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Green Bond and International Financial Markets: Spillover, Co-movement and Diversification

by

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Dedicated to My Beloved Parents

CERTIFICATE OF APPROVAL

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Abstract

To achieve the results univariate and multivariate GARCH, Copula, VaR, Copula-VaR, and Hedge ratios have been used. Results show a significant persistence statistically significant persistence of volatility in the long run and a time-varying conditional correlation exists between the Global green bonds and international financial markets. Individually green bond seems less risky instrument than the oil, global conventional equity, and global Islamic equity but in pair, it increases the risk profile. Because with time when it becomes mature green bond becomes a very good investment opportunity. For the dependence structure, the highest upper and lower tail dependence has been witnessed by the pair of global green bond and Sukuk. The lowest tail dependence has been witnessed by the global green bond and world conventional bond. Hedge ratios showed an optimal hedge opportunity between the global green bond with the oil market and Sukuk against the market volatility. So, investors can use this for the profit-optimization, and construction of the portfolios.

Keywords: Green Bond, International Financial Markets, GARCH, DCC, VaR, Copula, Copula-VaR, profit-optimization.

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Abbreviations

ARCH	Autoregressive conditional Heteroscedasticity
CB	FTSE World Government Bond Index
CE	S&P Global 1200
CoVaR	Conditional Value at Risk
DCC	Dynamic Conditional Correction
E-GARCH	Exponential GARCH
GARCH	Generalized Autoregressive conditional Heteroscedasticity
GB	S&P Green Bond Index
GFC	Global Financial Crisis
GJR-GARCH	Gloesten Jagannathan Runkle GARCH
IE	Dow Jones Islamic Market world indexe
O	S&P Global Oil Index
S	Dow Jones Sukuk Total Return Index
T-GARCH	Threshold GARCH
VaR	Value at Risk

Chapter 1

Introduction

Green bonds are those debt instruments that are used to finance projects which are environment friendly to mitigate the negative impact of economic activities on the climate. Due to global warming and other adverse change in climate conditions the concern of policymakers to create a green economy by integrating the financial markets and economy through offering environment friendly financial assets has increased.

It is appears that with the help of financial tools green finance can be presented. During the past decade in the domain of sustainable finance green bond is one of the most innovative and prominent innovation. In the global financial markets, green debt is one of the youngest segments that is attracting the the interest of market participants. The green bond is a unique financial instrument which is classified on the basis of the usage of its proceeds by the issuer. The generated proceeds from the issuance of green bond contribute towards adoption and mitigation to the climate change, conservation of the natural resources, prevention of pollution in the environment and for the purpose of control, etc (Broadstock and Cheng, 2019). This topic has been covered by the growing body of literature such as energy finance, climate, and green finance that focus on the tremendous growth of green bonds for more investigation (Zhang, 2018).

The green bond is one of the most emerging financial debt instruments used for fundraising because the global green bond market is emerging as an avenue to implement the low carbon and resilient economy (Banga, 2019). The green bond market is introduced in 2007 and has 51% growth in the volume of a green bond primarily driven in 2019 by European, Asia-Pacific, and North American markets. According to Climate Bonds Initiative (2019) report, the volume of the green bond market in the European market is 45% of global issuance, 25% for the Asia-Pacific, and 23% of the North American markets of global issuance. Based on statistics, in the last four years green bond market experienced tremendous growth and its issuance has been increased every year fivefold from the previous year up to US$ 257 billion annually. By the year 2030, it is estimated that this value will jump to US$ 1 trillion (Fatin, 2019; MacAskill et al., 2020). The most of the issuing authorities of green bonds are private authorities such as the World Bank and European Investment Bank, public, private corporations, and the local and national government. Proceeds from green bonds are used to finance the projects with the criteria of renewable energy, energy efficiency, low-carbon transport, sustainable water, waste, and pollution, accounting in 2015 for 45.8%, 19.6%, 13.4%, 9.3%, and 5.6%, respectively, of issuances (European Commission, 2016; Reboredo and Ugolini, 2020).

It is the well-understood thing that every investor comes into the business world to maximize his/her wealth as it is a primary purpose of business as well. Where Alarming climate change issues opens the market for new financial instruments also spread awareness of climate protection. Over the past few years, investors have become more concerned about the environmental impacts of businesses. Having common features like a conventional bond, green bonds become more likely to encouraging financial instruments for these investors. Besides this several empirical studies showed the effectiveness of green bonds emerge as an effective instrument for the portfolio managers and investors to diversify their portfolios. i.e., (Flammer, 2020; Huynh et al., 2020; Pham, 2016). A common volatility factor affects the market dynamics and restrains the financial markets to absorbs the information swiftly. Such uncertainty or volatility influence the returns of financial assets. The aforementioned green bonds share some similar characters to conventional bonds, also get influenced by the internal volatility patterns as well as by the market patterns. It is important to learn these patterns and macroeconomic variations to have an eye on future expected returns (Bansal et al., 2014).

In the past few years, some studies are conducted on green finance to measure the volatility modeling of green bonds with the purpose to find out the volatility spillover between the green bond market and conventional market. Because volatility modeling of the green bond market with an overall conventional bond market will provide information that how much shock of the global conventional bond market will contribute to the volatility of the green bond market and vice versa. Due to its importance and more significant benefits economically and environmentally it becomes important to understand and examine the market dynamics of green bonds. So, the goal of this research is to provide in-depth insights into green bond markets with global conventional, Islamic, and energy markets. Moreover the results of this study provide information that how much information spillover exists between the green bond market and the overall conventional bond market.

Therefore, this information spillover leads towards cause and effect relationship between financial markets. The cause and effect relationship between the financial markets depicts how quickly and efficiently one market responds to the information spillover. If one financial market responds to the information spillover of the other financial market, then it indicates the presence of co-movement in the data (Zeng et al., 2021). So, co-movement between financial markets that how these financial markets move together, and investors will use these co-movement results to predict future returns based on the past prices to diversify their portfolios and maximize their returns.

For portfolio diversification and hedging securities with negative or zero correlation are added for risk-return tradeoff optimization (Asness et al., 2001). Several financial tools are used by investors for global diversification such as a global conventional bond, stocks, Islamic bonds and stocks, commodities, currencies and precious metals, etc. Due to this reason, a green bond is used for developing a climate-resilient economy as a financial tool by the institutional and individual investors in their portfolios (Reboredo and Ugolini, 2020). For global diversification, now the interest of investors shift towards investment which is environment friendly (Dutta et al., 2020). So, to exploit investment opportunities in global green bonds for maximizing returns and minimizing the risk of portfolios investors must understand the volatility modeling, co-movement dynamics, and their risk and return behavior in the portfolios with multiple asset classes. Therefore, this study provide in-depth information after examing the volatility dynamics, market risk of the global green bond market co-movement dynamics, and their impact on portfolio diversification.

1.1 Theoretical Background

Theoretical support for this study has been derived from a major finance theory i.e. Efficient market theory proposed by Fama 1960 based on the assumption that capital markets are efficient and securities reflect all available information. According to the efficient market theory, prices of securities adjust on the arrival of new information. Based on information adjustment there are three types of market efficiency which are the weak form of efficiency, the semi-strong form of efficiency, and the strong form of efficiency. In the weak form of efficiency, prices reflect all historical available information. So, securities prices reflect the effect of all historical information. In the semi-strong form of efficiency major concern related to information, adjustment is also based on other information which is publicly available information such as stock split and dividend announcement, etc.

In the last strong form of efficiency which is the third and last form of efficiency based on the efficient market model and in this form of efficiency security prices reflect the information of historical data, publicly available information, and insider information (Fama, 1970). So, according to this theory prices of information adjust on the arrival of new information and information spillover from one market to another market which lead towards the adjustment of prices based on the arrival of new information. So, the spillover of information between the green bond market and other financial markets exits which lead towards adjustment of prices according to new information.

1.2 Research Gap

Limited studies have been conducted to find out the volatility modeling of the green bond that creates a gap in the body of knowledge. Due to the importance of climate resilient economy it is the need of finance literature to explore the volatility dynamics of green bond because green bond is one of the most important and prominent innovation in the area of sustainable finance. Pham (2016) conducts the first study in order to understand the risk and return behavior of green bond market volatility of the green bond market, and in this study volatility of green bond has been analyzed with the overall conventional bond market. There is no other study on the volatility modeming of the green bond. Reboredo (2018) examines the dependence structure, diversification, and price spillover effects between the green bond and other related financial markets which are corporate and treasury-fixed income markets and stock and energy commodity markets. This is the first study that finds out the co-movement dynamics of green bond with other financial markets.

This study concludes that co-movement dynamics of green bond with corporate and treasury-fixed income markets, stocks, and energy commodity market creates a gap in the literature. To find out the volatility modeling and co-movement dynamics of green bond with other financial markets such as energy, Islamic financial instruments, conventional equity, and bond market. Therefore, to fill the gap of finance literature the purpose of this research is to find out the volatility modeling and dependence structure of Global Green Bond with World Islamic Equity, Global Sukuk market, World Equity, Global Conventional Bond market, and with the Energy market. Further, this study investigates how green bonds integrate with major asset classes.

1.3 Problem Statement

Green bond market is not independent from other financial markets in terms of volatility. Therefore, green bond has been used by the investor to earn positive returns on their investment along with the development of a climate-resilient economy (Huynh et al., 2020). However, the response of the bond, stock, energy, and green bond market is different for the arrival of new information such as green and black bond market is sensitive to change in multiple factors related to macro economical consisting like change in the returns of financial markets and volatility, uncertainty of economic policy and economic activity on daily basis (Broadstock and Cheng, 2019). This different response on the arrival of new information leads to study the volatility modelings, risk estimation, co-movement, and portfolio diversification dynamics between the global green bond market and other financial markets.

1.4 Research Questions

1. What are the volatility dynamics of green bonds?
2. What is the market risk of investing in green bonds?
3. Is the risk of green bonds lower than other assets of the same asset class?
4. Does dependence exist between the green bonds market and global financial markets?
5. How does this dependence influence the risk of a portfolio comprising of green bonds and other asset classes?

1.5 Research Objectives

1. To provide insight about the volatility dynamics of green bonds
2. To estimate the market risk of investing in green bonds.
3. To explore the dependence structure between green bonds and international financial markets.
4. To explore the possibility of risk diversification through green bonds.

1.6 Significance of the Study

Green bond market are introduced in 2007 but shows tremendous growth in the overall bond market. Green bond market has been grown from $0.8b in 2007 to $257.7bn in 2019 (Climate Bonds Initiative, 2019). In the literature of green bonds, there is one study on volatility and one study on co-movement dynamics which tries to provide the volatility dynamics of green market and co-movement dynamics of green bond with related financial market of stock and energy (Broadstock and Cheng, 2019). As the green bond market is not independent of other financial markets so this study fill, the gap and contribute to the body of knowledge by providing the volatility modeling of green bond market and co-movement dynamics between the green bond and other financial markets which are conventional, Islamic and energy.

Being an emerging concern over environmental protection green bonds catches the eyes of various institutions and investors. Explored volatility and joint dependence dynamics of green bonds help to understand the risk nature of green bonds and their effect on the financial environment (Reboredo, 2018). This fulfills the wealth maximization objective along with the environmental concern of individuals. Therefore, the outcomes of the study enhance the investors' knowledge about how green bonds integrates with other major asset classes. Not only this, hedging properties of green bonds along with aforementioned financial instruments will motivate and assist investors for their portfolio diversification and restructuring with aiming of returns maximization on the given required risk of a portfolio because green bond index is the most effective hedge for carbon futures and perform outstandingly to hedge the market volatility even in the crisis period (Jin et al., 2020). The empirical work on volatility dynamics helps investors to understand the connected risk behavior and volatility clustering of green bonds with other financial markets. Similarly to understand the phenomenon of how the price of green bonds affected due to price oscillations in other financial markets (Reboredo and Ugolini, 2020). Apart from investment and investors, this study opens a new direction for policymakers to devising strategies to develop the climate-resilient economy with mutual benefits.

1.7 Organization of Study

The study is divided into five chapters. The first chapter introduce, the topic along with defining it and provide information regarding Introduction, Theoretical Background, Research Gap, Problem Statement, Research Questions, Research Objectives, and Significance of Research. The second chapter of this study consist, of a literature review of all available empirical studies related to the topic of research to develop a testable statement. The third chapter of this study consist, of information on variables, data, the time frame of the study, and econometric models which is employed to find the results. Econometric models that used in this study are GARCH modeling, DCC GARCH, VaR, Copula function, Copula-VaR and hedge ratios. Chapter four of this study discuss, the results of econometric models along with their reporting and the last chapter five of this study provide information on the conclusion of results and policy implication.

Chapter 2

Literature Review

Among the financial markets, the importance of equity and bond is inevitable. So, for this reason, the dynamics of these markets related volatility transmission and dependence structure and co-movements with other financial markets and between the bond and equity financial markets has been one of the most important dimensions for the financial researcher and market participants. This chapter is organized to present a few studies in the background of volatility dynamics, market risk, comovement, and portfolio diversification. Limited studies have been conducted on green bonds and in the domain of volatility modeling and co-movement there is not a single study which examines the volatility modeling of green bond with Islamic, conventional and commodity financial markets.

