FINANCIAL RISK MEASUREMENT
USING EXTREME VALUE THEORY APPROACH
IN INDIAN STOCK EXCHANGE

TABLE OF CONTENTS

ABSTRACT:

This project aims to explore the application of Extreme Value Theory (EVT) in analysing the financial performance of four major Indian banks—IDFC First Bank, ICICI First Bank, State Bank of India (SBI), and HDFC Bank—over past five years from October 2019 to September 2024. We focus on extreme daily stock returns and assess risk using Value at Risk (VaR) and Expected Shortfall (ES) as key measures.

To achieve this, we collect historical stock data to calculate daily returns and analyse essential statistics. We employ the Peak Over Threshold (POT) method to fit a Generalized Pareto Distribution (GPD) to extreme returns, using Maximum Likelihood Estimation (MLE) for parameter estimation.

Our findings emphasize the importance of extreme value distributions in understanding risks associated with banking stocks, providing valuable insights for investors and risk managers regarding potential losses as indicated by VaR and ES.

Keywords:

- Extreme Value Theory
- Peak Over Threshold
- Value at Risk
- Expected Shortfall

INTRODUCTION:

In finance, understanding risk is really important for both investors and banks.

Market risk refers to the risk faced by a portfolio of assets due to changes in market movements or market-wide risk factors. Market risk becomes highly pronounced when certain events, which are assumed to be rare within the distribution of asset returns, lead to substantial alterations in the portfolio's valuation. These infrequent events are typically located in the tails of the distribution of asset returns, and they can result in either substantial gains or significant losses in the portfolio's value. Given that most investors are primarily concerned with avoiding extreme losses rather than pursuing substantial gains, our focus is on loss severity or downside risk within the portfolio.

One effective way to assess risk, especially when it comes to rare and extreme market situations, is through a method called Extreme Value Theory (EVT). This theory looks at how extreme values behave, which helps in predicting potential losses in investments.

For this project, we focused on four major Indian banks: IDFC First Bank, ICICI Bank, State Bank of India (SBI), and HDFC Bank. We analysed their financial performance over a five-year period, from October 2019 to September 2024.

We used EVT to understand extreme market movements better and apply a Generalized Pareto Distribution (GPD) to the extreme values.

Before investing, it's important for investors to understand both the expected returns and the risks involved. One way to assess investment risk is by measuring it using Value at Risk (VaR). Value at risk (VaR) is a statistical measurement used in measuring the level of risk associated with a company's stock portfolio, and VaR shows the estimated value of the maximum loss that is likely to occur with a level of confidence over a certain period.

Additionally, Conditional Value at Risk (CVaR) also known as expected shortfall provides insight into the average loss that could occur beyond the VaR threshold, helping investors understand potential extreme losses.

Another method, the Peaks Over Threshold (POT) approach, focuses on analyzing the most significant losses that exceed a certain threshold, offering a deeper understanding of risk in extreme market conditions.

Through this project, we hope to gain insights into the risk profiles of these banks and how they interact during extreme market conditions. Our findings would be useful for investors and risk managers, helping them to make better decisions in the Indian banking sector.

OBJECTIVES:

1. To do a comparative study of risk management strategies in major Indian banks: IDFC bank, ICICI bank, SBI bank and HDFC bank.
2. Estimating financial risks i.e. Value at Risk (VaR) and Expected Shortfall (ES) using the Peaks Over Threshold (POT) approach of Extreme Value Theory (EVT).
3. To evaluate the accuracy of the EVT models in capturing extreme market risks

DATA PRE-PROCESSING:

- In this study, we have used secondary data in the form of daily stock closing prices of IDFC bank, ICICI bank, SBI bank and HDFC bank obtained from the finance.yahoo.com website, over the past 5 years i.e. for the period October 01, 2019 to September 30, 2024.

Oct 01, 2019 - Nov 12, 2024 | Historical Prices | Daily

Currency in INR

Date	Open	High	Low	Close	Adj Close	Volume
Nov 12, 2024	1,276.15	1,295.00	1,264.50	1,270.60	1,270.60	13,485,977
Nov 11, 2024	1,262.00	1,275.90	1,246.65	1,269.30	1,269.30	8,387,780
Nov 8, 2024	1,270.00	1,275.00	1,252.70	1,258.85	1,258.85	11,195,808
Nov 7, 2024	1,297.15	1,302.80	1,275.25	1,278.70	1,278.70	9,909,035
Nov 6, 2024	1,300.25	1,315.00	1,292.70	1,302.35	1,302.35	12,037,405
Nov 5, 2024	1,273.00	1,301.30	1,263.10	1,296.70	1,296.70	16,431,920
Nov 4, 2024	1,290.10	1,291.80	1,270.05	1,277.20	1,277.20	14,309,121
Nov 1, 2024	1,289.95	1,296.20	1,286.25	1,291.80	1,291.80	1,007,022
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

