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Forecasting Extreme Downside Risk in the Nifty 50 Index Using Extreme Value Theory

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Abstract

Stock market crashes are rare but can cause major problems for investors, financial institutions, and policymakers. The standard risk models used tend to assume that stock returns are normally distributed, leading to an underestimation of extreme movements in the stock market. The purpose of this study is to analyse the performance of probability distribution models developed by Extreme Value Theory (EVT) on extreme negative returns of the NIFTY 50 index to check if the prediction of stock market crashes can be improved. The study investigates the characteristics of events with large market losses and provides an estimate of the likelihood of such events based on the Peak Over Threshold (POT) and the Generalised Pareto Distribution (GPD). The results demonstrate that the NIFTY 50 returns are fat-tailed and considerably deviated from normal distribution, implying that extreme losses are not all that rare. Contrary to traditional models like Value-at-Risk (VaR), EVT models can provide more precise estimates of the probability and intensity of extreme market events, resulting in a more holistic approach to risk analysis of financial products. This study contributes to the existing literature on financial risk management in emerging markets by demonstrating the usefulness of EVT in understanding extreme market behaviour and forecasting crashes. The results have implications for investors, portfolio managers, risk managers, and policymakers, as they help them make informed investment decisions, build better risk management strategies, and make the equity market more resilient.

Keywords: *Extreme Value Theory (EVT); Stock Market Crashes; NIFTY 50; Generalised Pareto Distribution (GPD); Tail Risk; Financial Risk Management.*

Introduction

There is a lot of financial volatility and crash cycles worldwide, which affect global markets and societies. The dominoes of financial instability include the disappearance of wealth, the disintegration of credit markets, rising unemployment and loss of consumer and investor confidence. A few examples of the impact of extreme volatility on global markets include the bursting of the dot-com bubble, the Global Financial Crisis of 2008, the pandemic of 2020, and other historic global financial crises. India has experienced such ups and downs in the market and financial crises, too. The Harshad Mehta securities scam of 1992, the Ketan Parekh scam and subsequent 2001 crash, the Lehman Brothers collapse, and the Global Financial Crisis of 2008 are all examples of high volatility in the Indian financial system. The 2020 pandemic, with the steepest single-day declines in the history of the Indian stock market, demonstrates how vulnerable emerging markets are to global financial crises and underscores the need for reliable metrics and tools to understand and measure extreme volatility. The goal is to empower consumers, investors, and policymakers to better prepare for and mitigate the consequences of financial crises.

Drawing from the notable research of Reinhart and Rogoff (2009), financial crises are not uncommon. They are regular elements of the world economy. Their research shows that financial crises are often associated with prolonged economic stagnation, extending into the "lost decades" of economic growth. The Global Financial Crisis (GFC) is a good example that shows the impact of a major financial crisis. The GFC of 2008 triggered a global recession that was the worst since the Great Depression. The GFC caused several banks to require a government bailout, a series of European countries to experience a government debt crisis, and several changes in financial regulations aimed at global financial system stability. Continued interlinking of international financial markets is speeding the transmission of economic shocks to an increasing number of countries and markets. Financial contagion (Kaminsky & Reinhart, 1999) describes how disturbances originating in one market can be rapidly and globally transmitted to other markets and economies, thereby posing a growing systemic financial risk. Consequently, the most important and long-lasting challenge faced globally by researchers, policymakers, and investors is predicting market instability, especially stock market crashes. At the same time, rapid advances in Big Data analytics, machine learning (ML), and modern econometric techniques have opened new avenues for understanding financial markets. These technologies enable researchers to analyse massive volumes of financial information, identify complex patterns, and detect potential early warning signals of financial crises with greater accuracy than many traditional statistical approaches. As financial markets continue to evolve in complexity and interconnectedness, these advanced analytical methods are becoming increasingly important for improving risk assessment and strengthening financial stability.

Literature Review

It is well established that stock returns have historically been assumed to be normally distributed (Gaussian). But successive economic crises and stock market crashes have shown that this is not always the case in times of market turmoil. In practice, however, financial markets undergo large swings in value far more extreme than traditional models would suggest. This has given rise to research on other statistical methods that can be more informative about rare but potentially significant events. Extreme Value Theory (EVT) has become one of the most popular methods for analysing tail risk and modelling extreme fluctuations in financial markets.

An early and important study in the field was that of Embrechts et al. (1997), who showed that the normal distribution-based models greatly underestimate the probability of large financial losses. Their research shows that conventional risk models are not well-suited to extreme market behaviour, as they fail to account for the heavy-tailed distribution of financial returns. Their work provided a theoretical basis for the use of EVT in financial risk management.

The special significance of the knowledge of extreme financial events was reinforced by the influential study by Kaminsky and Reinhart (1999) on "twin crises". They demonstrated that banking crises and currency crises tend to happen at the same time and may easily spread from country to country in short order by means of "financial contagion." They demonstrated that the financial markets of the world are very interconnected and that the standard rules of the game that are used to forecast are not always able to capture the fragilities of the financial system in periods of financial crisis. The study did not just examine normal market conditions but also rare, economically important events.

The shortcomings of traditional risk models are even more evident during the COVID-19 crisis. Mazur, Dang, and Vega (2021) noted that the market was extremely volatile and posted unprecedented negative returns in March 2020. During the crisis, they found that returns exceeded normal random returns in the frequency of extreme moves, with both fat tails and excess kurtosis. That finding further fuels scepticism about the usefulness of traditional statistical measures for capturing downside risk during periods of deep uncertainty, like the current one.

Based on this evidence, numerous studies have investigated the applicability of EWT to the study of financial market extremes. Novak and Beirlant (2006) used EVT to study the Black Monday stock market crash in 1987. They demonstrated that EVT models provide more reliable estimates of losses during extreme events than standard risk measurement models. Similarly, LeBaron and Samanta (2005) examined the distribution of stock returns in both developed and emerging equity markets. They concluded that robust evidence supports the hypothesis that return distributions are not normally distributed but are heavy-tailed. Their results were clear and empirical evidence for using EVT to analyse market crashes and measure tail risk.

The same results have been found in the emerging markets. Chauhan (2011) analysed risk estimation for Indian and international stock indices and concluded that EVT (along with the Generalised Pareto Distribution (GPD)) accurately estimated Value at Risk (VaR) and Expected Shortfall (ES) compared to Gaussian-based models. The study suggests that EVT can be well adapted to markets with significantly more volatile prices, such as those in financial markets.

EVT is gaining popularity, but it also has constraints on its application. According to Uppal and Mudakkar (2014), characteristics such as structural breaks, volatility clustering, limited historical data and the proper selection of threshold values to define extreme events can influence the performance of EVT models in emerging markets. Likewise, Diebold, Schuermann and Stroughair cautioned that although EVT has proven to be a major improvement in measuring tail risk, careful model specification and parameter estimation are crucial for its forecasting power. These studies suggest that EVT can be an important enhancement to the Gaussian models, and that the quality of the data used, the model structure and construction, and the market properties of the financial market under analysis are important contributors to the success of EVT predictors in forecasting crashes.

Research Gap

The literature review shows that stock market returns are not necessarily normally distributed, particularly during financial crises. Instead, they are known to have heavy tails, meaning they can be expected to exhibit larger price variations than standard price models. Although the applications of Extreme Value Theory (EVT) to model tail risk and analyse extreme financial events are numerous and widely discussed, there has been little study of the potential of EVT to predict stock market crashes in the Indian equity market, using the NIFTY 50 index. Further, EVT models must take into account the model specification, the choice of threshold and the quality of the data. In order to fill this gap in the literature, the present study uses Extreme Value Theory to explore the properties of extreme returns of the NIFTY 50 and its ability to forecast stock market crashes in India.

Research Objectives

Primary Objective

- To examine the effectiveness of Extreme Value Theory (EVT)-based probability distributions in predicting stock market crashes in the NIFTY 50 index.