So, this study tries to present a glimpse of the studies that are conducted in the background of volatility spillover and co-movement among Islamic, conventional, and oil markets.

2.1 Volatility Dynamics

In literature, we find a growing focus emphasis on the conventional and Islamic equity linkage. Nazlioglu et al. (2015) studied the volatility transmission between the Islamic and conventional equity markets based on fact that Islamic equity market reached the market capitalization of 1.6 trillion dollars in 2013 and a fast-growing investment in this domain. Study explored the pre and post GFC 2008 volatility spill over dynamic between the European, Asian and US conventional and Islamic equity markets along with the US Monetary policy, oil prices, VIX and US economics uncertainty index by using GARCH. Empirical results of study showed a transformation of risk between seemingly different markets. Volatility structure found short-run in first phase and long run in second phase and similar transmission pattern of volatility has been observed. Further study found Islamic equity market was more affected from risk factor (VIX) then the oil prices and US economic policy uncertainty index.

Sanin et al. (2015) criticized the performance of GARCH based model ARMAX-GARCH model due to existence of outlier in data. The study used stochastic jump process, to improve the performance they used time varying jumps that can handle the increased volatility arises due to increase in volume of transactions and transmission of shocks. Pham (2016) was the first who studied the volatility modeling of green bond market in response to the conventional bond market. He tried to relate the three key atrands of literature starting from the modeling of volatility followed by the key work of Bollerslev (1986) and Engle (2002) for univariate GARCH and Multivariate GARCH analysis. Secondly, the performance of fixed income financial instruments and third related to the literature of environment friendly financial instruments. Empirical investigation on S&P green bond index, S&P green project bond, and S&P US aggregate bond showed that both univariate and multivariate GARCH showed a volatility clustering in each instrument. As well as DCC GARCH showed a time varying relation of volatility between the conventional and green bond exists. Study suggested that optimal risk minimizing can be achieved by constructing the portfolio of both green and conventional bonds.

Jebran et al. (2017) also investigated the co movement and volatility transformation between the Islamic and conventional equity markets. Study applied various form of cointegration tests as well as applied the GARCH and EGARCH model to investigate the volatility transformation. Study found a bidirectional volatility transformation. Further study mentioned that with Islamic equity domestic investor had fewer opportunities to diversify the portfolio. Naifar (2018) also tried to explore the behaviour of volatility in sukuk bond indices and how volatility impact the prices of sukuk bonds. Study applied DCC GARCH model to explore the volatility and time varying correlation between the sukuk and commodity prices. Results showed a negative time varying relationship between sukuk of GCC and commodity prices. The study also mentioned that the understanding of volatility dynamics and dynamic correlation was much needed for optimum portfolio allocation. Katsiampa (2019) tried to capture the volatility dynamics and how volatility of past shocks affects the current conditional variance and covariance. Results showed that past volatility effect the current variance. Empirical results suggested that the events that affect the volatility structure of financial instruments had significant impact on investors' portfolios.

Akkoc and Civcir (2019) studied the volatility spillover and dynamic linkages between the Turkish equity market, gold, and oil prices. According to them, increase in commodity prices had impact on the performance of equity market of emerging markets. To explore the dynamic linkage, they applied SVAR DCC GARCH model using daily international prices of gold, oil and Turkish equity index (BIST). Results showed a time varying relation and conditional variance spillover from gold and oil to Turkish equity market. Results suggested gold cannot be used as save heaven in portfolio with Turkish equity as it has greater impact on volatility spillover than the oil prices.

Hou et al. (2019) also tried to analyse the volatility spillover of Chinese fuel oil and stock market futures by applying the time variant DCC GARCH model. The study observed that different pattern exits in volatility spillover due to some structural breaks and this will be more helpful for risk management.

Literature support the argument of asymmetric volatility patterns in financial instruments. To check the existence of asymmetric volatility in bond green bonds Park et al. (2020) examined the green bond market properties. Study used S&P 500 equity market index and S&P green bond index to explore the asymmetric volatility and relationship of green bond and equity market. Results confirmed that the volatility exists in green bonds and react like conventional equity market but in less intensity. Both markets have some conditional variance spillover effect with greater impact of positive news on returns.

2.2 Market Risk

Cabedo and Moya (2003) used Value at Risk (VaR) to quantify the risk of oil prices and study mentioned VaR offered an estimation of the maximum change in oil prices associated with the level of probability that can be used to build risk management strategies. Three VaR estimation methods were evaluated: the traditional approach to historical simulation, the historical simulation with ARMA predictions (HSAF) approach, implemented in their paper, and the method to variance-covariance based on predictions of autoregressive conditional heteroscedasticity model. The results showed that the HSAF technique provides a complex VaR quantification that fits well with the continuous fluctuations in oil prices and provides an effective risk assessment. Because of shifts in market conditions, Angelovska (2013) forecasts market risk and uncertainty regarding potential earnings. The basic measure that financial analysts use to calculate market risk has become Value at Risk. The problem is that different ways of estimating volatility can lead to very different VaR estimates for estimating risk.

Several studies found a time varying dependency between the two different financial instruments i.e.,Lee and Long (2009) found the time varying dependency in forex of three different economies, Wu and Lin (2014) studied the stock market with conventional bonds, Jammazi et al. (2015) studied the time varying dependency first time between the stock and long term government bonds. All of these studies used the unique conditional time varying based GARCH model with copula to enhance the power of model. This approach helped to cover the time variance and linkage between the two financial instruments. Another study by Ghorbel and Trabelsi (2014) studied the Value at Risk VaR and the statistical modeling of the dependency structure between the three energy product markets (WTI crude oil, natural gas and heating oil) using the copula principle and propose a method for estimating the Value at Risk (VaR) of the energy portfolio based on the combination of time series extreme value theory models prior to copula fitting. Other studies on risk measuring technique "VaR" like Chen (2014) argued that VaR is an important tool of financial risk management but has the short fall and assume that risk is random in nature and can't be predicted. During the start of the Greek debt crisis, Reboredo and Ugolini (2015) examined systemic risk in European sovereign debt markets, taking the conditional value-at-risk (CoVaR) as a systemic measure of risk, defined and measured using copulas. They noticed that the sovereign debt markets were all tied up before the debt crisis, and the structural risk for all countries was identical. However, with the advent of the Greek crisis, the debt markets decoupled and the systemic risk to the European debt market as a whole for the countries in crisis (except Spain) decreased, while that of non-crisis countries increased to a small degree.

Charfeddine and Benlagha (2016) investigated the time varying dependency between the twelve commodities and equity markets i.e., S&P 500, CAC40, DAX30 and FTSE 100 indices for the time span of 23 years. Study evaluated the seven copulas and results showed Student's-t copula as a significant model to measure the tail dependency. Study found the heterogeneity as a dependence between the equity markets and commodities and must be a fundamental for analysis. Investor can use this heterogeneity element while compiling the portfolio or reallocation of their portfolio.

By using a Copula-GARCH method and generating empirical distribution to incorporate the liquidity risk and market risk of corporate bonds, Lin et al. (2019) set an index for calculating the liquidity of corporate bonds. While applying the VaR during the designing of wealth maximization strategy or trying to reduce the future expected losses risk minimizer(investor) gets the same least upper bond he/she can get without applying the VaR (Armstrong and Brigo, 2019).

Huynh et al. (2020) studied the portfolio diversification and mentioned that "portfolio diversification and safe heaven assets were important element for investigation of strategies". Study used the daily data of NASDAQ AI, Oil bit coin, green bond, MSCI world index, MSCI USA index, GOLD and VIX. To test the tail dependency copulas and Generalized Forest decomposition position for volatility interconnectedness had been used. Study further applied the GARCH(1,1) model to check the volatility transmission after finding the tail dependence.

Results showed that the presence of these assets in portfolio creates the high dependency it means at time of financial distress as it had a significant probability of losses. Further in short run transmission of volatility found to be greater than the long run. Which mean shock in short run created more volatility whereas, holding of this portfolio in long run volatility transmission decreased. Study suggested to use buy and hold strategy at given level of risk associated with the portfolio because of in long run volatility transmission reduces.

Liu et al. (2021) highlighted the dependence structure of green bonds and clean energy along with the risk spillover. The study applied the different variant of copula approach from both time variant and time invariant. Then applied the CoVaR (conditional value at risk) and Delta CoVaR to estimate the risk spillover of downside and upside for both green bonds and clean energy markets. Study found that a positive time varying and tail dependence exists in sample markets. Further in extremes price spillovers was also present between the green bond and clean energy with asymmetric risk.

2.3 Co Movement

Sriboonchitta et al. (2014) studied the co movement of equity returns and tail dependency of three important equity markets of ASEAN. For the estimation of conditional variance and margins distribution with GJR GARCH. To check the co movement and conditional dependency, Vine copula along with combination of Monte Carlo simulation to estimate the VaR. Study also explored the structure of vines and found D-vines performed better than the C-vines and more appropriate to used. Results also showed leverage effect existence in all three equity markets. Also, they mentioned vine copula based GJR GARCH effectively captured the VaR. Further study mentioned VaR and ES also confirmed the risk diversification and its significance.

Lu et al. (2014) studied the marginal distribution function using GARCH and joint distribution using copula function. Afterward estimated results were used to compute the value at risk for the portfolio of oil and other energy market futures. Study applied different constant and time varying copulas and found constant student t distribution copula outperformed other copulas that capture the dependence structure more effectively. Results were compared by estimated VaR at 95% and 99% by using monte Carlo simulations. Further study mentioned use of these multivariate copulas will help to estimate the multi assets portfolios. Similarly another study by Krzemienowski and Szymczyk (2016) presented a copula based conditional VaR. and tried to optimize the portfolio as it uses the risk minimizing scaler for multivariate random variables.

Al Rahahleh and Bhatti (2017) tried to revaluate the former studies of Bhatti and Nguyen (2012) on stochastic copula and Wei (2013) study on DCC performance over the copula. Study tried to capture the lagged variance linkage, spillover effect and the co movement between the returns both backward and forward. Study found a bidirectional co movement between the Australian equity market, Hong Kong and japan equity market whereas, a univariate co movement from Australia to Taiwan was found. Similarly, a higher lagged variance spillover was found between the US, UK and Australia but UK equity market had higher lagged variance spillover effect on Australian equity market than the US.

Reboredo (2018) studied the co movement of conventional financial markets and green bonds. To define the dependence structure, marginal distribution function, for univariate margins TGACH was used with the assumption of conditional volatility. For dependence structure of copula function different variant of copula i.e., Gaussian, Student-t, and Gumble were used.

Results showed that persistence of volatility was observed whereas no ARCH and leverage effect were founded in green bond and energy commodity market. Study found that dependency of green bonds and other financial instruments. Empirical results showed that price spill over from conventional financial instrument to green bonds. But weekly co movement of green bond showed the time varying and weak systematic tail dependence.

Hassan et al. (2018) investigated co movement of sukuk and conventional bonds with respect to long run and dynamic correlation. For this purpose, they applied the Johansen cointegration test and DCC GARCH model under student t distribution assumption. Results found an increased co movement exist between the sukuk international bonds. Further results showed a sukuk and conventional bonds were less responsive to conditional variance and higher persistent than the investment grade bonds. Further they mentioned time varying correlation and conditional variance increase with the shocks in markets. Overall results of study showed sukuk as a sophisticated candidate for portfolio with valuable parallel properties of conventional bonds.

Karmakar and Paul (2019) forecasted the value at risk and conditional value at risk for three different pairs of different equity markets using intraday data. ARMA-GARCH model was used to estimate the margins individually for each stock market. For pairwise dependence structure different copula (Student t copula, Clayton copula, Gumbel copula and BB1 copula based on dependence structure were used. Forecasting accuracy of CGARCH-EVT Copula outperformed the other models. Based on simulation they computed an optimal portfolio with subject to conditional VaR and estimate the conditional VaR frontier. Hung et al. (2020) highlighted the drawback of VaR while presence of liquidity which weakens the risk measuring power. The study used GARCH-t and GJRGarch model to measure the margins while taking liquidity into account. Results of study showed multivariate GARCH outperformed the univariate GARCH in estimating the Value at risk and managing the portfolio.

2.4 Portfolio Diversification

As worlds become more integrated investors trying to diverse their portfolios as well. Roots of international diversifications were connected back in 1960s and 1970s when investors started diversification of international investments in their portfolios. Preliminary US investors gain a lot with such diversifications (Gilmore and McManus, 2002). Another study by Phylaktis and Ravazzolo (2005) also illustrated the linkages of capital markets in developing economies through the implications for diversification of foreign portfolios and international diversification.

Liu (2016) explored the gains in corporate bond market portfolio diversification, and according to study it was an ignored area of financial portfolio diversification. Analysis of study showed that resulted portfolio decreased the lagged variance and enhanced the risk adjustment of portfolio for the investor sitting in US. Further study highlighted that despite of GFC 2008 bond market produced quite sufficient returns and performed better than the equity market.

