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The Behavior of Extreme and Cumulative Stock Price Random Variables during the Crisis Periods-A Study of Nifty 50 Stocks

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Abstract

In this paper, we attempt to identify the probability structure of extreme and cumulative stock price random variables for the Nifty 50 stocks, during six time periods between 2007 and 2020, where the major financial crises have occurred. We estimate the tail index for each stock to identify the corresponding probability model for extreme stock prices (minimum and maximum) and the domain for the cumulative stock prices. From our analysis, we found Weibull distribution as an appropriate model that fits the extremes for many stocks during the periods and for other stocks, Fréchet and Gumbel distributions form the domains. Similarly found that the domain of cumulative stock price oscillates between normal and stable. Interestingly, for many stocks normal remained to be the domain during the periods. We present a table towards the end that gives the classification of the stocks, based on the number of times the domain changes from normal to stable, as Highly affected, moderately affected, and low affected stocks. This can be considered by the decision-makers while concluding on these stocks.

Keywords: Cumulative and Extreme prices, Financial Crises, Normal domain, Stable domain, Tail index

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1. Introduction

When studying the behavior of the stock prices, either investors or portfolio managers may be interested in extreme stock prices. For example, maximum stock price or minimum stock price. One of the reasons being, the interest in knowing whether the recent happenings (either positive or negative) in the market have improved (deteriorated) the level of stock prices. The happenings also include the financial crisis either at the local level or the global level. This will help them to plan the investments and know the stocks that are volatile to the happenings in the market. If the happenings impact highly, then the prices tend to have a higher mass on the right tails and the left tails if the happenings impact the prices negatively. In such cases, the domination by the actual prices will be replaced by the extreme prices and the focus will be on the behavior of the extreme prices. Taking the uncertainty aspect, it is suggested to calculate the chances of the extreme prices (minimum or maximum) exceeding a threshold. For this, it is important to identify the probability model that best fits the maximum or minimum stock price random variables. Using the Probability model identified, one can compute the probability of extreme prices exceeding the threshold and the same can be used to make right investment decisions and

measure the associated risk. Value at Risk (VaR) and expected shortfall (ES) are used to measure the associated risk. It a regular practice to measure the index for the variable under study and based on the value of the index, the domain for the extremes is identified. In the current study, we attempt to identify the probability model for the extreme prices for each of the stocks during the periods of crisis between 2007 and 2020. We use generalized extreme value (GEV) distribution to identify the distribution for extremes. We continue this process for each of the stocks at all the time points considered and note the changes in the behavior. Studies on the use of extreme value theory (EVT) in stock market behavior are presented in the literature review section.

The next important property of the stock prices is the cumulative stock price. Note that, each stock price can be considered as a resultant value of the stock due to the information generated on the stock and, the level of the stock price indicates the impact of the information of the stock. An investor chooses a stock that is less volatile to the events related to the market. Sometimes it is not possible to observe these changes by looking at the individual stock prices and in such cases, one can look at the cumulative stock price. If an event affects the stock, then the cumulative stock price belongs to a class of distributions that will have infinite variance. This acts as an indication of the adverse impact of the events on the stock prices. The cumulative stock price provides adequate information to the investor on a selected stock and also helps one to take appropriate decision on the stock. A normal model is an obvious choice to model the cumulative stock price random variable. But not always. When the tails are heavy or extremes dominate the cumulative prices, the variance is infinite, the normal model fails, and even the central limit theorem fails. In such cases, one has to make use of stable models. The stable index or the exponent decides the model that one has to adopt. This process can be used to study the impact of extreme events (market boom or crashes) on stocks. In the current study, we attempt to identify the domain of cumulative stock price random variable for each of the stocks, during the crisis periods between 2007 and 2020. We also note the changes in the stable index for each of the stocks during the time points considered. Studies related to the use of stable models in the stock market are presented in the literature review section. We now present the extreme value distributions and details related to stable distributions in brief.

1.1. Brief introduction to Extreme Value Distributions (EVD)

The limiting distributions for the extremes (maximum and minimum), properly normalized, form the class of distributions, called Extreme value distributions. Gumbel (type-1), Fréchet (type-2), and Weibull (type-3) are the most common limiting distributions and the domains to which the extremes belong are decided based on the extremal index value. The discussion on these limiting distributions can be found in the works of Fréchet (1927), Fisher and Tippet (1928), von Mises (1936), and Gnedenko (1943). de Haan (1970) proposes the domains of attraction of the extreme, termed as max-stable or min-stable laws. One can refer to the book of Galambos (1987) for complete details on the extreme value distributions. We now present the three types of extreme value distributions.

Type-1: Gumbel law

The distribution function of a Gumbel law is given by.

$$F(x;\mu,\sigma,0) = e^{-e^{(x-\mu)/\sigma}}, for\ x \in R \quad (1)$$

The ξ value for a Gumbel law is at level zero and the domain for extremes is identified based on the value of ξ.

Type-2: Fréchet law

The distribution function of a Fréchet law is given by.

$$F(x;\mu,\sigma,\xi) = e^{-y^{-\alpha}}, y \geq 0 \tag{2}$$

where $\xi = \frac{1}{\alpha} > 0$ and $y = 1 + \xi(x-\mu)/\sigma$. If $\xi > 0$, then the corresponding distribution is classified under Fréchet law.

Type-3: Weibull law of domain

The following is the distribution function of the Weibull law.

$$F(x;\mu,\sigma,\xi) = e^{-(-y)^{\alpha}}, y < 0 \; and = 1\,, y \geq 0. \tag{3}$$

Here $\xi = -\frac{1}{\alpha} < 0$ and $y = -(1 + \xi(x-\mu)/\sigma)$. If $\xi < 0$, then we classify the corresponding distribution under a Weibull law.

