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Extreme Value Theory and COVID-19 Pandemic: Evidence from India

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Abstract:
The COVID-19 pandemic has become major problem for financial markets and world economy. In this paper we investigated the extreme tail behavior of NIFTY 50 index during the COVID-19 pandemic. The extreme behavior of the stock market is examined through GPD model by suing high frequency data (5-min interval) of log returns ranging from 11th March 2020 to 30th Sept 2020 which provide more precise description of NIFTY 50 tail distribution in the pandemic period. The result indicates GPD give a real picture of uncertainties associated with COVID-19. The finding of study will assist in decision making to monitor COVID-19 impact on financial markets.

Keywords: COVID-19, Extreme Value Theory, Generalized Pareto Distribution, Value at Risk, NIFTY 50

JEL classification: C55, C58, G15

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1. Introduction

COVID-19 has spread across the world in 216 countries and affected millions of lives with 87,589,206 confirmed cases and 1,906,606 deaths as at 9th January, 2021. The global economy and activities are extremely affected by the catastrophic COVID-19 pandemic. The fear associated with COVID-19 has indirectly affected financial markets and their respective risk (Aslam et al., 2020a; Zhang et al., 2020).

A strong response has been reported in the global financial markets against the COVID-19 pandemic (Alexakis et al., 2021; Aslam et al., 2020b; Aslam, et al., 2020c; Aslam et al., 2020d;

Baker et al., 2020; Erdem, 2020; Mazur et al., 2020; Narayan et al., 2021). The evidence shows that the COVID-19 has a higher impact on the Asian emerging markets as compared to European markets (Topcu and Gulal, 2020).

In Asia, India has become an epic center with the highest confirm cases 10,413,417 and 150,570 deaths as of 9th Jan 2021. Among Asian markets, the Indian stock market shows the most volatile behavior (Chaudhary et al., 2020a; Mishra et al., 2020), and experienced a significant declined in stock returns at the beginning of COVD-19 lockdown from 24th March 2020 to 6th March 2020 . Despite this, the Indian stock market is the most attractive market for international investors (Chhimwal and Bapat, 2020) with a market capitalization of $2.5 trillion. Therefore, the aim of this paper to investigate the impact of COVID-19 on Indian stock market risk.

Economic activities in India have been severely affected by the COVID-19 pandemic (Ozili and Arun, 2020). The evidence shows that the Indian GDP dropped by 18% in the April-June quarter.[1] Particularly, the Indian aviation sector contributes up to $72 billion to the country's GDP and due to the COVID-19 lockdown, a decline of 25% has been estimated in this particular sector (Chaudhary et al., 2020b). The Indian economy was struggling even before the pandemic and the COVID-19 lockdown created high unemployment and increased poverty in the country (Kapoor, 2020). Moreover, the Indian stock market has shown volatile behavior and negative returns during the pandemic (Mishra et al., 2020a).

Historically, various methods have been adopted to examine tail behavior and the associated risk, such as CAViaR (Kwon, 2020), the block maxima approach (Szubzda and Chlebus, 2020), GARCH (Horvath and Šopov, 2016) or copula models (Li, 2017; Liu et al., 2019). The probability of a black swan effect is a major concern of researchers in the field of risk management. The Generalized Pareto Distribution (GPD) model is considered an effective method to provide relevant information regarding extreme losses (Jakata and Chikobvu, 2019), especially in a crisis period. Andreev et al. (2009) examined the tail distribution of RTS index returns using Peak Over Threshold (POT) and GPD models, finding that the GPD model is a better estimator of extreme risk than other risk estimation methods.

Recent literature has documented significant negative financial impacts of the Covid-19 outbreak (Ashraf, 2020; Aslam et al., 2020b; Topcu and Gulal, 2020). The NIFTY-50 index has experienced its worst losses since 2014 due to the COVID-19 lockdown. However, no study focuses particularly on the tail behavior of the Indian stock market during Covid-19. This study contributes to the existing literature on Extreme Value Theory (EVT) in relation to the NIFTY-50 index using GPD. In particular, it provides assistance to investors, financial analysts and policy-makers in monitoring and tackling market risk associated with the COVID-19 pandemic.