Antonakakis et al. (2018) highlighted the Hedging ratio and optimal wight strategy for portfolio diversification along with study explored the co movement and lagged variance spillover between the oil and stock prices. Results of hedging and optimal weight strategy showed optimal weight strategy was more effective because of unpredictable hedge ratio. Whereas optimal weight strategy catered this phenomenon more effectively and offer low risk which helped in optimal international risk diversification.

Guesmi et al. (2019) studied hedging strategies based on the commodities prices, emerging equity markets, and crypto currencies for optimal portfolio with decreased portfolio risk. Study applied multivariate GARCH models and suggested VARMA (1,1) DCC-GJR-GARCH model as best fitted model for combine dynamics and volatility confirmation. On the other hand, study highlighted the use of crypto currency as a short position for hedging against the risk profile of portfolio. In final remarks, study suggested use of commodities prices, emerging equity markets, and crypto currencies produced a diverse portfolio which reduced the overall portfolio risk as compared to the portfolio of just commodities and equities.

Akhtaruzzaman et al. (2020) tried to find the optimal portfolio diversification with bond, global industry portfolio, and bitcoins using the VARMA DCC-GARCH model. Study found a lower time varying relationship between the selected financial instruments. Further investment in Bitcoin as hedge increased the risk for other instruments. In lieu of global business portfolios and Bitcoin, the findings were robust with the use of US industry portfolios and a cryptocurrency index. With respect to risk assessment and portfolio research, their findings helped investors to make better decisions.

Jin et al. (2020) studied the relationship between the carbon market with green bond, VIX, Commodity index, and energy index. They applied different hedging ratio i.e., DCC-APGARCH, DCC-TGARCH and DCC-GJR GARCH with comparison of OLS based content hedge ratio. Results showed that Dynamic hedging ratios performed better than the OLS during volatile period and these methods were able to capture the volatility spillover as well as the dynamic correlation between these markets. Further empirical results depicted that green bonds produced more sophisticated results from hedging with carbon market returns then the other three markets and the mentioned green bond as the best hedging option with carbon futures even in disaster.

Elsayed et al. (2020) presented a study on portfolio diversification and hedging strategies using clean energy, oil prices, conventional energy stock indices, stock prices of global financial markets, World Commodity Price Index, IT Industry Price Index, US Treasury Bond 10, VIX index, and US Economic Policy Uncertainty Index. The study tried to capture the lagged variance structure and spillover of volatility shocks. For portfolio diversification hedging ratio and optimal weights methods was used by the study. Study produced several empirical outcomes but as for hedging concern, authors observed an unpredictable pattern of hedge ratio and found a maximum hedge ratio value during GFC 2008. Saver studied argued the volatility dynamics and spillover effect of green bonds and with other financial instruments.

Saeed et al. (2020) argued the lack of evidence about the hedging capabilities of green bonds. However, clean energy and black/dirty energy assets has a time varying relationship. The Study applied DCC-GARCH model to find dynamic conditional correlation, then applied hedge ratio. Results suggested that one should apply dynamic hedging ratio for portfolio diversification. Study also mentioned clean energy instrument performed better then green bonds in portfolio optimization.Regression results showed a negative impact of implied lagged variance of equities and crude oil on the returns of hedge portfolio.

2.5 Hypothesis of the Study

H1: Spill over exist between the green bond markets and international financial markets.

H2: The risk of green bond market is lower than international financial market.

H3: The dependence structure between green bond and international financial markets optimizes risk.

Chapter 3

Data Description and Methodology

This chapter discusses the data description and empirical methodology to achieve the objective of study. This chapter is divided into two main sections. The first section of the chapter deals with description of data and sample period. The second section of chapter deals with econometric models which are used for the estimation of results which are GARCH, T-GARCH, E-GARCH, DCC-GARCH, VaR, Copula, Copula-VaR, and Hedge ratio.

3.1 Data Description

The objective of the study is to find out the volatility dynamics, spillover, co-movement, and risk diversification between green bond and international financial markets. In this study international financial markets are represented by equity, bonds, and commodity. In the equity S&P Global 1200 (Gross Total Return) represent the global conventional equity and Dow Jones Sukuk Total Return Index (ex-Reinvestment) represents the world Islamic equity. FTSE World Government Bond Index (WGBI in USD) is used to capture the world conventional bond market and Dow Jones Sukuk Total Return Index (ex-Reinvestment) represents the world Islamic bond market (Sukuk).

Table 3.1: Indices Details

SN	Indices	Time Period
1	S&P Global 1200 (Gross Total Return)	July 2014 to May 2020
2	Dow Jones Islamic Market World Index	July 2014 to May 2020
3	FTSE World Government Bond Index (WGBI in USD)	December 2017 to October 2019
4	Dow Jones Sukuk Total Return Index (ex-Reinvestment)	July 2014 to May 2020
5	S&P Green Bond Index	July 2014 to May 2020
6	S&P Global Oil Index	July 2014 to May 2020

In order to capture the volatility dynamics, spillover, and co movement dynamics of green bond S&P Green Bond Index is selected. To capture the dynamics of the oil market S&P Global Oil Index is used. Data of all indices are in US dollar and extracted from the data source of S&P Dow Jones Indices and Thomson Reuters.

As, we are concerned with exploring the volatility, co-movement dynamics, and risk diversification through green bond so data is collected for all the indices from the launching date of S&P Green Bond Index and on the basis of its availability. Name and time periods of all indices are represented in Table 3.1.

Data time period of all indices is from July 2014 to May 2020 except the index of FTSE World Government Bond Index (WGBI in USD) which is from December 2017 to October 2019. And, the data time period of FTSE World Government Bond Index (WGBI in USD) is matched with S&P Green Bond Index by making it comparable. Daily prices of green bond and international financial markets are converted into returns by the given formula.

$$R_t = ln(P_t/P_{(t-1)}) \tag{3.1}$$

Whereas, in the following formula:

Ln represents the natural log, R_t represents the calculated returns of the daily prices of the selected indices of green bond and international financial markets, P_t represents the price of selected index at the time t, P_{t-1} represents the price of selected index at first lagged.

3.2 Econometric Models

3.2.1 GARCH modeling

The volatility dynamics of financial time series data is measured by the GARCH models. GARCH family has multiple stochastic modeling models based on linear and non-linear assumptions to capture the different factors which increase the volatility. In this study, we are using GARCH, T-GARCH, and E-GARCH.

3.2.1.1 GARCH Model

To measure the conditional volatility in the returns of financial time series, GARCH is proposed by Engle (1982) and Bollerslev (1986) to quantify the volatility. GARCH model is most effectively implemented when the variance of the current financial time series is not independent from the volatility of lagged time and variance of the past period. Because in GARCH model strength of the shocks in the short term is measured by the ARCH term and persistence of volatility in long run is measured by adding the coefficients of ARCH and GARCH.

$$O_t = \omega_\circ + \omega_1 O_{t-1} + \varepsilon_t \tag{3.2}$$

$$\vartheta_{i^2} = \lambda_\circ + \lambda_1 \varepsilon_{t-1}^2 + \lambda_2 \vartheta_{t-1}^2 \qquad whereas,\ \lambda_\circ > 0, \lambda_1 > 0, \lambda_2 \geq 0 \tag{3.3}$$

In the above mean equation O_t denotes the return of financial asset at time t, and $_{t-1}$ is the lagged return and ε_t the uncaptured portion of the error term. In the variance equation, ε_{t-1}^2 describes the ARCH effect and ϑ_{t-1}^2 represent the GARCH term. The value of λ_1 and λ_2 relates with changes in ARCH and GARCH term.

3.2.1.2 T-GARCH

To capture the effect of asymmetric behavior of financial time series, Zakoian (1994) introduced T-GARCH due to failure of ARCH and GARCH for measuring the asymmetric behavior. Because volatility is not constant and additionally volatility of future has asymmetrical relation with the past innovation. Moreover, bad news of the past creates more asymmetric and impacts the volatility as compared to the positive news. So, asymmetric GARCH model is used to capture the impact of asymmetric stochastic process for improving the forecasting of future's return which is named as GJR-GARCH given below.

$$O_t = \omega_\circ + \omega_1 O_{t-1} + \varepsilon_t \tag{3.4}$$

$$\vartheta_i^2 = \lambda_\circ + \lambda_1 \varepsilon_{t-1}^2 + \lambda_2 \varphi \varepsilon_{t-1}^2 + \lambda_3 \vartheta_{t-1}^2 \tag{3.5}$$

3.2.1.3 E-GARCH

E-GARCH model is proposed in order to overcome the limitation of previously GARCH based model to capture the dynamics of lagged variance. Nelson (1991) proposed the advanced GARCH model to capture asymmetric behavior and its impacts on volatility. E-GARCH is used to predict the asymmetric volatility dynamic because it is based on the assumption of exponential growth.

$$O_t = \omega_\circ + \omega_1 O_{t-1} + \varepsilon_t \tag{3.6}$$

$$\ln|\vartheta_i^2| = \lambda_\circ + \lambda_1 \left| \frac{\varepsilon_{t-1}}{\vartheta_{t-1}} \right| + \lambda_2 \frac{\varepsilon_{t-1}}{\varphi_{t-1}} \lambda_3 \vartheta_{t-1}^2 \tag{3.7}$$

Whereas,

In the above mean equation O_t denotes the return of financial asset at time t, and O_{t-1} is the lagged return and ε_t the uncaptured portion of the error term. In the above variance equation $\lambda_1 \left| \frac{\varepsilon_{t-1}}{\vartheta_{t-1}} \right|$ is the size effect measures that how much volatility is created by the past shock. Moreover, according to the size effect, big shock will create more volatility as compare to small shock. $\lambda_2 \frac{\varepsilon_{t-1}}{\varphi_{t-1}}$ represent the sign effect to provide information that negative error term creates more volatility and $\lambda_3 \vartheta_{t-1}^2$ is the GARCH term used to measure the persistence of volatility.

3.2.1.4 DCC GARCH

Multivariate GARCH model is used to measure the dynamic conditional correlation because in this model past returns are used to predict future volatility. To overcome the computational limitations, this study employs an econometric model which is dynamic conditional correlation (DCC). DCC-GARCH is an extended form of constant correlation estimator (CCC). DCC outperforms the constant correlation estimation because it includes time-varying effect in calculating the correlation matrix.

In the following equations multivariate DCC econometric model as followed by Antonakakis et al. (2018) is shown:

$$O_t = \omega_t + p_t \; whereas \, p_t|\vartheta_{t-1} \sim N(0, C_t) \tag{3.8}$$

$$p_t = C_t^{\frac{1}{2}}\omega_t, \;\; where \;\; \omega_t \sim N(0,1) \tag{3.9}$$

$$C_t = D_t O_t D_t \tag{3.10}$$

where $_t$ = (O_{it},.... ., O_{Nt}) is a $N \times 1$ vector of volatilities (specifically, the global green bond, global conventional equity ,world Islamic equity, world government conventional bond, Sukuk and oil volatilities, thus $N = 6$; $\omega_t = (\omega_{it}, \ldots ..\omega_{Nt})'$ is a denotes the conditional 6×1 mean vector of ω_t, conditional covariance matrix is denoted by C_t, diagonal matrix square root of the conditional variances is represented by D_t = diag $(C_t^{\frac{1}{2}}, \ldots ..C_{NN,t}^{-\frac{1}{2}})$ whereas the univariate GARCH-type model is defined by the $C_(ii, t)$ and in the last $_t$ is the $t \times (\frac{N(N-1)}{2} A)$ matrix consisting of the time varying correlation.

$$O_t = diag(q_{ii,t}^{-\frac{1}{2}}, \ldots ..\, q_{NN,t}^{-\frac{1}{2}})Q_t diag(q_{ii,t}^{-\frac{1}{2}}, \ldots ..q_{NN,t}^{-\frac{1}{2}})'' \tag{3.11}$$

However, symmetric positive definite matrix is represented as Q_t =($q_{ij,t}$) is an $N \times N$ and defined as follows.

$$Q_t = (1 - \alpha - \beta)Q + \alpha\omega_{t-1}{\omega'}_{t-1} + \beta Q_{t-1} \tag{3.12}$$

In the above equation $\omega_t = (\omega_{1t}, \omega_{2t}, \ldots..\omega_{Nt})' N \times 1$ vector of the standardized residuals and Q represent the unconditional variance matrix of ω_t. Non negative scalar parameters are meeting the condition of $\alpha + \beta < 1$.

