CHAPTER 2

REVIEW OF LITERATURE

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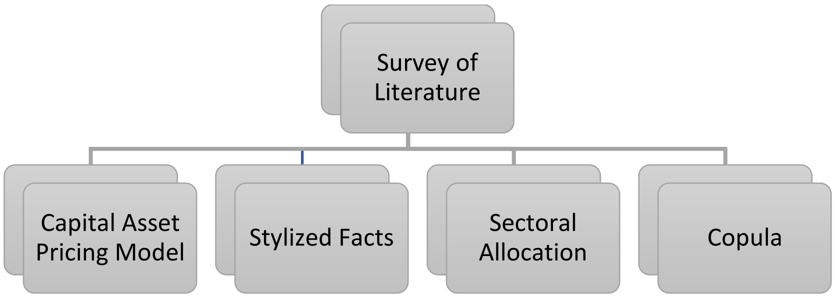

The review of literature is divided into four sections, the first section discusses a brief review of the capital asset pricing model literature along with its modifications. The second section entails the literature survey of the various properties of return distribution termed as stylized facts. The third section includes literature on India's sectoral analysis carried out over the period of time. Finally, the fourth section reviews the literature on copula.

2.1 STUDIES ON CAPITAL ASSET PRICING MODEL

This section describes and outlines the literature surrounding the capital asset pricing model and its critiques as well as economic arguments in favor of the inclusion of skewness and kurtosis into the CAPM model. Investors invest their money into an asset to earn returns; while bearing a certain amount of risk given that their investments are uncertain. This risk could either be idiosyncratic or be a systematic risk. In theory, an idiosyncratic risk that is related to particular security can be diversified, similar to unsystematic risk; while the systematic risk is very difficult to diversify or reduce. Hence, the portfolio selection must be such to minimize as much risk possible through diversification.

Harry Markowitz, in 1952, wrote a paper called 'Portfolio Selection' that changed the approach towards portfolio selection. In his paper, he proposed to analyze the quality of the portfolio with the help of means and variances of the assets included in the portfolio which can be determined by the combination of risk and return (i.e., maximum return or minimum risk). This risk does not only consist of individual variance but also consist of covariance with other assets in the portfolio. The theory is based on the assumption of normal distribution and a rational investor who always prefers more to less.

Markowitz (1952) showed that an efficient portfolio can be created by reducing the risk of a portfolio without reducing the return of the portfolio through diversification. Through diversification, the portfolio can be free from idiosyncratic risk and consist only of systematic risk for which an investor can claim reward instead of total risk. Finally, a portfolio is deemed efficient when it has the highest expected return along with a certain amount of variance or has the lowest variance given a certain expected return. This theory is considered as a stepping stone towards the formation of the capital asset pricing model. The Capital Asset Pricing Model (CAPM) was formulated by Treynor (1961), Sharpe (1964), and Linter (1965) individually, it explains the relationship between return and systematic risk based on certain assumptions.

In support of the model, an early test revealed that higher stock returns were generally associated with higher betas. Miller and Scholes (1972), Black et al. (1972), and Fama and MacBeth (1973) supported the CAPM and demonstrated a relationship between beta and asset return outcomes. However, CAPM has been criticized subsequently by many academicians and practitioners for a long time. One of the first academicians to find a flaw in the CAPM was Roll (1977). The capital asset pricing model holds that the model is dependent on the market portfolio which is a mean-variant efficient; if not then the CAPM will not be valid. Moreover, until the exact composition of the true market portfolio (including all individual assets) is established the theory cannot be tested (Roll, 1977).

Few studies also suggest that a single factor CAPM linear relationship does not always hold true and beta alone cannot explain the excess risk-return relationship. There are other factors that contribute to the asset returns such as earnings price ratio, market capitalization, firm size included in studies by Stattman (1980), Basu (1983), Tinic and West (1984), Banz Bhandari (1988), etc. These studies of the single factor CAPM provide weak empirical evidence on these relationships. Consecutively, Chan et al (1991) found that book-to-market equity has a strong role in explaining the influence of the cross-section of average returns on Japanese stock markets. Further, Fama and French (1992) constructed a three-factor model to include size and book-to-market and the results of the regression indicate a cross-section of average stock returns.

Furthermore, the CAPM is criticized based on its assumption of homogeneity. Hong & Stein (2003) adopts the heterogeneity of investors to justify and clarify the returns asymmetry. Kirchler and Huber (2007) argue that due to heterogeneity in the fundamental information there is evidence of higher volatility and emergence of fat tails which is a characteristic of leptokurtic distribution. According to their study, periods with constant dividend payments lead to similar estimates of asset values by investors. On the contrary, periods with fluctuating dividend payments lead to different interpretations of information and different estimates of asset values which increase the possibility of extreme values occurring.

Finally, another important assumption of the CAPM is that the returns are distributed normally which is often violated. Literature has suggested that there exists another stable distribution which is more preferable known as the Cauchy distribution used to study the heavy tails displayed by the distribution (Liu, Zhang, Dai & Xie, 2012). Others suggests that return distributions are explained better with the help of Laplace distribution rather than a normal distribution (Toh & Jones, 2019). Moreover, the most recent studies have also considered levy stable distribution superior due to its theoretical base and analysis to demonstrate the behavior of crash in the stock market (Bielinskyi et al, 2019). These distributions represent the returns distribution much better than the normal distribution.