The three types of distributions can be represented using generalized extreme value (GEV) distribution. The following is the distribution function of the GEV

$$F(s;\xi) = \begin{cases} \exp(-(1+\xi s)^{-1/\xi}) & \xi \neq 0 \\ \exp(-\exp(-s)) & \xi = 0 \end{cases} \tag{4}$$

where $\xi \in R$ is the shape parameter, $s = (x-\mu)/\sigma$, $\mu \in R$ is the location parameter, and $\sigma > 0$ is the scale parameter. Based on the value of the shape parameter, the three types of extreme value distributions can be represented. If the value of $\xi = 0$, then one gets a Gumbel law. If the value of $\xi > 0$, then one gets a Fréchet law. If the value of $\xi < 0$, then one gets a Weibull law.

In the current study, we compute the value of ξ for each stock and the distribution of the maximum stock is identified based on the level of ξ. The distribution of minimum is obtained by considering the negative of the random variable considered. That is, -X is substituted in the place of X to obtain the distribution of the minimum stock price random variable. We consider each stock and study the change in the extreme domain with a change in the periods.

1.2. Importance of studying the cumulative stock prices

It is a well-known fact that extremes affect the sums or total (Hall (1984)). If there are extremes in the data set, then they either increase or decrease the value of the sums and exclusion of the same improves the performance of the sums (Csorgo et al. (1988), Berkes et al. (2012)). Studying the cumulative prices will help one to understand the impact of the extreme prices or outliers, on

the behavior of the stock prices. It is a well-known fact that extremes affect the sums or total. If there are extremes in the data set, then they either increase or decrease the value of the sums and exclusion of the same improves the performance of the sums. The same can be sometimes used to test the behavior of the stock prices. We propose this process through the current study.

For each of the stocks considered, we try to identify the distribution of the cumulative stock price random variable. From the early discussion presented, we recall that the cumulative price random variable can belong either to the domain of normal or to the domain of stable law. This process will be applied for every period considered and the same will be recorded. If any period has extremes and affects the stock, then the domain will be stable. If not, then the domain will be normal. The domain is stable, which implies that the variance of the random variable is infinite, and the tails are heavier. This implies that the market crashes have affected the stock prices and the domain of the total stock price changes from normal to stable. We apply this process for each of the stocks considered and note the frequency of the change in the domain. If a stock has more domain changes from normal to stable, then we classify that stock as a highly unstable stock. That is, it has got affected by market crashes or the financial crisis, frequently. Based on the analysis, we classify present the stocks in a table and the same can be used for further decision making.

The decision on the domain will be made based on the value of the stable exponent or tail index. The domain is considered normal if the value of the exponent is equal to 2. Otherwise, the domain is considered stable.

If the domain is normal, we conclude that the market crashes have not affected the behavior of the stock price random variable much. Note that the mean, variance and other moments might have got affected. But the probability structure of the total stock price random variable might not have got affected. That is, the extremes generated by the market crashes didn't affect the behavior of the total stock price random variable. In practical terms, one can say that the cumulative stock price behavior did not get affected and hence the basic structure of the stock price random variable is not affected. For example, let us consider stock A. Assume that its behavior is normal, and a market crash has happened. One can expect that the stock prices have got affected and the answer may be yes. But the original structure of normality might not have got affected. This can be checked by studying the behavior of the cumulative stock price random variable. The stock prices can be seen as the sequence of random variables and the total stock price is the sum of the sequence of random variables. If there are extremes, then the sum gets affected. Assume that the market crash has occurred, and the stock prices got affected. Then, the values of the stock price random variable may be low or high or lower than the expected values. Individually the values may be high or low. But when taken the aggregate of all the values, the high and low values get adjusted and the cumulative price will have normal behavior. This can be taken as a test for the influence of the market crashes or the financial crisis, on the stock prices. For each of the stocks considered, we propose to check this and draw conclusions. If the domain is stable, then we conclude that the market crashes have a significant effect on the stock prices. They increase the variance or thickness of the tails so that, a normal model cannot be used. Further details can be found in the books of Gnedenko (1956), Feller (1950), Hahn (1991) and Rohatgi (2015).

We adopt this process to classify the stocks and check if the market crashes or financial crisis have affected them. Note that, this process can be used to check if the normal behavior of the stock prices is affected or not. We now present in brief about stable distributions.

1.3. Brief introduction to stable distributions

Stable distributions are characterized by four parameters- tail index or exponent ($\alpha \in (0,2]$), skewness parameter ($\beta \in [-1,1]$), scale parameter ($\sigma > 0$), and location parameter ($\mu \in R$). Based on the value of the tail index, one can understand the rate at which the tails of the distribution taper off. The resulting distribution is normal if $\alpha = 2$ and the resulting distribution has infinite variable if $\alpha < 2$ and the tails are asymptotically equivalent to a Pareto law. When $\alpha > 2$ stable distributions exhibit a crossover from a power decay to the true tail with exponent α. When $\alpha > 1$then the mean of the distribution exists and equal to μ. The moments do not exist if $\alpha < 1$. If $\beta > 0$, then the distribution is positively skewed (the right tail is thicker) and negatively skewed if $\beta < 0$. When $\beta = 0$ one gets symmetric stable distribution. β loses its effect, as α approaches 2 and the resulting distribution is a Gaussian distribution. μ and σ are respectively the location and the scale parameters. While σ determines the width, μ determines the shift of the mode. When $\mu = 0$ and $\sigma = 1$, one gets a standard stable distribution. A stable distribution is denoted by $X \sim S_\alpha(\sigma, \beta, \mu)$. Except for normal distribution and few other distributions, density functions are not known in a compact form for stable distributions. One can refer to the book of Samoradnitsky and Taqqu (1994) for further details.

Investors or portfolio managers can use the probability models identified, for calculating the risk associated and help them to make appropriate investment decisions in the stocks. Also, help them to note the change a crisis has brought in the respective stocks and study their sustenance to the crisis. Our study will help them to list out the stocks that get influenced fast by the crisis and classify them appropriately. This forms the main objective of the study.

