CHAPTER 8

STOCK MARKET RISK: AN EMPIRICAL INVESTIGATION (III)

STOCK MARKET RISK: AN EMIPIRICAL INVESTIGATION

8.1 INTRODUCTION

One of the most contentious issues in economics is whether the stock market can be used to forecast economic growth or vice versa. Many people believe that a substantial drop in stock prices signals an impending recession, whereas a significant gain in stock prices signals an impending economic boom. However, there have been issues that have cast doubt on the stock market's ability to predict the future, such as the stock market crash of 1987, which was followed by a global recession, and the Asian financial crisis of 1997. Furthermore, we find that similar research over the last thirty years has mostly concentrated on the impact of financial development in encouraging economic expansion, while ignoring stock market development. The stock market's evolution has a substantial impact on the operations of financial institutions in developing countries (Levine & Zervos, 1996). According to Paudel (2005), the stock market's liquidity allows businesses to obtain much-needed funds rapidly, allowing capital allocation, investment, and growth. As a result, the United States' stock market is predicted to have a considerable impact on economic growth.

Since the beginning of economic reforms in the 1990s, the Indian economy has undergone substantial structural changes; financial development reforms have also been adopted as part of these economic advancements. The expansion and depth of the capital market in the 1980s and 1990s demonstrates the market's broadening and deepening. Debentures have been a potent tool for resource mobilisation in the primary markets since the mid-1980s. In 1985–1986, India's financial development took on a new dimension with the introduction of public sector bonds. From 1984 to 1985, the secondary market grew rapidly in terms of the number of institutions, listed firms, paid-up capital, and market capitalization.

The market capitalization of Indian stock exchanges has risen over time, indicating that more companies are trading on their platforms. At the end of March 2011, India's market capitalization was around 68,430,493 million dollars. The cash segment of Indian stock exchanges saw a 44 percent increase in turnover in 2010, rising to 55,184.7 billion from 38,525.8 billion in 2009. The Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) jointly accounted for 99.9% of the capital market's turnover. The NSE accounted for 74.9 percent of total cash market turnover, while the BSE accounted for 24.9 percent of overall revenue. During the years 1994–1995, the annual growth rate was over 6.2 percent. The rise slowed significantly in 2002 to 3.8 percent, but accelerated to 9.7 percent in 2006–2007. It is possible to say that the growth of the economy's financial sectors is dependent on the performance of the financial sectors.

The stock market's success has been proved to have an impact on the economy's overall gross domestic product (GDP). The movement of aggregate stock market indices, on the other hand, is not always in lockstep with the trend of aggregate economic development. There is a possibility of sector-specific growth due to the stock market's pertinent sector-specific growth. As a result, it is vital to research and capture the sector-specific sensitivity of the economy's economic growth in a portfolio. The empirical question of whether stock market development effects or is a result of increased economic activity has long been a source of debate in the study of economics (Goldsmith, 1969; Gurley & Shaw, 1967; Jung & Marshall, 1985). However, there hasn't been much research into the impact of stock market performance on sector-specific economic growth. Using a sector-specific paradigm, the current study seeks to fill this research vacuum by assessing the influence of stock market development on economic growth. This is done by studying the association among the stock market indices and sectoral/thematic indices.

The following is the chapter's outline: The chapter's objectives are presented in the second part. The grange causality is shown in the fourth section, and copula graphs of various sectors are explored in the fifth section. The conclusion is discussed in the final part.

8.2 OBJECTIVES OF THE CHAPTER

The objectives of the chapter are as follows:

1. To study the causality between S&P BSE Sensex and its sectoral analysis.

2. To study the causality between Nifty50 and its sectoral as well as thematic analysis.

3. To study the causality within the sectors of Bombay stock market and National stock market.

4. Using Clayton copula, Frank copula, Normal copula, and T copula, explore the relationship between Bombay stock exchange sectoral indices and its market index S&P BSE Sensex.

5. To investigate the association between sectoral as well as thematic indices of National stock exchange and its market index Nifty50 with the help of Normal copula, T copula, Clayton copula, and Frank copula.

8.3 GRANGER CAUSALITY

One of the most important and, at the same time, one of the most challenging concerns in economics is determining causality between variables. The challenge derives from social science's non-experimental nature. Researchers in natural science can conduct experiments in which all other probable explanations are held constant except for the single item under consideration. The causal structures among components or variables can be identified by repeating the process for each plausible cause. There is no such thing as luck in social science, and economics is no different. All variables affect the same variable at the same time, making repeated studies under control impossible (experimental economics is no solution, at least, not yet).

The following are the two most difficult challenges:

1. Correlation is not the same as causation. It's difficult to distinguish between these two.
2. There is always the chance of common factors being overlooked. When the previously overlooked shared causes are taken into account, the causal link between variables may vanish.

While there is no satisfactory answer to any of these problems, and there may never be one, philosophers and social scientists have sought to address the second issue using graphical models. When it comes to the first problem, time series analysts turn for help from the time arrow's peculiar unidirectional property: cause comes before effect.

Clive W.J. Granger presented a workable definition of causality based on this concept, dubbed Granger causality, which uses foreseeability as a yardstick.

There are two assumptions here.

1. The past cannot be caused by the future. The present or future is influenced by the past. (How about the concept of expectation?)
2. A cause contains one-of-a-kind information about an effect that isn't found somewhere else.

According to Granger causality, if a signal X1 "Granger-causes" (or "G-causes") a signal X2, prior values of X1 should contain information that helps forecast X2 beyond the information offered in previous data of X2. The concept of causality was created by Wiener (1956) and Granger (1969), and it is a basic concept for analyzing dynamic interactions between time series. Predictability is the most important factor to consider when analyzing Wiener-Granger causation, which is why it is so important to economists and policymakers. Granger-causality is frequently researched in practice for bivariate processes. Granger's (1969) original definition, which has been used in this literature, implicitly presupposes that all relevant data is available and used for causality analysis. However, in practice, only a small amount of data is considered, and omitting essential factors (auxiliary variables) may result in spurious causality or fail to discover a probable indirect causality between the variables that matter.

To investigate the causality ties between the various sectors of the Indian stock market and its market indices, the study uses granger causality. During the study period, the first table shows the causation relationships between the Bombay stock exchange's sectoral indexes and its benchmark index, the S&P BSE Sensex.

Table 8.1: Granger Causality (BSE)

Null Hypothesis	P-value
Sensex does not Granger Cause Bank	0.0093
Sensex does not Granger Cause Basic materials	0.0031
Basic materials does not Granger Cause Sensex	2.00E-196
Sensex does not Granger Cause Consumer discretionary	0.000
Consumer discretionary does not Granger Cause Sensex	1.E-196
Sensex does not Granger Cause Consumer durables	0.0189
Sensex does not Granger Cause Energy	0.0357
Energy does not Granger Cause Sensex	4.00E-194
Sensex does not Granger Cause Finance	1.00E-06
Finance does not Granger Cause Sensex	0
Sensex does not Granger Cause FMCG	0.0252
FMCG does not Granger Cause Sensex	0.0012
Sensex does not Granger Cause Industrials	0.0341
Industrials does not Granger Cause Sensex	1.00E-184
Sensex does not Granger Cause IT	0.0264
Power does not Granger Cause Sensex	0.0171
Telecom does not Granger Cause Sensex	1.00E-39
Utilities does not Granger Cause Sensex	5.00E-61

Source – Author's estimation

The table displays the null hypothesis and the probability values at 5% significance levels. The results show that changes in Sensex has an uni-directional relationship with bank, consumer durables and informational technology. A change in Sensex may lead to change in all these sectors. While other sectors such as power, telecom and utilities also have uni-directional relationship with Sensex; however, a change in these sector lead to change in Sensex. Sectors such as basic materials, consumer discretionary, energy, finance, FMCG and industrials form a bi-directional relationship with Sensex. Changes in either sector led to change in Sensex, while change in Sensex lead to changes in either of the sectors.

Below table represents the granger causality between the sectoral as well as thematic indices and the market index i.e., Nifty50 of the National stock exchange.

Table 8.2: Granger Causality (NSE)

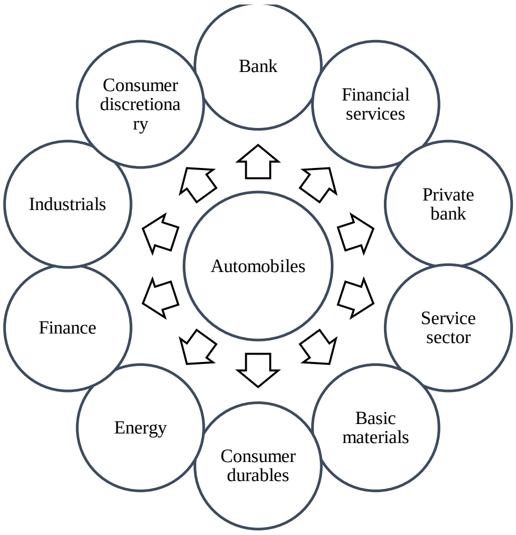
Null hypothesis	P-value
Nifty50 does not Granger Cause Service sector index	0.0047
Service Sector index does not granger cause Nifty50	0.0575
Nifty50 does not granger cause India Manufacturing index	5.e-33
India Manufacturing index does not granger cause Nifty50	2.e-05
PSU bank index does not granger cause Nifty50	0.0565
Nifty50 does not granger cause Financial services index	0.0049
Nifty50 does not Granger Cause Media index	0.0039
Nifty50 does not Granger Cause Private bank index	0.0469
India Consumption index does not Granger Cause Nifty50	0.0061
Infrastructure index does not granger cause Nifty50	0.0556

Source – Author's estimation

Here, Nifty50 has a bi-directional causality with the service sector index, manufacturing index and uni-directional relation with indices such as financial services, media and private bank. Accordingly, consumption index, infrastructure index, and PSU bank index also have uni-directional relationship with Nifty50.