Secondary Objectives

- To analyse the tail behaviour of returns in the NIFTY 50 index.
- To evaluate the effectiveness of Extreme Value Theory in modelling extreme downside risk.
- To compare the performance of EVT-based probability distributions with conventional distribution models in estimating extreme market events.
- To assess the suitability of Extreme Value Theory as a tool for predicting stock market crashes in an emerging market such as India.

Research Question

Can probability distributions based on Extreme Value Theory effectively predict stock market crashes in the NIFTY 50 index?

Research Methodology

The National Stock Exchange of India (NSE) uses the NIFTY 50 as its main index, which comprises the top 50 most liquid and largest companies on the exchange. During the 15-year study period (from January 2010 to June 2025), the index covered unprecedented ground, from recovery from the Global Financial Crisis to a series of macro shocks, a pandemic black swan, and a prolonged bull market that reached record highs above 26,000.

The research uses quantitative and analytical methods, applying the Extreme Value Theory (EVT) to test the hypothesis that probability distributions can predict stock market crashes. The probability distribution outlines the probability of the various outcomes in a data set. This research is based on the NIFTY 50 index, a representative benchmark of the Indian equity market. The study uses secondary data, including the daily closing prices of the NIFTY 50 index from the National Stock Exchange of India (NSENIFTY) during the period under study, covering critical moments of market volatility and stress, such as the Global Financial Crisis and the COVID-19 market crash. Daily logarithmic returns are calculated from index prices to give percentage changes and volatility over time, which are used to analyse market behaviour.

The study uses Extreme Value Theory, which is a standard tool in financial risk management, for the estimation of the probability and size of rare and extreme market losses, or negative returns, in the tails of the distribution. In detail, the Peak Over Threshold (POT) approach is used for tail risk estimation and the Generalised Pareto Distribution (GPD) is employed to assess the probability of extreme market downturns. Other statistical metrics like skewness, kurtosis, Value at Risk (VaR), and Expected Shortfall (ES) are also used to evaluate the occurrence of fat tails and deviations from the normal distribution assumptions.

The methodology also involves a comparison of the EVT-based estimations and traditional Gaussian distribution techniques for assessing how well EVT performs in forecasting stock market crashes. The data analysis is performed with the help of statistical and econometric methods in Python. The study is to find out if EVT is a better alternative to predict extreme downside risk and crash probability in developing equity markets like India.

The data on Yahoo Finance was taken from 1st January 2010 to 31st December 2025 from the NIFTY 50 database.

Primary Data Sources

Source	Data / Purpose
NSE India (nseindia.com)	NIFTY 50 historical OHLC prices, volumes, index methodology
SEBI Annual Reports 2010–25	FII/FPI flow data, market breadth, volatility statistics
RBI Monetary Policy Reports	Repo rate decisions, macroeconomic context, CPI/WPI data
Bloomberg Terminal	High-frequency volatility, VaR estimates, intraday extremes
Refinitiv Eikon	Cross-verification of NIFTY 50 returns & FII net positions
AMFI India (amfiindia.com)	Domestic SIP inflows, mutual fund AUM trends
IMF World Economic Outlook	Global GDP context, EM risk-oV/risk-on environment
Coles, S.G. (2001), Springer	An Introduction to Statistical Modelling of Extreme Values
Embrechts et al. (1997), Springer	Modelling Extremal Events for Insurance and Finance
McNeil, A.J. (1999), RISK Books	Extreme Value Theory for Risk Managers

Theoretical and Mathematical Framework

Probability Distribution and Financial Returns

Probability distributions are statistical functions that describe the likelihood of different outcomes within a dataset. In financial markets, probability distributions are used to model stock returns and estimate the likelihood of gains or losses over a given period. Traditional financial models generally assume that stock returns follow a normal, or Gaussian, distribution, characterised by symmetry and thin tails. However, empirical evidence shows that financial returns rarely follow a perfect normal distribution. When financial crises occur and markets are uncertain, returns are more likely to be skewed, have excess kurtosis and be heavy tailed, that is, large price changes are more likely to happen than a traditional model would assume. This means that Gaussian models will tend to underestimate the chance and extent of large market losses.

Extreme Value Theory (EVT)

Extreme Value Theory (EVT) is an established statistical approach to study rare and extreme events in the tails of a probability distribution. The upshot of this is that traditional statistical analysis tends to look at the average or typical market behavior, whereas EVT highlights the "abnormal" observations, such as a steep drop in the stock market or a huge financial loss. Given its potential for economic implications, EVT has been an important risk management tool in financial markets to estimate the likelihood of rare but extreme market events and measure the tail risk. In this research, the Extreme Value Theory (EVT) is used to compute the extreme negative returns of the NIFTY 50 index. The aim is to find out if the probability distribution of EVTs can more accurately describe and identify stock market crashes compared to the normal distribution assumed by traditional stock market models.

Logarithmic Returns

The daily closing prices of the NIFTY 50 stock index are used to calculate daily logarithmic returns to study the behaviour of the stock market. The use of logarithmic returns is popular in financial research because it stabilises price changes over time, minimising the impact of changing variance. They are also useful for assuming continuously compounded returns, which is a characteristic that is useful in statistical analysis and financial modelling. The day's log change is computed as:

$$R_t = In\left(\frac{P_t}{P_{t-1}}\right)$$

Where:

- R_t = logarithmic return at time t
- P_t = closing price at time t
- P_{t-1} = closing price at time $t-1$

Peak Over Threshold (POT) Approach

Using the Peak Over Threshold (POT) method in the Extreme Value Theory (EVT) framework, this study aims to detect and analyse extreme negative returns exceeding the threshold. The POT method does not fit the entire distribution of returns for a stock, but rather only the most extreme observations in its tail. The method centres on these very infrequent but very strong events. It offers a better way to estimate the probability and magnitude of extreme movements, particularly stock market crashes and other periods of financial crisis.

The POT condition may be expressed as:

$$X_i > u$$

Where:

- X_i = extreme return observations
- u = selected threshold value

Observations exceeding the threshold are treated as extreme events and modelled separately using the Generalised Pareto Distribution.

Generalised Pareto Distribution (GPD)

The Generalised Pareto Distribution (GPD) is used to model the distribution of excess returns above the selected threshold. GPD is particularly suitable for estimating the probability and magnitude of extreme market losses and tail-risk behaviour.

The cumulative distribution function of the GPD is expressed as:

$$G_{\xi,\beta}(x)=\begin{cases}1-\left(1+\dfrac{\xi x}{\beta}\right)^{-1/\xi}, & \xi\neq 0\\ 1-e^{-x/\beta}, & \xi=0\end{cases}$$

Where:

- ξ = shape parameter representing tail heaviness
- β = scale parameter
- x = excess value above the threshold

A positive value of the shape parameter indicates fat-tailed behaviour and a higher probability of extreme market losses.

Value at Risk (VaR)

Value at Risk (VaR) is a statistical measure that estimates the maximum expected loss within a given confidence interval over a specified time period. EVT-based VaR provides improved estimates of downside risk by incorporating tail behaviour ignored in normal distribution models.

The general expression for VaR is:

$$VaR_\alpha = \mu + \sigma z_\alpha$$

Where:

- μ = mean return
- α = standard deviation
- z_α = critical value at confidence level

Expected Shortfall (ES)

Expected Shortfall (ES), also referred to as Conditional Value at Risk (CVaR), estimates the average loss that is expected to occur once losses exceed the Value at Risk (VaR) threshold. Unlike VaR, which only indicates the maximum expected loss at a given confidence level, ES also reflects the magnitude of losses in the most extreme scenarios. Thus, it is commonly believed to be a more comprehensive indicator of tail risk, especially when markets are in high-volatility mode and during financial crises.