Identifying the extreme value distribution for each stock separately will help one to calculate the risk measures associated with the extreme returns. Knowing the model will help one to make appropriate decisions on the stocks and compare the stocks before taking any decision. Attempts have been made to fit extreme value distributions like GEV, GPD etc. But not many studies have been considered in the Indian context to observe the change in the domains of extreme prices during the crisis periods. Also, not many studies have been considered in identifying the domains for the cumulative stock prices and use the same for checking the impact of the crisis.

Taking the above, we consider the following as the major objectives of the study.
1. To estimate the tail index and identify the domain of attraction for the maximum, minimum, and total for the stocks considered.
2. To examine the changes in the domains of the total price random variables during the market crash periods and identify the stocks that got affected by the market crashes.
3. To build a classification table for the stocks based on the analysis.

2. Literature review

In this section, we present the studies that have considered periods during which crisis have occurred studied their impact on the stock markets. Also, present those studies that have used extreme value theory to understand the behavior of the stock market prices/returns.

Mandal and Bhattacharjee (2012) consider the pre-recession period (January 2002-November 2007) and post-recession period (December 2007-July 2010) and study the impact of the great recession of 2007 on SENSEX. The study finds an increase in the volatility during the post-recession period and no significant difference between returns for both periods. It also finds strong co-movements in returns and volatility between SENSEX and other major stock indices during the post-recession period. It concludes that global factors influence the Indian stock market during crisis periods. Sakthivel et al. (2014) studies the impact of the global financial crisis on the stock market volatility and shows that volatility of the mean returns had increased during the post-crisis period (From March 01, 2005, to January 30 2008) as compared to the pre-crisis period. Also, that the recent financial crisis impacted mean returns and the volatility of the Indian stock market. Grima and Caruana (2017) consider BRIC's stock market returns and check if they were affected by US financial stress during the 2008 financial crisis. Their study analyzes the data series from 2003 to 2014 and then sub-divided the data to analyze the post-crisis effects on the BRICS equity market. Samsi et al. (2019) considers a study where they examine the impact of the Asian financial crisis (AFC) and the Global financial crisis (GFC) on the economic growth on the ASEAN-5 countries. They show that Indonesia, Malaysia, and Thailand have got affected by the AFC and not by GFC. The real output responded significantly positively to the shocks for Malaysia and Thailand.

Ali et al. (2020) looks at how the pandemic affects the global financial markets and finds that China stabilized, and global markets are facing turbulence mainly in the later phase of the spread of the virus. They show that even safer commodities have suffered as the virus spread into the US. At this stage, one can question the impact of the increase in the number of COVID cases on the stock market. Al-Awadhi et al. (2020) uses panel data analysis to examine the effect of COVID-19 on the Chinese stock market. They find that both the daily growth in total cases and cases of death have a significant negative effect on the stock returns. Ziemba (2020) studies the changes in the US equity market during the COVID-19 period in the first half of 2020 and show that there were a rise and record fall and recovery. Also, throughout the period there was extreme volatility. Contessi and De Pace (2020) considers 18 major European countries during the pandemic and finds robust evidence of instability and crashes spreading from China to these countries. Engelhardt et al. (2020) considers a sample of 64 national stock markets that covers 94% of the world's GDP and find that stock markets decline due to higher news attention than the rational expectation. Salisu and Vo (2020) show that the health news generated on the pandemic have an impact on the predictability of stock returns.

We now present the studies that have used extreme value theory (EVT) in stock markets.

The studies conducted by Longin (1996), Jondeau and Rockinger (2003), Tolikas and Gettinby (2009) indicate that the assumption of normality may lead to underestimation of risk. Parkinson (1980) notes that the tail of the empirical distribution contains important information for the variance of the returns. Login (2000) uses EVT to calculate the VAR of a fully aggregated position and multivariate EVT to calculate the VAR of a position decomposed on risk factors. Ho et al. (2000) considers six Asian financial markets and computes the VAR using EVT by modelling the tails of their return distributions. They show that for markets whose Leptokurtosis is high, the maxima and minima were appropriately modelled using EVT as compared to other traditional methods. Gencay et al. (2003) calculates the VAR using EVT and compare the performance with other well-known modelling techniques such as GARCH, variance-covariance method, and historical simulation. The study finds that generalized Pareto distribution (GPD) is a robust model in the calculation of VAR. Carvalhal et al. (2003) considers 10 Asian stock markets and uses EVT to identify the type of extreme value distribution that fits historical extreme value