- **Return calculation**: We need to model the distribution of the returns of the stocks therefore we first need to calculate returns. We calculated return of each stock closing price in R software itself by formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where,
R_t: return value at time t
P_t: stock closing price at time t
P_{t-1}: stock closing price at time (t-1)

- **Data cleaning**: After calculating the return, we checked the null values present in the data and removed that null values using R software.

METHODOLOGY:

1. Descriptive Statistics of Stock Returns:

Figure 1. Shows that value of stock return in the four companies often fluctuates and is full of uncertainty. Fluctuations that occur in IDFC, ICICI, SBI and HDFC cause extreme values to occur in specific periods.

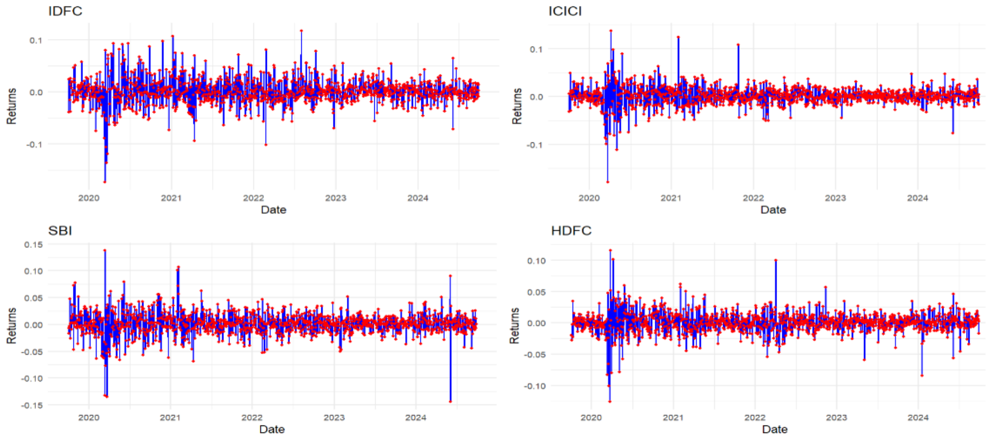
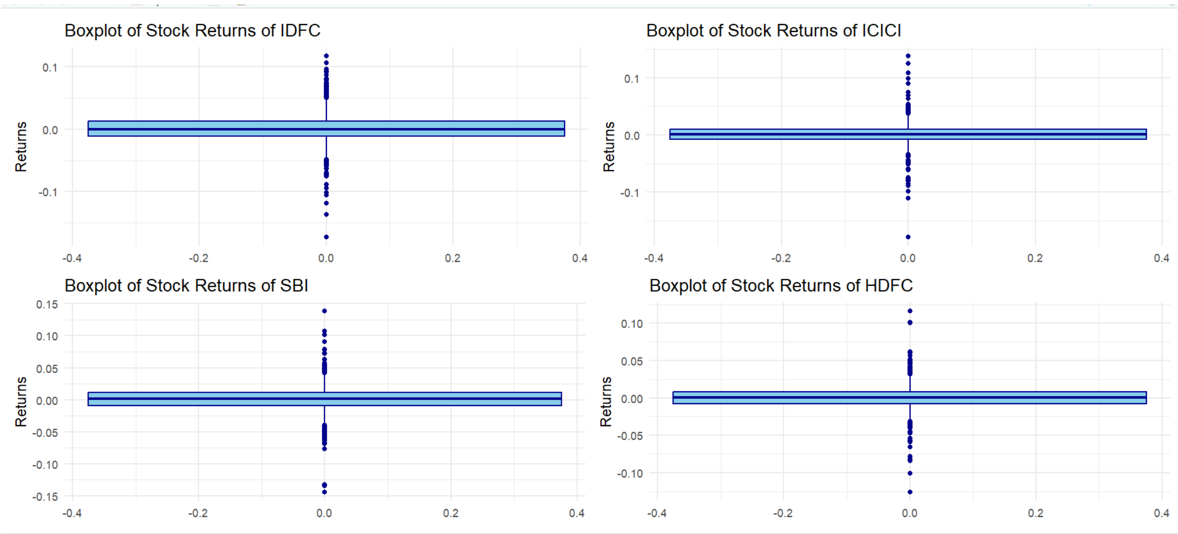