This study will examine whether stock market crashes in the NIFTY 50 index can be identified and predicted using probability distribution techniques: Extreme Value Theory (EVT), Peak Over Threshold (POT), Generalised Pareto Distribution (GPD), Value at Risk (VaR), and Expected Shortfall (ES). The results will help to create a more comprehensive framework for modelling extreme downside risk and enhance risk assessment in emerging financial markets.

Analysis and Interpretation

The theoretical background of Probability Distribution and Extreme Value Theory (EVT) is explained and then the NIFTY 50 index is analysed empirically. In this part, the methods of statistics presented above are applied to the analysis of market return in past years and to the study of the characteristics of extreme negative price changes. They will be assessed on how well EVT measures tail risk and how well they predict stock market crashes. Moreover, it attempts to calculate the probability of extreme losses. It takes into account the implications of these calculations for financial risk management, market stability and building a more reliable early warning system for financial crises.

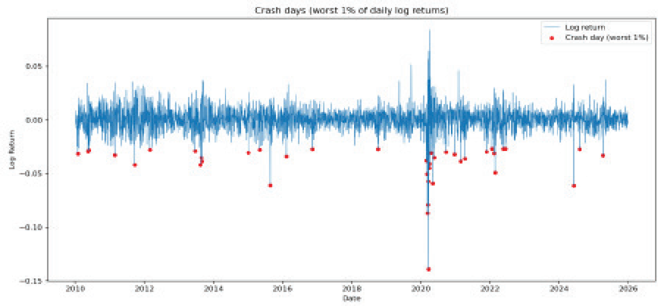

Figure 1: Depicting Crash Days

Data Source and Study Period

Table 2. Depicting the dataset overview.

Item	Value
Index	NIFTY 50
Ticker	^NSEI
Frequency	Daily OHLC and closing prices
Study period	5 January 2010 to 30 December 2025
Total trading days	3,927
Training period	2010-2020
Testing period	2021-2025
Test observations	1,235

Daily data from the NIFTY 50 index are used in the study, as they are informative enough to capture extreme market volatility and stock market crashes and are still considered appropriate for a quantitative research study for students. To assess the robustness of the analysis, the data are split into two sets: a training set and a test set. The training data are used to estimate the model parameters. The testing data, on the other hand, enable the model to be evaluated on data it has not observed before, providing a more realistic estimate of its predictive ability.

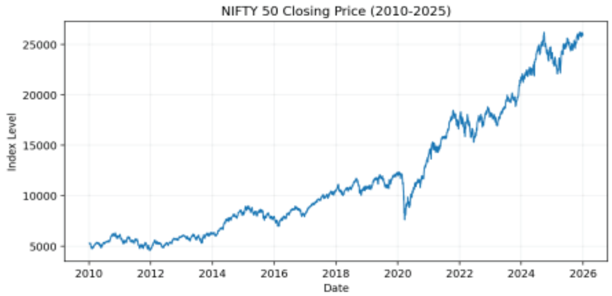

Figure 2. NIFTY 50 price series, 2010-2025.[1]

1 *This graph plots the closing level of the NIFTY 50 across the full sample. It shows the long-term rise in the index while also revealing sharp crisis-period drawdowns, especially during 2020. The purpose is to give visual context before converting prices into returns.*

Return Calculation

The price data were converted into daily log returns using:

Calculation: Daily log return

r_t = ln(P_t / P_(t-1))
P_t = current NIFTY 50 closing price
P_(t-1) = previous trading day closing price
Log returns are used because they are additive over time and more suitable for statistical modelling than raw price levels.

Crash Definition

Table 2. Objective crash definition

Metric	Value
Crash definition	Worst 1% of daily log returns
Crash threshold return	-2.67%
Crash days identified	40

Model Selection

Table 3. Models used for comparison.

Model	Purpose in the Study	Core Assumption
Normal distribution	Baseline model	Returns follow a symmetric bell-shaped distribution.
Student-t distribution	Heavy-tail comparison model	Returns have heavier tails than a Normal distribution.
EVT-GPD	Extreme-tail model	Only extreme losses above a threshold are modelled.

Empirical Analysis

Descriptive Statistics of Returns

Table 4. Distribution summary for full, training and testing returns.

Set	N	Mean	Std Dev	Min	1% Q	5% Q	Max	Skew	Excess Kurtosis
Full Sample	3927	0.0408%	1.0438%	-13.90%	-2.67%	-1.57%	8.40%	-0.909	13.69
Training	2692	0.0365%	1.1102%	-13.90%	-2.73%	-1.68%	8.40%	-0.998	14.68
Testing	1235	0.0500%	0.8821%	-6.11%	-2.30%	-1.36%	4.63%	-0.436	4.38

The descriptive statistics of the training data provide important insights into the characteristics of NIFTY 50 returns. The results clearly show that the return series does not follow a normal distribution, exhibits significant skewness, and is more likely to exhibit extreme market movements. The estimated skewness of −0.998 indicates that the negative returns are larger than the corresponding positive returns. In other words, when markets are uncertain, they can fall sharply rather than rise. This is an indication of the downside risk in the market.

It is also found that there is excess kurtosis of 14.68, which is much larger than that of a normal distribution. This suggests that the price distribution is fat-tailed – meaning that specific price movements happen more often than a standard statistical distribution. Risk-management-wise, that implies the market has not crashed as often as Gaussian models suggest, and that the normal distribution is not well-suited to analysing returns in financial markets.

All this points to the fact that if only the normal distribution is used, market risk associated with extreme events might be underestimated. The return series for NIFTY 50 is found to have heavy tailed returns thus requiring more flexible statistical models in order to be able to capture these extreme returns. The study is beyond the Gaussian Modelling and explores the Student's t-distribution and Extreme Value Theory (EVT) which are suitable for tail risk modelling and improve the crash analysis of the stock market.

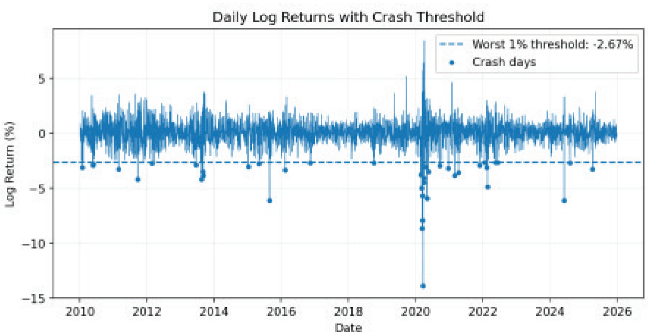

Figure 3. Daily log returns with a crash threshold[2].[9]

Interpretation of Daily Log Returns with Crash Threshold

The figure shows the daily log returns of the NIFTY 50 index between 2010 and 2025, along with the crash threshold, defined as the bottom 1% of daily returns. The horizontal dashed line at about −2.67% is the cutoff value, and any day that falls below this line is considered a crash day. The blue markers show the days on which the returns were below this threshold and, therefore, the days of extreme negative market movements.

Some interesting features of the figure include: the distribution of daily returns is concentrated around zero, indicating that price movements are relatively small under normal market conditions. But there are a few cases where returns are well below the crash threshold, indicating that large losses occur occasionally and are much larger than typical daily swings. This is the same as the descriptive pattern above, where the return distribution is found to be heavy-tailed and highly kurtotic.

Another striking feature of the graph is the tendency of volatility clustering in financial markets, that is, periods of high volatility followed by periods of high volatility, not randomly. This is especially evident in 2020 where there are a series of extremely poor returns in a fairly short time duration. This is the time when the most significant losses are observed in the dataset, and daily returns are around −14%. The large decline took place at a time when the country was facing unprecedented uncertainty and nationwide lockdowns due to the COVID-19 pandemic, while it wreaked havoc on the Indian and global financial system, sparking investor panic. In general, the value suggests that the most extreme negative returns occur only during periods of financial stress. These observations further support the need to develop statistical models capable of capturing the tail risk and justify the use of Extreme Value Theory (EVT) for the analysis and prediction of stock crashes.