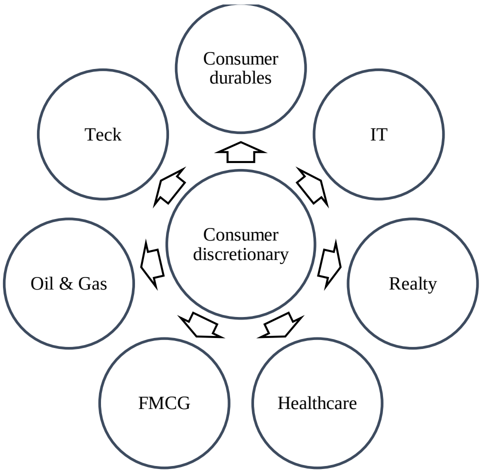
Granger causality was also carried out within the sectors whose results in tabular form are present in the appendix. The results indicate 31 bi-directional relationship and 68 uni-directional relationship among various selected sectoral indices of BSE. Whereas, in case of NSE, there exist 9 bi-directional and 18 uni-directional relationship among the selected sectoral and thematic sectors of the stock exchange. The bi-directional causality amongst sectors is summed up in following diagrams.

Figure 8.1: Bidirectional causality – S&P BSE Automobile



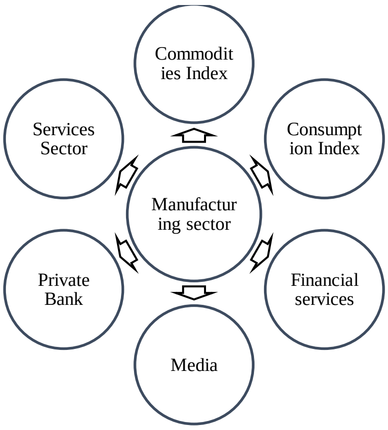
Source – Author's estimation

Figure 8.2: Bidirectional causality – S&P BSE Consumer discretionary



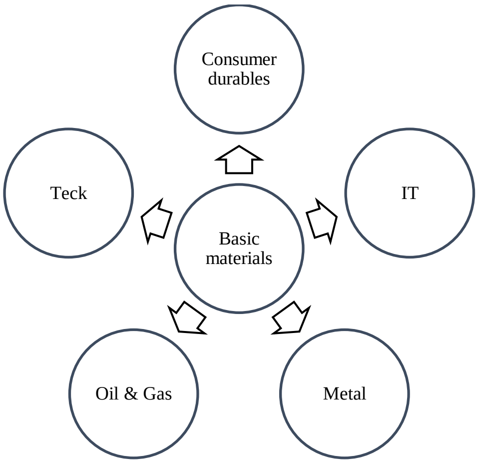
Source – Author's estimation

Figure 8.3: Bidirectional causality – India Manufacturing Index



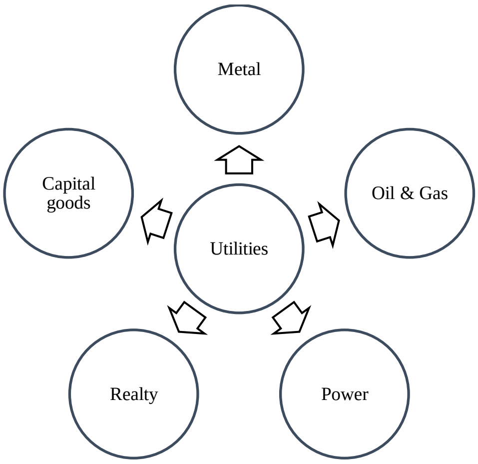
Source – Author's estimation

Figure 8.4: Bidirectional causality – S&P BSE Basic materials



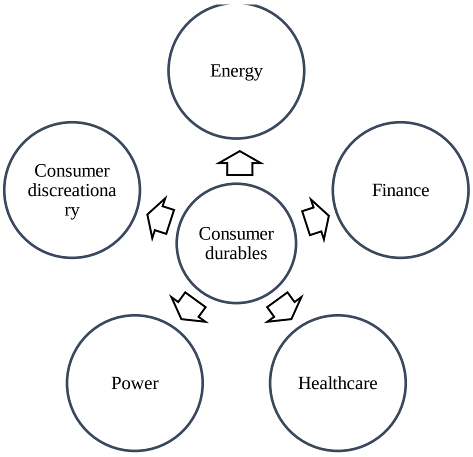
Source – Author's estimation

Figure 8.5: Bidirectional causality – S&P BSE Utilities



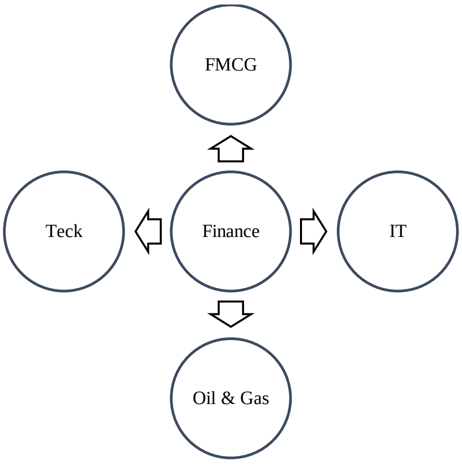
Source – Author's estimation

Figure 8.6: Bidirectional causality – S&P BSE Consumer durables



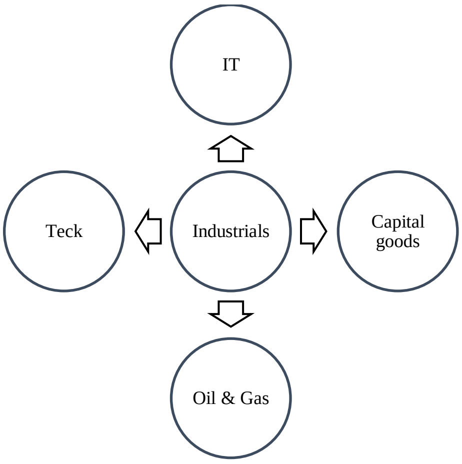
Source – Author's estimation

Figure 8.7: Bidirectional causality – S&P BSE Finance



Source – Author's estimation

Figure 8.8: Bidirectional Causality – Industrials index



Source – Author's estimation

Other bidirectional causality exists between: I) India Consumption Index and Services sector index, II) Energy index and Oil & Gas index, III) Realty index and Telecom index, IV) Financial services index and Media index, V) Financial services index and Private bank index.

8.4 COPULA MODELS

A significant skill of the risk analyst is the ability to identify and model dependencies. A realistic model of dependency allows us to model assets and price financial instruments more fairly, among other things. Historically, correlation has been used to measure and model dependencies. However, it is uncommon for distributions to meet the rigorous spherical assumptions required by correlation, such as a constant dependency across the distribution. The good news is that practitioners can now use copula techniques to get around correlation's restrictions. General insurance actuaries are familiar with Copula techniques, but investment and pensions actuaries are only recently learning about them and applying them to their fields. When it comes to analysing the co-movement of financial time-series, copulas have a number of advantages over other econometric techniques, including the capacity to characterize dependency beyond linear correlation and a high degree of flexibility.

It's a model of interdependence that's recently garnered a lot of momentum. Sklar's theorem, which is the foundation theorem for copulas, asserts that a copula function exists that connects a given joint multivariate distribution function and the relevant marginal distributions. Using a copula to construct multivariate distributions is a versatile and powerful method because it separates the choice of dependence from the choice of marginals, which is unlimited.

The question now is who to choose an appropriate copula from the wide range of copulas. Frequently, the characteristics of familiarity, convenience of usage, and analytical tractability are used to make the decision. Extreme distributions are represented by the Gumbel copula, linear correlation is represented by the Gaussian copula, and tail dependency is represented by the Archimedean copula and the t-copula. The multivariate Gaussian or Normal distribution is used to create the Gaussian copula. Other methods of construction, such as the Frank copula, may employ geometry and the definition above to construct copula functions.

The study constructs five types of copulas

1. Elliptical copula
   - I. Normal copula
   - II. T copula,
2. Archimedean copula
   - I. Clayton copula,
   - II. Frank copula and
   - III. Gumbel copula.

The results of S&P BSE Sensex (Bombay stock exchange) and Nifty50 (National stock exchange) in terms of parameters of the copulas, their information criteria along with correlation matrix and the diagrammatic representation of the best fit copula is being represented below.

Table 8.3: Parameters of Copulas (BSE)

Copula	Parameter	SIC	AIC	HQIC
Clayton	0.8709563	-22355.49	-22361.69	-22359.48
Frank	2.9572564	-21366.3	-21372.49	-21370.29
Gumbel	1.4354781	-21510.18	-21516.38	-21514.17
Normal	-	-76752.69	-77795.47	-77434.96
T	6	-82628.82	-83677.6	-83315.08

Source – Author's estimation

Table 8.4: Parameters of Copula (NSE)

Copula	Parameter	SIC	AIC	HQIC
Clayton	1.7843131	-18879.27	-18885.46	-18883.26
Frank	5.2438173	-32868.44	-32874.64	-32872.43
Gumbel	-1.892157	-33052.85	-33059.05	-33056.84
Normal	-	-80973.49	-81617.92	-81392.43
T	6	-86683.46	-87333.97	-87106.39

Source – Author's estimation

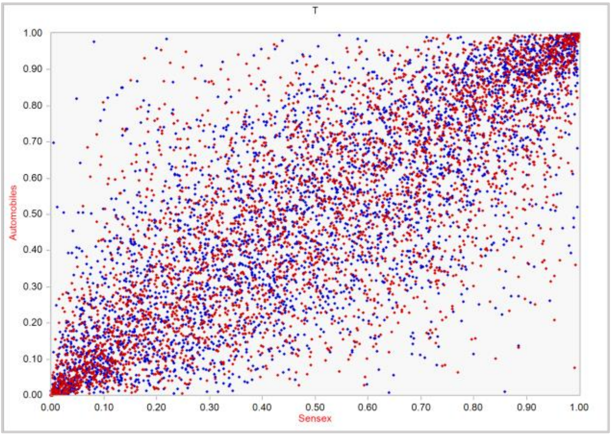
The research reveals that the correlation values are similar when using the old method. However, the tails analysis, i.e., the numerous copulas fit, takes a different approach to data measurement. Based on the AIC, SIC, and HQIC results from various copulas deployed, we infer that the T copula is a better fit model than the other copulas.