events. The study finds that normal distribution is not an appropriate distribution under the influence of extreme market events and maxima and minima were modelled using EVT. Also, show that VAR calculated using EVT was a more conservative method than the traditional methods. Byström (2004) adopts unconditional and conditional EVT models for the management of extreme risks in stock markets and finds that the conditional EVT model gives accurate VAR values and as compared to GARCH models the VAR calculated using EVT models were superior. Longin (2004) finds that EVT will be useful to study the behavior of the asset returns and for understanding the characteristics of the distribution of the asset returns. Gilli and Evis (2006) use EVT for measuring the risk while handling rare and extreme events. Cumperayot et al. (2006) considers 26 countries and investigate the link between extreme events and stock markets by estimating a simultaneous equations probit model. A sample of 2500 daily returns for the period between 1996 and 2005 was used and show that, for currency markets, within regions have got affected due to spillover of extreme and outside regions have less affect. The study claims that, when originated from the US, extreme events were interrelated globally. Wentzel and Mare (2007) use EVT to fit the returns of the South African equity market and show that EVT best fits the returns than a normal distribution do. Straetmans et al. (2008) apply EVT to US sectoral indices to assess if the tail risk were significantly altered by 9/11. Considering 9/11 as the midpoint, they find that tails often increase in a statistically significant way. Assaf (2009) use EVT for analyzing the four emerging markets belonging to the MENA region. The study estimates the tails of the unconditional distribution of the returns and show that the tails are significantly fatter than that of a normal distribution and compute the maximum daily loss by calculating the VAR in each of the markets. Kourouma et al. (2010) use Peak over Threshold (POT) and generalized Pareto distribution of EVT to measure VAR and expected shortfall for CAC 40 and S&P 500 indexes during the 2008 financial crisis. They consider 1 day, 5 days and 10 days time horizons. The results obtained using EVT are compared with the traditional simulation through the backtesting process on 250 days. They show an underestimation of the risk of loss for VAR models and this underestimation is stronger for the historical VAR model than the EVT VAR model. Anđelić et al. (2010) investigates the performance of EVT on the daily stock returns of four emerging markets and attempts to estimate the tails of daily return distribution of the analyzed stock indexes. Singh et al. (2013) consider ASX-All Ordinaries (Australian index) and the S&P-500 (USA) index and apply univariate extreme value theory to model the extreme market risk. They demonstrate that VAR, CVAR, and expected return level and daily VAR can be successfully calculated using EVT. The Studies of Cotter (2007), Marimoutou et al. (2009), Allen et al. (2013), and Karmakar (2013) reveal that extreme stock returns in the US can be characterized by the generalized extreme value (GEV) distribution and can be used for calculating VaR measures and capital requirements. Hussain and Li (2015) study the distribution of the extreme daily returns of the Shanghai Stock Exchange (SSE) composite index. Their results suggest that Generalized Logistic (GL) is a better fit for the minima series and the Generalized extreme value (GEV) is a distribution for the maxima series. Gabriel (2017) uses EVT to model the daily loss probability for the Peruvian stock market returns and estimates the maximum quantiles, tail probabilities of the distribution and models extremes through a maximum threshold. VAR and ES are computed using the same and show that Gumbel and Fréchet fit the extreme returns. Also, show that Generalized Pareto distribution (GPD) in comparison with normal distribution, gives better estimates for VAR and ES. Louangrath (2016) use EVT to review three models: modern portfolio theory, Black-Scholes, and Jarrow-Rudd models. The study uses the daily close price from a period of 30 days from 100 companies in the SET 100 Index. They calculate the tail index and, based on the same they classify each of the securities. The study found that the Weibull distribution was the right choice for a majority of the stocks and the remaining Fréchet distribution was the choice. Empirically they show that stocks

from different sectors have the same distribution and stocks from the same sector have different distributions.

From the above review, we note that not many studies have considered the study of the behavior of the extremes for the Indian sectoral indices during the crises periods and the current study aims to fill the gap.

Stable distributions are used in cases where the tails of the return distribution become heavy due to the presence of extremes (Fama (1965), Mandelbrot (1963)). Studies of Akgiray and Booth (1988), Tucker (1992), Mittinik and Rachev (1993), Anna (1996), McCulloch (1996), Hoechsoetter et al. (2005), Belov (2006), Xu Weidong et al. (2011), Borak et.al (2011), Gűnay (2015), Marc (2016), Başeğmez (2017), Bielinskyi (2019) suggests the use of stable models in understanding the stock markets and in the financial applications. The work of Nolan (2014) gives an extensive discussion on the use of stable distributions in modelling the stock market returns.

From the above one can note that not many studies have been considered in the Indian context, to study the impact of the crises on the cumulative stock prices and the current study has been considered to fill the gap. Also, observing the behavior of the stock market data during the crises periods is contemporary and, motivated by this we aim to examine the changes in the behavior of the cumulative stock prices during different periods, where major financial crises have occurred.

3. Research methodology

Descriptive research design is used to describe the characteristics of the population under consideration. We have considered all the 50 stocks listed under NSE-Nifty 50 and the following table gives the details of the same.

Table 1 - Details of the Stocks Listed under NSE-Nifty50

Symbol	Date of Inclusion in NSE	Symbol	Date of Inclusion in NSE
ADANIPORTS	27.Nov.2007	IOC	24.Jul.1996
ASIANPAINT	31.May.1995	ITC	23.Aug.1995
AXISBANK	16.Nov.1998	JSWSTEEL	23.Mar.2005
BAJAJ-AUTO	26.May.2008	KOTAKBANK	20.Dec.1995
BAJAJFINSV	26.May.2008	L&T	23.June.2004
BAJFINANCE	01.Apr.2003	M&M	03.Jan.1996
BHARTIARTL	15.Feb.2002	MARUTI	09.Jul.2003
BPCL	13.Sep.1995	NESTLEIND	08.Jan.2010
BRITANNIA	05.Nov.1998	NTPC	05.Nov.2004
CIPLA	08.Feb.1995	ONGC	19.Jul.1995
COALINDIA	04.Nov.2010	POWERGRID	05.Oct.2007
DRREDDY	09.Jul.2003	RELIANCE	29.Nov.1995
EICHERMOT	07.Sep.2004	SBIN	01.Mar.1995
GAIL	02.Apr.1997	SUNPHARMA	08.Feb.1995
GRASIM	10.May.1995	TATAMOTORS	22.Jul.1998
HCLTECH	06.Jan.2000	TATASTEEL	18.Nov.1998
HDFC	23.Oct.1996	TCS	25.Aug.2004

HDFCBANK	08.Nov.1995	TECHM	28.Aug.2006
HEROMOTOCO	11.Apr.2003	TITAN	24.Sep.2004
HINDALCO	08.Jan.1997	ULTRACEMCO	24.Aug.2004
HINDUNILVR	06.Jul.1995	UPL	23.Jan.2004
ICICIBANK	17.Sep.1997	VEDL	13.May.1998
INDUSINDBK	28.Jan.1998	WIPRO	08.Nov.1995
INFRATEL	28.Dec.2012	YESBANK	12.Jul.2005
INFY	14.June.1993	ZEEL	09.Sep.1998

Source: Based on the information Collected from Market Tracker by the researcher

3.1. Market crash details

In the current study, we aim at noting the behavior of the indices during the periods where the major crises have occurred. The following table gives important market crashes from the year 2007 to 2020. We also present, in brief, the details of the crisis.