Table 5: Depicting Additional clusters of crash days

Year / Period	Event	Impact on Financial Markets
2011	European Sovereign Debt Crisis	Concerns about global growth and fears of sovereign defaults increased volatility in international and Indian equity markets.
2013	Taper Tantrum	Capital outflows from emerging markets following signals of reduced US monetary stimulus led to heightened volatility in India.
2015 – 2016	Global Market Weakness and Domestic Economic Uncertainty	Slowing global growth, weakness in commodity markets, and domestic uncertainty contributed to increased market instability.
2018	IL&FS Liquidity Crisis	The collapse of IL&FS triggered liquidity concerns and systemic stress within India's financial sector.
2022	Russia–Ukraine Conflict and Inflation Shock	Rising inflation, aggressive interest-rate hikes & geopolitical tensions caused renewed volatility in global and Indian markets.

Crash distribution over time shows that there is a nonrandom and nonindependent distribution of losses in the market. Instead, they tend to gather when there

2 This graph plots daily log returns and marks the crash threshold at the worst 1% cuto`. It visually shows that most returns cluster around zero, while a small number of large negative observations form the left tail studied by EVT.

is more financial uncertainty and stress in the system. It highlights that markets do not necessarily become "volatile" in every situation, which is one of the basic tenets of the normal distribution theory used in conventional financial analysis. This implies that these models generally underestimate the likelihood of extreme market losses. The modelling of rare but severe events, in contrast, is better done with heavy-tailed probability distributions and extreme value theory (EVT), which are more suited to financial market risk.

The extreme observations from this study are very close to a number of important events that have occurred in the world and in the Indian economy from 2010 to 2025. Some of the years with high volatility include the European sovereign debt crisis, the 2013 Taper Tantrum, India's demonetisation in 2016, the IL&FS financial crisis in 2018, and, most significantly, the COVID-19 market crash in 2020. In all these instances, NIFTY 50 has seen a dramatic decline, reflecting increased uncertainty, shifts in investor sentiment, and financial instability.

The study's most severe episode of financial stress is the market crash triggered by the COVID-19 pandemic. The NIFTY 50 posted negative returns during this period, suggesting that extreme returns are more frequent and larger in magnitude during crises. The observations clearly indicate that the other scenarios have missed the mark on the probability of large market declines, as they have a normally distributed return assumption. The EVT-based model, by contrast, can handle these extreme observations, and successfully incorporate both the size of tail risk and the times when the crash risk is greatest. The overall results indicate that Extreme Value Theory is a more suitable approach to analysing extreme downside movements and estimating financial risk when markets are unstable.

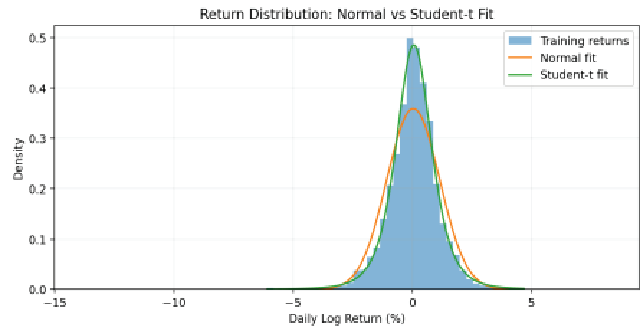

Figure 4. Distribution overlay: empirical returns vs fitted distributions.[3]

Analysis of Return Distribution: Normal vs Student-t Fit

The figure shows the distribution of daily logarithmic returns of the NIFTY 50 in comparison to two theoretical probability distributions, the Normal distribution and the Student's t-distribution. The figure shows that the student's t-distribution is a much closer fit to the data than the Normal distribution. It reflects not only the concentration of returns around the mean but also the tails, where extreme market movements occur. Compared to these, they do not adequately represent the characteristics of the Normal distribution. It assumes that gains or losses are very rare, which is not borne out by the empirical evidence. The above observations are in line with the descriptive statistics mentioned earlier. The negative skewness suggests that large losses happen more often than large profits, and the high kurtosis confirms that the returns have fat tails. All these points point to the fact that the NIFTY 50 index is not normally distributed, particularly during turbulent market conditions. In practical terms, that means a model that assumes a normal distribution of market losses might underestimate the likelihood and magnitude of very large losses. The student's t-distribution, however, is a more realistic distribution of financial returns, as it accounts for the higher likelihood of extreme observations. This result also points to the use of Extreme Value Theory (EVT) in further analysis: EVT is a special class of models developed to model rare but high-impact events in the tails of financial return distributions.

3 This graph compares the observed return distribution with fitted benchmark distributions. It is used to show whether the Normal model captures the actual shape of returns. Deviations in the tails support the use of heavier-tail models.

Annual Return, Volatility and Drawdown Evidence

Table 6. Annual calculated summary[4]

Year	Annual Return	Annualised Vol.	Max Drawdown	Crash Days	Worst Daily Return
2010	16.23%	16.33%	-10.66%	3	-3.14%
2011	-24.90%	21.17%	-26.20%	2	-4.17%
2012	23.92%	15.51%	-13.76%	1	-2.77%
2013	5.18%	18.17%	-14.58%	4	-4.17%
2014	33.14%	12.79%	-6.50%	0	-2.13%
2015	-5.35%	16.44%	-15.98%	3	-6.10%
2016	5.06%	15.20%	-11.66%	2	-3.37%
2017	28.75%	9.02%	-4.11%	0	-1.57%
2018	4.03%	12.90%	-14.55%	1	-2.70%
2019	12.75%	13.87%	-11.45%	0	-2.16%
2020	14.77%	31.82%	-38.44%	13	-13.90%
2021	23.79%	15.66%	-10.08%	3	-3.84%
2022	2.72%	17.36%	-16.47%	5	-4.90%
2023	19.42%	9.81%	-7.06%	0	-1.62%
2024	8.75%	14.13%	-10.93%	2	-6.11%
2025	9.25%	11.80%	-8.71%	1	-3.30%

4 Table 5 connects statistical tail behaviour with market regimes. Years with higher volatility and deeper maximum drawdowns, such as 2020, also contain more crash days and more severe worst daily returns.

This table displays the performance and risk characteristics of the NIFTY 50 from 2010 to 2025, highlighting how market conditions have changed over time. The results indicate some changes over the years, which can be categorised as a stable period and a period of financial pressure. 2020 is the most difficult year compared to all the others. It had the highest annualised volatility (31.82%), the largest maximum drawdown (−38.44%), and the most crash days (13). These extreme values were mainly caused by the COVID-19 pandemic era financial market turmoil, related to severe stock price drops and increased uncertainty in financial markets worldwide. 2014, 2017 and 2023 were relatively stable years compared to the other years listed above. The years delivered strong positive returns and reduced market volatility, with no crash days, suggesting positive market conditions and increasing investor confidence. On the other hand, years with negative annual returns (2011 and 2015) saw increased volatility and sharp declines, indicating greater market uncertainty and less investor confidence. From the table, it can be concluded that during periods of high market volatility, there is a tendency to incur larger losses and more extreme negative days. This pattern suggests that during financial distress, extreme market moves are more likely, while there is considerable tail risk in the NIFTY 50. These results further validate the usefulness of Extreme Value Theory (EVT) models for analysing and quantifying the risk of such extreme events, as opposed to traditional models.