2.1.1 Skewness

One of the first studies to consider the influence of systematic skewness on valuation was Kraus and Litzenberger's (1976). They claim that while the market portfolio is optimal for investors' utility functions, it violates the mean-variance framework. A desire for positive skewness, besides an aversion to variance, should be part of an investors' utility function. Thus, to investigate the impacts, they extended the CAPM to add systematic skewness as a higher moment. They believed that negative empirical findings of CAPM can be attributed to the CAPM's faulty specification due to the removal of skewness as a factor. While Harvey and Siddique (2000)'s research is quite similar to Kraus and Litzenberger's, they focus on conditional skewness. According to them conditional skewness or co-skewness is a metric that determines whether an asset's return is more skewed than the markets return. They conclude that their model is economically important, useful in justifying differences in asset returns, and displays a negative premium for skewness risk.

Hung, Shackleton, and Xu (2004) presents (poor) evidence for inclusion of higher moments in the model for pricing in markets other than the United States, namely United Kingdom. Zhang (2005) tests idiosyncratic skewness on the stock market and find strong evidence that positively skewed stocks have a lower average return. Chung et al (2006) discovers that skewness has an effect on asset price. Mitton and Vorkink (2007) in their study show evidence of a negative relation among idiosyncratic skewness in the return distribution on stock prices. Post van Vliet and Levy (2008) provides a theoretical explanation and empirical proof that risk aversion assumption of the CAPM model is violated when higher moments are considered in the model, which in turn questions implied utility function. According to their study when risk aversion is enforces, it reduces the explanatory power of skewness. Moreno and Rodriguez (2009) in their study on mutual funds show that consideration of co-skewness in the model increases the explanatory power of the model and is also economically as well as statistically significant. Not all research yields similar outcomes, these theoretical understanding of researches could be incorrect, implying that co-skewness is a proxy for another yet neglected component that genuinely drives asset prices; nevertheless, the identification of these unknown factors was left to future research (Poti and Wang, 2010). Nevertheless, empirical data from a broad body of literature underlines the necessity of including skewness as a higher moment in the standard CAPM, in addition to the theoretical understanding of known deviations.

2.1.2 Kurtosis

The importance of skewness in asset pricing models has received far more attention than that of kurtosis and the inclusion of the fourth moment in asset pricing models can be equally more essential. More researches are focusing on the importance of skewness but comparatively less focus on laid on kurtosis. Fama (1965a) evaluated daily returns of 30 Dow Jones Industrial Average equities from 1957 to 1962. In the distribution of returns, he noticed leptokurtosis, which he stated was "indisputable." Likewise, longer time series data also produced identical results. For instance, Ding, et al (1993) examined daily returns of the S&P 500 from 1928 to 1991 to estimate a higher kurtosis. Similar results were found by Ding and Granger (1996) who studied the returns of the Nikkei index between 1970 and 1992. Fang and Lai (1997) derived a model that includes variance, skewness, and systematic kurtosis and find that investors are compensated for holding a portfolio with higher systematic co-kurtosis. Dittmar (2002) provides an intuitive explanation for the aversion of investors for kurtosis and links decreasing absolute prudent to kurtosis which confirms the aversion. Doan et al. (2010) studies the CAPM with higher moments on the Australian stock market and compare them with the US market. The study suggests a positive relation of stock returns with conditional kurtosis and negative relation of stock returns with conditional skewness based on the firm's characteristics and the risk preference of investors.

Recently, Karoglou (2010) empirically tested the distribution of daily returns of 27 OECD countries from 1994 to 2006 to find the presence of excess kurtosis. During the same time Doan, et al (2010) found excess kurtosis in the return distribution of 25 US and 25 Australian stock portfolios from 1992 to 2007. Similar results were found in studies carried out in Africa (Li et al, 2010). Alternatively, most returns do exhibit weaker leptokurtosis than daily or intraday returns (Schrimp (2010))

2.2 STUDIES ON STYLIZED FACTS

A growing body of knowledge in financial economics has centered on time series models for asset return volatility and co-movements. This section will focus on the studies examining the nature and properties of the data set. The concept of stylized facts was first introduced by Kaldor (1957) which was then applied by academicians to the concept of financial data. A century ago, Bachelier suggested that changes in the prices of stocks can be considered as independent random variables and modeled with a random statistical procedure. He assumed that these price movements were infinitely regular with identical distribution and had finite variance. His proposal was derived by Osborne (1959) which received extensive attention. Later, Ryden & Terasvirta (1998) estimated 10 subseries of the S&P 500 return series to reproduce the stylized facts. He used the hidden Markov model to describe the higher-order dependence observed in the return series. Subsequently, a wide literature developed worldwide on methods of statistically modeling the stylized facts of stock prices.