The t copula is derived from the multivariate t distribution in the same way as the Gaussian copula is derived from the multivariate normal. Because the degree of tail dependency may be changed by modifying the degrees of freedom parameter 'v', the t copula is rapidly gaining popularity. A Gaussian distribution is approximated by large values for v, such as v = 100. Small values for v, such as v==3, on the other hand, increase tail dependency until v = 1 simulates a Cauchy distribution. Thus, we can use a t copula to simulate the joint distribution and subjectively assign a degree of freedom that represents tail dependency.

The use of multivariate copulas such as the t copula has the disadvantage that tail association is controlled by only one parameter, and various pairings of variates may have different tail associations. Conditioning, on the other hand, provides a way to combine distinct copula designs. The t-copula exhibits symmetric tail dependency, which could be a disadvantage. However, latest research suggests that it can be extended to account for asymmetric dependence. The graphs below show the spread between various sectors. Only significantly highly associated sectors are been projected in the graphs.

In the Bombay stock exchange market, there are 17 strong associations all of which are shown in the figures below. All these associations are also checked for correlation and found to be higher than 0.8.

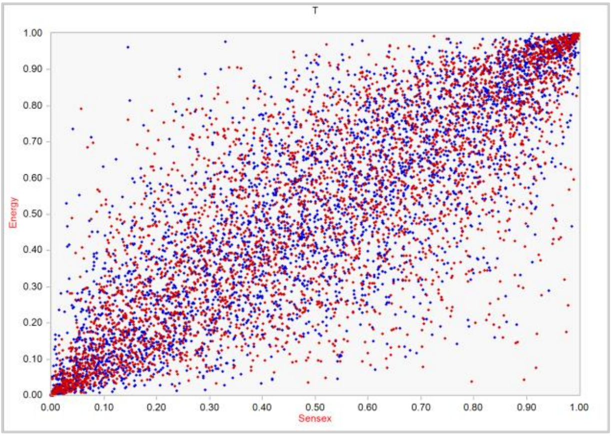
Figure 8.9: T-copula spread (S&P BSE Sensex – S&P BSE Automobile)



The graph represents the association between Sensex and automobiles sector. Here, we can see the spread more around the tails of the distribution for both. The correlation coefficient between the two remains 0.8 which confirms the robust positive connection between Sensex returns and automobiles returns. It implies that an increase in the stock prices of vehicle businesses will result in an increase in the Sensex.

Source – Author's Estimation

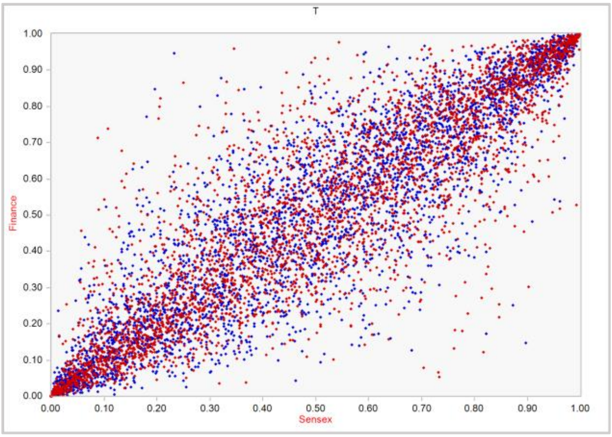
Figure 8.10: T-copula spread (S&P BSE Sensex – S&P BSE Energy)



The graph depicts the association between the Sensex and the Energy sector. For both, the spread is more visible at the tails of the distribution. The correlation coefficient between the two remains at 0.8, confirming the strong positive relationship between the Sensex returns and the energy returns. It implies that an increase in the stock prices of energy companies will lead to an increase in the Sensex.

Source – Author's Estimation

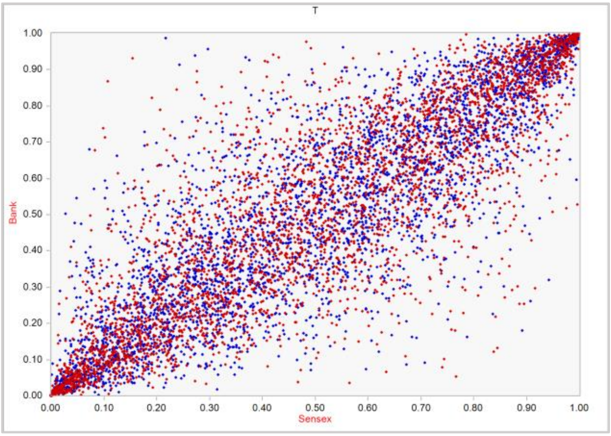
Figure 8.11: T-copula spread (S&P BSE Sensex – S&P BSE Finance)



The graph shows the association between the Sensex and the Finance sector. The spread of data points of both the variables show very strong association and more of it is visible at the tails of the distribution. The correlation coefficient between the two remains at 0.9, confirming the strong positive relationship between the two. It indicates that if the stock prices of financial companies rise, the Sensex will rise as well.

Source – Author's Estimation

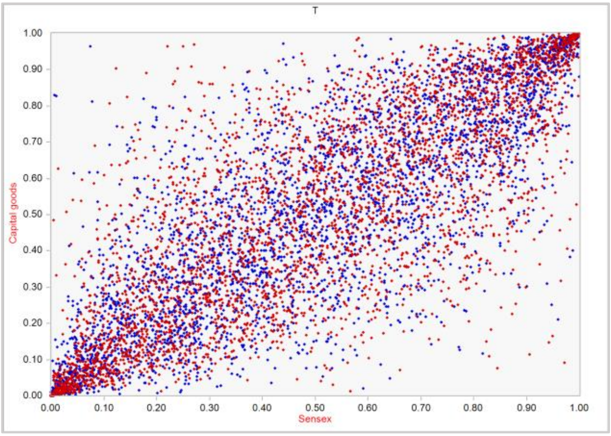
Figure 8.12: T-copula spread (S&P BSE Sensex – S&P BSE Bank)



The graph represents the association between the Sensex and the Bank sector. The spread of data points of both the variables show strong association and more of it is visible at the tails of the distribution. The correlation coefficient between the two remains at 0.9, confirming the strong positive relationship between the Sensex returns and the bank returns. It implies that a rise in bank stock prices will lead to an increase in the Sensex.

Source – Author's Estimation

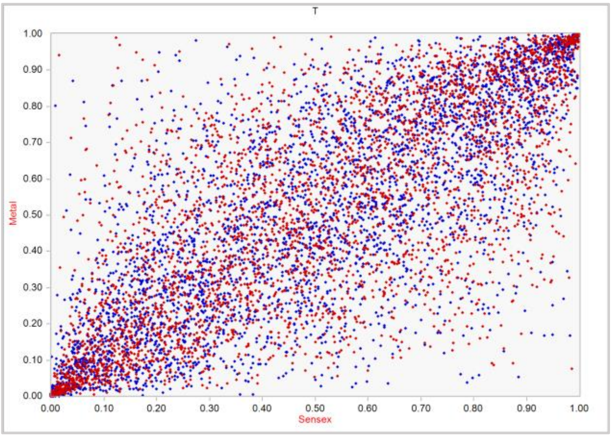
Figure 8.13: T-copula spread (S&P BSE Sensex – S&P BSE Capital goods)



The graph shows the association between the Sensex and the Capital goods sector. Both variables' data points reveal a strong relationship, with more of it observable at the tails of the distribution. The correlation coefficient between the two remains at 0.9, indicating the existence of a strong positive association. It suggests that a gain in the Sensex will be accompanied by an increase in the stock prices of capital goods companies.

Source – Author's Estimation

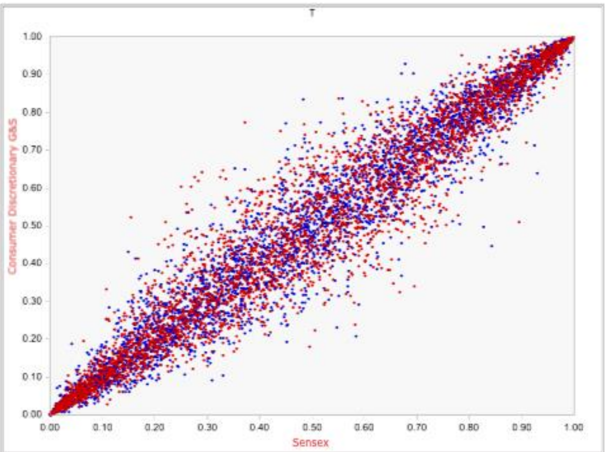
Figure 8.14: T-copula spread (S&P BSE Sensex – S&P BSE Metal)



Source – Author's Estimation

The graph displays the association between the Sensex and the Metal sector. Both variables' data points reveal a strong relationship, with more of it observable at the tails of the distribution. The correlation coefficient between the two remains at 0.9, indicating that the Sensex returns and the metal returns have a strong positive association. It suggests that a gain in the Sensex will be accompanied by an increase in the stock prices of metal companies.