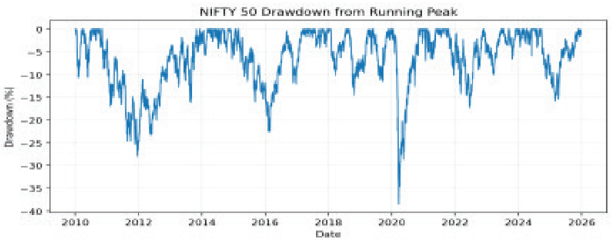

Figure 6. Drawdown series.[5]

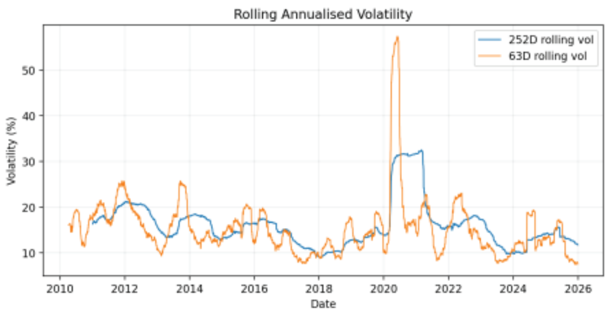

Figure 6. Rolling volatility.[6]

The short-term volatility has increased sharply in 2020, reaching over 55%, and the long-term volatility has also increased to above 30%. This came at a time when financial markets were facing unprecedented uncertainty due to the onset of the COVID-19 pandemic. There was a widespread panic sale, a lockdown, and fears about the global economy had a strong impact on stock prices in both domestic and foreign markets. The unprecedented increase in volatility during this period is a testament to the systemic risk of financial markets and underscores how uncertainty grows during key crises. There are other times of increased volatility as well, as indicated in the figure. The market became more volatile between 2011 and 2013, a period marked by the European sovereign debt crisis and the 2013 Taper Tantrum.

Similarly, volatility rises during the 2015-2016 timeframe and in 2022 due to uncertainty in the global economy, differing monetary policies, and geopolitical tensions. Years such as 2023 and 2017, on the other hand, were relatively low-volatility years, suggesting more stable markets and higher investor confidence. Overall, the market is found to be non-stationary. On the contrary, it usually increases rapidly when the financial and economic situation is poor, then gradually returns to its normal level as the market situation improves. This behaviour also reinforces the need to adopt market risk models that are able to handle times of high volatility and extreme moves.

The figure also shows the famous phenomenon of 'volatility clustering' - high market volatility tends to be preceded by high volatility. The short-term volatility measure is highly dependent on short-term market fluctuations and sensitive to the reception of new information and unexpected events as they occur. The volatility measure over a longer time period, on the other hand, changes more slowly and captures the underlying trend in market volatility over that time horizon. In general, this signals that market volatility is not stationary, but rather evolves over time. It spikes significantly during financial crises, economic uncertainty, and geopolitical events, then gradually decreases to a state of stability once market conditions improve. This behaviour raises questions about the validity of the classical models based on constant volatility for describing financial markets. However, more flexible methods, such as Student's t-distribution and Extreme Value Theory (EVT), are more appropriate for the modelling of the evolving risk profile of financial markets and the frequency of extreme price movements.

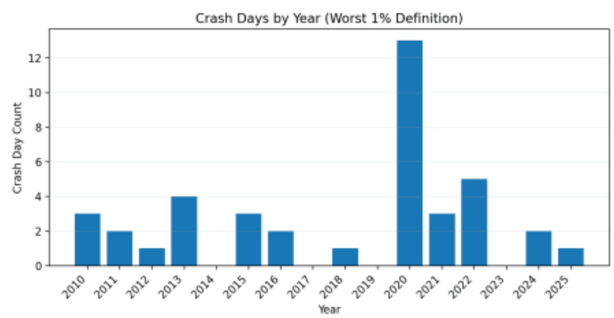

Figure 7. Crash days by year.[7]

EVT Tail Modelling: POT-GPD

Peaks Over Threshold Method

Table 6. POT-GPD setup

EVT Component	Value / Meaning
Method	Peaks Over Threshold (POT)
Tail model	Generalised Pareto Distribution (GPD)
Loss transformation	Loss = -log return
Threshold	1.68% loss
Threshold quantile	95th percentile of training losses
Exceedances	135

5 This graph measures the percentage fall from the previous peak. It is important because stock market crashes are often experienced as peak-to-trough losses rather than single-day losses. The 2020 drawdown is clearly visible as the most severe episode.

6 This graph plots short term and long term rolling volatility. It shows how market risk changes over time rather than remaining constant. Spikes in volatility coincide with stress periods, supporting the argument that crash risk is regime dependant.

7 This graph counts how many worst-1% crash days occurred in each year. It shows that extreme events cluster in certain crisis years instead of occurring evenly through time, which is consistent with fat-tail and volatility-clustering behaviour.

POT-GPD does not depict normal daily returns. It first converts negative returns to positive losses and subsequently examines only losses above the high threshold. This leaves the model to be directly aimed at crash-like observations.

The structure of the Extreme Value Theory (EVT) framework for modelling extreme gains/losses in NIFTY 50 returns is shown in Table 6. The study uses the Peaks Over Threshold (POT) approach, which considers only observations above a chosen extreme threshold rather than modelling the return distribution. This is a great method for analysing financial crashes, as it focuses on rare but important loss events. The tail distribution used is the Generalised Pareto Distribution (GPD) to model these extreme losses.

The use of the GPD is consistent with the theory of EVT, which assumes that the GPD can approximate the distribution of exceedances over a sufficiently high threshold. By converting returns to losses, the expression Loss = –log return directly accounts for downside risk and extreme negative market movements. The threshold is set to the 95th percentile of the training set's loss distribution, which is 1.68%. This implies that only 5% of the losses are considered extreme and consequently included in the tail analysis. Selecting a threshold too low means the EVT model will not identify true extremes but will simply detect large random market fluctuations.

There are 135 exceedances over the chosen threshold, giving a reasonably good sample of extreme values and a good estimate of tail risk parameters. In general, the POT-GPD model is a methodical and statistically suitable model for modelling rare and extreme downside moves in the Indian stock market.

Calculation: Exceedance above threshold

Loss L_t = -r_t
Threshold u = 1.68% loss
Exceedance Y_t = L_t - u, for all L_t > u
Example: if loss is 3.00%, exceedance = 3.00% - 1.68% = 1.32%.

GPD Parameter Estimates

Table 7. GPD parameter estimates.8

Parameter	Symbol	Value	Interpretation
Shape parameter	xi	0.361	Positive value confirms heavy-tailed behaviour.
Scale parameter	beta	0.00556	Measures the spread of extreme losses above the threshold.
Number of losses	n	2,692	Training losses are used for fitting.
Exceedances	nu	135	Extreme observations fitted by the GPD.

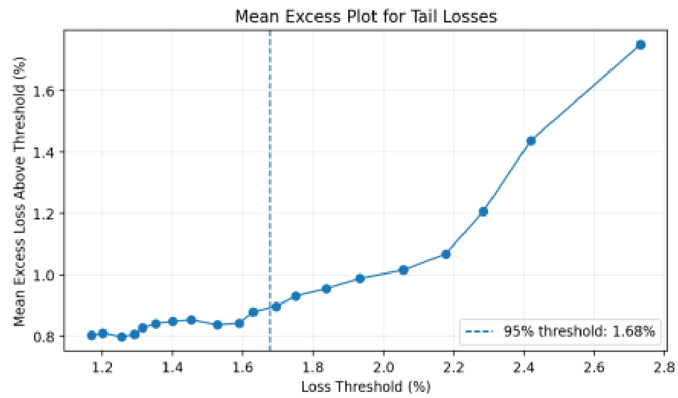

Figure 8. Mean excess plot.[9]

Interpretation of the Mean Excess Plot using GPD Parameter Theory

The Mean Excess Plot is an important diagnostic tool in Extreme Value Theory (EVT) used to assess whether the Generalised Pareto Distribution (GPD) is appropriate for modelling extreme losses. The graph plots the average excess loss above different threshold levels against the corresponding thresholds for the NIFTY 50 returns.