Stylized facts are essentially statistical property present in series of observed stock prices or returns (Cont, 2001; Taylor, 2005). Given below are the stylized facts considered in the study:

Distribution properties:

1. Heavy tails
2. Aggregational gaussianity

Dependence properties:

1. Absence of autocorrelation in linear function
2. Slow decay of autocorrelation in absolute returns
3. Volatility clustering

Other properties:

1. Leverage effect
2. Gain/loss asymmetry
3. Volatility persistence
4. Long memory

2.2.1 Heavy tails

The most widely stereotyped aspect regarding stock returns is the peaked and heavy tailed structure, and therefore non-normality, of the empirical distribution of daily stock returns. Non-normality tends to be less prominent in empirical monthly returns series distributions. A distribution is considered to have heavy tails and be peaked if it allocates higher probability density to extreme data points and to data points near the mean than the normal distribution. As a result, then in a normal distribution, extreme data points or outliers and data points near the mean are more common. The presence of heavy tails and "peakedness" can be detected using summary statistics and kurtosis is a popular example of one such statistic.

Daily stock returns were discovered to be leptokurtic as early as the 1960s. Fama (1965a) found leptokurtosis in the observed distribution of returns for each stock using a data set of daily returns from the 30 equities that were then included within the DJIA (Dow Jones Industrial Average) between 1957 and 1962. The presence of leptokurtosis in the empirical distribution of daily stock returns was "indisputable," according to Fama (citing earlier study) (Fama, 1965a). This claim has gained widespread acceptance (Pagan, 1996).

Ding, et al (1993) estimate kurtosis of 25.42 using a dataset of daily returns (1928-1991) for the S&P500. Ding and Granger (1996) observed that the Nikkei index had similar results between 1970 and 1992. Excess kurtosis can also be detected in more recent returns series investigations. The foregoing observations are far from unique, and it's now commonplace to expect leptokurtosis and consequently non-normality in almost any set of daily stock returns (Andersen et al, 2001; R Cont, 2001). Between 1980 and 1998, Yu (2002) finds significant leptokurtosis in daily NZSE40 returns in New Zealand index returns. The evidence of leptokurtosis appears to be much more extreme for intraday results (R Cont, 2001; Areal and Taylor, 2002; Taylor, 2005).

Taylor (2005) claims that leptokurtosis can be observed in almost any sequence of daily stock returns. To demonstrate this, Taylor examines daily returns for the S&P 500, FT 100, and Nikkei 225, as well as NYSE and LSE listed equities, from the 1980s to the 1990s. For all of these data sets, he shows that the sample kurtosis is greater than 10 standard errors. Karoglou (2010) discovered excess kurtosis in the daily returns distribution of market indices in twenty seven OECD countries between 1994 and 2006. During the period 1992 to 2007, excess kurtosis was identified in the daily returns of twenty-five US and Australian stock portfolios organized by size.

2.2.2 Aggregational gaussianity

Sen & Manavathi (2019) performed two normality tests on the data for fifty constituents' stock of Nifty50 index traded on NSE and compared them for daily, weekly, monthly and quarterly data. The study confirms that the distribution of returns appears more and more like a normal distribution as the time scale t over which they are calculated rises.

2.2.3 Absence of autocorrelation in linear function

Bailey and Chung (1995) studied the return distribution of forty-four security from 1986 to 1994, there was a substantial first order correlation of returns on the Mexican stock exchange indices. Similarly, Aggarwal et al (1999) tested return distribution in Latin America and Asia from 1985 to 1995 and confirm the presence of autocorrelation in the market. The absence of Auto Correlation in daily returns is a widely accepted stylized feature (Pagan, 1996; Taylor, 2005; Ding et al, 1993; Cont, 2001). The same results were found by Yu (2002) when he studied the NZSE40 returns between 1980 and 1998.

2.2.4 Slow decay of autocorrelation in absolute returns

Ding et al (1993) discovered that the autocorrelations of squared and absolute returns diminish slowly over time. The first order autocorrelation of absolute returns, for example, was found to be 0.318 after 100 delays, but only 0.162 after 1000 delays. Pagan (1996), Ding and Granger (1996), Aggarwal et al (1999), R Cont (2001), among several others, deliver identical findings regarding the significance and slow decay of the autocorrelation of absolute returns and squared returns using returns series for indices and stocks listed on the emerging as well as developed stock exchanges. The autocorrelation of squared and absolute daily stock returns dissipates gradually, which is well comprehended; however, what this means about the process that stock returns follow is a point of contention (see Diebold and Inoue, 2001; Granger and Hyung, 2004; Banerjee and Urga, 2005; Taylor, 2005; Stărică and Granger, 2005).

Stock returns following a stationary process with a long memory could explain the delayed decay of absolute return autocorrelation (i.e. events that may have happened many periods ago are relevant to the present mobility of returns). Non-stationarities in the stock return (for instance, structural abnormalities or alterations in the unconditional mean level of returns over time) may cause the autocorrelation function of absolute returns to fade over time. The latter theory appears to be gaining favor in recent literature.