Table 2 - Market Crash details

The financial crisis of 2007–08	2009 Dubai debt standstill	European sovereign debt crisis	2010 flash crash	2015–16 Chinese stock market crash	2015–16 stock market selloff	2018 Global Stock Market Downturn	2020 stock market crash
16-Sep-08	27-Nov-09	27-Apr-10	06-May-10	12-Jun-15	18-Aug-15	20-Sep-18	24-Feb-20

Source: Retrieved from https://en.wikipedia.org/wiki/List_of_stock_market_crashes_and_bear_markets as on 08.04.2020

During the period 2007-08, the world had experienced a financial crisis, which is the result of the failure of the large financial institutions in the US. In 2009, the global stock markets have dropped due to the request made by Dubai for debt deferment following its massive renovation and development projects. The year 2010 had witnessed the European sovereign debt crisis following S&P's downgrading Greece's sovereign credit rating to junk, leading to the downfall of the stock markets worldwide, and the Euro's value. During the period 2015-16, the world had experienced the Chinese stock market crash and Dow Jones fell 588 points and 1300 points from August 18-21. On August 24, stock markets were down wiping out the gains made in the year 2015 and commodities like oil prices hit a six-year low and most of the Asian currencies hit low. This had resulted in a loss of 10 trillion dollars from the books of global markets since June 3. The world had experienced a Cryptocurrency crash in the year 2018 and experienced COVID-19 as the major crisis in the history of humanity. We consider these crisis periods in the current study and observe the behavior of the sectoral indices during these periods. We also consider other periods and compare the behavior of the indices with the crisis's periods.

3.2. Data and period

The daily stock prices of the 50 stocks listed on NSE are considered as the data points in the current study. We have considered the daily stock prices between the years 2007 to 2020.

We have considered daily stock prices from the year 2007 to 2020 and the same are divided into six blocks/groups. The first group consists of the daily stock prices from the year 2007 to 2009, the second consists of daily stock prices for the year 2010, the third has the stock prices from the year 2011 to 2014, the fourth group has stock prices taken for the years 2015 and 2016, the fifth group has the stock prices from the year 2017 to 2019 and the last group has the daily stock prices for the year 2020. The cut-off points considered to divide the stock prices are chosen based on the critical events/ market crashes that happened at those time points. For example, the year 2007 is when the market recession has started and continued till the year 2009. Hence, 2007 and 2009 are chosen as cut-off points and the stock prices during this period is considered as one group. Similarly, in the year 2010, there is a flash crash, during 2015-16 the world has experienced the Chinese stock market turbulence, markets have collapsed again in the year 2020 due to the covid-19 issue. To observe the changes, the stock prices between the year 2017 and 2019 are taken as a separate group. The main objective of such divisions is, to observe the change in the distributions during market crashes and other times. This will help the practitioners to model the stock prices using the suitable probability distribution and use the same for building the predictive models.

3.3. Methods used for estimating Index

1. To estimate the tail index for each of the stocks we fit the generalized extreme value (GEV) distribution and compute the extremal index. Based on the value of the index we identify the corresponding type of extreme value distribution for the maxima as either Fréchet or Weibull or Gumbel. The following is the distribution function of GEV distribution.

$$F(s;\xi) = \begin{cases} \exp(-(1+\xi s)^{-1/\xi}) & \xi \neq 0 \\ \exp(-\exp(-s)) & \xi = 0 \end{cases} \tag{5}$$

R package "evd" was used to fit the GEV distribution. Stocks with the value of $\xi=0$ or close to 0, are classified as Gumbel, stocks with a value of $\xi>0$, are classified as Fréchet, and stocks with a value of $\xi<0$, are classified as Weibull distribution (Galambos (1987).

2. The stable index or exponent was estimated using the Koutrouvelis (1980) method, which is a regression-type method. Under this, initial values for the parameters are estimated and continued iteratively till a prespecified convergence criterion is satisfied. Each iteration consists of two weighted regression runs. The number of points to be used in these regressions depends on the sample size and starting values of α. Typically, no more than two or three iterations are needed. The speed of the convergence, however, depends on the initial estimates and the convergence criterion. The regression method is based on the following observations concerning the characteristic function:

$$\ln(-\ln|\phi(t)|^2) = \ln(2\sigma^\alpha) + \alpha \ln|t|. \tag{6}$$

We use the package "libstableR" to estimate the stable index or exponent and the function used is, stable_fit_koutrouvelis () which implements Koutrouvellis' method based on the characteristic function.

Based on the value of the index, we classify the distribution as either normal or stable. If the index value is equal to 2, then the distribution is classified as normal. if the value of the index is less than 2, then we classified it as stable distribution. We present the complete analysis in the next section.

3.4. Process adopted to classify the stocks based on the cumulative price index

We now present the steps adopted to classify the stocks and the same are extracted from the standard theory on probability, the theory on the sums of the random variables and the extreme values. The book of Rohatgi (2015) can be referred to for understanding the link between the tail behavior and the probability model. One can refer to the book of Gnedenko (1968) for complete discussion related to sums and refer to the book by Hahn et al. (1991) for the details on the impact of extremes on sums and discussion on trimmed sums. Samoradnitsky and Taqqu (1994) can be referred for a complete discussion on stable distributions. The steps presented below are extracted from these books.

Step1: For each of the stocks, we identify the distribution of the cumulative stock price random variable by estimating the stability index. This is done for every crisis period considered and the domain for the cumulative price is identified based on the value of the tail index. A stock with index value 2 belongs to a normal domain and a stock with an index value less than 2 belongs to a stable domain.

Step2: For any period, if the domain is normal, then we conclude that the crises have not affected the behavior of the cumulative price random variable much. If the domain is stable, then we conclude that the crisis has affected the stock prices.

Step3: If a stock has more changes of the domain, then we classify the sector as a highly affected stock. In other words, we conclude that it has got affected by the financial crisis, frequently. Based on the number of times that domain shifts from normal to stable and vice-a-versa, we classify the index as highly affected (>3 times), moderately affected (between 2 and 3 times) and low affected (<=1 times) by the crisis event during the period.

Stocks are classified using these steps and check if the market crashes or financial crisis have affected them. The same is used to check if the normal behavior of the stock prices is affected or not.

4. Empirical findings

The following tables give the results of the analysis for each of the stock, both for maximum, minimum stock price and cumulative stock price random variables.