3.2.2 Value at Risk (VaR)

To measure market risk VaR is significantly used because it indicates how much a loss an investor can bear on at a given confidence interval. Among its numerous benefits, the major advantages of VaR methodology are its universality, application in different areas, and implementation. So, returns of financial returns area represented by $m_1, m_2, m_3, \ldots..m_n$ and all of these returns are independent random variables which are identically distributed. F(m) is used to demonstrate the cumulative distribution function, $F(m) = P_m(m < m|\varphi_{(t-1)})$ conditionally on the information set φ_{t-1} which is available at lagged time t-1.Let assume stochastic process is followed by (Hsu et al., 2012).

$$m_t = \mu + \varepsilon_t \tag{3.13}$$

$$\varepsilon_t = x_t \sigma_t \qquad x_t^{\Delta iid(0,1)} \tag{3.14}$$

Where $\sigma_t^2 = E(X_t^2|\varphi_{t-1})$ and $_t$ have the conditional distribution function $G(_t), G(_t)$ $=p_m(X_t < X|\varphi_{t-1})$. At a given probability $\gamma\varepsilon(0,1)$, VaR is denoted by the VaR(α), and explains in terms which is the quantile of the probability distribution consisting of financial returns.

$$F(VaR(\alpha)) = p_m(m_t < VaR(\alpha)) = \alpha \, or \, VaR(\alpha) \inf\{v(p(m_t \leq v) = \alpha) \tag{3.15}$$

Two different methods can be used to estimate the quantile of the probability distribution which are by inverting the F(m) or distribution function of the financial returns and the second one is by inverting the distribution function of the conditional distribution $G(_t)$. For this reason, we have to estimate the value of variance α_t^2.

$$VaR(\alpha) = F^{-1}(\alpha) = \mu + \sigma_t G^{-1}(\alpha) \tag{3.16}$$

However, VaR includes the specification of the following distribution function F(m) or G( ) and its value is calculated by using following three methods which are non-parametric methods, parametric methods and semi-parametric methods. This study use, the semi-parametric method named Monti-Carlo simulation for computing the above function.

3.2.3 Copula Approach

For handling correlation between the markets and risk, a copula is the the most effective econometric model due to its parameters which allows handling the market correlation and risk at greater flexibility (Hsu et al., 2012). Suppose $M_1, M_2, \ldots..M_n$, are representing the set of n random variables with a joint distribution function.

$$Fm_1, m_2, \ldots m_n(m_1, m_2, \ldots..m_n) = p \tag{3.17}$$

$$Fm_1, m_2, \ldots m_n(m_1, m_2, \ldots..m_n) = p \tag{3.18}$$

$"Fm_1"$, $x, m2\ldots..mn(m1, m2, \ldots..mn) = p(M1 < m1, M1 < m2, \ldots..Mn)$, for $(m1, m2, m3\ldots..mn) \in R^n$ Let marginal distribution function of M1, M2,……., Mn is

$$F_{m1}(m1) = (m1) = p(M1 \leq m1) \tag{3.19}$$

$$F_{m2}(m2) = (m2) = p(M2 \leq m2) \tag{3.20}$$

-

-

$$F_{mn}(mn) = (mn) = p(Mn \leq mn) \tag{3.21}$$

According to Sklar (1959) theorem, if $Fu_1; Fu_2; \ldots; Fu_n$ are continuous functions, then there exists a unique copula such that

$$Fm1, m2, \ldots.., m(m1, m2, \ldots..mn) = c(FM1(m1), FM2(m2), \ldots..F(mn)) \tag{3.22}$$

For bivariate variables such as the green bonds returns r_{gb} and change in international financial markets rim, the above equation can be rewritten as

$$C(a, b) = p(Zgb \leq zgb, Zim \leq zim),\ \ for(a, b) \in [0, 1]^2 \tag{3.23}$$

Whereas Z_{gb} and Z_{im} are the marginal distribution functions of the return residual sets of z_{gb} and z_{im} respectively, a and b are uniform distribution of green bonds and international financial markets and C(a,b) is the copula function. To examine the tail dependence, Gaussian, t-student, Gumbel, Clayton, and Frank copula are used to the modeling of risk. The Gaussian copula explains the normal distribution of data, t-student explains the data distribution at both tails, Gumbel copula describes the upper tail dependence, the Clayton copula includes the dependence at lower tail and in last frank copula exhibit the maximum negative and positive dependence.

The Gaussian copula function is defined as:

$$C_G(a, b) = \int_{-\infty}^{\cup-1(b)} da \int_{-\infty}^{\cup-1(b)} db \frac{1}{2\pi\sqrt{1-\delta^2}} \exp\left\{-\frac{a^2 - 2\delta ab + b^2}{2(1-\delta^2)}\right\} \tag{3.24}$$

$$= \phi_s(\cup^{-1}(a), \cup^{-1}(b))$$

where U represent a univariate standard normal distribution and δ is a bivariate standard normal distribution with the correlation coefficient $-1 \leq \delta \leq 1$. Gauusina copula is very easy to compute the tail dependence but the bivariate normality assumption limits its effectiveness for exploring the co-movement dynamics between financial time series data and also neglect the crucial dimension of tail dependence. For this t-student copula is used to measure the tail dependence at both tails due to its bivariate asymmetrical assumption. The t-student copula is based on the multivariate t distribution. Huang et al. (2009) described t-copula as follows:

$$C_T = (m1, m2; p, d) = t_{d,p}(t_d^{-1}(m_1), (t_d^{-1}(m_2)) \tag{3.25}$$

The t-student copula is one of the most used copula to measure tail dependence because degree of freedom can be changed for setting the tail dependency. To measure the upper tail dependency or heavy tail at the upper side of the distribution Gumbel copula is proposed by (Gumbel, 1960).

$$C_{GU}(a, b) = \exp\left\{-[(-\ln(a)^{\delta}) + (-\ln(b)^{\delta})]\frac{1}{\delta}\right\}, \delta \geq 1 \tag{3.26}$$

In the above equation, δ denotes the degree of dependence between a and b. There is no upper tail dependence between a and b when value of δ is equal to 1 or becomes minimum. When value of δ reaches maximum which demonstrates the perfect upper tail dependence.

To measure the lower tail dependence between a and b Clayton copula is used which is proposed by Clayton (1978) as below:

$$C_{LA}(a, b) = \max\left[(a^{-\delta} + b^{-\delta} - 1) - \frac{1}{\delta}, 0\right], 0 < \delta \leq \infty \tag{3.27}$$

Whereas, δ in the equation of shows the extent of dependence between the a and b. When the value of δ is 0 then there is no lower tail dependence between pairs. As δ value increases which shows increase in lower tail dependency until it reaches to ∞ and this is the maximum point of lower tail dependence.

Frank copula is introduced by the Frank (1979) to measure the upper tail dependence between a and b which is given below:

$$C_F = (a, b; \lambda) \tag{3.28}$$

$$= \frac{-1}{\lambda} \log \left(\frac{\lambda(1 - e^{-\lambda}) - (1 - e^{-\lambda b})}{1 - e^{-\lambda}} \right) \quad (3.29)$$

$$where\ \lambda\varepsilon(-\infty, 0) \cup (0, +\infty)$$

3.2.4 Copula-VaR

The Copula-VaR is one of the most significantly used methodology for the estimation of market risk of multiple series. Bianchi et al. (2010) applies Copula-VaR in their study because it is derived from Sklar (1959) theorem and creates a multivariate density function for estimating the VaR of combined series and explained as follows.

$$M_{1,t} = \omega_1 + \sum\nolimits_{i=1}^{n} \sum\nolimits_{l=1}^{p} \varphi_1 M_{i,t-1} + \sqrt{h_{1,t}\gamma_{1,t}} \quad (3.30)$$

$$\begin{matrix} . & . & . \\ . & . & . \\ . & . & . \end{matrix}$$

$$M_{n,t} = \omega_1 + \sum\nolimits_{i=1}^{n} \sum\nolimits_{l=1}^{p} \varphi_1 M_{i,t-1} + \sqrt{h_{n,t}\gamma_{n,t}} \quad (3.31)$$

In the Eq(3.30) $M_{1,t}$ represent the dependent variable, ω_1 is the intercept, $\sum_{i=1}^{n} \sum_{l=1}^{p}$ $\varphi_1 M_{i,t-1}$ is the autoregressive term of endogenous variable of order p and $\sqrt{h_{1,t}\gamma_{1,t}}$ denotes the error term which is standardized $\gamma_{1,t}$ and have zero mean and variance. In addition, standardized error term has the conditional joint distribution $H_t(\gamma_{1,t}, \ldots..\gamma_{n,t}; \delta)$ along a parameter δ that can be explained according to (Sklar, 1959).

$$(\gamma_{1,t}, \ldots..\gamma_{n,t}; \vartheta) \sim H_t(\gamma_{1,t}, ...\gamma_{n,t;}\vartheta) \quad (3.32)$$

$$C_t = (F_{1.t}(\gamma_{1,t}; \alpha_1), ...F_{1,t}(\gamma_{n,t}; \alpha_n); \gamma) \quad (3.33)$$

Conditional joint distribution of the standardized error term or innovation denoted by H_t and $C_t(.;\gamma)$ represent the copula's commutative distribution margin of the standardized error term or innovation's marginal expresses in the above equation as ${}_{1,t}(\gamma_{1,t};\alpha_1),\ldots.._{1,t}(\gamma_{n,t};\alpha_n)$. Moreover, γ denotes the copula and marginal parameter is expressed as $\alpha_1,\ldots..\alpha_n$. However, function of copula connect two or multiple marginal distributions in order to construct a multivariate joint distribution to measure the dependence structure between different variables at a time in a very effective manner and does not required identical marginal distribution.

3.2.5 Hedge Ratio

The rationale behind hedging is to create a position to become ineffective against market volatility. Because in an optimal portfolio combination of long and position is taken by the investor in assets while structuring the portfolio so that market fluctuation is not able to affect the returns of the portfolio (Chen et al., 2004). So, for this hedging purpose hedge ratio approach is used in this study for creating the optimal portfolio by the green bond and international financial markets. The hedge ratio is one of the most significant empirical methodology followed by saveral studies i.e., Antonakakis et al. (2018); Balcılar et al. (2016); Maghyereh et al. (2017) for creating the optimal portfolio by calculating the hedge ratio of the financial assets and also an optimal portfolio weights for investment at the minimum and maximum level. The conventional hedge ratio method is based on OLS regression in which the hedge ratio is calculated by the slope of the OLS line (Chen et al., 2004). Let suppose, the investor takes a long position in green bonds gb_l and a short position in the rest of the assets of international financial markets im_s for constructing the portfolio.

The OLS regression equation is given defined as:

$$\vartheta_t = \omega_\circ + \omega_1 X_t + \in_t \tag{3.34}$$

In the above OLS regression equation ϑ_t is representing the dependent variable and ${}_t$ is the independent variable. $\in_t$ is the unexplained portion of the ϑ_t.The hedge ratio is denoted by the ω_1 and it is calculated by following way:

$$\omega_1 = \frac{\lambda_{gbt,imt}}{\lambda_{imt}} \tag{3.35}$$

Whereas, $\lambda_{gbt,imt}$ is the conditional covariance of green bond and international financial markets at time t and λ_{imt} is the conditional variance of the international financial markets at time t. Based on the above-calculated hedge ratio optimal weights for investment in a portfolio is calculated for green bond and international financial markets is given below.

$$w_{gbimt} = \frac{\lambda_{imt} - \lambda_{gbt}}{\lambda_{gbt} - 2\lambda_{gbt,imt} + \lambda_{imt}} \tag{3.36}$$

$$W_{gbimt} = \frac{\lambda_{imt} - \lambda_{gbt}}{\lambda_{gbt} - 2\lambda_{gbt,imt} + \lambda_{imt}} \tag{3.37}$$

Chapter 4

Results and Discussion

4.1 Descriptive Statistics

Descriptive statistics of green bonds and international financial markets are presented in a very comprehensible form in Table 4.1. Descriptive statistics are further comprised of two measures which are central tendency and variability. Mean and median are included in the measure of central tendency and measure of variability comprised of standard deviation, minimum, maximum, and skewness, and Kurtosis provides information about the location of data and helps to understand identify the normality of data.