It is known from the GPD theory that, if the exceedances over a threshold follow a GP Distribution, the mean excess function should have an approximately linear upwards trend for large enough thresholds. The plot shows exactly this behaviour outside of the chosen threshold (dashed vertical line) at around 1.68% (the 95th percentile of the training losses). From this point onward, the mean excess values rise gradually with increasing threshold, indicating that higher losses are associated with larger exceedances.

8 The most important result is the positive shape parameter xi = 0.361. In EVT, xi > 0 indicates a heavy-tailed distribution, meaning extreme losses occur more frequently than predicted by a Normal distribution.

9 This graph helps assess whether the selected threshold is reasonable for POT modelling. It plots the average exceedance above di`erent thresholds. A stable or approximately linear pattern beyond the selected threshold supports the use of GPD tail modelling.

The upward trend indicates a positive shape parameter (◎[10] > 0) in the GPD model. A positive shape parameter indicates a heavy-tailed distribution in EVT, meaning that extreme losses decline slowly and that very large market crashes remain statistically possible. This behaviour is consistent with the financial return data, which has rare but severe downside events occurring more often than expected by the normal distribution.

The relative smoothness and near linearity of the plot outside the threshold also provide evidence of the appropriateness of the chosen POT threshold. A threshold that is too low would be misleading when interpreting the tail behaviour of the observations. At the same time, one that is too high would yield insufficient exceedances to allow stable estimates. Thus, the observed pattern suggests that the selected threshold works well with these considerations and provides a good foundation for modelling the Generalised Pareto Distribution.

Overall, the Mean Excess Plot provides strong empirical evidence that the tail losses of the NIFTY 50 exhibit heavy-tailed characteristics and can be appropriately modelled using the POT-GPD framework under Extreme Value Theory.

Figure 9. GPD Q-Q plot.[11]

10 This plot compares observed tail losses with losses predicted by the fitted GPD. If points lie close to the diagonal line, the GPD provides a reasonable tail fit. Deviations at the far end show the di`iculty of modelling the most extreme losses.

11 This is the original GPD diagnostic generated from the script. It provides an additional visual check that the theoretical GPD quantiles are broadly aligned with empirical tail-loss quantiles.

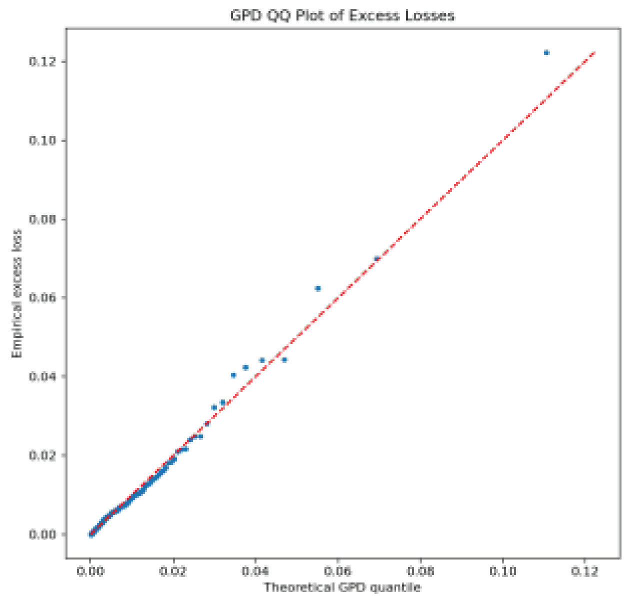

Figure 10. Original GPD Q-Q diagnostic.⚜

Risk Measures: Value-at-Risk and Expected Shortfall

10.1 Value-at-Risk Results

Table 8. VaR and ES at 99.0% confidence.

Model	VaR Return	VaR Loss	Expected Shortfall	Actual / Expected Breaches
Normal	-2.55%	2.55%	—	11 / 12.4
Student-t	-2.84%	2.84%	—	7 / 12.4
EVT-GPD	-2.89%	2.89%	-4.45%	7 / 12.4

Table 9. VaR and ES at 99.5% confidence.

Model	VaR Return	VaR Loss	Expected Shortfall	Actual / Expected Breaches
Normal	-2.82%	2.82%	—	7 / 6.2
Student-t	-3.50%	3.50%	—	4 / 6.2
EVT-GPD	-3.67%	3.67%	-5.67%	3 / 6.2

Interpretation of Value at Risk (VaR) Estimates

VaR estimates the loss threshold that should only be exceeded with a small probability. EVT-GPD estimates a daily loss of -3.67% at 99.5% confidence level, whereas the Normal model estimates only -2.82%. It reveals how understated the Normal risk model is.

Value at Risk (VaR) is the maximum loss that could be incurred over a specified period of time with a specified level of confidence. The value of the 99.5% confidence level in this study is that losses will occur more than the estimated VaR on only 0.5% of trading days in a typical market situation. The EVT-GPD model estimates a loss threshold of –3.67% per day, while the Normal distribution model estimates only –2.82% per day. This is an important consideration, as these estimates vary considerably, reflecting the shortcomings of the Normal distribution for modelling financial risk. The assumption of thin tails in the Normal model underestimates the probability and size of extreme market moves. The EVT-GPD framework, in contrast, has a specific focus on tail behaviour, and thus has a greater ability to capture the worst effects of downside risk.

The EVT-GPD higher VaR estimate indicates that extreme losses in NIFTY 50 are more probable than expected under a Gaussian assumption. This finding is consistent with the earlier evidence of negative skewness, excess kurtosis and heavy tails in the return distribution. Consequently, EVT-based risk measures provide a more realistic assessment of crash risk and are better suited for financial risk management during periods of market stress.

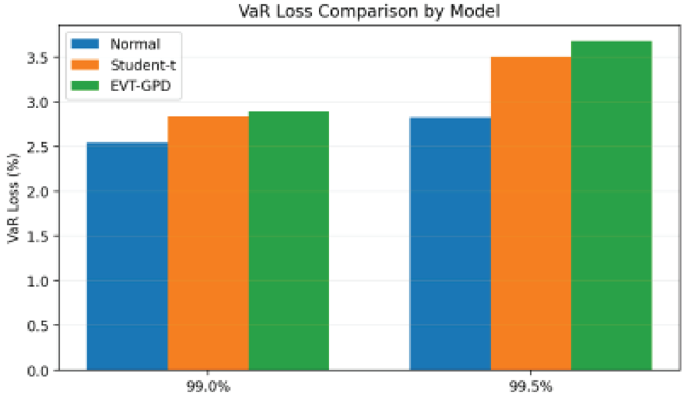

Figure 11. VaR comparison across models[12].

Table 11. EVT-GPD Expected Shortfall.

Confidence	Normal VaR Loss	Student-t VaR Loss	EVT VaR Loss	EVT - Normal	EVT vs Normal
99.0%	2.55%	2.84%	2.89%	0.35 pp	13.56%
99.5%	2.82	3.50%	3.67%	0.85 pp	30.15%

12 This graph compares the estimated VaR across Normal, Student-t and EVT-GPD models. EVT gives the deepest loss threshold, especially at the 99.5% level, showing that it is the most conservative model for crash-risk estimation

Confidence Level	EVT-GPD VaR	EVT-GPD Expected Shortfall	Meaning
99.0%	-2.89%	-4.45%	Average loss once the 99% VaR line is breached.
99.5%	-3.67%	-5.67%	Average loss once the more extreme 99.5% VaR line is breached.

Expected Shortfall is more informative than VaR during crashes because it measures how severe losses become after the VaR threshold has already been crossed. Expected Shortfall (ES) provides a more comprehensive measure of risk than Value at Risk (VaR) because it estimates the average loss that occurs once the VaR threshold is exceeded. While VaR only identifies the cut-off point for extreme losses, ES captures the severity of losses during crash periods. This makes ES particularly useful during financial crises, when market losses can exceed the initial VaR estimate. Therefore, ES offers a more realistic assessment of tail risk and potential downside exposure.