Table 3 - Results for the Automobile Stocks

	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Bajaj Auto	Domain for Maximum	Fréchet	Fréchet	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Normal	Normal	Normal	Stable
Hero Motors	Domain for Maximum			Gumbel	Gumbel	Weibull	Weibull
	Domain for Minimum			Weibull	Weibull	Weibull	Fréchet
	Domain for total	Stable	Normal	Normal	Stable	Normal	Stable
Eicher	Domain for Maximum	Fréchet	Weibull	Fréchet	Gumbel	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Stable	Normal	Stable	Stable	Normal	Normal
Mahindra & Mahindra	Domain for Maximum	Weibull	Fréchet	Fréchet	Gumbel	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Stable	Stable	Normal	Normal	Stable
Maruti Suzuki	Domain for Maximum	Fréchet	Weibull	Fréchet	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Stable	Normal	Stable	Stable	Normal	Stable
Tata Motors	Domain for Maximum	Weibull	Fréchet	Fréchet	Weibull	Weibull	Weibull
	Domain for Minimum	Gumbel	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable

Source: From researcher's data analysis

Table 4 - Results for Banking Stocks

	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Axis	Domain for Maximum	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable
HDFC Bank	Domain for Maximum	Weibull	Weibull	Fréchet	Gumbel	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable
ICICI Bank	Domain for Maximum	Weibull	Fréchet	Weibull	Weibull	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Stable	Stable
Indus Bank	Domain for Maximum	Fréchet	Weibull	Fréchet	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Gumbel
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable
Kotak Mahindra Bank	Domain for Maximum	Gumbel	Weibull	Gumbel	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Fréchet	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Stable	Normal	Stable	Stable	Normal	Stable
SBI	Domain for Maximum	Gumbel	Gumbel	Weibull	Weibull	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Gumbel	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Stable	Stable
Yes Bank	Domain for Maximum	Weibull	Weibull	Fréchet	Fréchet	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Normal	Normal	Stable	Stable	Stable	Stable

Source: From researcher's data analysis

Table 5 - Results for Consumer Goods

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Asian Paints	Domain for Maximum	Gumbel	Weibull	Weibull	Fréchet	Gumbel	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Gumbel
	Domain for total	Stable	Normal	Normal	Stable	Stable	Normal
Britannia Industries	Domain for Maximum	Weibull	Weibull	Fréchet	Weibull	Fréchet	Weibull
	Domain for Minimum	Weibull	Fréchet	Weibull	Weibull	Weibull	Gumbel
	Domain for total	Normal	Normal	Stable	Stable	Normal	Stable
Hindustan Unilever	Domain for Maximum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Normal	Normal	Normal	Normal	Normal	Normal
ITC Limited	Domain for Maximum	Gumbel	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Gumbel	Weibull	Fréchet
	Domain for total	Stable	Normal	Normal	Normal	Stable	Stable
Nestlé India	Domain for Maximum	Fréchet	Weibull	Weibull	Gumbel	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Fréchet	Fréchet
	Domain for total	Stable	Stable	Normal	Normal	Normal	Stable
Titan Company	Domain for Maximum	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Gumbel
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable

Source: From researcher's data analysis

Table 6 - Results for Cement Stocks

Stock	S.No.	1	2	3	4	5	6
Grasim Industries	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
	Domain for Maximum	Weibull	Weibull	Gumbel	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Gumbel	Weibull	Fréchet
	Domain for total	Normal	Normal	Normal	Stable	Normal	Stable
Ultratech cement	Domain for Maximum	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Normal	Stable	Stable	Stable

Source: From researcher's data analysis

Table 7- Results for Energy Power Stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
NTPC	Domain for Maximum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Fréchet	Gumbel
	Domain for total	Normal	Stable	Normal	Normal	Normal	Stable
Power Grid Corp of India	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Gumbel
	Domain for total	Stable	Normal	Stable	Stable	Normal	Stable
	Domain for Maximum	Gumbel	Wxeibull	Fréchet	Fréchet	Weibull	Weibull

Source: From researcher's data analysis

Table 8-Results for Energy and Oil Gas Stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Bharat Petroleum	Domain for Maximum	Gumbel	Weibull	Weibull	Weibull	Gumbel	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Stable	Normal	Normal	Normal	Stable	Stable
GAIL	Domain for Maximum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Gumbel	Fréchet
	Domain for total	Normal	Normal	Normal	Normal	Stable	Stable
Indian Oil Corporation	Domain for Maximum	Gumbel	Weibull	Weibull	Gumbel	Weibull	Fréchet
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Gumbel
	Domain for total	Stable	Normal	Normal	Stable	Normal	Stable
Oil and Natural Gas Coporation	Domain for Maximum	Weibull	Weibull	Fréchet	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable
Reliance Industries	Domain for Maximum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Normal	Normal	Normal	Normal	Normal	Stable

Source: From researcher's data analysis

Table 9 - Results for Financial Services Stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
HDFC	Domain for Maximum	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Gumbel	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Stable	Stable
Bajaj Finance	Domain for Maximum	Weibull	Fréchet	Weibull	Gumbel	Weibull	Weibull
	Domain for Minimum	Gumbel	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Stable	Stable	Normal	Normal	Stable
Bajaj Finserv	Domain for Maximum	Gumbel	Weibull	Gumbel	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Stable	Normal	Stable

Source: From researcher's data analysis

Table 10 - Results for IT stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
HCL Technologies	Domain for Maximum	Gumbel	Weibull	Fréchet	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Gumbel	Fréchet
	Domain for total	Stable	Normal	Normal	Stable	Stable	Stable
Infosys	Domain for Maximum	Weibull	Weibull	Weibull	Fréchet	Gumbel	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Normal	Stable	Normal	Stable
TCS	Domain for Maximum	Weibull	Fréchet	Fréchet	Weibull	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Stable	Normal	Stable	Stable	Stable
Tech Mahindra	Domain for Maximum	Weibull	Fréchet	Fréchet	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Gumbel	Fréchet
	Domain for total	Normal	Stable	Stable	Stable	Normal	Stable
Wipro	Domain for Maximum	Weibull	Fréchet	Gumbel	Weibull	Fréchet	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Normal	Stable	Stable	Stable

