coefficient is very high, indicating that volatility persistence is very high, showing that the market remained volatile for a longer period during the Covid time.

MGARCH estimate depicts whether the impact of volatility on return is significant or not. We found that the impact of variance on volatility is significant since the prob. value is less than 0.05. This implies that the impact of variance on the returns is significant to validate a risk-return relationship in the returns. A similar result has been shown by Similar evidence has been obtained by Banumathy and Azhagaiah 2015; Duttilo et al. (2021).

Conclusion

The study has analyzed the volatility of returns with respect to GARCH effects, level of persistence, and asymmetries caused by Covid-19. The reason for the volatility is due to persistence. During Covid-19, the infrastructure sector of India has shown that the impact of any news, whether positive or negative, volatility has remained for a considerable period of time. Thus the volatility of the infrastructure returns in India is the outcome of news or shock in the market. Also, the high degree of volatility persistence has been detected in the reruns series, signifying that volatility takes some time to fade out from the market. This will help the investors in predicting the nature of volatility while making portfolio investment decisions in the specific sectors of the Indian economy. Both the size effect and the significant effect of the news had a significant impact on the volatility of the returns in the infrastructure sector during the Covid times. The study found the presence of the asymmetric effect of positive and negative news in the market. The negative news increases the volatility, and the positive news decreases the volatility in the infrastructure sector. MGARCH model has been used to understand the relationship between volatility and return in the infrastructure sector. The current study also found that significant and positive relationship exists between the variance and the returns in the infrastructure sector during Covid-19.

Implications of the research

An understanding of the specific sectors of the nation is necessary in order to make investment strategies. The current research will help investors across the globe to understand the volatility dynamism of the Indian Infrastructure sector. The presence of leverage effect in the returns in the infrastructure sector signifies that investors should be cautious when they see the arrival of negative news in the market. Also, while making portfolio investment decisions, higher variance in the returns of the portfolio generates higher returns holds true for the infrastructure sector. Also the asymmetric nature of volatility gives the signal that negative news breeds panic in the infrastructure sector as compared to positive news.

Scope for future research

The study was focused on only the infrastructure sector of India. In the future, an inter-sectoral comparison can be made by taking the returns from other sectors of the Indian economy such as pharmaceutical, energy, education, etc.

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