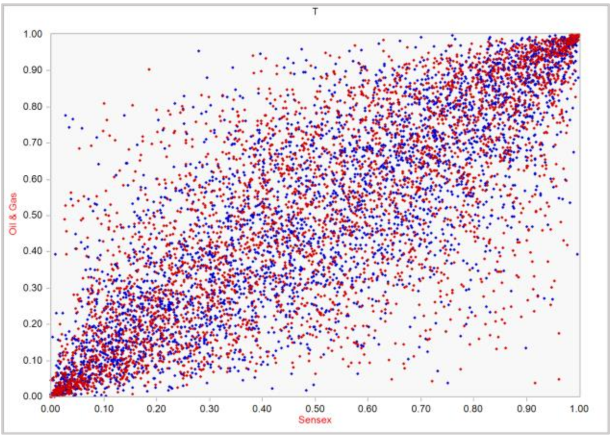
Figure 8.15: T-copula spread (S&P BSE Sensex – S&P BSE Consumer discretionary G&S)



Source – Author's Estimation

The graph shows the association between the Sensex and the Consumer discretionary sector. Both variables' data points reveal a strong relationship, with more of it observable at the tails of the distribution. The correlation coefficient between the two remains at 0.96, indicating that the Sensex returns and the consumer discretionary returns have a strong positive association. It suggests that a gain in the Sensex will be accompanied by an increase in the stock prices of consumer discretionary companies.

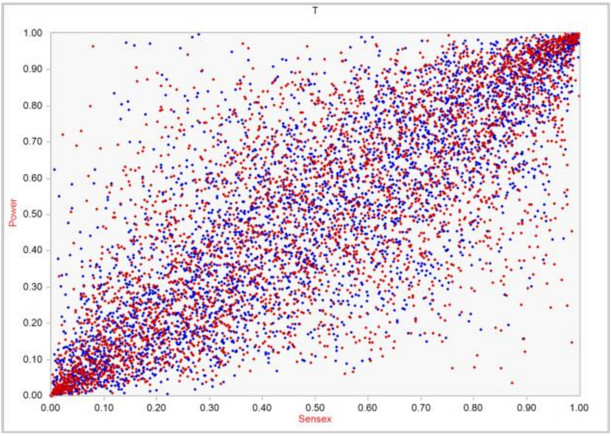
Figure 8.16: T-copula spread (S&P BSE Sensex – S&P BSE Oil & Gas)



Source – Author's Estimation

The association between the Sensex and the Oil & Gas sector is depicted in the graph. The data points for both variables show a significant link, with more of it visible at the tails of the distribution. The correlation coefficient between the two remains at 0.9, demonstrating a strong and positive relationship between the Sensex and the Oil & Gas returns. It predicts that a rise in the Sensex will be accompanied by a rise in oil and gas company stock prices.

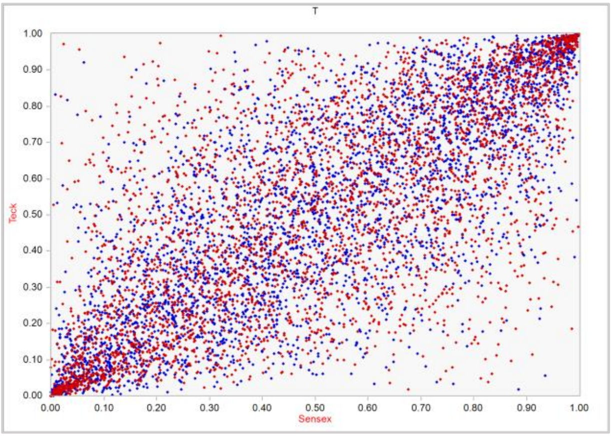
Figure 8.17: T-copula spread (S&P BSE Sensex – S&P BSE Power)



Source – Author's Estimation

The graph represents spread data points of Sensex and Power. The data points for both variables show a significant relationship, with more of it visible at the tails of the distribution. The correlation coefficient between the two remains at 0.9, illustrating that the Sensex and the Power returns have a strong positive association. It implies that an increase in the Sensex will be accompanied by a rise in the stock prices of power firms.

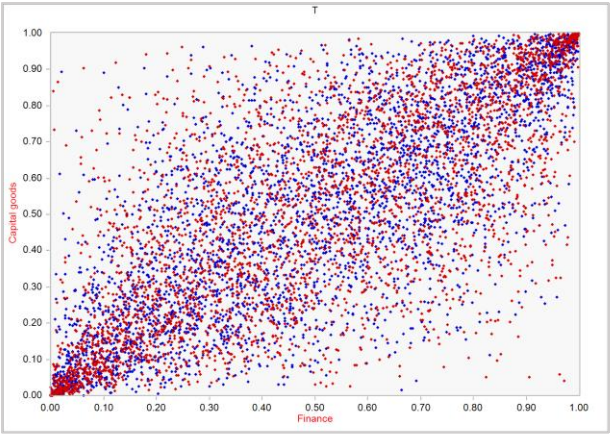
Figure 8.18: T-copula spread (S&P BSE Sensex – S&P BSE Teck)



Source – Author's Estimation

The graph displays Sensex and Teck data points over a period of time. There is a substantial association between the data points for both variables, with more of it observable near the tails of the distribution. The correlation coefficient between the two stays at 0.9, indicating that the Sensex and the Teck returns have a strong positive link. It means that a gain in the Sensex will be mirrored by a rise in Teck company stock prices.

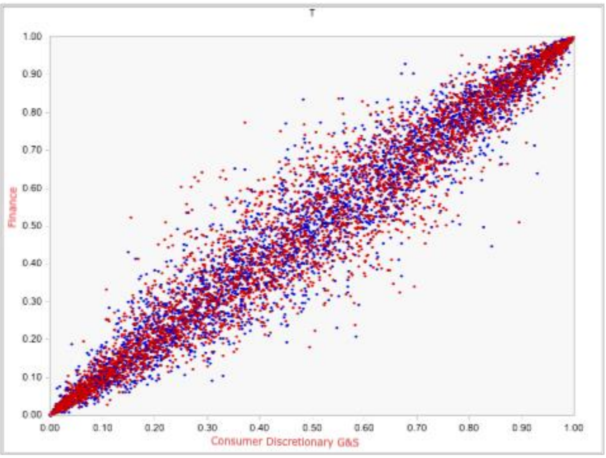
Figure 8.19: T-copula spread (S&P BSE Finance – S&P BSE Capital goods)



Source – Author's Estimation

The graph depicts the relationship between the data points of the finance and capital goods sectors. For both variables, there is a significant correlation between the data points, with more of it visible near the tails of the distribution. The correlation coefficient between the two remains at 0.9, demonstrating a significant positive relationship. This means that if the stock prices of finance businesses rise, so will the stock prices of capital goods companies.

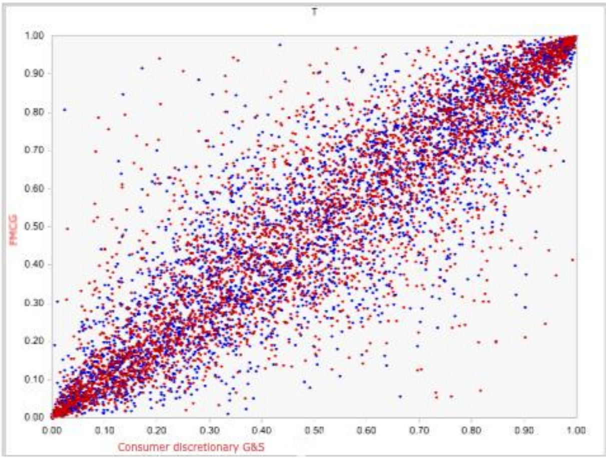
Figure 8.20: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE Finance)



The graph displays the association between the data points of consumer discretionary sector and finance sector. There is a substantial association between the data points for both variables, with more of it observable near the tails of the distribution. The correlation coefficient between the two stays at 0.96, indicating the existence of a strong positive link. This means that if the stock prices of consumer discretionary businesses rise, so will the stock prices of finance companies.

Source – Author's Estimation

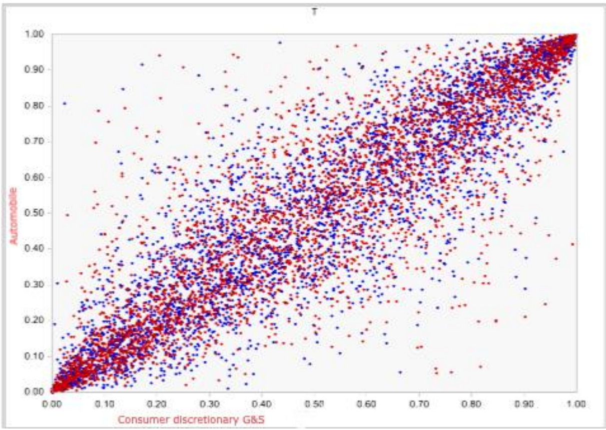
Figure 8.21: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE FMCG)



The graph shows the association between the data points of consumer discretionary sector and FMCG sector. There is a substantial association between the data points for both variables, with more of it observable near the tails of the distribution. The correlation coefficient between the two stays at 0.9, indicating the existence of a strong positive link. This means that if the stock prices of consumer discretionary businesses rise, so will the stock prices of FMCG companies

Source – Author's Estimation

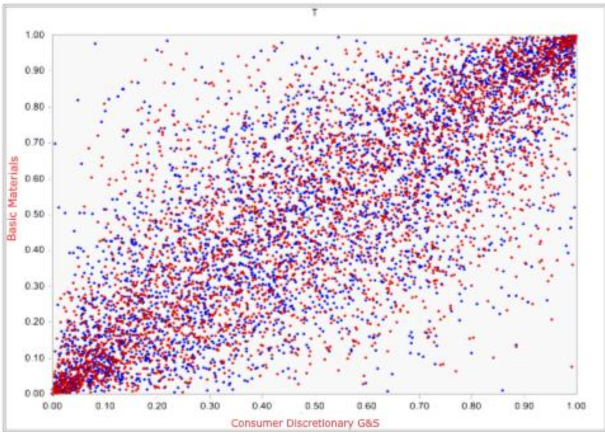
Figure 8.22: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE Automobile)



The graph represents the association between the data points of consumer discretionary sector and automobile sector. There is a substantial association between the data points for both variables, with more of it observable near the tails of the distribution. The correlation coefficient between the two stays at 0.9, indicating the existence of a strong positive link. This means that if the prices of consumer discretionary businesses rise, so will the prices of automobile companies.