Source: From researcher's data analysis

Table 11 - Results for Metal Stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Hindalco Industries	Domain for Maximum	Weibull	Gumbel	Fréchet	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Normal	Stable
JSW Steel	Domain for Maximum	Weibull	Weibull	Gumbel	Fréchet	Gumbel	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	-	Fréchet
	Domain for total	Normal	Normal	Normal	Normal	Stable	Stable
Tata Steel	Domain for Maximum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Normal	Normal	Normal	Stable

Source: From researcher's data analysis

Table 12 - Results for Pharmaceutical Stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Cipla	Domain for Maximum	Fréchet	Weibull	Fréchet	Weibull	Weibull	Weibull
	Domain for Minimum	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Stable	Normal	Stable	Normal	Normal	Normal
Dr Reddy's	Domain for Maximum	Gumbel	Gumbel	Fréchet	Fréchet	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Stable	Normal	Stable	Stable	Normal	Normal
Sun Pharma	Domain for Maximum	Gumbel	Weibull	Gumbel	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Gumbel	Weibull	Weibull	Weibull	Fréchet
	Domain for total	Normal	Stable	Stable	Stable	Normal	Normal

Source: From researcher's data analysis

Table 13-Results for Other Stocks

Stock	S.No.	1	2	3	4	5	6
	Year	2007-2009	2010	2011-2014	2015-2016	2017-2019	2020
Adani Ports	Domain for Maximum	Gumbel	Weibull	Fréchet	Weibull	Weibull	Weibull
	Domain for Minimum	Weibull	Weibull	Weibull	Weibull	Gumbel	Fréchet
	Domain for total	Stable	Stable	Stable	Normal	Stable	Stable
Bharati Airtel	Domain for Maximum	Weibull	Weibull	Weibull	Gumbel	Gumbel	Weibull
	Domain for Minimum	Gumbel	Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total	Stable	Normal	Normal	Normal	Stable	Normal
Coal India	Domain for Maximum		Gumbel	Weibull	Gumbel	Weibull	Weibull
	Domain for Minimum		Weibull	Weibull	Weibull	Weibull	Weibull
	Domain for total		Stable	Normal	Stable	Normal	Normal
Infratel	Domain for Maximum			Fréchet	Gumbel	Weibull	Weibull
	Domain for Minimum			Weibull	Weibull	Weibull	Fréchet
	Domain for total			Stable	Stable	Normal	Stable
L & T	Domain for Maximum	Gumbel	Weibull	Weibull	Weibull	Gumbel	Weibull
	Domain for Minimum	Weibull	Weibull	Gumbel	Weibull	Weibull	Fréchet
	Domain for total	Normal	Normal	Stable	Normal	Stable	Stable
UPL	Domain for Maximum			Weibull	Weibull	Weibull	Weibull
	Domain for Minimum			Weibull	Weibull	Weibull	Fréchet
	Domain for total			Normal	Normal	Normal	Stable
Vedl	Domain for Maximum				Fréchet	Weibull	Weibull
	Domain for Minimum				Weibull	Weibull	Fréchet
	Domain for total				Normal	Normal	Stable
Zeel	Domain for Maximum	Weibull	Weibull	Fréchet	Gumbel	Weibull	Weibull
	Domain for Minimum	Weibull	Fréchet	Weibull	Weibull	Fréchet	Gumbel
	Domain for total	Normal	Stable	Normal	Stable	Stable	Stable

Source: From researcher's data analysis

Tables 3 to 13 give the results of the analysis for all the stocks, divided based on the sector they belong to. The division of the stocks into sectors is based on their listing in NSE. One can observe that Weibull distribution turned out to be the domain for the maximum and minimum

for most of the stocks. In few cases, Fréchet and Gumbel distributions turned out to be the domains. Using these distributions, one can compute the respective probabilities for the extreme stock prices. This will help to find the density at the tails and based on this, one can ascertain the heaviness of the tails and the impact of the crisis on the stock price random variable.

One can observe the domain of the cumulative stock prices during the crisis periods. Among the automobile stocks, Bajaj Auto could sustain the shocks from the market crashes and during the current COVID times, the behavior has changed from normal to stable. This indicates that the current COVID has an impact on the Bajaj Auto stock prices, as expected due to a decline in sales and reduced production. Similarly, one can observe the change in the domain from normal to stable. Among these stocks, we classify Bajaj Auto as the stock with low effect, Maruti Suzuki as the highly affected stock, and other stocks as moderately affected stocks. One can observe that Maruti Suzuki stock has stable distribution as its domain and this indicates that it has got affected the most due to the crises. Among the banking stocks, YES Bank and Kotak Bank have got affected the most during the crisis periods. Table B below gives the stocks that got affected during the crisis periods.

Overall, one can observe that the total stock prices fluctuate between normal and stable distributions. In many cases, the behavior has equally shifted from each other. If the value of the index is close to 2, then one can conclude that the behavior is almost normal. If not, then the behavior is stable.