The performance of green bonds and international financial markets is measured by average returns. Average returns of all variables are positive except oil. Maximum average returns are earned by the Dow Jones Islamic Market World Index which is (0.03126%) shows the best average daily return and worst average returns are reported by the S&P Global Oil Index which is (-0.05273%). Maximum and minimum values show the variability in returns that how much maximum and minimum return in one day can offer by these instruments. Maximum returns in one day can be earned is 13.79691% and maximum loss of -21.86461% is incurred in one day by the S&P Global Oil Index. Skewness is defined by the distortion in the normal distribution of data or asymmetry in a normal bell-shaped curve. Skewness measures how much data varies from the normal distribution. In the

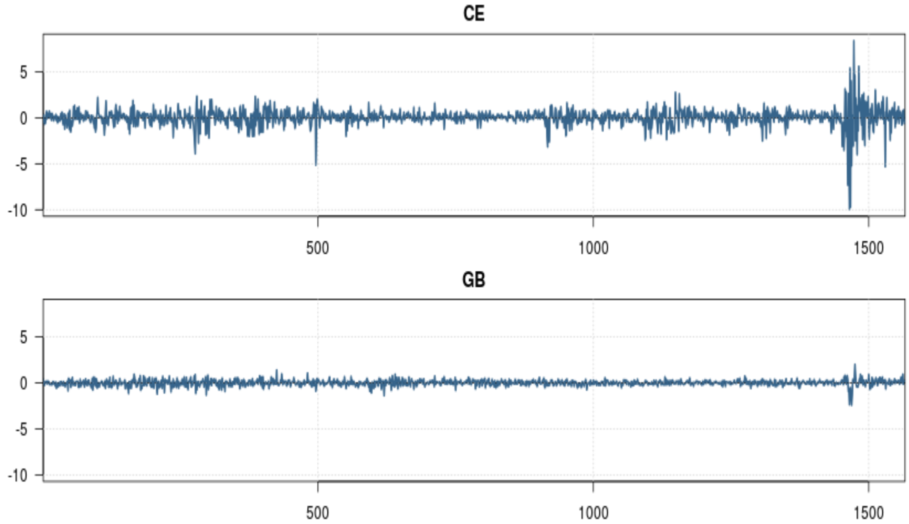
Table 4.1: Descriptive Statistics

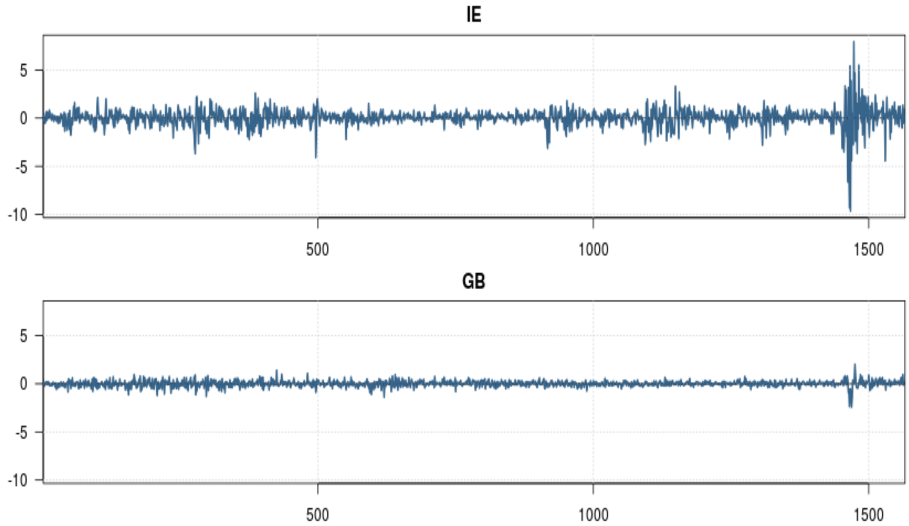
Variables	Mean	Std.Dev	Skewness	Min	Max	Median
CE	0.00019	0.00957	-1.48757	-0.09976	0.08370	0.00046
IE	0.00031	0.00938	-1.24887	-0.09639	0.07916	0.00055
CB	0.00002	0.00101	-0.20515	0.00806	0.00556	0.00000
S	0.00017	0.00129	-2.02294	-0.01340	0.00729	0.00018
GB	0.00006	0.00318	-0.58763	-0.02410	0.02013	0.00007
O	-0.00053	0.01622	-2.18563	-0.21865	0.13797	-0.00026

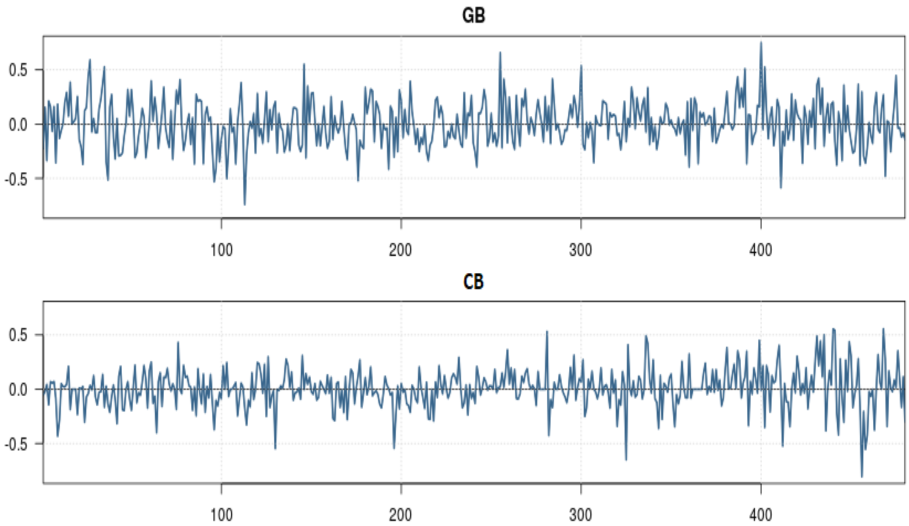
This table displays the descriptive statistics of green bonds and international financial markets. Whereas CE = Logged returns of S&P Global 1200 (Gross Total Return), IE=Log returns of Dow Jones Islamic Market World Index, CB=Logged returns of FTSE World Government Bond Index, S =Logged returns of Dow Jones Sukuk Total Return Index (ex-Reinvestment), GB= Logged returns of S&P Green Bond Index, O=Logged returns of S&P Global Oil Index.

following sample, values of skewness demonstrate that the data of all the International financial markets are left-skewed and have long-tail distribution on the left side. S&P Global Oil Index and Dow Jones Sukuk Total Return Index have the most long-tail distribution on the left side of the curve because their value of skewness is -2.185634 and -2.022941 which are the highest value of skewness. The risk of international financial markets is measured by the standard deviation. The Standard deviation of the S&P Global Oil Index is 1.621686% which is the highest among all other international financial markets shows more riskiness among all series and the FTSE World Government Bond Index has the lowest risk because its standard deviation is 0.10137785%.

Returns of the series of the green bond and international financial markets are presented in figure 1 given below:


CE
5
0
-5
-10
500
1000
1500
GB
5
0
-5
-10
500
1000
1500


IE
5
0
-5
-10
500
1000
1500
GB
5
0
-5
-10
500
1000
1500


GB
0.5
0.0
-0.5
100
200
300
400
CB
0.5
0.0
-0.5
100
200
300
400

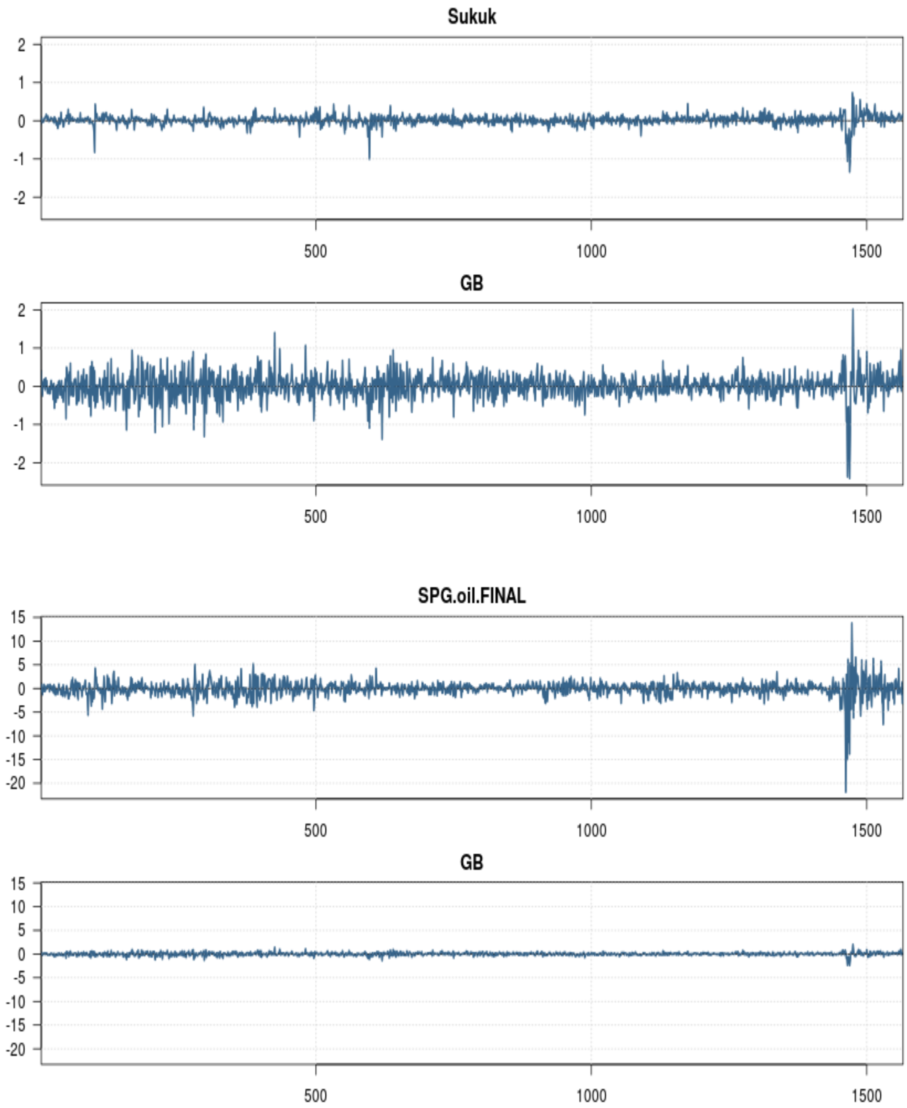


FIGURE 4.1: Descriptive Statistic

4.2 GARCH Modeling

In financial times series, the volatility dynamics of the green bond and international financial markets are measured by GARCH modeling. As most the studies have recommended the use of GARCH family. From the GARCH family, GARCH, T-GARCH and E-GARCH are used to measure the volatility. An appropriate model is selected on the criteria of AIC criteria. Linear relation of lagged variance relationship has been measured by GARCH and exponential relation of lagged variance relationship has been measured by the E-GARCH and T-GARCH. E-GARCH and T-GARCH measure the impact of Good and bad news on volatility and GARCH term measures the persistence of volatility. T-GARCH also known as GJR-GARCH provides information about the difference in volatility due to good and bad news.

Table 4.2 shows the results of GARCH model used to forecast the volatility of green bonds and international financial markets. Returns of series are used in computing results. Volatility of S&P Global 1200, Dow Jones Islamic Market World Index, and S&P Global Oil Index are modeled by the E-GARCH. However, volatility of FTSE World Government Bond Index and Dow Jones Sukuk Total Return Index are measure by the T-GARCH and volatility dynamics of S&P Green Bond Index is captured by the GARCH model, lagged returns are statistically significant for all the series which gives information that future returns can be predicted based on historical returns except for FTSE World Government Bond Index and S&P Green Bond Index because both of these series have statistically insignificant lagged returns term. ARCH effect for FTSE World Government Bond Index, Dow Jones Sukuk Total Return Index (ex-Reinvestment), and S&P Green Bond Index are statistically significant and positive which confirm that past price behavior affects the current volatility so present paired price shocks can be used to predict future's volatility.

In Table 4.2 GARCH for all the series is statistically significant indicating the persistence of volatility. And the total of ARCH and GARCH coefficients are close to 1 which provides insights into the persistence of volatility in the long run and transmission of volatility in the future. Results of $D \times ARCH$ for FTSE World Government Bond Index is statistically significant and negative which means that there is asymmetric behavior in the market and less volatility due to good news. Value of $D \times ARCH$ is statistically significant and positive for the Dow Jones Sukuk Total Return Index confirm that bad news creates more volatility and asymmetric behavior in the market.

Size effect is statistically significant and positive which means that a big shock will create more volatility and vice versa. Sign effect is statistically significant which means bad news have positive relation indicating that bad news creates more volatility.

Table 4.2: GARCH Model for Forecasting Volatility

	GB	CB	S	CE	IE	O
Model	GARCH	T-GACRH	T-GACRH	E-GARCH	E-GARCH	E-GARCH
AIC	-8.8468	-9.8332	-10.8732	-7.1688	-7.1554	-6.0431
Lag	0.0133	0.0459	0.1611	0.0676	0.0818	0.1378
	(0.6307)	(0.2474)	(0.000)	(0.0017)	(0.0007)	(0.000)
ARCH	0.0719	0.0391	0.1611	-	-	-
	(0.000)	(0.0074)	(0.000)			
GARCH	0.9127	0.9691	0.1327	0.9618	0.9617	0.9805
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D $\times$ ARCH	-	-0.0517	0.0090	-	-	-
		(0.0055)	(0.0001)			
Size Effect	-	-	-	0.2917	0.2450	0.1603
				(0.000)	(0.000)	(0.000)
Sign Effect	-	-	-	-0.1345	0.1328	-0.1027
				(0.000)	(0.000)	(0.000)

**Model selection was based on Minimum AIC value for respective Index, News effect = D $\times$ ARCH, *p $<$ 0.05, Size effect = $C(4)$, Sign effect = $C(5)$*

4.2.1 Application of Time-Varying Conditional Correlation DCC GARCH

To measure the correlation whether it is constant or time-varying between the green bond and international financial markets, Dynamic Conditional Correlation is used. To test the heteroskedasticity initially ARCH effect has been measured in all of the series. Table 4.3 reports the results of ARCH test which depicts the presence of heteroscedasticity in S&P Global 1200 (Gross Total Return), Dow Jones Islamic Market World Index, FTSE World Government Bond Index, of Dow Jones Sukuk Total Return Index (ex-Reinvestment), S&P Green Bond Index and S&P Global Oil Index. The presence of the ARCH effect leads towards the application of volatility models. After testing the ARCH effect, further DCC GARCH is applied to find the presence of time varying volatility.