2.2.5 Volatility Clustering

Volatility clustering is the persistence of periods of extreme & slight absolute returns. Despite the fact that most daily stock returns do not have an autocorrelation of squared and absolute returns are substantial for many lags, most daily stock returns do not have an autocorrelation of squared. Ding et al. (1993) empirically analyzed a data set of daily returns on the S&P 500 from 1928 to 1991, finding that autocorrelation estimates for absolute and squared returns over the last 1 to 100 are substantial, with autocorrelation of squared and absolute returns decaying slowly. By examining return series for indices and equities listed on the develpped countries stock exchange - NYSE, LSE, and Nikkei, as well as emerging countries, Ding and Granger (1996), Pagan (1996), Aggarwal et al (1999), R. Cont (2001), and Taylor (2005) discovered comparable conclusions about the significance and gradual fading of autocorrelation of absolute and squared returns.

2.2.6 Leverage effect

The Leverage effect, defined by Black (1976) and Christie (1982), is the realized tendency of an asset's volatility to be negatively associated with its return. Christe (1982) estimated regression for 379 NYSE listed firms from 1962 to 1978 using standard deviation as the volatility measure to study the leverage effect. Likewise, the other most common measure for volatility is the size of absolute or squared returns than the standard deviation. Pagan (1996) uses daily stock returns for the S&P 500 from 1928 to 1987 to project the sample cross-correlation among squared returns and lagged returns for lag lengths ranging from l to 12 periods.

A similar study was carried out by Bouchaud et al., (2001) with the most recent data from 1991 to 2000 of daily stock prices of S&P500, NASDAQ, CAC40, FTSE, DAX, Nikkei, and Hang Seng to find that there is a large negative correlation between squares and lagged returns in individual stocks and indices. Typically, as the asset price increases the volatility decreases, and as the asset price decreases, the volatility increases (R.Cont, 2001). Consequently, a drop-in stock price will result in negative returns and is associated with an increase in volatility levels, whereas a rise in stock price will result in positive returns and is associated with a decrease in volatility. As a result, the influence of positive and negative returns on volatility metrics is asymmetric (Taylor, 2005). These were the studies carried out to study the stylized facts of the stock returns distribution individually. Many studies have studied all the stylized facts altogether.

2.2.7 Gain/loss asymmetry

Huang and Zhang (2014) use market index data to compare asymmetry indices of historical prices from ten stock markets. They discovered that in most stock markets, price declines outpace price rises, however in China and India, price rises outpace price declines. The findings of Sen & Manavathi's (2019) study for the Indian stock market confirm this.

2.2.8 Volatility persistence

The literature on volatility dates back to Black (1976) who established that volatility is not highly serially correlated, at the same time the stock market returns and change in volatility are negatively correlated. This was refuted by Poterba and Summers (1984) who studied the influence of volatility on the stock market prices and stated that volatility is weakly serially correlated and shocks, therefore, have a small impact on stock market prices. He further proved that changes in volatility affect the expected return for a relatively shorter duration of time. However, later French, Schwert & Stambaug (1987) examined the time-series relationship between the risk of a portfolio and its expected risk premium and found evidence of a positive relationship between expected risk premium and volatility. They found a strong negative relation between unpredictable volatility and realized risk premium. There is a vast literature supporting his findings from various parts of the world, however, here we discuss in detail the literature focusing on the Indian stock markets. Some of the most significant and contemporary literature are among the ones discussed in the ensuing paragraphs.

The majority of the earlier literary works used linear models to understand volatility; even though, linear models are not robust in explaining certain features of volatility. Thus, later there was a paradigm shift to the use of non-linear methods such as autoregressive conditional heteroscedastic (ARCH) and generalized autoregressive conditional heteroscedastic (GARCH) family models for estimating volatility.

Batra (2004) studied the pattern of stock market volatility in India from 1979 to 2003 and found that in the post-liberalization period, the bull phases are longer with higher volatility and amplitude than the bear phase. Rashid and Ahmad (2008) use the daily stock market to forecast stock index volatility to evaluate the relative performance of linear versus non-linear methods and find that GARCH class models dominate linear models of stock price index volatility. Nateson et al. (2013) examined the spill-over effect of volatility in the Bombay stock exchange and its sectoral indices. The results conclude that there is volatility transmission from Sensex to auto, bankex, consumer durables, capital goods, FMCG, healthcare, IT, metal, oil & gas, realty, and PSU; while there is no transmission from Sensex to power and Teck indices.

Mohandas & Renukadevi (2013) modeled the volatility of sectoral indices of the Bombay stock exchange from 2001 to 2012 and found that GARCH (1,1) model is the best to model the volatility of the return series. Lakshmi (2013) examined the volatility patterns in sectoral indices of the national stock exchange of India between 2008 to 2013. The research found the realty, energy, and metal sectors are highly volatile than the benchmark index of the national stock exchange i.e. Nifty50. Shanmugasundram & Benedict (2013) showed that there is a significant difference of risk within the sector while estimating the risk facto differences across the risk of various sectoral indices of the national stock exchange from 2004 to 2012 with the help of one-way ANOVA test. Anbukarasi and Nithya (2014) provided an empirical finding to identify the volatility in sectoral indices and Nifty50 from Jan 2013 to June 2014. The study deduces that there is a significant correlation within the sectors except for metal, pharma, PSU bank, and realty. Tripathy and Gil-Alana (2015) tested the presence of asymmetry and persistence and time-varying volatility in the Indian stock market during the crisis period of the 2008 global recession.