Figure 1. Time Series Plot of Stock Returns

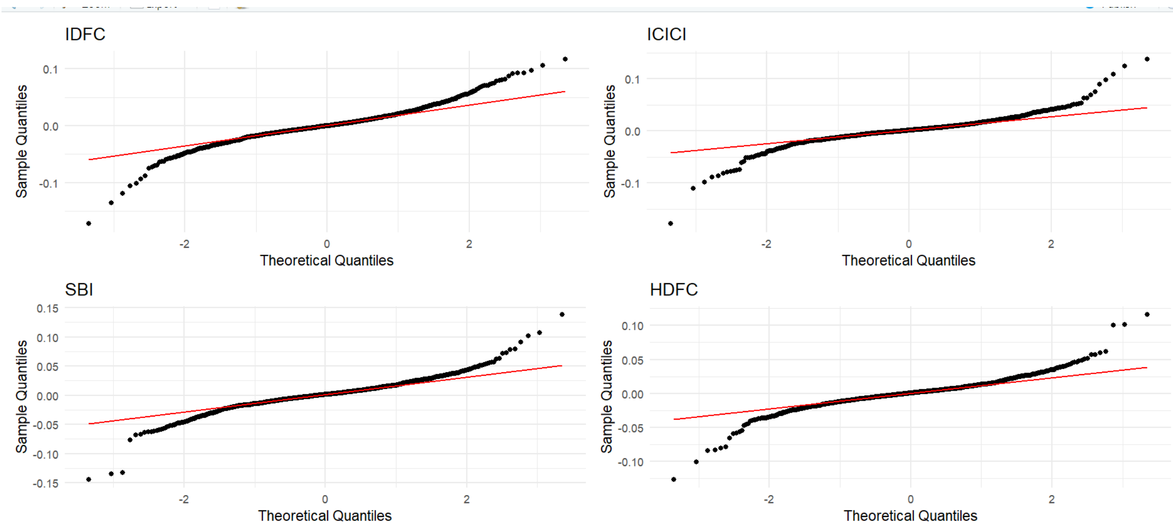
Descriptive Statistics of Stock Returns

Size	IDFC	ICICI	SBI	HDFC
Mean	0.0008417648	0.001141901	0.001200178	0.000421452
Variance	0.0006252118	0.0004049982	0.0004484552	0.0002930733
Minimum	-0.1726727	-0.1784784	-0.1440402	-0.126069
Maximum	0.1171771	0.1376245	0.1382879	0.1159958

2. Identify Extreme Values and Heavy Tail



In Figure 2. It can be seen that the return values of IDFC, ICICI, SBI and HDFC stocks have extreme values which can be seen by the presence of black dots that cross the upper and lower limit.



From the Figure 3. it can be conclude that, data does not follow normality that is data has heavy tail distribution. As stock returns of od IDFC, ICICI, SBI and HDFC data located outside the standard deviation line.

To find out more specially, we have performed the following hypothesis

$H_0: F(x) = F_0(x)$ (Stock return data follow normal distribution)
$H_1: F(x) \neq F_0(x)$ (Stock return data does not follow normal distribution)

Reject H_0 if $D_{count} > D_{table}$ or $p - value < \propto$

Kolmogorov-Smirnov Test Results Data Normality

Company	IDFC	ICICI	SBI	HDFC
D count	0.073875	0.087653	0.0722946	0.083655
D table	0.03869951	0.03869951	0.03869951	0.03869951
P-Value	2.798e-08	1.147e-06	3.917e-06	6.224e-08
Decision	Reject H_0	Reject H_0	Reject H_0	Reject H_0