Source – Author's Estimation

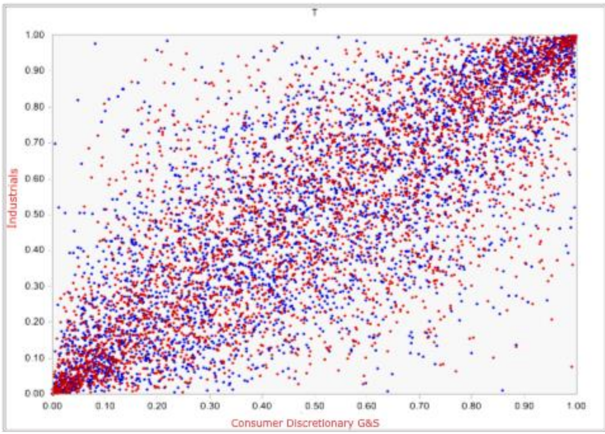
Figure 8.23: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE Basic materials)



Source – Author's Estimation

The graph depicts the association between the consumer discretionary and the Basic materials sector. For both, the spread is more visible at the tails of the distribution. The correlation coefficient between the two remains at 0.89, confirming the strong positive relationship between the both the indices returns. It implies that an increase in the stock prices of basic materials companies will lead to an increase in the consumer discretionary firms.

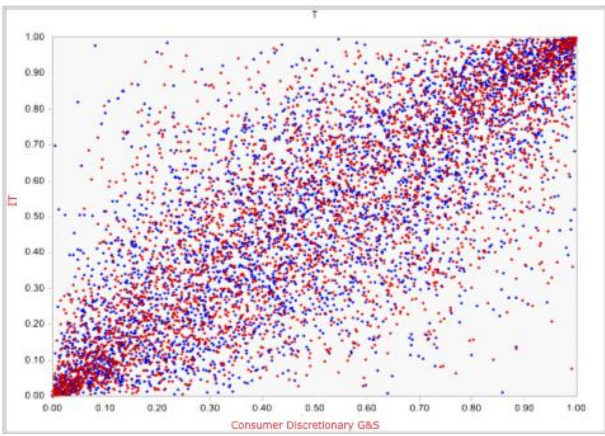
Figure 8.24: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE Industrials)



Source – Author's Estimation

The graph shows the association between the consumer discretionary and the Industrials sector. For both, the spread is more visible at the tails of the distribution. The correlation coefficient between the two remains at 0.85, confirming the strong positive relationship between the both the indices returns. It implies that an increase in the stock prices of industrials companies will lead to an increase in the consumer discretionary firms.

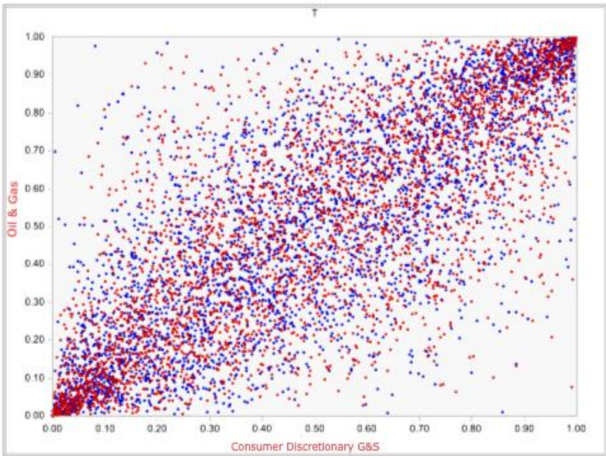
Figure 8.25: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE IT)



Source – Author's Estimation

The graph represents the association between the consumer discretionary and the IT sector. For both, the spread is more visible at the tails of the distribution. The correlation coefficient between the two remains at 0.89, confirming the strong positive relationship between the both the indices returns. It implies that an increase in the stock prices of IT companies will lead to an increase in the consumer discretionary firms.

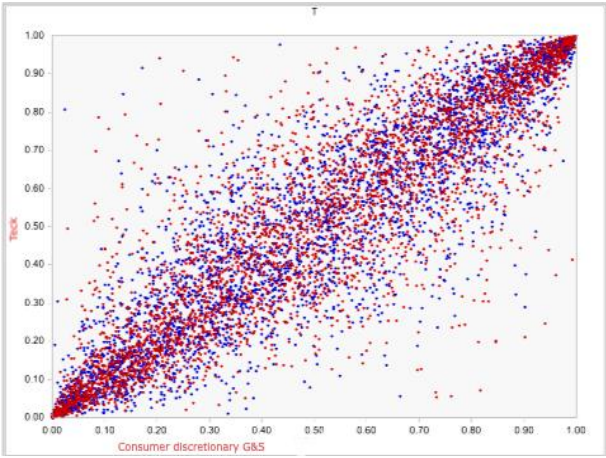
Figure 8.26: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE Oil & Gas)



The graph displays the association between the consumer discretionary and the Oil & Gas sector. For both, the spread is more visible at the tails of the distribution. The correlation coefficient between the two remains at 0.8, confirming the strong positive relationship between the both the indices returns. It implies that an increase in the stock prices of oil & gas companies will lead to an increase in the consumer discretionary firms.

Source – Author's Estimation

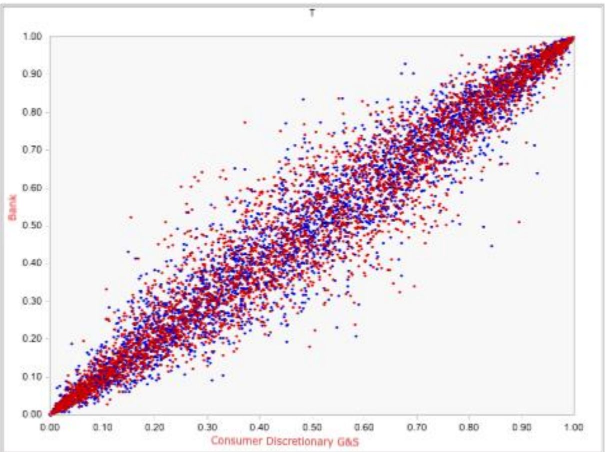
Figure 8.27: T-copula spread (S&P BSE Consumer discretionary G&S – S&P BSE Teck)



The graph shows consumer discretionary and Teck data points over a period of time. There is a substantial association between the data points for both variables, with more of it observable near the tails of the distribution. The correlation coefficient between the two stays at 0.9, indicating that both their returns have a strong positive link. It means that a gain in the consumer discretionary will be mirrored by a rise in Teck company stock prices.

Source – Author's Estimation

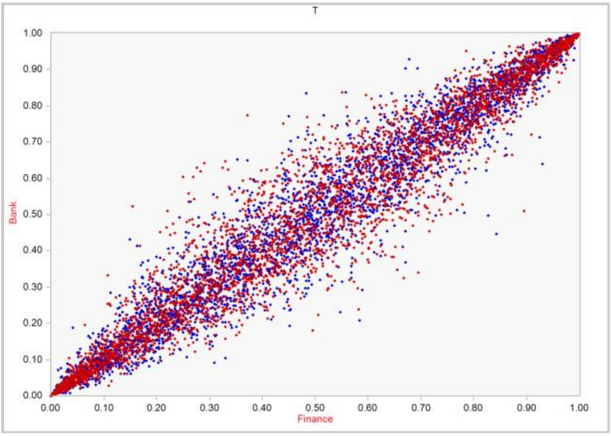
Figure 8.28: T-copula spread (S&P BSE Consumer discretionary G&S– S&P BSE Bank)



The graph represents the link between the Consumer discretionary G&S and banks' data points. There is a considerable correlation between the data points for both variables, with more of it visible at the distribution's tails. The correlation coefficient between the two is still 0.95, indicating that there is a considerable positive association between them. This means that as the stock prices of consumer discretionary firms rise, so will the stock prices of banks.

Source – Author's Estimation

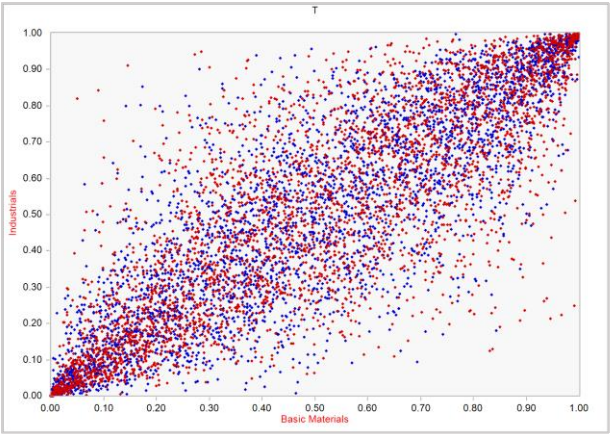
Figure 8.29: T-copula spread (S&P BSE Finance – S&P BSE Bank)



Source – Author's Estimation

The graph depicts the link between the bank and financial sectors' data points. There is a considerable correlation between the data points for both variables, with more of it visible at the distribution's tails. The correlation coefficient between the two is still 0.9, indicating that there is a considerable positive association between them. This means that as the stock prices of financial firms rise, so will the stock prices of banks.