Birau and Trivedi (2015) investigate long term volatility in the Indian stock market using the GARCH models and concludes the existence of minor and major shocks, bullish growth, and strong volatility after 2013. Further, while testing the CNX-100 stock market index consisting of 38 sectors of the economy is found to be more volatile clockwise and thus create a great opportunity for investors and alike. Majumder and Nag (2017) estimated the transmission of shock and volatility spillovers among various equity sectors of the India stock market viz., national stock exchange. The estimation revealed bidirectional volatility spillover among finance and information technology. The study also finds a high correlation among the sectors during the global financial crises.

2.2.9 Long memory

The long-term memory analysis was first carried out by Greene and Fielitz (1977) who used the rescaled range analysis on 200 daily stock returns to demonstrate the evidence of long-term memory in the data. Ding et al (1993), who identified long memory stochastic volatility in stock returns, came to the same conclusion. Furthermore, using the Fractionally integrated exponential GARCH model, Baillie et al (1996) caught the long-run reliance in the US stock market (FIEGARCH).

A number of studies have looked into the impact of long memory on volatility in advanced markets, specifically the US. (See, Ding et al 1993; Crato and Lima 1994; Ding and Granger 1996; Andersen and Bollerslev 1997; Granger et al 1997; Comte and Renault 1998; Lobato and Savin 1998; Andersen et. al. 2003, Andreano 2005). Nevertheless, there has been minimal focus on the problem of long memory in emerging markets, with the exception of a few recent research that have provided some existence of a long memory in volatility.

During the period 1997-2002, Cavalcante and Assaf (2005) found a substantial correlation in the absolute and squared returns series of the Brazilian market. Using data from 12 emerging markets between 1995 and 2005, Mendes and Kolev (2006) discovered a significant presence of long memory in volatility. Oh et al (2006) looked at eight international indexes from advanced and underdeveloped markets and discovered strong evidence of long memory. Long memory in volatility was also evident in MENA markets, especially Egypt, Jordan, Morocco, and Turkey, but this was not due to sudden shifts in variance (Assaf, 2007). This position is supported by Kang and Yoon (2007), who suggest that the long memory in volatility is inherent in the data generation process and not due to any shocks. Floros et al. (2007) indicate that stock market volatility in Portugal has a long memory. The empirical proof of existence of long memory in volatility in African markets is ambiguous.

The study concludes that the existence of structural fractures causes long memory to be volatile. Returns volatility has a long memory, according to studies from Turkey (Kasman and Torun 2007; DiSario et al 2008). Jefferis and Thupayagale (2008) discovered proof of long memory in volatility in South Africa and Zimbabwe, but no similar evidence was found for the United States. McMillan and Thupayagale (2009) discovered presence of long memory in volatility in seven out of the eleven African markets they studied. The longer memory was considered to be caused by illiquidity and trading conditions in these marketplaces. The evidence for long memory in the volatility process in emerging markets is conflicting. However, no significant study of long memory in volatility has been undertaken in India, one of the fastest-growing rising nations. As a result, the focus of this thesis is on long memory in volatility in two major Indian stock markets, the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE).

2.2.7 Overall studies

Hommes (2002) used simple non-linear adaptive systems for modeling and explaining the stylized facts of financial markets. Bulla & Bulla (2006) used the hidden semi-Markov model to reproduce most of the stylized facts of daily stock returns. They have illustrated that stylized facts can be described much better by employing hidden semi-Markov models. Malmsten & Terasvistra (2010) tests three well-known models of volatility to daily or weekly financial series such as stock and exchange rate returns to find out how well these models can reproduce characteristics features of such series. All three models produce distinctive results and none of the models is superior to the other. Terasvistra & Zhao (2011) evaluated the capacity of the volatility models to reproduce the stylized facts with the help of GARCH family models to provide a fresh view of the stylized facts.

Mukherjee, Sen & Sarkar (2011) studied the stylized facts of the Indian stock market and registered the presence of long-term dependence in the daily return’s series along with long memory in the data. Masset (2011) investigated the existence of the stylized facts in the emerging and mature market for both bull & bear market condition and confirm the presence of stylized facts. Later, Pekkaya & Gokbulut (2014) carried out an empirical investigation of the average return and conditional variance of financial markets of Turkey from 2002 to 2004 to find the presence of long memory along with other stylized facts. Jilla, Nayak & Bathula (2017) tested stylized facts of the ten fastest-growing stock markets along with checking the stationarity of the series with the help of the Augmented Dickey-Fuller test & Phillips-Perron test.

2.3 STUDIES ON SECTORAL ALLOCATION

This section will elaborate on the literature with an emphasis on understanding the linkage within the Indian stock market's sectoral indexes, namely the national stock exchange and the Bombay stock exchange.

In the context of correlation of the various sectors of the economy, Karmakar (2005) examined 50 individual stocks and concluded that various GARCH models produce accurate volatility projections and are useful for portfolio allocation, performance evaluation, option valuation, and other purposes. Kumar and Dhankar (2009) examined the cross-correlation in stock returns of south Asian stock markets, their regional integration, and interdependence. The results confirm the presence of autocorrelation, conditional volatility in all the Asian stock markets. Further, they propose a significant relationship between stock returns and unexpected volatility, and the presence of regional interdependence. Gupta and Basu (2009) estimated the dynamics of correlation of stock returns between ten industry sectors in India using daily and monthly market data from 1997 to 2007. The results state that investors can earn a high risk-adjusted return by investing in a diversified portfolio among various sectoral indices is much better than investing in the benchmark index.