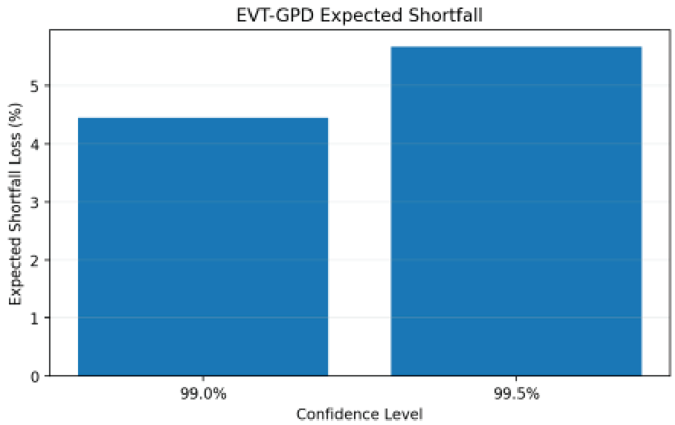

Figure 12. Expected Shortfall comparison for EVT-GPD.[13]

Backtesting and Model Evaluation: VaR Breach Analysis

Table 12. Out-of-sample VaR breaches, 2021-2025.

Confidence	Model	Actual Breaches	Expected Breaches	Observed Breach Rate
99.0%	Normal	11	12.4	0.891%
99.0%	Student-t	7	12.4	0.567%

13 This graph displays the EVT Expected Shortfall estimates. The 99.5% ES is more negative than the 99% ES, which is expected because a more extreme confidence level focuses on rarer and more severe tail losses.

99.0%	EVT-GPD	7	12.4	0.567%
99.5%	Normal	7	6.2	0.567%
99.5%	Student-t	4	6.2	0.324%
99.5%	EVT-GPD	3	6.2	0.243%

Back-testing is the process of comparing actual breaches to the model's prediction of the number of breaches. Too many breaches means a lower estimate of risk; too few breaches means a higher estimate of risk than is warranted. In this case, the Normal model has the higher number of breaches at 99.5%, which is higher than the EVT-GPD model.

A backtest is used to test the accuracy of a risk model by comparing the number of losses actually recorded that exceed the model's risk threshold to the number of losses predicted by the model to exceed the risk threshold. A model with excessive breaches indicates that it is understating market risk and not capturing extreme losses well. If there are not enough breaches, however, it could mean that the model is too conservative or that the risk is being overestimated. Based on the results of this study, the Normal distribution model shows a greater number of breaches at the 99.5% confidence level, indicating that it would have less ability to estimate tail risk. The EVT-GPD model, meanwhile, looks more conservative, and it is more likely to be able to capture extreme movements of the NIFTY 50 on the downside.

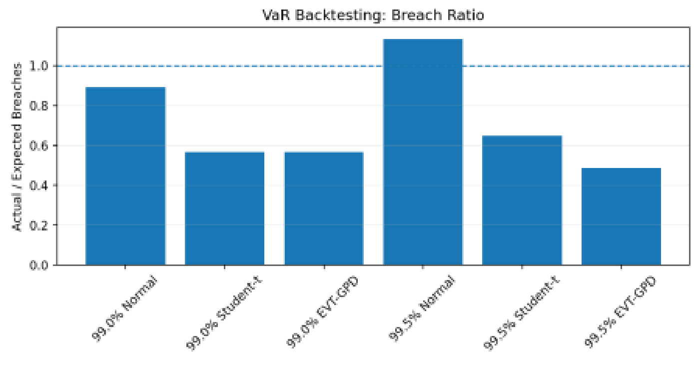

Figure 13. Actual-to-expected breach ratio.[14]

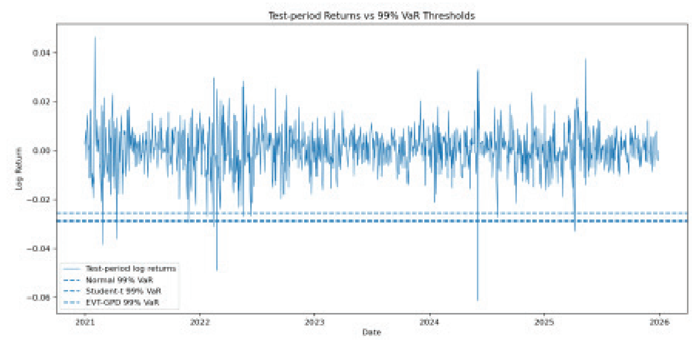

Figure 14. VaR backtest over time.[15]

14 This graph compares actual VaR breaches with expected breaches. A value near 1 means the model breach frequency is close to expectation. Values below 1 indicate conservative estimates or fewer observed breaches than expected.

15 This chart plots test-period returns against VaR thresholds. It shows when actual returns breached each model threshold, giving a time-based view of model performance rather than only a summary count.

Kupiec Test

Table 13. Kupiec unconditional coverage test.

Confidence	Model	Actual	Expected	Actual/Expected	LR_uc	p-value
99.0%	Normal	11	12.35	0.891	0.155	0.694
99.0%	Student-t	7	12.35	0.567	2.775	0.096
99.0%	EVT-GPD	7	12.35	0.567	2.775	0.096
99.5%	Normal	7	6.18	1.134	0.106	0.745
99.5%	Student-t	4	6.18	0.648	0.880	0.348
99.5%	EVT-GPD	3	6.18	0.486	2.027	0.155

The Kupiec test determines if the number of VaR breaches is statistically consistent with the expected frequency of breaches. The p-values presented do not provide robust statistical evidence of rejection at the $p = 0.05$ level. The model comparison still shows that EVT-GPD yields more conservative tail estimates as compared to the Normal model,

The Kupiec test can be used to assess the consistency between the observed and expected numbers of VaR violations at a given confidence level. For this study, the p-values reported for the two models are insufficient to reject either at conventional levels of significance, indicating that both models are reasonably effective statistically. The comparison suggests, however, that the EVT-GPD model provides more conservative estimates of tail risk than the Normal model, as it forecasts higher potential losses and fewer unexpected breaches. This further confirms the appropriateness of the EVT-GPD model for modelling extreme downside risk in financial markets.

Discussion

Does Extreme Value Theory Predict Stock Market Crashes?

Based on the results of this study, extreme value theory (EVT) should not be interpreted as a forecasting tool for the timing of a stock market crash. Rather, it offers a statistically sound approach to estimating the probabilities and consequences of an extreme market loss. EVT does not predict when a crash will occur, but rather the severity of a crash and the probability of one occurring. It is significant because many unpredictable economic, political, and behavioural factors affect financial markets, and no statistical model can perfectly predict any of them. To test the reliability of the risk estimates, this study uses the Kupiec Proportion of Failures (POF) test, which assesses whether the number of times the VaR is exceeded is similar to the number expected at a given confidence level. A VaR breach occurs when the market loss exceeds the VaR. Under a 99.5% confidence level, for instance, only 0.5% of trading days are likely to end up having losses in excess of the envisioned loss. Thus, the Kupiec test provides a quantitative means to assess the validity of the VaR model in capturing the true level of market risk.

The empirical results reveal that the p-values for both the Normal distribution and the EVT-Generalised Pareto Distribution (EVT-GPD) models exceed the conventional 5% significance level. As a result, the statistical evidence is insufficient to decide between the two models, meaning that the models yield breach frequencies that, in the broad sense, are similar to what is expected from theory. Statistically, both methods are satisfactory. Upon closer inspection, however, there's a significant distinction between the two models. Although both pass the statistical test, the EVT-GPD model produces more conservative estimates of extreme losses. It is expected to experience larger potential losses when times are tough and therefore have fewer VaR breaches. This indicates that EVT-GPD provides greater protection from extreme downside risk. The Normal distribution, on the other hand, has thin tails and thus underestimates the occurrence and size of extreme market movements. Consequently, it provides a less realistic estimate of the risk of a crash, especially during periods of heightened financial uncertainty.