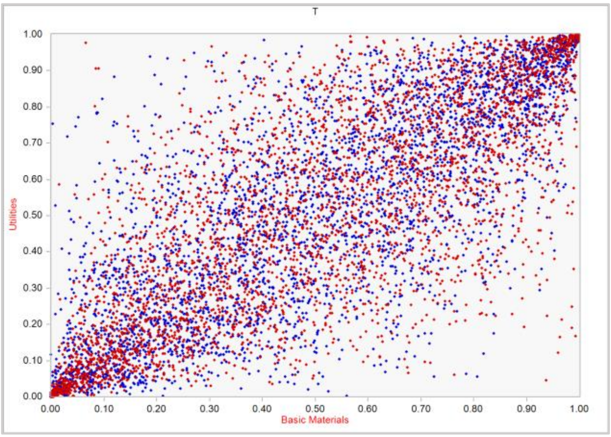
Figure 8.30: T-copula spread (S&P BSE Basic materials – S&P BSE Industrials)



Source – Author's Estimation

The graph displays the link between the basic materials and industrials sectors' data points. There is a substantial correlation between the data points for both variables, with more of it visible at the distribution's tails. The correlation coefficient between the two is still 0.9, indicating that there is a considerable positive association between them. This indicates that if the stock prices of basic materials firms rise, so will the stock prices of industrials companies.

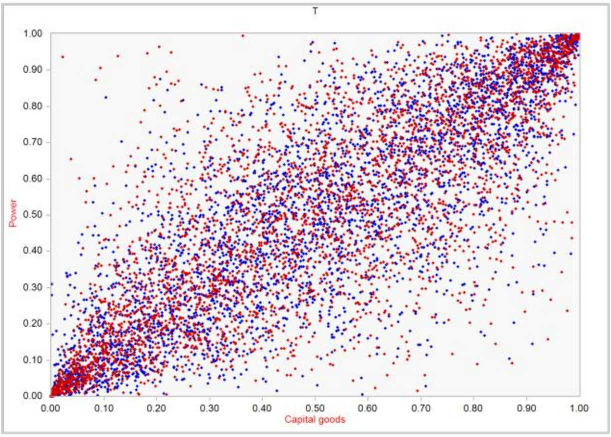
Figure 8.31: T-copula spread (S&P BSE Basic materials – S&P BSE Utilities)



Source – Author's Estimation

The graph shows the link between the basic materials and utilities sectors' data points. There is a considerable correlation between the data points for both variables, with more of it visible at the distribution's tails. The correlation coefficient between the two is still 0.9, indicating that there is a considerable positive association between them. This means that if basic materials businesses' stock prices rise, utility company stock prices will climb as well.

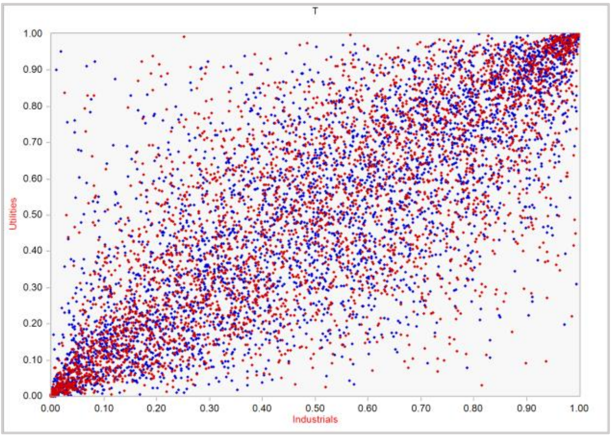
Figure 8.32: T-copula spread (S&P BSE Capital goods – S&P BSE Power)



Source – Author's Estimation

The graph displays the link between the capital goods and power sectors' data points. There is a significant association between the data points for both variables, with more of it visible at the distribution's tails. The correlation coefficient between the two is still 0.9, indicating that there is a considerable positive association between them. This means that if capital goods businesses' stock prices rise, the power sector's stock prices will climb as well.

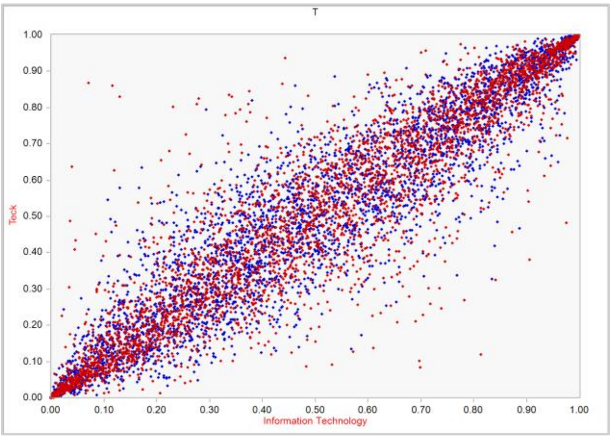
Figure 8.33: T-copula spread (S&P BSE Industrials – S&P BSE Utilities)



Source – Author's Estimation

The graph shows the relationship between the data points of the industrials and utility sectors. There is a substantial relationship between the data points for both variables, with the tails of the distribution showing more of it. The correlation coefficient between the two remains at 0.9, showing that they have a strong positive relationship. This means that if utilities businesses' stock prices rise, the industrials sector's stock prices will soar as well.

Figure 8.34: T-copula spread (S&P BSE IT – S&P BSE Teck)

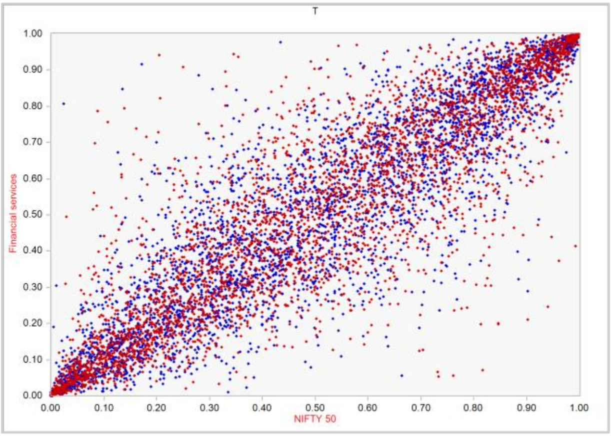


Source – Author's Estimation

The graph depicts the relationship between the data points of the IT and Teck sectors. There is a substantial relationship between the data points for both variables, with the tails of the distribution showing more of it. The correlation coefficient between the two remains at 0.9, showing that they have a strong positive relationship. This means that if the stock prices of IT businesses grow, so will the stock prices of the Teck industry.

NATIONAL STOCK EXCHANGE

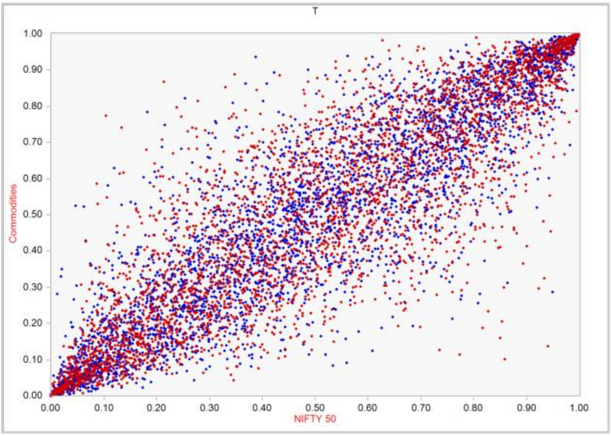
Figure 8.35: T-copula spread (Nifty50 – Financial services index)



Source – Author's Estimation

The graph displays the association between the Nifty50 and the financial services sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between Nifty50 and financial services sector. The correlation coefficient between Nifty50 and financial services sector is 0.8. It implies that an increase in the Nifty50 will be accefected by a rise in the stock prices of financial services firms.

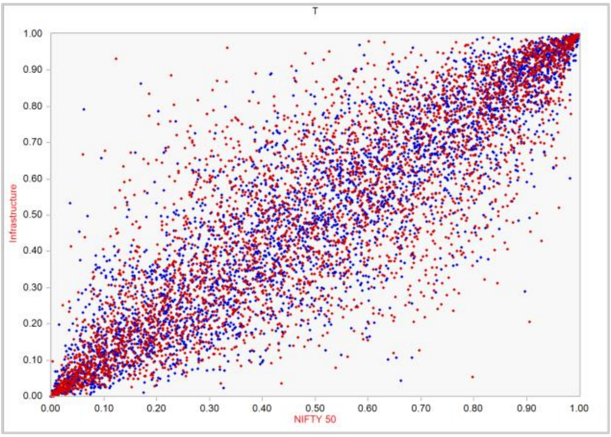
Figure 8.36: T-copula spread (Nifty50 – Commodities index)



Source – Author's Estimation

The graph displays the association between the Nifty50 and the commodities sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between Nifty50 and commodities sector. The correlation coefficient between Nifty50 and commodities sector is 0.8. It implies that an increase in the Nifty50 will be accompanied by a rise in the stock prices of commodities sector.

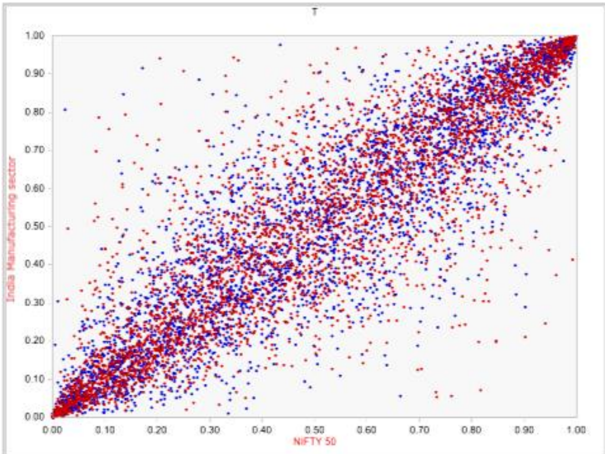
Figure 8.37: T-copula spread (Nifty50 – Infrastructure index)



Source – Author's Estimation

The graph displays the association between the Nifty50 and the infrastructure sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between Nifty50 and infrastructure sector. The correlation coefficient between Nifty50 and infrastructure sector is 0.8. It implies that an increase in the Nifty50 will be accompanied by a rise in the stock prices of infrastructure firms.