This research is designed as follows. The next section provides a brief description of the data followed by models and then a discussion of the results and the conclusion.

2. Data

COVID-19 was officially declared as a global pandemic on 11th March 2020 by the World Health Organization (WHO) (Mamaysky, 2020). In order to examine the extreme tail behavior of the

[1] India faces worst quarterly GDP slump ever after lockdown By Anirban Nag and Vrishti Beniwal https://www.bloomberg.com/news/articles/2020-08-30/india-s-economy-faces-worst-quarterly-slump-ever-after-lockdown

Indian stock market during the COVID-19 pandemic, we use high frequency data (5-min interval) of the NIFTY-50 index. The data range from 11th March 2020 to 30th September 2020 and were obtained from dukascopy.com. The intraday log return of the NIFTY-50 index is calculated by:

$$r_t = \ln(S_t) - \ln(S_{t-1}) \quad (1)$$

Table 1 and Figure 1 illustrate the behavior of NIFTY-50. The Indian market showed significant volatility, with fluctuations ranging from 0.095 to -0.097. Intraday average returns of NIFTY-50 are close to zero, as expected, with a value of 0.001%. The kurtosis of the stock market is extremely high (Kurtosis = 404) with the distribution showing a positive skewness of 1.16, which suggests fat tail behavior of returns.

Table 1 - Summary statistics of NIFTY-50 index

Variable	Statistics
Mean	0.00001
S.D.	0.0028
Skewness	1.1654
Kurtosis (Excess)	404.93
Max	0.0952
Min	-0.0969
Observation	13133

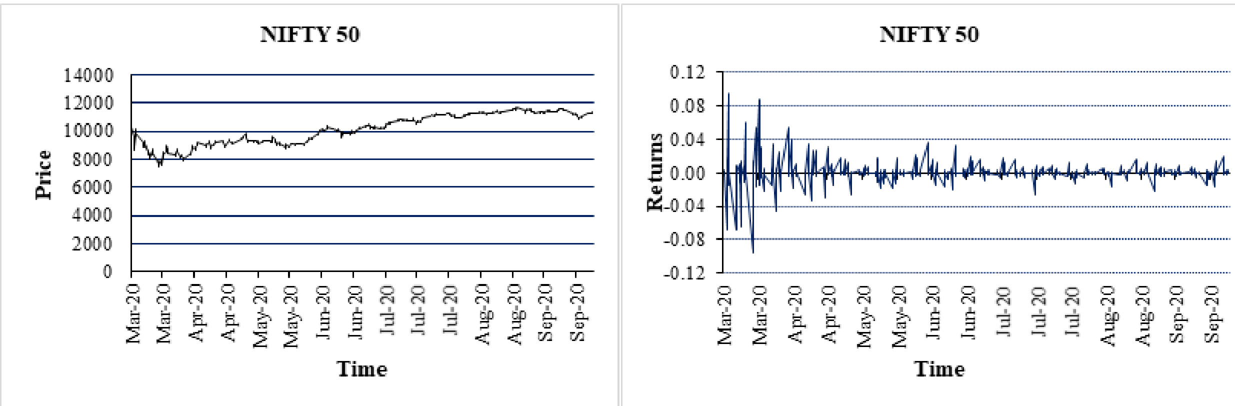

Figure 1 - Price trend and returns fluctuation of 5-minute frequency for NIFTY-50 index

3. Extreme Value Modeling (EVT), Generalized Pareto Distribution (GPD) and Peak Over Threshold (POT)

EVT has two main approaches to risk modeling: Block Maxima and POT (Dombry and Ferreira, 2019; Jin-Cheng, 2017) with the POT approach being considered as the most effective method for modeling extreme events. Therefore, we applied POT to analyze the tail behavior of the Indian stock market during the COVID-19 pandemic.