The results are in complete agreement with the descriptive analysis conducted earlier, which showed that returns from NIFTY 50 stocks are negatively skewed, exhibit excess kurtosis, and exhibit strong fat-tail characteristics. All these properties suggest that extreme loss events are more common than expected under the Normal distribution. Hence, EVT-GPD is a more reliable and economically sound model for modelling extreme downside risk in the Indian equity market, whereas both models meet the Kupiec validation criterion.

EVT-GPD versus the Normal Distribution

Due to its mathematical simplicity and the ease of analysis, the Normal distribution has been the hallmark of financial risk modelling research for a long time. But in the real world, financial returns do not meet the assumptions of normality. This is clearly evident in the empirical study of the Nifty 50. The distribution of returns is negatively skewed and very leptokurtic, indicating that large negative returns are more common than would be predicted under a Gaussian framework. The estimated positive shape parameter of the Generalised Pareto Distribution gives further evidence of the heavy-tailed behaviour of the extreme loss distribution. Furthermore, the Value-at-Risk (VaR) and Expected Shortfall (ES) estimates based on the EVT are always larger than those based on the Normal model. Such deeper estimates of risk suggest that significant market losses are more likely and may be more severe than traditional risk estimates indicate.

The distinction between the two models is that one treats rare events, while the other does not. The concept underlying the Normal distribution is that it aims to capture the entire return series in a single probability distribution, hiding extreme returns amid many normal days. However, the EVT-GPD focuses only on the tail of the distribution, where market crashes occur; it is not concerned with the rest of the distribution. It simulates only extreme losses, which is more representative of financial markets' behaviour under extreme stress. The overall picture suggests that the Normal distribution might underestimate tail risks and the magnitude of crashes in the Indian stock market system. EVT-GPD, by contrast, captures the true financial risk and is well-suited to financial applications, such as stress testing, capital allocation and risk management.

Why EVT-GPD is Better Suited for Crash-Risk Modelling

A major advantage of EVT-GPD is that it emphasises extreme market losses. The financial markets exhibit unique features in both crisis and non-crisis periods. Normal daily movements are generally within reasonable limits, but during crash periods, prices change more rapidly and reach higher extremes than usual. There is no single probability distribution that would be a suitable model for these two behaviours, as this could lead to inaccurate risk estimates.

The Peaks Over Threshold (POT) approach addresses this by eliminating some of the observations below the threshold. Such extreme losses are then modelled using the Generalised Pareto Distribution, enabling analysis in the part of the distribution where catastrophic events occur. This is a better way to account for heavy tails, volatility clustering, and the persistence of extreme losses than conventional methods. Therefore, Value at Risk (VaR) and Expected Shortfall (ES) calculations under EVT-GPD yield higher values because there is a higher likelihood of significant losses during financial crises. EVT-GPD is a more suitable tool for crash risk assessment as it does not dilute the effect of rare events; instead, it focuses on them at the centre of the analysis. However, it is important to understand the model's range. EVT-GPD does NOT predict when a market crash will happen. Instead, it measures the risk and severity of the worst losses. It is especially useful for investors, portfolio managers, regulators and policymakers who must plan for down markets, rather than foretell them.

Limitations of the Study

The results illustrate the applicability of the EVT-GPD model to extreme market risk, but several limitations should be noted.

The first problem is that the analysis is based solely on historical price data. Financial markets are constantly changing due to economic, government, technological and investor changes. Therefore, in the future, crises can be quite different to past events and past market behaviour may not be adequate predictors of future financial instability.

Second, EVT is not a forecasting model per se, but is fundamentally a risk estimation technique. It is an educated guess about the odds and severity of extreme losses, but it cannot predict when or what will cause a market crash.

Third, the Peaks Over Threshold methodology depends on selecting an appropriate threshold, which directly affects GPD parameters and tail risk calculations. The lower the threshold, the more likely it is to pick up fluctuations in the normal market, while the higher the threshold, the fewer observations there are for statistical estimation. The threshold recommended in this study is based on the theoretical recommendation; however, it can change depending on the criterion.

The disadvantages of this study are that the daily closing prices were used. Intraday price movements, flash crashes and recoveries within the day may not happen on a daily basis. High-frequency data may provide more detailed information on extreme market behaviour. Further, all data used in the study are from Yahoo Finance, which has data for the NIFTY 50. Although the database is widely used in academia, it is important to note that there are minor differences from the official information provided by the National Stock Exchange due to adjustments and/or revisions. The differences are small, but they can be a marginal contributor to returns and risk calculations. Finally, the model includes only statistical characteristics of market returns and omits macroeconomic variables, monetary policy indicators, liquidity measures, investor sentiment, and volatile market indices such as India VIX. All these have the potential to influence the onset and propagation of financial crises and may improve the explanatory and predictive capabilities of future financial crises models.

Future Scope

The present research has several implications. It would be very interesting to combine EVT with macroeconomic variables such as interest rates, inflation, exchange rates, liquidity conditions, and investor sentiment indicators. These variables can help better understand the economic drivers of extreme market events. Furthermore, future studies may incorporate intraday/high-frequency trading data to incorporate information about flash crashes and short-term volatility that may not be captured by daily closing prices. This would provide a much better understanding of the market in financial distress. The other exciting research direction is the use of Extreme Value Theory in conjunction with machine learning and Artificial Intelligence techniques. Hybrid AI-EVT models can capture intricate nonlinear relationships and enhance early warning systems, and better predict financial instability while maintaining the theoretical benefits of EVT. Last but not least, comparing emerging and developed financial markets can provide insights into systemic risk, financial contagion, and cross-market effects. This could be used as part of a larger project to gain deeper insight into global financial stability and to improve risk management for investors, financial institutions, and policymakers.

Conclusion

The results of this study support the fact that the daily returns of the NIFTY 50 have substantial deviation from the assumptions of the Normal distribution and hence have a significant heavy-tail property. The empirical analysis shows that the data is negatively skewed, exhibits excess kurtosis, and tends to have large downside moves, all of which suggest that large losses are more likely in the market than would be predicted by traditional Gaussian models. These features are also corroborated using the Extreme Value Theory (EVT) and the Peaks Over Threshold (POT) technique. The value of the Generalised Pareto Distribution (GPD) shape parameter ($\xi = 0.361$) suggests the presence of fat tails in the distribution of the excess returns over extreme losses, meaning that extreme losses fade away slowly, and that values still exist at very low probabilities.

Furthermore, the number of exceedances of the chosen threshold (135) indicates the regularity of large downside market moves over the sample period. The results show that the Indian stock market is significantly tail-risky, particularly during periods of financial trouble and economic uncertainty. Another example of the limitations of the Normal distribution paradigm is the comparative Value-at-Risk (VaR) analysis. The EVT-GPD model estimates the daily VaR at the 99.5% confidence level as –3.67%, while the Normal distribution estimates a smaller loss of –2.82%. This is a significant difference, indicating that the Normal model is unlikely to describe the probability and severity of extreme crash events due to its assumption of a thin tail. The EVT-GPD Expected Shortfall (ES) estimate, at the same level of confidence, indicates that losses can be substantial if market conditions are extreme and the out-of-the-VaR value is –5.67%. The overall results indicate that EVT-GPD is a more realistic and robust modelling tool for financial market crash risk. In contrast to traditional probability distributions, EVT will not indicate exactly when and under what conditions a crash will occur, but it can provide a much more accurate estimate of the probability and severity of extreme downside crash events. Therefore, EVT methods play an important role in financial risk management, financial portfolio protection, and the development of an early warning system (EWS) for financial market instability.

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