Kumar & Singh (2011) attempted to investigate the movement of sectoral returns and their contributions to the BSE Sensex returns. The BSE Sensex returns might be explained using chosen sectoral index returns, according to the study. Bhunia, (2012) conducted a study on the short and long-term correlations between BSE (BSE 500, BSE 200, and BSE 100) and crude price. Ramkumar et al. (2012) examined BSE's 13 sectoral indices and discovered that 8 of the 13 indices, notably the BSE Automobile index and the BSE Bankex, had positive returns. The BSE Capital Goods index, the BSE Consumer Durables index, the BSE Healthcare index, the BSE Metal index, the BSE PSU index, and the BSE Realty index all followed the normal distribution and received higher returns. The stability of the Bombay Stock Exchange Sectoral Indices was investigated by A. Srivastava (2012). For the period 2003 to 2012, he looked at eleven sectors of BSE: automobiles, bank, consumer durables, consumer discretionary, healthcare, FMCG, IT, metal, Oil & gas, power, and realty.

According to his findings, FMCG, Healthcare, and IT are the least sensitive to market changes when compared to the Sensex and BSE500, whereas reality and metal are the most volatile.

Joshi and Pandya (2012) studied the closing price from 2002 to 2009 and found the volatility persistence is more in the Indian stock market with the help of ARCH and GARCH models. Joshi (2012) tested the daily closing price of BSE and NSE and found strong evidence of the presence of long memory in the conditional variance of the stock market rather than in the return series.

Radhika (2013) studied the correlation coefficient to establish a relationship between sectoral indices and Bombay stock exchange benchmark index Sensex during the global recession and found six sectors to have a significant impact on the economy. Nateson et al. (2013) looked at the BSE SENSEX's spillover transmission to its sectoral indices. The study discovered that the BSE Sensex transmits volatility to other sectoral indices and that shocks to stock returns in the BSE SENSEX do not transmit to BSE power and BSE Teck. Anbukarasi and Nithya (2014) looked at the return and volatility of 11 sectors indexes as well as the Nifty50 index. The study discovered that majority of the indexes have a substantial association. The data for the study was collected between April 2, 2001 and March 31, 2011. The study concluded that BSE (BSE 500, BSE 200, and BSE 100) and crude price have a long-term co-integrated relationship. Granger causality results show a one-way causality relationship between BSE (BSE 500, BSE 200, BSE 100) and crude price, but not the other way around.

Marisetty (2014) investigated the linkages between the Nifty50 index and the national stock exchange of India's industrial index. The result shows that monthly average returns have been correlated with most of the sectoral indices and their performances are along the lines with that of Nifty50 except for pharma and FMCG who are less influenced by other indices. Rajamohan and Muthukamu (2014) attempted to understand the nature and extent of the influence the banking sector has on other sectors during the bull and bear market conditions with the help of correlation analysis. The study concluded that the bank index has a positive influence on all the other sectors during the bull and bear phase. Tripathi and Kumar (2014) examined the efficiency of the sectoral indices of the Indian stock market with the help of eleven sectoral indices of the national stock exchange from 2004 to 2014. The findings state a weak form of inefficiency in bank, metal, PSU bank and realty sector. Noor et al. (2014) researched the long-run and short-run sectoral correlation in the Bombay Stock Exchange (BSE), and the findings show that no other long-run relationships were found except for bank-IT and consumer durables-realty. There was also limited evidence for the short-run link.

Sharma and Banarjee (2015) analyzed the pattern of the movement of the sectoral indices and their correlation for a period of eight years between 2006 to 2014 of the Bombay stock exchanges. The results show a significant presence of cross-correlation among the sectors. Further, most of the sectors show a higher correlation during large fluctuation than in normal periods. Ramkumar et al. (2015) measured the random distribution and weak-form efficiency in the Bombay stock exchange and national stock exchange sectoral indices to study the efficiency of sectoral indices in the Indian stock market.

Guha, Dutta, and Bandhyopadhyay (2016) examine the risk in terms of beta for all sectoral indices of the national stock exchange of India and their performances in various periods. Further, they carried out factor analysis to find that realty, metal, and information technology are sectors that are highly sensitive to Nifty50 than FMCG, pharmaceutical, and automobiles. The latter are top performers of Nifty50 in terms of returns per unit of risk. The factor analysis estimation reveals that Nifty50 returns explain 95 percent from six sectoral indices out of eleven namely automobiles, energy, FMCG, metal, pharmaceutical, and PSU bank. Gupta (2017) studied the relationship between various sectors for different investment periods. He found that for an investment period of fewer than five years there exists a positive correlation between the sectors; whereas, for an investment period of more than five years some sectors show a negative correlation. According to his study, FMCG and health sectors are the best sectors in terms of risk and reward while power and realty are the worst performers.