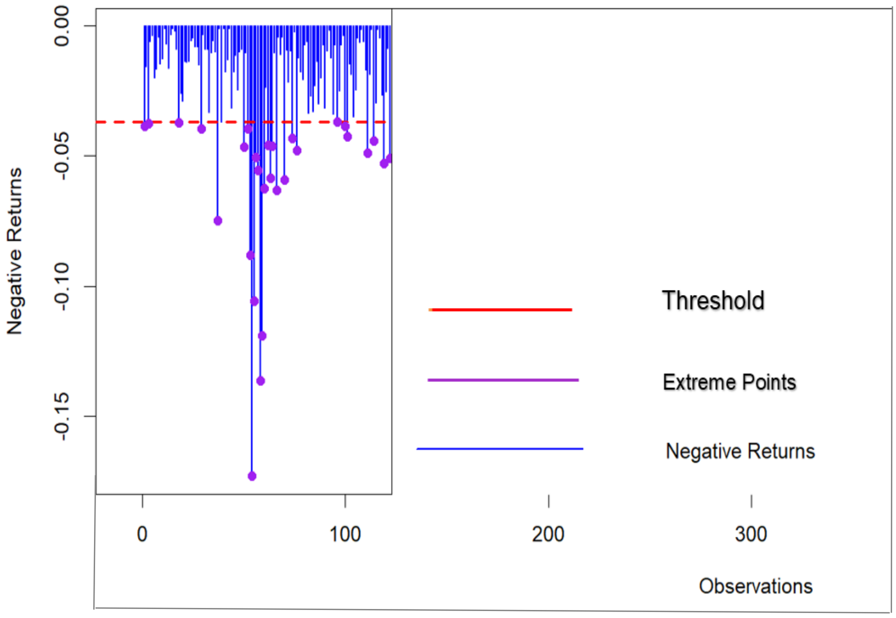
Based on above table, it is know that stock return data of IDFC, ICICI, SBI and HDFC have D_{count} value greater than D_{table} and a p-value is less than $\propto$=0.05. Therefore, the decision is to rejectH_0, which means that stock return data of the four banks do not follow the normal distribution.

3. Extreme Value Theory (EVT):

Extreme Value Theory focuses on the behaviour of tail of distribution. It is usually used to model extreme events, such as losses that are rare but have a huge impact. These losses can't be modelled with usual approaches such as normal but rather has a heavy tail. Hence, EVT can be widely used in finance and insurance. There are multiple approaches of EVT to identify movement of extreme values. One of the approach that we have used in our project is Peak Over Threshold method (POT).

4. Peaks Over Threshold (POT):

POT identifies extreme values by setting a certain threshold and ignoring timing of the event. In this method, we set a threshold and all the values above this threshold is considered as extreme values. The threshold is the maximum limit or limit of the company's ability to bear an operational loss. In our study we specifically focused on extreme negative returns i.e. left tail because in financial risk analysis, we're primarily concerned with large losses. This is especially relevant for investors and risk managers who need to prepare for the worst-case scenario where extreme losses could threaten financial stability. Now to apply POT methods, we used 10th percentile as our threshold. We set threshold percent as 0.10, meaning we are interested in the lowest 10% of negative returns. This approach helps us concentrate on the most significant losses. This 10% observation led to the conclusion that the extreme values in each market index conform to the Generalized Pareto Distribution.



Threshold Value

	IDFC	ICICI	SBI	HDFC
Threshold (u)	-0.03705888	-0.02703365	-0.0340385	-0.0245661
Number of Observations (n)	604	575	563	589
Number of Observations above Threshold (k)	61	58	57	59

5. Fitting the Generalised Pareto Distribution

The Generalized Pareto Distribution (GPD) is a probability distribution used in statistics to model extreme events. It is often employed in the field of extreme value theory, which focuses on the tail behavior of distributions. It is used to model extreme values, especially when you are using POT approach. The GPD is an extension of the Pareto distribution, allowing for a more flexible shape parameter.

Probability Density Function (PDF):

The probability density function of the GPD is given by:

$$f(x;\xi,\beta)=\frac{1}{\beta}\left(1+\frac{\xi x}{\beta}\right)^{-\frac{1}{\xi}-1},\quad x\geq 0$$

where,
ξ = shape parameter
β = scale parameter

The suitability of the GPD model was assessed through the implementation of the **fevd** function in the **R software**, which facilitated the fitting of the model parameters to the dataset.

```
fevd(x = -icici_negative_extremes, threshold = -icici_neg_threshold,
    type = "GP", method = "MLE")

[1] "Estimation Method used: MLE"


 Negative Log-Likelihood Value:  -162.7088


 Estimated parameters:
      scale      shape
0.01957249 0.12830603
```

Now, GPD has only 2 parameters i.e. scale and shape. It doesn't have location parameter as this distribution only describes the extreme tails of distribution. The scale parameter shows how far the data is spread from the mean value. The shape parameter shows the characteristic of distribution shape, indicates the heaviness of the tail. We got positive shape parameter for all four banks means that the distribution has a heavy tail. A higher positive value indicates a heavier tail, typically means extreme events are more likely to occur, leading to higher tail risk.