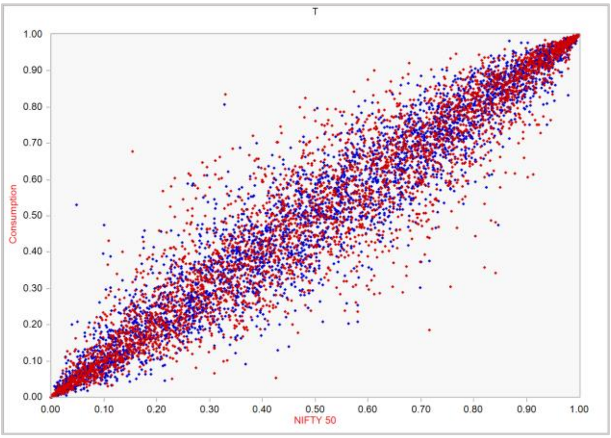
Figure 8.38: T-copula spread (Nifty50 – India Manufacturing index)



The graph displays the association between the Nifty50 and the manufacturing sector. The data points shows a cluster of data around the tail of the distribution which confirms a strong positive association between Nifty50 and manufacturing sector. The correlation coefficient between Nifty50 and manufacturing sector is 0.9. It implies that an increase in the Nifty50 will be accompanied by a rise in the stock prices of manufacturing sector.

Source – Author's Estimation

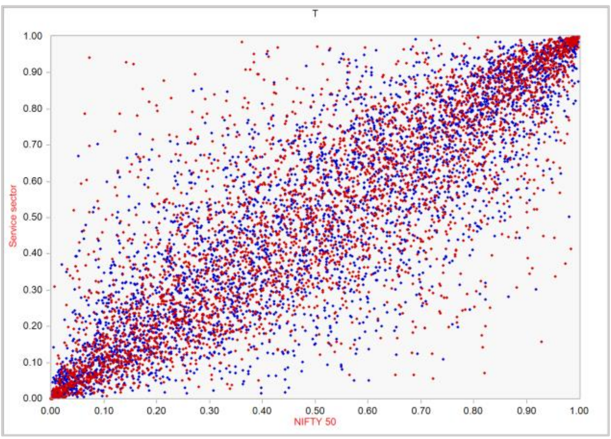
Figure 8.39: T-copula spread (Nifty50 – India Consumption index)



The graph displays the association between the Nifty50 and the consumption sector. The data points shows a cluster of data around the tail of the distribution which confirms a strong positive association between Nifty50 and consumption sector. The correlation coefficient between Nifty50 and consumption sector is 0.8. It implies that an increase in the Nifty50 will be accompanied by a rise in the stock prices of consumption sector.

Source – Author's Estimation

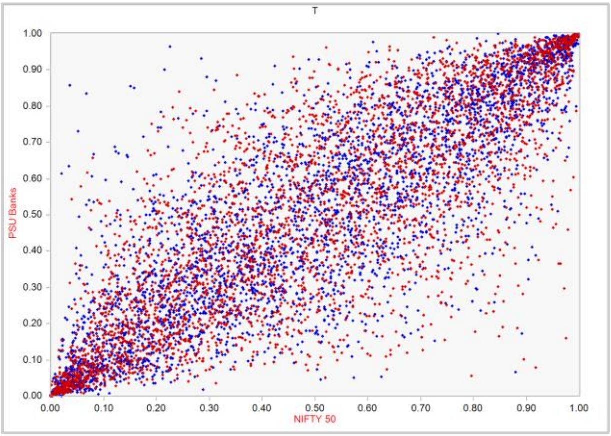
Figure 8.40: T-copula spread (Nifty50 – Services Sector index)



The graph displays the association between the Nifty50 and the services sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between Nifty50 and services sector. The correlation coefficient between Nifty50 and services sector is 0.8. It implies that an increase in the Nifty50 will be accompanied by a rise in the stock prices of services sector firms.

Source – Author's Estimation

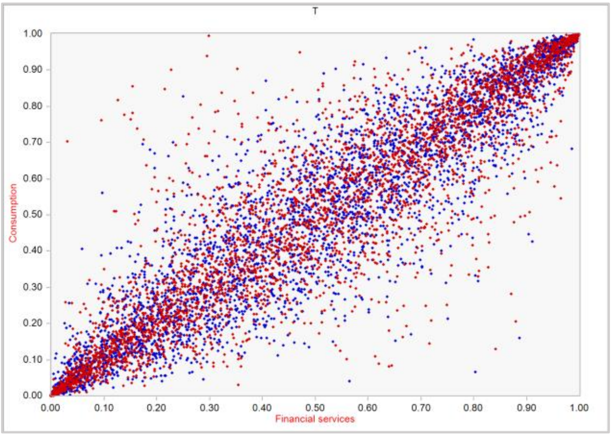
Figure 8.41: T-copula spread (Nifty50 – PSU bank index)



Source – Author's Estimation

The graph displays the association between the Nifty50 and the PSU sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between Nifty50 and PSU sector. The correlation coefficient between Nifty50 and PSU sector is 0.8. It implies that an increase in the Nifty50 will be accompanied by a rise in the stock prices of PSU firms.

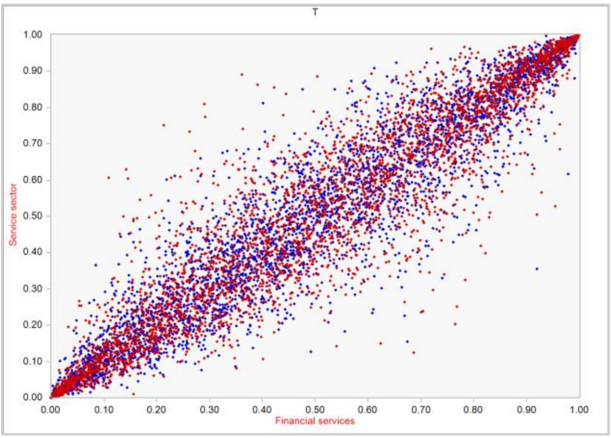
Figure 8.42: T-copula spread (Financial services index – India Consumption index)



Source – Author's Estimation

The graph displays the association between the consumption and the financial services sector. The data points shows a cluster of data around the tail of the distribution which confirms the existence of a favourable relationship between the two. The coefficient of correlation between the sectors is 0.8. It implies that an increase in the consumption companies will be caused by a rise in the stock prices of financial services firms.

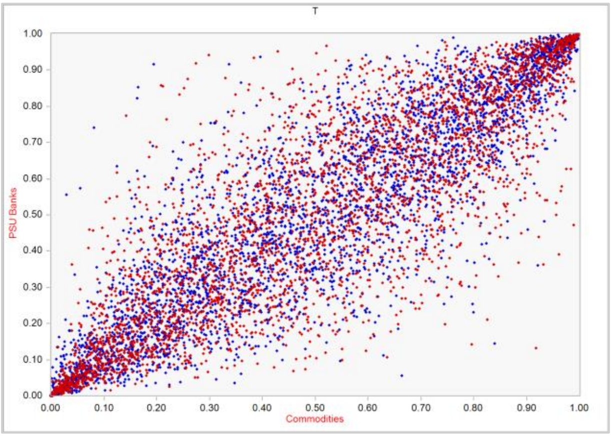
Figure 8.43: T-copula spread (Financial services index – Services sector index)



Source – Author's Estimation

The graph displays the association between the services and the financial services sector. The data points shows a cluster of data around the tail of the distribution which confirms a strong positive association between services and financial services sector. The correlation coefficient between services and financial services sector is 0.8. It implies that an increase in the services companies will be affected by a rise in the prices of financial services firms.

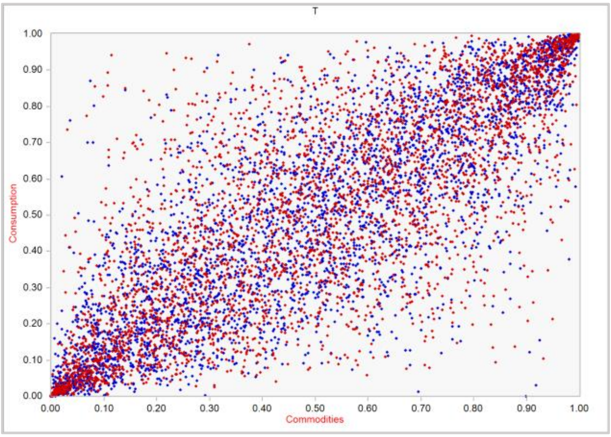
Figure 8.44: T-copula spread (Commodities index – PSU Bank index)



Source – Author’s Estimation

The graph displays the association between the PSU and the commodities sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between PSU and commodities sector. The correlation coefficient between PSU and commodities sector is 0.8. It implies that an increase in the PSU companies will be accompanied by a rise in the stock prices of commodities sector firms.

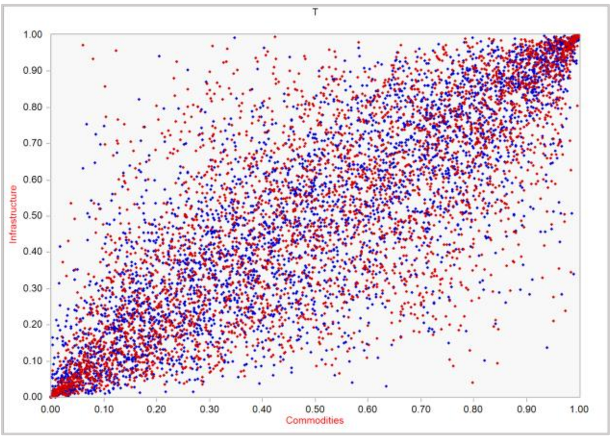
Figure 8.45: T-copula spread (Commodities index – India Consumption index)



Source – Author’s Estimation

The graph displays the association between the commodities and the consumption index. The data points shows a cluster of data around the tail of the distribution which confirms the existence of a favourable relationship between the two areas. The coefficient of correlation between both the indices are 0.8. It implies that an increase in the commodities sector companies will be accompanied by a rise in the stock prices of consumption sector firms.