Varughese and Mathew (2017) found the existence of volatility clustering and leverage effect in the market while studying the daily returns of the Indian stock market from 2003 to 2015 using GARCH family models. Amudha and Muthusamy (2018) reported evidence of volatility clustering and persistence in the stocks of the national stock exchange. They also found that return series react to good and bad news asymmetrically.

Mohanty, Satpathy, and Mohapatra (2019) studied the performance and correlation among the sectoral stock market indices of the Bombay stock exchange. They found that indices have positive correlations with Sensex except for health and telecom indices. Bhowmik and Wang (2020) provides a review of literature on previously studied generalized autoregressive conditionally heteroskedastic (GARCH) family-based model for stock market return and volatility over a period of twelve years (2008-2019) in fifty papers. The study found that major research was for developing countries' stock markets. Moreover, there has also been a significant change in research work in the last ten years.

2.4 STUDIES ON COPULA

The concept of copula originally dates back to Sklar (1959) who defined & later derived it with the help of mathematical derivations was made popular in finance through the pioneering work of Embrechts et. al (1999). They worked to devise a flexible tool to capture various patterns of dependence; simultaneously, Joe (1997) and Nelsen (1999) published their books, individually, introducing a model of joint (multivariate) distribution. However, generally in financial applications, univariate distributions have fat tails and, in such scenarios, the usage of multivariate distribution was less researched upon.

Copulas were used in various fields of economic time-series modeling, while risk management was one of the first areas of application. To present a bird eye view of few fundamental researches on copula - Various researchers studied the VaR of portfolios to estimate the probability of large losses that resulted in demand for models of dependence between sources of risk (Hull & White (1998); Embrechts et.al. (2002); McNeil et.al. (2005); Denuit et.al., (2005); Embrechts & Hoing (2006); Cherubini and Luciano (2011)) used copulas to provide solutions in risk management. Copula methods were also widely used in pricing credit derivatives since it involves various sources of risk. See Li (2000), Rosenberg (2003), Salmon and Schleicher (2006) and Taylor and Wang (2010). Another area where copula has served as a significant contribution is portfolio decision. Hong et.al (2007) studied eleven portfolios to make an investment decision; while, Christoffersen and Langlois (2011) considered four common equity market factors. These were earlier studies made to model various kinds of risk and portfolios. Embrechts, McNeil & Strautman (2002) developed a model to study extreme values in finance.

The primary motive to consider copulas is sensitivity of investors to downside risk. Extreme negative returns are extremely unappealing to the investors and as a result the dependence model should capture the risk posed by the tail behavior of returns while also considering diversification opportunities offered by returns distribution. The standard way of modeling dependency, the gaussian copula, largely depicts dependencies in the middle of the distribution and implies tail independence. The gumbel copula mainly concerned with tail dependency and being an extreme value theory strategy in risk management. Several authors including Glasserman et al. (2002), have advocated the student's t copula as an alternative to the gaussian copula. Clayton copula, on the other hand, is an asymmetric copula in which the negative tail shows more dependence than the positive tail.

The gaussian, student, clayton and gumbel copulas were studied by Breymann et al. (2003) and he found that student copula performs the best amongst the others. According to Malevergns and Sornette (2003), if the bivariate student copula has a significant degree of flexibility, it can be agreed upon for exchange rates and stocks. Daul et.al (2003) suggested the application of ‘grouped t’ copula. This copula entails that the upper and lower tail dependence are equal which is not true for equity returns. Further, another set of copula Archimedean copula allow for tail dependence and address certain forms of asymmetry; however, they only have one or two parameters to characterize the dependence between variables, as a result, are restrictive in higher dimension applications.

Various researchers emphasize the relationship between tail dependence and multivariate extreme value copula. The Gaussian copula is simple to implement but has a strong assumption of zero tail dependence and symmetric dependence during a crisis. Chen et al. (2004) used multivariate versions of the gaussian and t-copula to analyze 30 daily US stock returns and 200 daily exchange rates returns with the US dollar as a base. The study rejected the gaussian copula and concluded that student copula is capable of assessing stock returns with multivariate stochastic dependence. In general, a conditional student copula appears to be the best choice for defining pair-wise dependences, according to Goorbergh et al. (2005). Demarta & McNeil (2005) discusses various variants of student t distribution copula.

A conditional student copula outperforms a conditional gaussian copula, according to Jondeau and Rockinger (2006). Fischer et.al (2008) studied the usage of Gaussian and Student t copula to construct the model of the German stock market, foreign exchange rate, and commodities market. They conclude that the student t copula has a greater explaining power. Kenourgios, Samitas, & Paltalidis (2011) used copula methods to capture non-linear relationships in four emerging markets which are Brazil, Russia, India, China, and two developed countries – the USA, UK. They found evidence of higher dependence, especially during financial crises. Further, the study states that these crises spread through equity markets instead of macroeconomic fundamentals.

Krupskii & Joe (2013) investigated eight US stocks of the Information technology sector and found factor copula models to be the best fit. Recently, Berger and Missiong (2014) used elliptical (normal) copulas to study financial crises. Grover (2015) studied the dependence structure and asymmetric tail dependence in the Indian stock markets and found that they do not follow the elliptical (normal) dependence structure. Rather, the assets show downside returns in the bearish markets. Oh and Patton (2015) determined the efficiency of the copula in measuring non-linear correlation as well as tail dependence. Hence proving that financial risk can be measured more precisely with copula than any other multivariate distributions. Similarly, Reboredo and Ugolini (2015) and Pourkhanali et.al (2016) studied the system risk, VaR, financial crises, and dynamic correlation with the help of copulas. Badhani (2016) examined the financial contagion with the help of a copula. The study explored non-linearities and asymmetry in the association between the Indian and the US stock market to find the presence of lower tail dependence.