The objective of the POT method is to examine all intraday returns of the NIFTY-50 index and model all extreme returns which exceed a specified threshold u, while fitting the extreme returns above threshold u to the GPD.

The GPD function is represented by:

$$G_{\xi,\beta}(y) = \begin{cases} 1 - \left(1 + \xi \frac{y}{\sigma\beta}\right)^{-1/\xi} & \xi \neq 0 \\ 1 - e^{-y/\beta} & \xi = 0 \end{cases} \tag{2}$$

The extreme returns above threshold u developed a conditional excess distribution which is further employed to quantify tails and affiliated tail risk.

For a random variable X with distribution function F, the excess distribution above threshold u is represented by:

$$F_u(y) = P(X - u \leq y | X > u) = \frac{F(y+u) - F(u)}{1 - F(u)} = \frac{F(x) - F(u)}{1 - F(u)} \tag{3}$$

While the VaR of extreme value can be defined by

$$VaR_p(V_p) = F^{-1}(1 - p) \tag{4}$$

The inverse distribution function, also known as the quantile function, is represented by F^{-1}. VaR was subject to major criticism due to the inability to capture losses beyond a specified quantile, and therefore the expected shortfall (ES) tool is presented by Acerbi and Tasche (2002) and satisfies the criteria of capturing losses beyond VaR, being equal to:

$$ES_p = E(X | X > V_p) \tag{5}$$

4. Empirical result and discussion

The threshold for the extreme left tail distribution is estimated through the lower 5% quantile level, which satisfies the GPD condition. Figure 2 shows the mean excesses of intraday returns of the NIFTY-50 index. The value of the selected threshold by using a lower 5% quantile level is $u = 0.002$ for left tail distribution. As shown in Figure 2, the linear shape of the threshold (Positive Slope) shows an upward linear trend, the total exceeding observation above threshold u is equal to 657 observations and the most extreme value was observed on 23rd March with a value of 0.096.

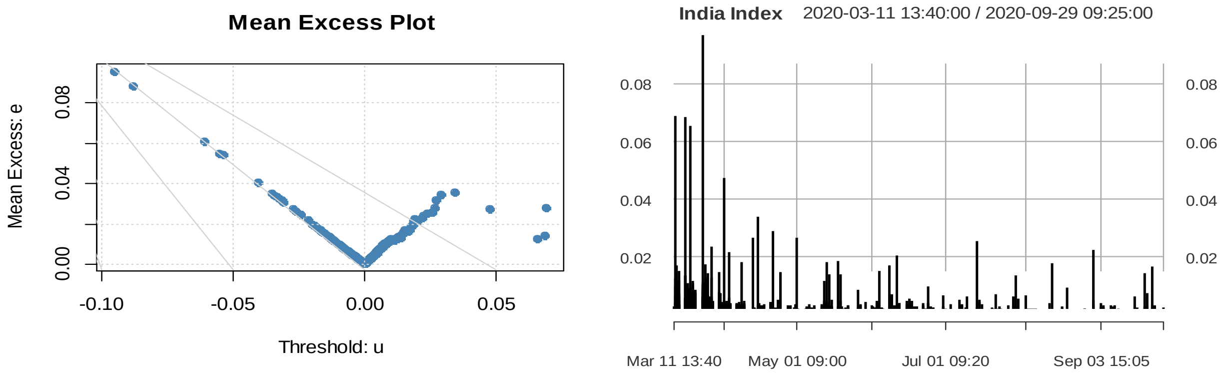

Figure 2 - Mean excess plot (left) and excess values (right) of NIFTY-50 over the threshold

Then, we move further towards GPD tail modeling of the NIFTY-50 index. Figure 3 shows the GPD graphs for NIFTY-50, based on high frequency returns (5-minute). The lower level of 5% high-frequency returns was fitted to GPD by applying maximum likelihood estimation (MLE). The result of MLE of GPD computed the shape and scale parameter which are $\xi = 0.597$ and $\beta = 0.0012$ with a threshold u of 0.002 (see Table 2). The QQ plot and excess distribution of the GPD model are shown in Figure 3. The excess distribution shape of each tail is different but is close to the diagonal line of the theoretical distribution in the QQ plot, suggesting that the model is well fitted.