Table B - Stocks Classification based on the change of domain

Symbol	Stable	Normal	Remarks
ADANIPORTS	5	1	High Affect
HCLTECH	4	2	High Affect
KOTAKBANK	4	2	High Affect
MARUTI	4	2	High Affect
POWERGRID	4	2	High Affect
TCS	4	2	High Affect
TECHM	4	2	High Affect
YESBANK	4	2	High Affect
ZEEL	4	2	High Affect
ASIANPAINT	3	3	Moderate Affect
BAJAJFINSV	3	3	Moderate Affect
BAJFINANCE	3	3	Moderate Affect
BPCL	3	3	Moderate Affect
BRITANNIA	3	3	Moderate Affect
DRREDDY	3	3	Moderate Affect
EICHERMOT	3	3	Moderate Affect
HDFC	3	3	Moderate Affect
HEROMOTOCO	3	3	Moderate Affect
ICICIBANK	3	3	Moderate Affect
INFRATEL	3	1	Moderate Affect
IOC	3	3	Moderate Affect
ITC	3	3	Moderate Affect

L & T	3	3	Moderate Affect
M&M	3	3	Moderate Affect
NESTLEIND	3	3	Moderate Affect
SBIN	3	3	Moderate Affect
SUNPHARMA	3	3	Moderate Affect
ULTRACEMCO	3	3	Moderate Affect
WIPRO	3	3	Moderate Affect
AXISBANK	2	4	Moderate Affect
BHARTIARTL	2	4	Moderate Affect
CIPLA	2	4	Moderate Affect
COALINDIA	2	3	Moderate Affect
GAIL	2	4	Moderate Affect
GRASIM	2	4	Moderate Affect
HDFCBANK	2	4	Moderate Affect
HINDALCO	2	4	Moderate Affect
INDUSINDBK	2	4	Moderate Affect
INFY	2	4	Moderate Affect
JSWSTEEL	2	4	Moderate Affect
NTPC	2	4	Moderate Affect
ONGC	2	4	Moderate Affect
TATAMOTORS	2	4	Moderate Affect
TITAN	2	4	Moderate Affect
BAJAJ-AUTO	1	5	Low Affect
RELIANCE	1	5	Low Affect
TATASTEEL	1	5	Low Affect
UPL	1	3	Low Affect
VEDL	1	2	Low Affect
HINDUNILVR	0	6	Low Affect

Source: From researcher's data analysis

From the above table, one can get the stocks that got affected by the market crashes. Those stocks that have stable domain a greater number of times have to be studied further, before considering for investment or taking any decision.

5. Discussion

From the analysis and findings, we have the following managerial implications:

1. An investor looks for a stock that gives better returns as well as a stable one. The word "stable" here means, a stock that gets less affected by the market crashes. Through the current study, we propose a mechanism to find stable stocks. One can calculate the tail index value at different time points, which are considered to be critical, and based on the level of the tail index, stock can be classified as stable or unstable. The tail index value can be observed at these time points and, if the index value falls below the value of 3 several times, then one can classify the stock as unstable.

2. In few cases, one may be interested in studying the behavior of the extreme stock prices-maximum and minimum. This may help to calculate the value at risk (VAR) or other risk measures. Through this study, we have identified the domain of extreme value distributions, to which the extremes of the stocks belong. Among the three types, Weibull and Gumbel laws form the important domains for the extremes. Fréchet law forms as domain sometimes. Note that, the domains are identified at all the time points considered. This will help one to note the changes in the domain with changes in the time points. Accordingly, one can calculate the required risk measures using the density function or other properties of the extreme probability models. Through this study, we propose the domains for each of the stocks, that can be considered for calculations.

3. When a market crash occurs, most of the stocks' price fall and sometimes there may be an increase in stock's price if the market booms. In such cases, it is expected that these extremes affect the performance of the stock. But few stocks may sustain the changes and perform as earlier or may not get affected drastically. To check this, one can consider the cumulative stock price random variable and study its behavior during the periods. It is well known that the total or cumulative stock price random variable converges either to a normal domain or to a stable domain. If the domain is normal, then one can conclude that the market crash didn't impact the behavior drastically. Note that, the prices might have fallen but still the behavior of the cumulative prices can be normal. That is, the majority of the stock prices tend towards the average stock price. This average stock price can be low or high. But still, the behavior of the stock can be normal. Through this study, we have identified the domain of the cumulative stock price random variable for all the 50 stocks considered. Based on the index value the domains are identified. We suggest the researchers or practitioners study the behavior of the total stock price random variable, before concluding on the stock. This has to be considered if one doubts that the stock may collapse due to the recent changes.

Any study will have limitations, and these can be considered as future work. We now present the limitations of the current study and the future work.
1. The current study considers major periods during which either the financial crisis or market crashes have occurred. We haven't considered events related to individual stocks. One can consider the events specific to each of the stocks and perform an in-depth analysis.
2. We have considered a descriptive research design as we wish to describe the behavior of the stock prices and through this, we have described the behavior at three levels. One can consider other research designs to find out the reasons for these changes, where the answers could be provided for "why".
3. One can fit a predictive model using the probability model for each of the stocks and predict the stock price movements. One can fit multivariate distributions and study the price movements.
4. One can use the extreme value distributions to calculate the risk measures and other measures to comment on the stock price movements.
These are the major limitations, and we propose them as the problems for future work.

6. Conclusion

The first objective of the study is, to identify the domain the maximum and minimum stock prices belong to. From the analysis, we conclude that most of the stocks have Weibull and Gumbel laws as the probability models and the same can be used to compute the associated

probabilities. In few cases the extremes belong to Fréchet law and the same can be used for the computation of probabilities. The second objective is to identify the behavior of the total price random variable. From the analysis, we conclude that the cumulative stock prices belong to the domain of normal in many cases and other cases to the domain of a stable distribution. This is interesting. In cases where the domain is normal, we conclude that the extremes generated during the market crash haven't affected the cumulative stock prices during those periods. It is a well-known fact that extremes affect the total or cumulative returns. If one wishes to check if there exist extremes or the effect of extremes, then one can study the behavior of the cumulative returns. In the current study, we use the same to study the effect of market crashes on stock price behavior. The analysis found those periods where the market crashes have affected the stock prices and cases where they haven't affected. In all the cases or periods where the domain is normal, we conclude that the market crashes haven't affected the stock prices. In all the cases or periods where the domain is stable, we conclude that the market crashes have affected the stock prices. When the domain is normal, the majority of the stock prices will be close to the average stock price and 99.73% of the stock prices lie within the 3-sigma limits. If the domain is stable, then based on the index value, one can conclude on the tail and the existence of the moments. When the index value is less than one, then the tails will be heavy and even mean do not exist. If the index value is between 1 and 2, then the mean exists but the variance will be infinite. This indicates that the market crashes have affected the stock prices. Table B gives the details of the stocks that have got affected by the market crashes.

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