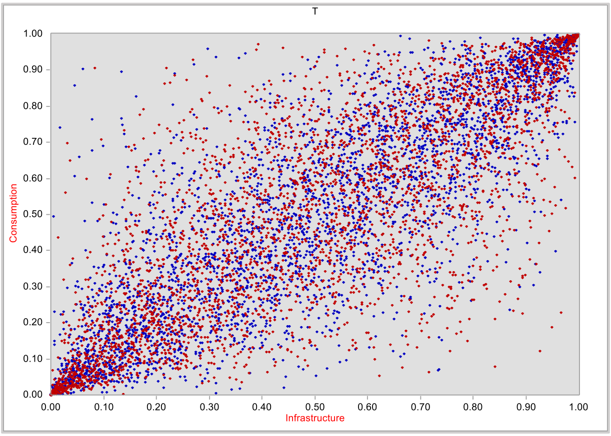
Figure 8.46: T-copula spread (Commodities index – Infrastructure index)



Source – Author’s Estimation

The graph displays the association between the commodities and the infrastructure sector. The data points shows a cluster of data around the tail of the distribution which confirms the existence of a favourable relationship between the two areas. The coefficient of correlation between both the index is 0.8. It implies that an increase in the commodities sector companies will be accompanied by a rise in the stock prices of infrastructure firms.

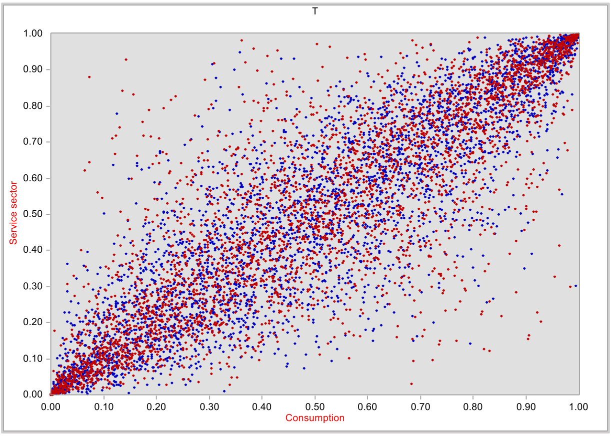
Figure 8.47: T-copula spread (Infrastructure index –India Consumption index)



The graph displays the association between the consumption and the infrastructure sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between consumption and infrastructure sector. The correlation coefficient between the sectors is 0.8. It implies that an increase in the consumption companies will lead to a rise in the stock prices of infrastructure firms.

Source – Author's Estimation

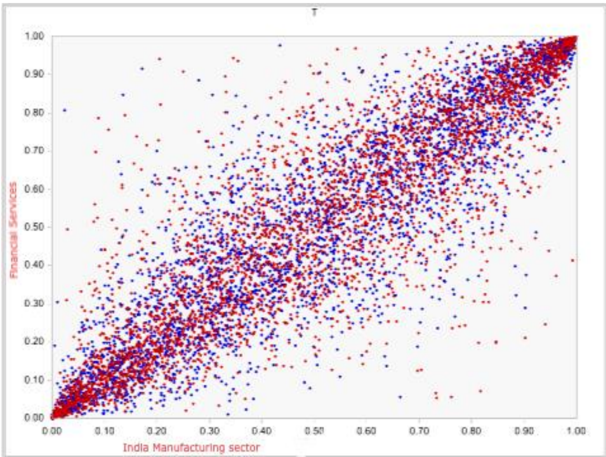
Figure 8.48: T-copula spread (India Consumption index – Services sector index)



The graph represents the association between the consumption and the services sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between consumption and services sector. The correlation coefficient between the sectors is 0.9. It implies that an increase in the consumption sector will be accompanied by a rise in the prices of services sector firms.

Source – Author's Estimation

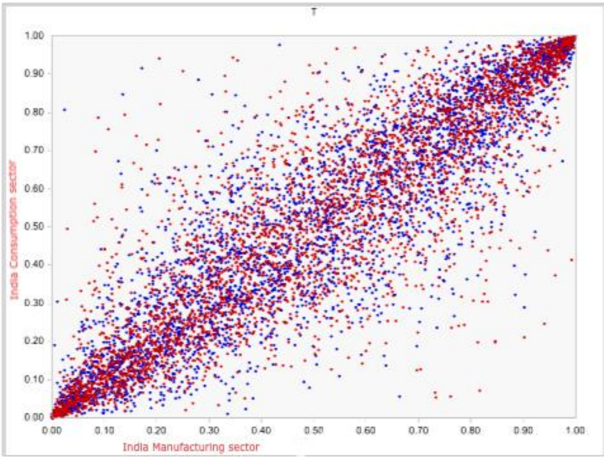
Figure 8.49: T-copula spread (India Manufacturing index – Financial Services index)



The graph displays the association between the India manufacturing index and the financial services. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between the two sector. The correlation coefficient between manufacturing and financial services sector is 0.89. It implies that an increase in the manufacturing sector will be accompanied by a rise in the stock prices of financial services firms.

Source – Author's Estimation

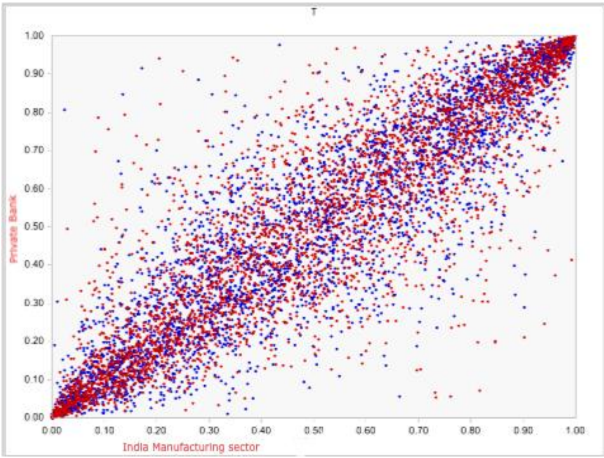
Figure 8.50: T-copula spread (India Manufacturing index – India Consumption index)



The graph displays the association between the India manufacturing index and the Consumption sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between manufacturing and consumption sector. The correlation coefficient between the two is 0.9. It implies that an increase in the manufacturing sector will be accompanied by a rise in the stock prices of consumption index.

Source – Author's Estimation

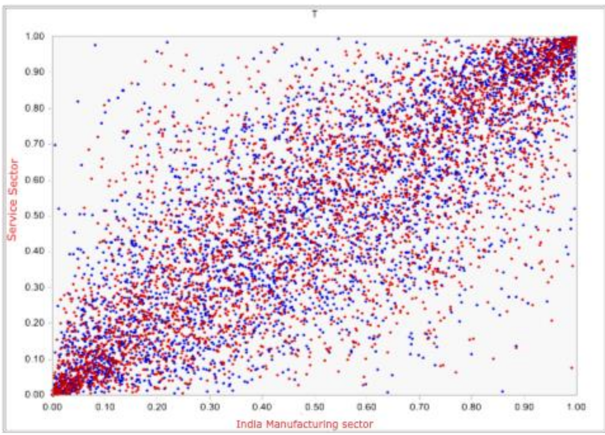
Figure 8.51: T-copula spread (India Manufacturing index – Private bank index)



The graph represents the association between the India manufacturing index and the private bank. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between manufacturing and private bank sector. The correlation coefficient between the two is 0.9. It implies that an increase in the manufacturing sector will be accompanied by a rise in the stock prices of private bank firms.

Source – Author's Estimation

Figure 8.52: T-copula spread (India Manufacturing index – Services Sector index)



The graph shows the association between the India manufacturing index and the services sector. The data points shows a cluster of data around the tail of the distribution which confirms a positive association between manufacturing and services sector. The correlation coefficient between the two is 0.9. It implies that an increase in the manufacturing sector will be accompanied by a rise in the stock prices of services sector.

Source – Author's Estimation

The above graphs represent the T-copula spread for each of the sectors which are highly associated with each other. The tail of the distribution in each of the graph shows a significant cluster of data points of the respective variables. These sectors with higher correlation tend to be more dependent upon the strength of the economy and are considered more ‘cyclical’. Whereas, other sectors having relatively lower associations with the market are considerably independent of business cycles and can be classified as sectors with a defensive nature. The spread between the cyclical and defensive nature sectors has been significant and provides a sense of diversification. In essence, it is optimal for an investor to construct a portfolio that includes a mix of highly associated and low associated industries.

Diversification of this type depends solely on an investors profile be it risk averse, risk loving or risk neutral where they assign their own level of risk. It can be classified into a moderate/ conservative profile, where the investor is either risk averse or risk neutral. Another profile could be of an investor who is risk loving and can be classified as an aggressive profile. The tolerance for risk amongst investors is an ever-evolving process which depends on their risk-taking capacities.

Sectoral allocation thus can assist in the most strategic positioning of funds in the stock market, with a focus on broad-based exposure. It helps the investors to understand what it means to be underweight, overweight or equal weight.

Conclusion –

Sectoral allocation first assessed with the help of causality test throws light on the uni-/bi-directional relationship among the benchmark, sectoral and thematic indices. With the help of this economists and policy makers can predict dynamic interaction with various time series indices data. Finally, copulas have a number of advantages over other econometric techniques, including the capacity to characterize dependency beyond linear correlation and a high degree of flexibility. The study suggests t copula model to be a better fit to the data and the spread diagrams suggest a mixture of highly associated and low associated sectors for portfolio diversification. Thus, sectoral allocation can help with the most strategic positioning of funds in the stock market.