Table 2 - Coefficient estimation of GPD model

Parameters	Estimate	Std.Dev
ξ	0.597462	0.051434
β	0.00119	0.000002
Log-Likelihood Value	-3374.844	

The fitted GPD model of NIFTY-50 is also used to attain the point estimates of VaR and ES of underlying high-frequency loss distribution, with the results presented in Figure 4. As shown there, the tail estimated plot illustrates the estimation of risk measure along with the confidence interval. Dark blue points on the graph indicate the 657 extreme values above the threshold and the smooth curve is known as a tail estimator. The vertical lines indicate the 95% VaR and ES, which determine the intersection point with the horizontal lines and tail estimator curves. The POT method estimated VaR and ES as, respectively, 0.0053 and 0.012. The dotted horizontal line in the graph represents the 95% confidence interval of VaR and ES point estimates.

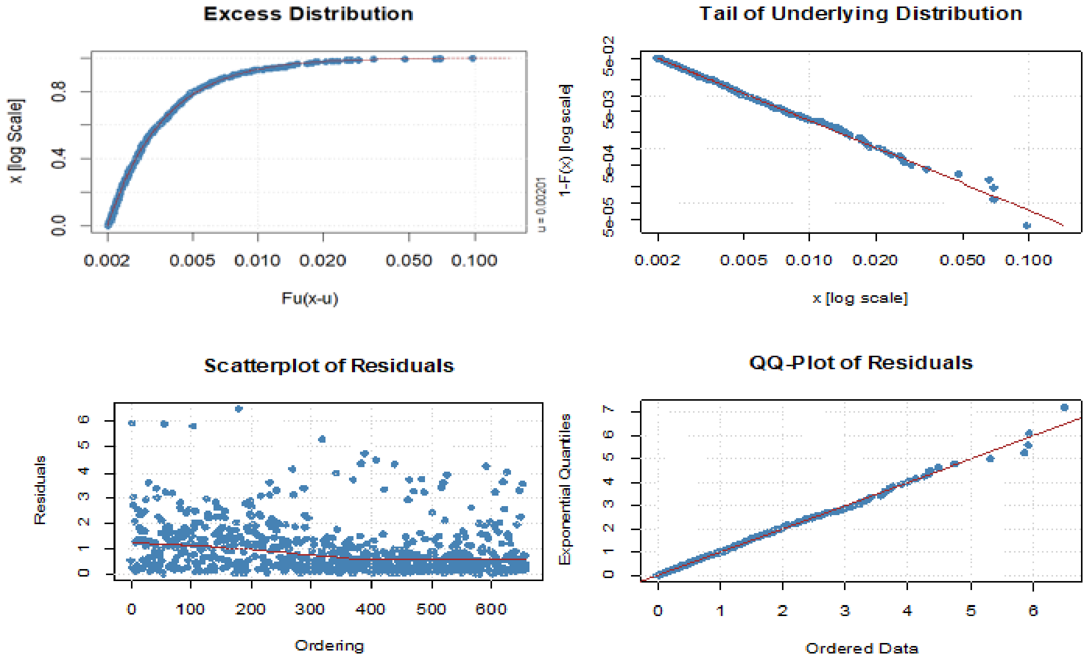

Figure 3 - GPD fitted plots of NIFTY-50 index (lower 5% quantile left tail)