Parameter Estimation of Peaks Over Threshold

Parameters	IDFC	ICICI	SBI	HDFC
Scale (ϑ)	0.01237413	0.01957255	0.0133620	0.01190168
Shape (ξ)	0.37958982	0.12830462	0.2351731	0.27793726

6. Risk Metrics: VaR and ES

Two risk metrics that we have calculated in out study are Value at Risk and Expected Shortfall. Suppose you want to know “What is the maximum loss I might face on a bad day?” That’s where VaR comes in. VaR estimates the maximum loss that may occur on aportfolio at a certail level of confidence. But VaR has it’s limitation – it doesn’t tell us how the loss can go beyond the thrrshold. This is where ES comes into the picture. ES answers the question: “If we breach the VaR threshold, what’s the average loss I can expect?”. So ES is a risk measure that estimates the average loss beyond the VaR over a given probability distribution tail.

We used the following formula to calculate VaR and ES:

$$P(X < \mathrm{VaR}) = 0.05.$$

$$\mathrm{CVaR} = \mathbb{E}[X \mid X \geq \mathrm{VaR}]$$

where:

$$VaR = u + \frac{\sigma}{\xi}\left(\left(\frac{n}{n_u}(1-q)\right)^{-\xi} - 1\right).$$

q = 0.05

σ = Scale parameter

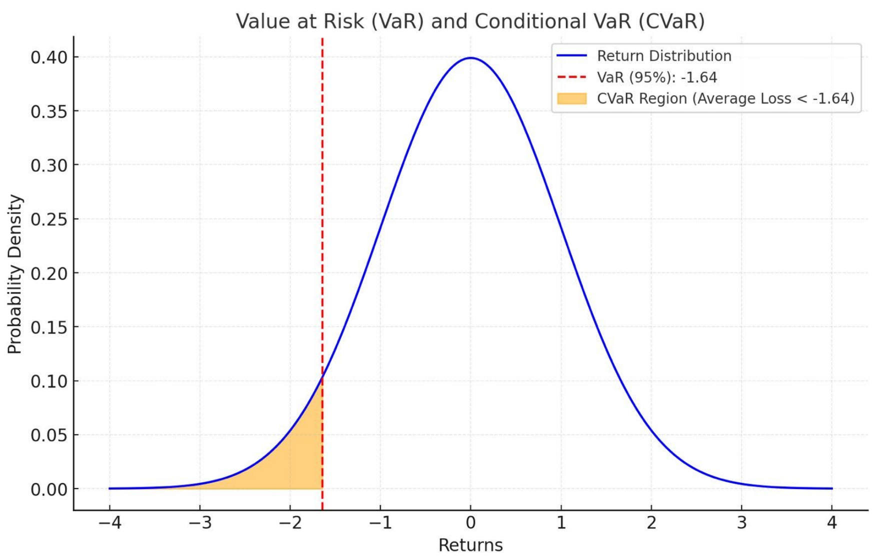
ξ = shape parameter

u = threshold

μ = mean

n = number of obs in the data

nu = number of extreme values



RESULTS AND DISCUSSION

After calculating the VaR and ES we get the following results:

	IDFC	ICICI	SBI	HDFC
VaR	-0.0557	-0.06517	-0.05729	-0.04447
Expected Shortfall	-0.08335	-0.093331	-0.08105	-0.07036

From the above table we can infer that

For IDFC

We are 95% sure that our losses in returns will not exceed more than -0.0557. If there is a situation worse than VaR then the average loss is expected to be 8.33% of portfolio or asset value.

For ICICI

We are 95% sure that our losses in returns will not exceed more than -0.0651. If there is a situation worse than VaR then the average loss is expected to be 9.33% of portfolio or asset value.

For SBI

We are 95% sure that our losses in returns will not exceed more than -0.0572. If there is a situation worse than VaR then the average loss is expected to be 8.105% of portfolio or asset value.

For HDFC

We are 95% sure that our losses in returns will not exceed more than -0.0444. If there is a situation worse than VaR then the average loss is expected to be 7.036% of portfolio or asset value.

CONCLUSIONS:

This study highlights the value of EVT in quantifying and comparing financial risks. Among the analysed banks:

- **HDFC** consistently demonstrates resilience and lower risk in extreme scenarios.
- **ICICI**, while potentially lucrative in favorable markets, poses the greatest risk under adverse conditions.
- **SBI and IDFC** fall in between, with moderate levels of risk and stability.

Such insights can guide investors, portfolio managers, and policymakers in risk management and decision-making processes, particularly in extreme market scenarios.