Das (2016) investigated the cointegration among returns of the Bombay stock exchange and that of stock markets of China, Hong Kong, Japan, and Taiwan. The results showed that BSE has stronger upper and lower tail dependencies, with Nikkei and Hang Seng being the strongest. Clayton copula was employed for lower tail reliance and Gumbel copula was used for upper tail dependency in this study. Besides, Aloui and Aissa (2016) analyzed the dynamic relationship among energy, stock, and currency markets with the help of copulas.

Song, Liu, and Sriboonchitta (2019) analyzed the performance of BRICS, G7, and G20 countries concerning the pre and post crisis with the help of various copulas. The study demonstrated that factor copulas out of vine and other Archimedean and Gaussian copula have better goodness of fit. Moreover, it also found that BRICS has the highest risk; whereas, G20 has the lowest risk in the group.

2.5 RESEARCH GAP

After studying various literary works on this field, following gaps are found in the area which are addressed in the study:

1. None of the literature studies the basic characteristics/nature of the data i.e., the stylized facts of the broad market, sectoral and thematic indices of the Bombay and National stock exchange at length.
2. Previous literature does not study the causality among all broad market, sectoral and thematic indices of the Bombay and National stock exchange at a wide scale.
3. Finally, copula analysis along with the spread graphs, though at a preliminarily stage, has been carried out for all the broad market, sectoral and thematic indices of the Bombay and National stock exchange which has not been done before.

2.6 OBJECTIVES OF THE STUDY

The objectives of the study are as follows:

1. The aim of the study is to determine the pattern of movement of the prices of the stock market using the benchmark indices of two main stock exchanges of India viz, Bombay stock exchange and National stock exchange. Also, to determine the trend of movement of prices of selected sectoral indices of the Bombay stock exchange as well as sectoral and thematic indices of the National stock exchange.

2. The study also estimates the basic statistics of both the benchmark indices and the selected sectoral and thematic indices of respective stock exchange to understand the type of data and its distribution; after which a normality test is carried out to check whether the data follows normal distribution.

3. Further, it also studies the beta risk associated with each of the sectoral and thematic indices with their respective market indices and also checks for correlation among the selected sectoral and thematic indices with the benchmark index.

4. The study's second primary purpose is to better understand the nature of the data of the stock exchanges. For this the stylized facts of the expected returns of each broad market indices of Bombay stock exchange and National stock exchange, selected sectoral and thematic indices of both the markets is examined individually.

5. Finally, in order to study the inter-relationship among the various selected sectors of the economy, to understand their dependence structure of each of these sectors a copula analysis is carried out to model their dependence structure.

2.7 BROAD HYPOTHESIS OF THE STUDY

In view of the above objectives following are the broad hypothesis of the study:

1. Null Hypothesis $H1_0$: The data follows normal distribution.

   Alternative Hypothesis $H1_1$: The data does not follow normal distribution.

2. Null Hypothesis $H2_0$: The data considered confirms the presence of the stylized facts.

   Alternative Hypothesis $H2_1$: The data considered does not confirm the presence of the stylized facts.

3. Null Hypothesis $H3_0$: The sectoral/thematic indices and the benchmark indices have causal relationships.

   Alternative Hypothesis $H3_1$: The sectoral/thematic indices and the benchmark indices do not have causal relationships.

4. Null Hypothesis $H4_0$: The sectoral and thematic indices have causality relationships within themselves.

   Alternative Hypothesis $H4_1$: The sectoral and thematic indices do not have causality relationships within themselves.

5. Null Hypothesis $H5_0$: The sectoral/thematic indices and the benchmark indices are closely associated.

   Alternative Hypothesis $H5_1$: The sectoral/thematic indices and the benchmark indices are not closely associated.

6. Null Hypothesis $H6_0$: The sectoral and thematic indices are closely associated within themselves.

   Alternative Hypothesis $H6_1$: The sectoral and thematic indices are not closely associated within themselves.

Conclusion –

Since Harry Markowitz (1952) study there has been constant debate on inclusion of various factors that affect a portfolio selection other than means and variance. With the introduction of the CAPM model by Treynor (1961), Sharpe (1964), and Linter (1965) individually, various other researchers followed which suggested addition of other elements to explain the risk-return relationship. Kraus & Litzenberger (1976) was one of the first study to incorporate the third moment skewness in CAPM; while Fama (1965a) noticed presence of kurtosis in his data. Each financial data has peculiar characteristics and quantifying those characteristics helps to understand the data. Hence the concept of stylized facts was first introduced by Kaldor (1957) and was applied to the concept of financial data by numerous researchers (Cont 2001, Taylor 2005). Further, literature on linkages between the Indian stock market indices has been discussed. Followed by literature on copula models used to study the sectoral associations.