Table 4.4 reports the results of DCC GARCH along with the appropriate model for measuring the dynamic conditional correlation. The best model for all the series is chosen on the criteria of lowest AIC. GARCH, T-GARCH, and E-GARCH are used to estimate the DCC GARCH for the green bond international financial markets. This table also reports the values of coefficients along with their p-value

Table 4.3: ARCH Effect

Series	Value	Prob
CE	146.8213	0.0000
IE	154.7061	0.0000
CB	5.8957	0.0152
S	95.34026	0.0000
GB	64.96662	0.0000
O	35.44657	0.0000

This table displays the ARCH effect of green bonds and international financial markets. Whereas CE = Log returns of S&P Global 1200 (Gross Total Return) or Global Conventional Equity Index, IE=Log returns of Dow Jones Islamic Market World Index, CB=Log returns of FTSE World Government Bond Index, S =Log returns of Dow Jones Sukuk Total Return Index (ex-Reinvestment), GB= Log returns of S&P Green Bond Index, O=Log returns of S&P Global Oil Index

and best-fitted model for all the pairs of green bonds with international financial markets.

The best-fitted model for estimating the DCC GARCH for the pair of green bonds with Islamic equity, Sukuk, and oil are T-GARCH and for the pair of green bonds with conventional equity and conventional bonds is E-GARCH. For all the series past residual shock is denoted by the α and lagged dynamic conditional correlation is denoted by β. The most important stability condition of DCC which is $\alpha + \beta < 1$ is met by all the series of green bonds and international financial markets.

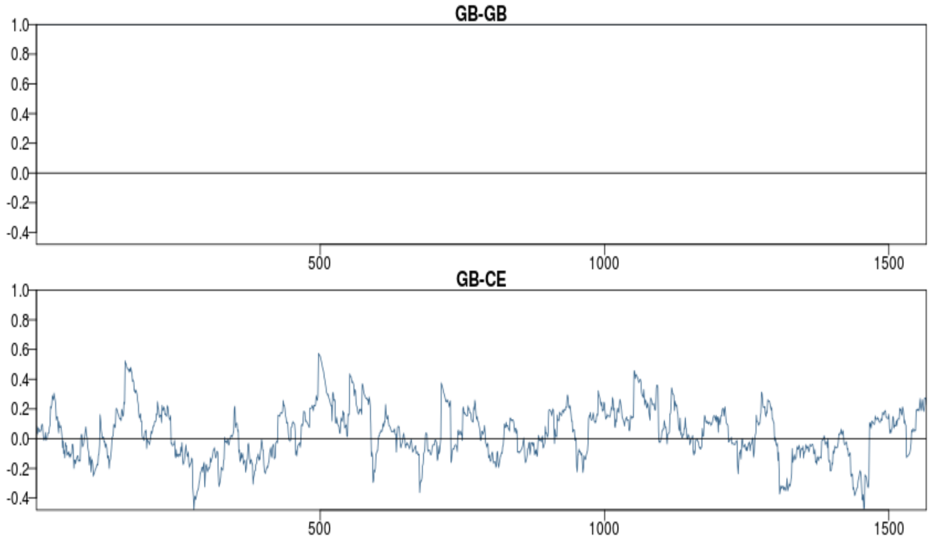
Past residual shocks for all the series is statistically significant which tell us about the impact of residual shocks on current volatility except the pair of green bond and conventional bond which is statistically insignificant as its p-value is greater than 0.05 indicates that there is no relationship of past residual shock on current volatility.

Lagged dynamic correlation for all the pairs is statistically significant and positive which tells us about the existence of time-varying correlation in all pairs of green bond with global conventional equity, world Islamic equity, conventional

TABLE 4.4: DCC GARCH

Series	α	β	**Selected Model**
GB & CE	0.0585 0.0000	0.8729 0.0000	E-GARCH
GB & IE	0.0590 0.0001	0.8571 0.0000	T-GARCH
GB & CB	-0.0229 0.1133	0.9612 0.0000	E-GARCH
GB & S	0.0138 0.0003	0.9818 0.0000	T-GARCH
GB & O	0.0492 0.0006	0.8956 0.0000	T-GARCH

Whereas CE = Logged returns of S&P Global 1200 (Gross Total Return) or Global Conventional Equity Index, IE=Log returns of Dow Jones Islamic Market World Index, CB=Log returns of FTSE World Government Bond Index, S =Log returns of Dow Jones Sukuk Total Return Index (ex-Reinvestment), GB= Log returns of S&P Green Bond Index, O=Log returns of S&P Global Oil Index



bond, Sukuk, and oil. Graphical representation of green bonds and international financial markets is presented in Figure 2.

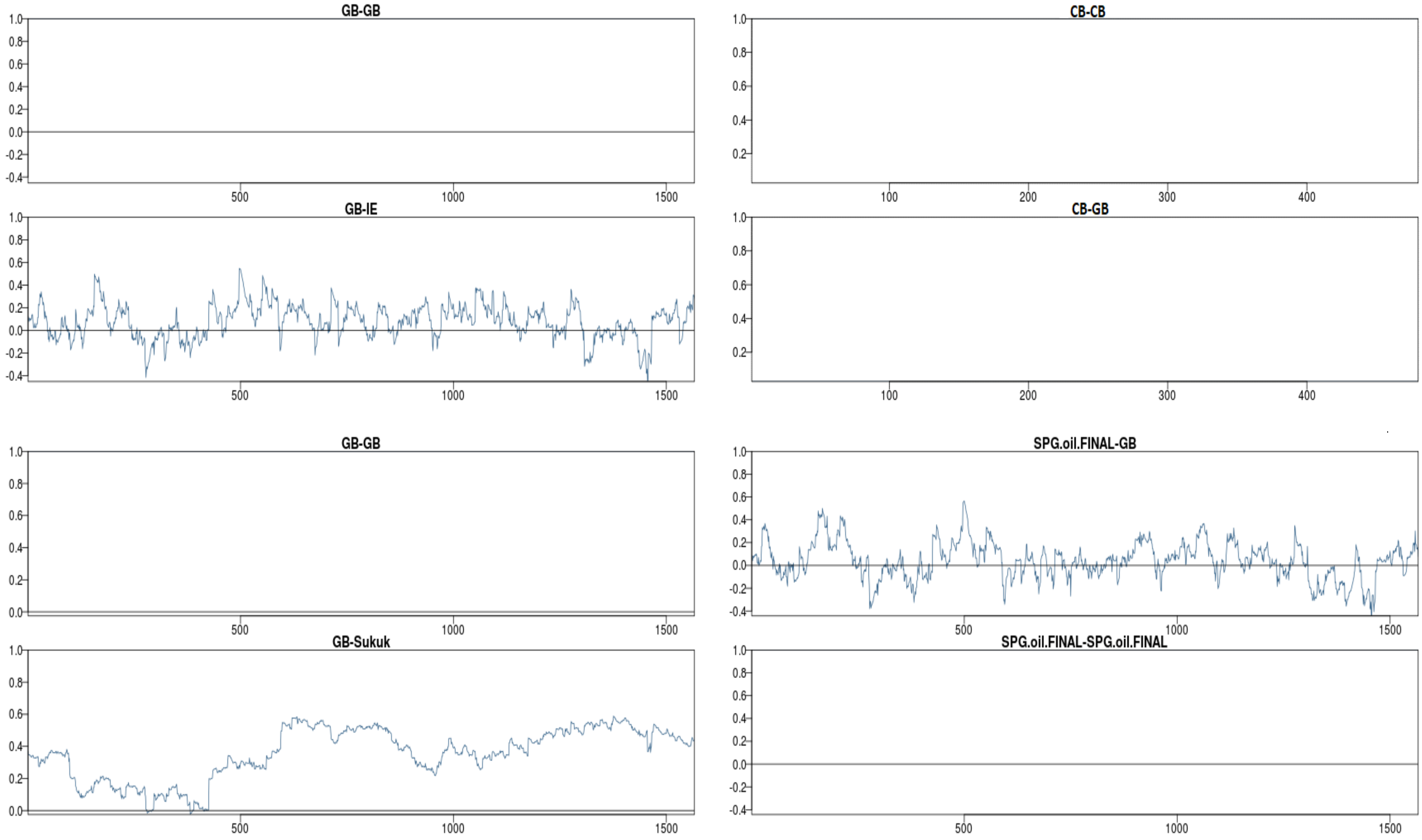


FIGURE 4.2: DCC outputs of Green bond and International Financial Markets

4.2.2 VaR Estimation Using Monte Corlo Simulation

For risk management, measuring the market risk is crucial. Value at risk is a standard measure used by the financial analyst for estimating the systematic risk of an asset, financial security, or portfolio. In this section, market risk of green bonds and the international financial market is measured by using Value at Risk and Conditional Value at Risk. Value at risk is estimated by using the Monte Carlo method because Monte Carlo simulation allows joint distribution of the asset returns. Computational results of VaR and CoVaR are presented for green bond and international financial markets have been presented in Table 4.5 at a confidence interval of 95% and 99%.

TABLE 4.5: V_a_R Estimation

Series	**Single Series**			
	VaR 95%	**VaR 99%**	**CoVaR 95%**	**CoVaR 99%**
CE	-1.29%	-1.82%	-2.15%	-2.63%
IE	-1.28%	-1.80%	-2.10%	-2.60%
CB	-0.29%	-0.41%	-0.40%	-0.48%
S	-0.20%	-0.28%	-0.36%	-0.53%
GB	-0.51%	-0.71%	-0.75%	-1.08%
O	-2.13%	-3.01%	-3.03%	-3.96%

Table 4.5 reports the computational outcomes of VaR by Monte Carlo simulation at 95% and 99% for green bond and international financial markets. At 95% confidence interval VaR for S&P Global 1200 (Gross Total Return) or Global Conventional Equity Index is 1.292% which means a potential loss that can be faced in one day is 1.292% or there are 95% chances that loss cannot exceed from 1.292% in one day. At a 99% confidence interval, the maximum loss that can be faced by an investor in one day is -1.818%.CoVaR for S&P Global 1200 (Gross Total Return) or Global Conventional Equity Index is -2.146% at 95% confidence interval. As CoVaR represents the average expected loss and it is higher than the 95% confidence interval at 99% for S&P Global 1200 (Gross Total Return). At 99% confidence interval estimation of CoVaR indicates that maximum loss that an investor can face is -2.63%

At a 95% confidence interval, VaR estimation for Dow Jones Islamic Market World Index, is -1.282% which means that there are 95% chances that loss will not exceed -1.282% in one day. VaR at 99% for Dow Jones Islamic Market World Index, is -1.80% which indicates that there are only 1% chances that loss will exceed -1.80% in one day. CoVaR for Dow Jones Islamic Market World Index at 95% confidence interval gives information about maximum potential monetary loss is -2.101% in one day. CoVaR at 99% is -2.598% which indicates that there are 1% chances that loss will exceed -2.598% in one day.

VaR at 95% confidence interval for FTSE World Government Bond Index is -0.294% which means that there are 5% chances that loss will exceed -0.294% Value of VaR at 99% is -0.4147% which indicates there are 99% chances that the maximum potential loss will not exceed from -0.4147% in a day for FTSE World Government Bond Index. An average expected loss at 95% is -0.399% depicts the maximum loss that can be earned by an investor in one day on FTSE World Government Bond Index. At a 99% confidence interval, the expected loss for the FTSE World Government Bond Index is -0.477%.

At 95% confidence interval, VaR for Dow Jones Sukuk Total Return Index is -0.204% which means a potential loss that can be earned in one day is -0.204% or there are 95% chances that loss cannot exceed from -0.204% in one day. At a 99% confidence interval, the maximum loss that can be faced by an investor in one day is -0.28%. CoVaR for Dow Jones Sukuk Total Return Index is -0.355% at a 95% confidence interval. As CoVaR represents the average expected loss and it is higher than the 95% confidence interval at 99% for S&P Global 1200 (Gross Total Return). At 99% confidence interval estimation of CoVaR indicates that maximum loss that an investor can suffer is -0.527% or there are 1% chances that loss will exceed from -0.527%.

VaR for S&P Green Bond Index at 95% confidence interval is -0.506% which means that there are 95% chances that loss will not exceed -0.506% in one day. VaR at 99% S&P Green Bond Index, is -0.713% which indicates that there are only 1% chances that loss will exceed -0.713% in one day. CoVaR for S&P Green Bond Index at 95% confidence interval gives information about maximum potential monetary loss is -0.745% in one day. CoVaR at 99% is -1.077% which indicates that there are 1% chances that loss will exceed -1.077% in one day.

VaR at a 95% confidence interval for the S&P Global Oil Index is -2.125% which means that there are 5% chances that loss will exceed -2.125%. The value of VaR at 99% confidence interval is -3.013% which indicates there are 99% chances that maximum potential loss will not exceed -3.013% in a day for S&P Global Oil Index. The average expected loss at 95% is - 3.025% depicts the maximum loss that can be earned by an investor in one day on the S&P Global Oil Index. At a 99% confidence interval, the expected loss for S&P Global Oil Index is -3.956%.

4.3 Application of Copula Approach

To measure the dependence structure between green bonds and international financial markets copula is used. Copula is used for accurately measuring the asymmetric structure and nonlinear relationship among multiple risk factors. This section is further comprised of a subsection which deals with the results of Copula-VaR.