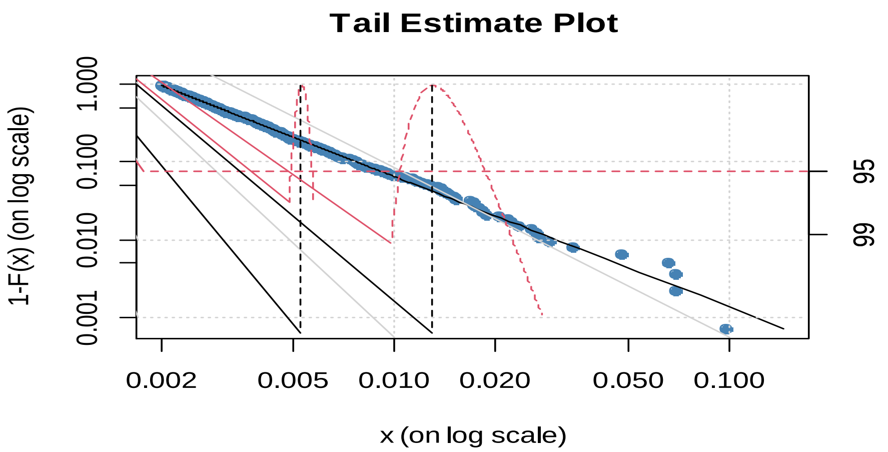

Figure 4 - Tail plot of NIFTY-50 Index

After fitting the GPD model, the next step is to compute the left tail VaR and ES of NIFTY-50 by using excess returns above the threshold of the lower 5% quantile, with the results shown in Table 3. Note that the positive VaR and ES are assigned to the left tail distribution (returns < 0) which indicates a lower tail of negative returns.

Table 3 - Risk measure of VaR and ES for left tail of NIFTY-50

Probability	Value at Risk (VaR)	Expected Shortfall (ES)
0.950	0.0020	0.0050
0.975	0.0030	0.0075
0.990	0.0052	0.0130
0.995	0.0079	0.0196
0.999	0.0206	0.0513

Table 3 shows the estimation of VaR and ES across different risk levels. This shows that the GPD model is a better estimation for the estimation of VaR. The EVT method predicted the 99.9% VaR and ES of the Indian stock market with a value of 0.02 and 0.05 respectively. The result reveals the leptokurtosis behavior in financial time series which strengthens the prediction of VaR for both low and high confidence levels of risk.

5. Conclusions

Since the COVID-19 pandemic, it has been crucial to analyse the volatility of financial markets. In this paper, we investigate the tail behavior of the NIFTY-50 index by using the POT approach of EVT, for statistical modeling of extreme value returns above a specified threshold. This study illustrates that EVT modeling is very useful for quantifying extreme stock markets. POT is a more comprehensive approach for extreme value modeling as well as to obtain VaR and ES estimates. This study identifies 657 extreme return points over the specified threshold during the COVID-19 pandemic, amounting to about 5% of total observations (13133). The findings of this study can have important implications for investment and risk management strategies. For instance, the estimation of shape (ξ), scale β and location u paremeters during crises can be used as tools to assess risk level or investment decisions, i.e. buying or selling orders. Furthermore, the presence of extreme events in the Indian stock market during the Covid-19 pandemic also contradicts the assumptions of normality and indicates how investors should approach risk management in the Indian stock market during this pandemic. The major conclusion of this study is that the GPD model estimation approach is very effective in assessing the extreme market events at times of crisis such as the COVID-19 pandemic.

The influence of the COVID-19 pandemic can be observed in the market movements of the NIFTY-50 intraday returns. More specifically, we observed that NIFTY-50 market returns fell by up to 9 percent during the pandemic period. The high resistance in Indian market returns settles and recovers over time. This finding shows that the EVT method is capable of modeling extreme events in financial markets The performance of the Indian stock market depends on various factors such as response towards political stability (Joshi, 2013) and inflation (Garg and Kalra, 2018). COVID-19 emerged from China and affected investor decisions in a very short time due to the major lockdown worldwide.

Since COVID-19 is an ongoing crisis, and the strategic response policies have been not effective in the short term. The resistance in stock market risk has created fear among investors during COVID-19 (Chen et al., 2020; Liu et al., 2020; Lyócsa et al., 2020). The finding of this study provides a better understanding of Indian market risk which will assist the financial investors and fund managers to reevaluate their investment decisions in order to minimize the potential risk in the stock market. Such financial anomalies can also be addressed by policymakers in order to secure the financial stability of an economy.

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