4.3.1 Modeling of Dependence Structure

Table 4.6 presents the dependence structure between the green bond and equity markets. It is comprised of information related to initial and final parameters, Log-likelihood, AIC, BIC, and upper, lower tail dependence. The pseudo-maximum likelihood technique is used to estimate the copula to examine the dependence structure. In this technique, initial parameters and final parameters are used to calculate the copula. Firstly, we calculate initial parameters, and then the final parameters are estimated based on initial parameters.

Five different types of copulas are estimated to provide comprehensive results regarding the dependence structure in upper and lower tail distribution. These copulae are Gaussian, t-student, Gumbel, Frank, and Clayton. The rationale behind the tail dependence is the quantum of dependence in the quadrant of the lower left and upper right of the tail distribution of two random variables.

To measure the dependence structure at both sides of the tails t-student copula is used. Gaussian copula does not measure any type of tail distribution. To measure the upper tail dependence in this study Gumble coupla is used and for measuring the dependence in the lower tail Clayton coupla is used. Frank copula is used to measure the greatest range of dependence because it allows the modeling of positive and negative dependence in the data.

4.3.1.1 Dependence Structure of Green Bond and Equity Markets

For the selection of the best-fitted copula from the various copula's AIC and BIC, criteria are used. To estimat the accurate dependence structure of green bonds and international financial markets copula is selected based on the lowest AIC.Based on AIC t-student copula is selected for the pair of S&P Green Bond Index and S&P Global 1200 (Gross Total Return). The marginal tail distribution is symmetric because the t-copula measure the dependence structure at both sides of the tail and the lower tail dependence is 0.09437162 and the upper tail distribution is 0.09437162.

Computational results of the marginal tail distribution of green bond and Dow Jones Islamic Market World Index are presented in table 4.6. Results consist of information related to initial and final parameters, log-likelihood, lower and upper tail dependence, Akaike information criterion values (AIC), and Bayesian information criterion (BIC) for all the models. Based on the lowest AIC t-copula is selected for the pair of S&P Green Bond Index and Dow Jones Islamic Market World Index which provides the information about the asymmetric marginal tail distribution between these two series.

4.3.1.2 Dependence Structure of Green Bond and Bond Markets

Table 4.6 represents estimates of different models of copula along with the values of AIC and BIC for selecting the best-fitted models, initial and final parameters, and upper and lower tail dependence. Based on the lowest AIC values, the frank copula is selected for measuring the tail dependence between S&P Green Bond

Index and FTSE World Government Bond Index. S&P Green Bond Index and FTSE World Government Bond Index are independent of each other because the value of upper and lower tail dependence is zero and Frank copula measures the greatest range of dependence.

Computational results of the marginal tail distribution of the S&P Green Bond Index and Dow Jones Sukuk Total Return Index (ex-Reinvestment) are presented in table 4.7. Results consist of information related to initial and final parameters, log-likelihood, lower and upper tail dependence, Akaike information criterion values (AIC), and Bayesian information criterion (BIC) for all the models. Based on the lowest AIC t-copula is selected for the pair of S&P Green Bond Index and Dow Jones Sukuk Total Return Index (ex-Reinvestment) which provides the information about the asymmetric marginal tail distribution between these two series. The value of upper tail dependence is 0.1982 and lower tail dependence is 0.1982.

4.3.1.3 Dependence Structure of Green Bond and Oil Market

Table 4.7 present the criteria for the selection of the best-fitted copula based on copula's AIC and BIC. To estimat the accurate dependence structure of green bonds and oil market, copula is selected based on the lowest AIC between sample of normal distribution and t-distribution. Based on AIC t-student copula is selected for the pair of S&P Green Bond Index and S&P Global Oil Index. The marginal tail distribution is symmetric because the t-copula measure the dependence structure at both sides of the tail and the marginal tail distribution at both upper and lower sides for the pair of S&P Green Bond Index and S&P Global Oil Index is 0.09642789.

TABLE 4.6: Dependence Structure between Green bond and International Financial markets

	Copula	Initial Parameters	Final Parameters	Log Likelihood	AIC	BIC	Lower Tail Dependence	Upper Tail Dependence
GB-CE	Gaussian	0.0816	0.0285	0.6247 (df=1)	0.7506	6.1069	0.0000	0.0000
	t-Student	0.0816	0.0292	25.5272 (df=2)	-47.0545	-36.3419	0.0944	0.0944
	Gumbel	1.0204	1.0400	5.9621 (df=1)	-9.9241	-4.5678	0.0000	0.0526
	Clayton	0.0409	0.0414	1.4533 (df=1)	-0.9066	4.4496	0.0000	0.0000
	Frank	NA	0.1860	0.7097 (df=1)	0.5806	5.9369	0.0000	0.0000
GB-IE	Gaussian	0.0285	0.0554	2.3651 (df=1)	-2.7302	2.6261	0.0000	0.0000
	t-Student	0.0957	0.0561	27.0838 (df=2)	-50.1677	-39.4551	0.0979	0.0979
	Gumbel	1.0392	1.0520	8.3344 (df=1)	-14.6688	-9.3125	0.0000	0.0000
	Clayton	0.0784	0.0414	1.4533 (df=1)	-0.9066	-4.4496	0.0000	0.0000
	Frank	NA	0.3481	2.4815 (df=1)	-2.9630	2.3933	0.0000	0.0000
GB-CB	Gaussian	0.0285	0.0013	0.0009 (df=1)	1.9981	7.3544	0.0000	0.0000
	t-Student	0.0093	0.0012	-0.2382 (df=2)	4.4763	15.1889	0.0776	0.0776
	Gumbel	1.0204	1.0000	-2.41e-06 (df=1)	2.0000	7.3563	0.0000	0.0000
	Clayton	-0.0074	0.0414	1.4533 (df=1)	-0.9066	4.4496	0.0000	0.0000
	Frank	NA	-0.0344	0.0179 (df=1)	1.9643	7.3205	0.0000	0.0000

Table 4.7: Dependence structure between Green bond and International Financial Markets

	Copula	Initial Parameters	Final Parameters	Log likelihood	AIC	BIC	Lower Tail Dependence	Upper Tail Dependence
GB-S	Gaussian	0.0285	0.3269	87.2210 (df=1)	-172.4599	-167.1037	0.0000	0.0000
	t-Student	0.3890	0.3232	114.9367 (df=2)	-225.8735	-215.1609	0.1982	0.1982
	Gumbel	1.2618	1.2540	91.6665 (df=1)	-181.3331	-175.9768	0.0000	0.2620
	Clayton	0.5236	0.0414	1.4533 (df=1)	-0.9066	4.4496	0.0000	0.0000
	Frank	NA	1.9850	77.2536 (df=1)	-152.5071	-147.1508	0.0000	0.0000
GB-O	Gaussian	0.0898	0.0381	1.1204 (df=1)	-0.2408	5.1155	0.0000	0.0000
	t-Student	0.0898	0.0381	21.4395 (df=2)	-38.8790	-28.1665	0.0964	0.0964
	Gumbel	1.0255	1.0380	4.0578 (df=1)	-6.1157	-0.7594	0.0000	0.0501
	Clayton	0.0510	0.0548	2.3646 (df=1)	-2.7292	2.6271	0.0000	0.0000
	Frank	NA	0.2285	1.0746 (df=1)	-0.1493	5.2070	0.0000	0.0000

Table 4.8: Tail distribution selection

Series	Marginal	Marginal's AIC	Marginal's BIC	Selected
GB-CE	**Normal**	-13566.63	-13555.92	**T-student**
		-10114.31	-10103.60	
	T-student	-13777.16	-13761.09	
		-10912.85	-10896.78	
GB-IE	**Normal**	-13566.63	-13555.92	**T-student**
		-10176.46	-10165.74	
	T-student	-13777.16	-13761.09	
		-10885.99	-10869.92	
GB- CB	**Normal**	-13566.63	-13555.92	**T-student**
		-17145.11	-17134.40	
	T-student	-13777.16	-13761.09	
		-10912.85	-10896.78	
GB-S	**Normal**	-13566.63	-13555.92	**T-student**
		-16398.49	-16387.78	
	T-student	-13777.16	-13761.09	
		-10912.85	-10896.78	
GB-SPG	**Normal**	-13566.63	-13555.92	**T-student**
		-8462.061	-8451.35	
	T-student	-13777.16	-9050.39	
		-13761.09	-9034.32	

4.3.2 Modeling of Copula-VaR

For risk modeling of green bonds and international financial markets, VaR is used because it is a standardized model for measuring market risk. But, estimating the VaR becomes complicated for multiple series in a portfolio due to the entanglement of a joint multivariate distribution. In addition to this major difficulty for computing, the VaR of multiple series in a portfolio is to measure the dependence because the value at risk is concerned with tail distribution (Huang et al., 2009). So, for this reason, Copula-VaR is used to measuring the market because in this for computing the VaR of the portfolio is computed by using the mixed GARCH based model and Copula also known as conditional Copula-GARCH.

For computing, the Copula-VaR best copula model is selected based on AIC from the copula family as given in Table 4.8. After selecting the best model of copula for the pair green bond with selected international financial markets VaR has been computed at 95% and 99% confidence intervals.

For The Copula-VaR, model is selected based on lowest AIC and BIC and for all the pairs of green bond with international financial markets, t-student distribution is selected for computing the VaR of pairs at 95% and 99% confidence interval. The rationale behind having the lowest AIC and BIC of t-student distribution for all the pairs is due to the asymmetrical financial data and fatter tails.

4.3.2.1 Copual-Var Modeling for Green Bond and Equity Markets

For measuring markets risk of multiple random variables jointly Copula-VaR is used. Table 4.9 reports the estimation outputs of the Copula-VaR for the S&P Green Bond Index and S&P Global 1200 (Gross Total Return). The best-fitted model of a copula is selected based on the lowest AIC which is the t-student copula. VaR at a 95% confidence interval of the pair green bond and conventional equity is -2.702663%. This means a potential loss that can be faced in one day is -2.702663%. or there are 95% chances that loss cannot be exceed from -2.702663% in one day.

At a 99% confidence interval, the maximum loss that can be faced by an investor in one day is -3.118212%. CoVaR for S&P Green Bond Index and S&P Global 1200 (Gross Total Return) is -3.118212% at a 95% confidence interval. CoVaR represents the average expected loss and it is higher than the 95% confidence interval at 99%. At 99% confidence interval estimation of CoVaR indicates that the maximum loss that an investor can suffer is -3.118212%.

Table 4.9 shows that at 95% confidence interval t-student copula is selected for estimating the Copula-VaR of the pair S&P Green Bond Index and Dow Jones Islamic Market World Index is -2.743838% which means that there are 95% chances that loss will not exceed from this in one day. At 99% confidence interval, VaR for S&P Green Bond Index and Dow Jones Islamic Market World is -7.406581% which indicates that there are only 1% chances that loss will exceed from -7.406581% in one day.

CoVaR for S&P Green Bond Index and Dow Jones Islamic Market World Index at 95% confidence interval gives information about maximum potential monetary loss is -4.794387% in one day. CoVaR at 99% is -12.76856% which indicates that there are 1% chances that loss will exceed -12.76856% in one day.

4.3.2.2 Copual-Var Modeling for Green Bond and Bond Markets

Table 4.9 reports results related to Copula VaR for measuring the market risk of two random variables through their dependence. Based on the lowest AIC values, frank copula is selected for measuring the market risk of the S&P Green Bond Index and FTSE World Government Bond Index. VaR at a 95% confidence interval for the S&P Green Bond Index and FTSE World Government Bond Index is -2.744801% which means that there are 5% chances that loss will exceed -2.744801%. The value of VaR at 99% is -7.686212% which indicates there are 99% chances that maximum potential loss will not exceed -7.686212% in a day for S&P Green Bond Index and FTSE World Government Bond Index.

An average expected loss at a 95% confidence interval is -5.045767% depicts the maximum loss that can be earned by an investor in one day on a global green bond and conventional bond. At a 99% confidence interval, the expected loss for the S&P Green Bond Index and FTSE World Government Bond Index is -14.62732%.

Table 4.9 shows that at 95% confidence interval, t-student copula is selected for estimating the Copula-VaR of the pair S&P Green Bond Index and Dow Jones Sukuk Total Return Index (ex-Reinvestment) is -2.879557% which means that there are 95% chances that loss will not exceed from -2.879557% in one day. VaR at 99% for S&P Green Bond Index and Dow Jones Sukuk Total Return Index (ex-reinvestment) -7.660950% which indicates that there are only 1% chances that loss will exceed from -7.660950% in one day.

CoVaR for S&P Green Bond Index and Dow Jones Sukuk Total Return Index (ex-Reinvestment) at 95% confidence interval gives information about maximum potential monetary loss is -4.929597% in one day. CoVaR at 99% confidence interval is -12.804 % which indicates that there are 1% chances that loss will exceed -12.804 % in one day.

TABLE 4.9: Copula-VaR

Copula	Marginal	GB-CE				GB-IE			
		VaR 95%	**VaR 99%**	**CoVaR 95%**	**CoVaR99%**	**VaR95%**	**VaR99%**	**CoVaR95%**	**CoVaR99%**
Gaussian	Normal	-0.0234	-0.0312	-0.0269	-0.0344	-0.0230	-0.0307	-0.0265	-0.0339
	t-student	-0.0270	-0.0717	-0.0468	-0.1233	-0.0274	-0.0741	-0.0479	-0.1277
t-Student	Normal	-0.0234	-0.0312	-0.0269	-0.0344	-0.0230	-0.0307	-0.0265	-0.0339
	t-student	-0.0270	-0.0717	-0.0468	-0.1233	-0.0274	-0.0741	-0.0479	-0.1277
Gumbel	Normal	-0.0234	-0.0311	-0.0269	-0.0339	-0.0229	-0.0305	-0.0264	-0.0333
	t-student	-0.0270	-0.0657	-0.0484	-0.1443	-0.0273	-0.0682	-0.0500	-0.1554
Clayton	Normal	-0.0237	-0.0321	-0.0274	-0.0345	-0.0232	-0.0313	-0.0268	-0.0338
	t-student	-0.0271	-0.0758	-0.0467	-0.1157	-0.0273	-0.0776	-0.0476	-0.1193
Frank	Normal	-0.0234	-0.0308	-0.0268	-0.0336	-0.0230	-0.0303	-0.0263	-0.0331
	t-student	-0.0268	-0.0696	-0.0448	-0.1056	-0.0272	-0.0716	-0.0458	-0.1094
Copula	**Marginal**	**GB-CB**				**GB-S**			
		VaR 95%	**VaR 99%**	**CoVaR 95%**	**CoVaR99%**	**VaR95%**	**VaR99%**	**CoVaR95%**	**CoVaR99%**
Gaussian	Normal	-0.0077	-0.0103	-0.0089	-0.0112	-0.0087	-0.0115	-0.0100	-0.0126
	t-student	-0.0268	-0.0711	-0.0466	-0.1229	-0.0288	-0.0766	-0.0493	-0.1280
t-Student	Normal	-0.0077	-0.0103	-0.0089	-0.0112	-0.0087	-0.0115	-0.0100	-0.0126
	t-student	-0.0268	-0.0711	-0.0466	-0.1229	-0.0288	-0.0766	-0.0493	-0.1280
Gumbel	Normal	-0.0077	-0.0102	-0.0088	-0.0112	-0.0083	-0.0111	-0.0095	-0.0120
	t-student	-0.0266	-0.0669	-0.0447	-0.1112	-0.0283	-0.0665	-0.0547	-0.1978
Clayton	Normal	-0.0078	-0.0105	-0.0090	-0.0115	-0.0080	-0.0107	-0.0092	-0.0116
	t-student	-0.0271	-0.0707	-0.0472	-0.1189	-0.0271	-0.0758	-0.0467	-0.1157
Frank	Normal	-0.0077	-0.0101	-0.0088	-0.0109	-0.0083	-0.0111	-0.0095	-0.0121
	t-student	-0.0274	-0.0769	-0.0505	-0.1463	-0.0286	-0.0683	-0.0468	-0.1128

4.3.2.3 Copual-Var Modeling for Green Bond and Oil Market

Table 4.9 (B) reports results related to Copula-VaR for measuring the market risk of two random variables through their dependence. Based on the lowest AIC values, t-student copula is selected for measuring the market risk of the S&P Green Bond Index and the S&P Global Oil Index. VaR at a 95% confidence interval for the pair of S&P Green Bond Index and the S&P Global Oil Index is -3.330584% which means that there are 5% chances that loss will exceed the calculated VaR.

The value of VaR at 99% is -5.115381%. which indicates there are 99% chances that maximum potential loss will not exceed -5.115381%. in a day for S&P Green Bond Index and S&P Global Oil Index. An average expected loss at a 95% confidence interval is -4.098806% depicts the maximum loss that can be efaced by an investor in one day on a global green bond and conventional bond. At a 99% confidence interval, the expected loss for the S&P Green Bond Index and the S&P Global Oil Index is -6.064382%.

Copula	**Marginal**	**GB-O**			
		VaR 95%	**VaR 99%**	**CoVaR 95%**	**CoVaR99%**
Gaussian	Normal	-0.0392	-0.0523	-0.0449	-0.0570
	t-student	-0.0333	-0.0512	-0.0410	-0.0606
t-Student	Normal	-0.0392	-0.0523	-0.0449	-0.0570
	t-student	-0.0333	-0.0512	-0.0410	-0.0606
Gumbel	Normal	-0.0391	-0.0517	-0.0447	-0.0561
	t-student	-0.0332	-0.0497	-0.0408	-0.0595
Clayton	Normal	-0.0394	-0.0531	-0.0456	-0.0571
	t-student	-0.0336	-0.0526	-0.0417	-0.0602
Frank	Normal	-0.0391	-0.0512	-0.0447	-0.0555
	t-student	-0.0332	-0.0503	-0.0406	-0.0574

4.4 Comparison Between VaR and Copula-VaR

In this study for measuring the market risk of individual asset VaR is used because VaR is a standardized econometric model for estimating the market risk of financial assets. But to measure the market risk of asset classes jointly Copula-VaR is used due to the limitation of VaR in estimating the market risk of multiple asset classes in a portfolio. Table 4.10 reports the results of the VaR and Copula-VaR along with conditional VaR at confidence interval 95% and 99%.

Results of VaR at a 95% confidence interval shows that the S&P Green Bond Index is a risky financial instrument because combining it with other asset classes makes them riskier at both quartiles. Table 4.10 reports that individual VaR and CoVaR of S&P Global 1200 (Gross Total Return) is more than the S&P Green Bond Index at both confidence intervals 95% and 99%. But results of the Copula-VaR shows that the risk and tail-risk of the combined series S&P Green Bond Index and S&P Global 1200 (Gross Total Return) are increased at both confidence interval 95% and 99%.

The risk of the combined series of S&P Green Bond Index and Dow Jones Islamic Market World Index is increased from -1.282% to -2.743% at 95% confidence interval and at 99% confidence interval VaR is increased from -1.80% to -7. 406. Tail-VaR is also increasing from -2.101%to -4.794% at a 95% confidence interval. At a 99% confidence interval, CoVaR also shows the same pattern of increment in risk from -2.598% to -12.768% at a 99% confidence interval.

Values of VaR at a 95% confidence interval of the series of FTSE World Government Bond is -0.294% and it reaches -2.7138% by combining it with S&P Green Bond Index. At 99% confidence interval VaR is -0.4147% and it becomes -7.067%. The average expected return of the series of FTSE World Government Bond at 95% confidence interval is -0.399% and by combining it with S&P Green Bond Index it is increased and the resultant figure of CoVaR is -4.721%. At 99% confidence interval tail-risk is increased in the combined series of FTSE World Government Bond and S&P Green Bond Index from -0.477% to -11.886%.

Table 4.10: Comparison of VaR and Copula-VaR

Series	Single Series VaR		CoVaR		Series	Combined Series VaR		CoVaR	
	95%	**99%**	**95%**	**99%**		**95%**	**99%**	**95%**	**99%**
CE	-0.013	-0.018	-0.021	-0.026	**GB & CE**	-0.0270	-0.0717	-0.0468	-0.1233
IE	-0.013	-0.018	-0.021	-0.03	**GB & IE**	-0.0274	-7.4060	-0.0479	-0.1277
CB	-0.003	-0.004	-0.004	-0.005	**GB & CB**	-0.0271	-0.0707	-0.0472	-0.1189
S	-0.002	-0.003	-0.004	-0.005	**GB & S**	-0.0288	-0.0766	-0.0493	-0.1280
GB	-0.005	-0.007	-0.007	-0.011	-	-	-	-	-
O	-0.021	-0.03	-0.030	-0.040	**GB& SPGO**	-0.0331	-0.0512	-0.0410	-0.0606

The risk of Dow Jones Sukuk Total Return Index (ex-Reinvestment) is less as compared to the risk of the combined series of the S&P Green Bond Index and Dow Jones Sukuk Total Return Index (ex-Reinvestment). Because at 95% confidence interval risk is increased from -0.204% to -2.879% by combining Dow Jones Sukuk Total Return Index (ex-Reinvestment) with S&P Green Bond Index and at 99% confidence interval VaR is increased from -0.28% to -7.660%. Tail-VaR is also increasing from -0.355% to -4.929% at a 95% confidence interval. At a 99% confidence interval, CoVaR shows the same pattern of increment in risk from -0.527% to -12.804%.

The result of VaR in Table 4.10 shows that at a 95% confidence interval risk of the S&P Global Oil Index is -2.125% and it reaches -3.305% by combining it with S&P Green Bond Index. At 99% confidence interval, VaR is -3.013% and it becomes -5.115%. The average expected return of the series of FTSE World Government Bond at 95% confidence interval is -3.025% and by combining it with S&P Green Bond Index it is increased and the resultant figure of CoVaR is -4.098%. At 99% confidence interval, tail-risk is increased in the combined series of S&P Green Bond Index and the S&P Global Oil Index from -3.956% to -6.064%.

4.5 Application of Hedge Ratio

The following section of the study concludes the implication of green bonds for the purpose of international portfolio diversification and risk management. The hedge ratio is an econometric model used for creating an optimal hedge by estimating the hedging efficiency and optimal portfolio weight (Chen et al., 2004). For creating an effective and efficient hedge against the volatility of international financial markets with the help of green bonds for exploiting the opportunities of risk-minimizing and maximizing the return on an investment hedge ratio is employed. This section is further consist of hedge ratio (See Table 4.11) and portfolio weight table (See Table 4.12).

Estimating the optimal quantity of hedging financial instruments in a portfolio for hedging against the volatility is the most important step because optimal portfolio weights are calculated on the hedge ratio for the construction of a diversified portfolio. In this study hedge ratio is calculated by employing GARCH as the DCC of all the green bonds and international markets is volatile over the sample period and this hedge ratio is used to calculate optimal weights of green bonds and other financial instruments.

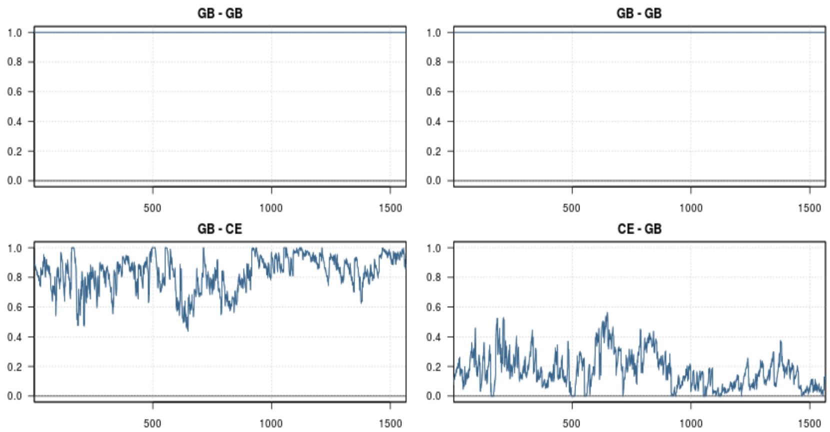
4.5.1 Hedge Ratio

For the construction of an optimal portfolio, i'll assumes that a long position is taken by the investor in GB and a short position in the rest of the assets of the portfolio. The long position in GB is taken due to the increase in volatility in the future. And only the combination in which GB's long position is taken in GB is interpreted. On this combination of assets in the portfolio successful optimal hedge can be created against the volatility with S and O. While are other combinations of other assets are not able to create the effective hedge with GB as their p-value of hedge ratio is > 0.05. In the case of GB and S hedge against the volatility can be achieved because the hedge ratio is statistically significant. For creating a hedge investors have to invest 1% in GB with a long position and 0.01% in S while taking the short position in S. Variation in this investment can be done to maintain the

TABLE 4.11: Hedge Ratio

	Mean	Std. dev	Min	Max	HE	P-value
GB/CE	0.02	0.07	-0.09	0.15	-0.07	0.20
CE/GB	0.06	0.59	-0.79	0.86	0.02	0.66
GB/IE	0.04	0.07	-0.06	0.16	-0.05	0.33
IE/GB	0.16	0.51	-0.57	0.85	0.02	0.68
Gb/CB	0.03	0.00	0.02	0.04	0.00	0.99
CB/GB	0.02	0.00	0.02	0.03	0.00	1.00
GB/S	0.01	0.04	-0.05	0.09	-0.11	0.04
S /GB	0.09	0.80	-1.27	1.18	0.01	0.80
GB/O	0.01	0.04	-0.05	0.09	-0.11	0.04
O/GB	0.09	0.80	-1.27	1.18	0.01	0.80

FIGURE 4.3: Hedge Ratio of the green bond and international financial markets



hedge effective is 4%. Maximum at 95% confidence interval and minimum at 5% confidence interval reports the extreme condition to maintain the hedge effective against market volatility.

The hedge ratio for GB and O is statistically significant because its p-value is 0.04. By taking a long position in GB investors have to invest 1% in GB while a parallel short position is taken by the investor in O and invested 0.01% to create an optimal hedge. The variation in the level of investment by the investor is +4%.At extreme quartiles maximum and minimum represents the level of investment in the long position in GB by the investor.Graphical representation of the hedge ratio of the green bond with all other financial assets is given below a figure 3.

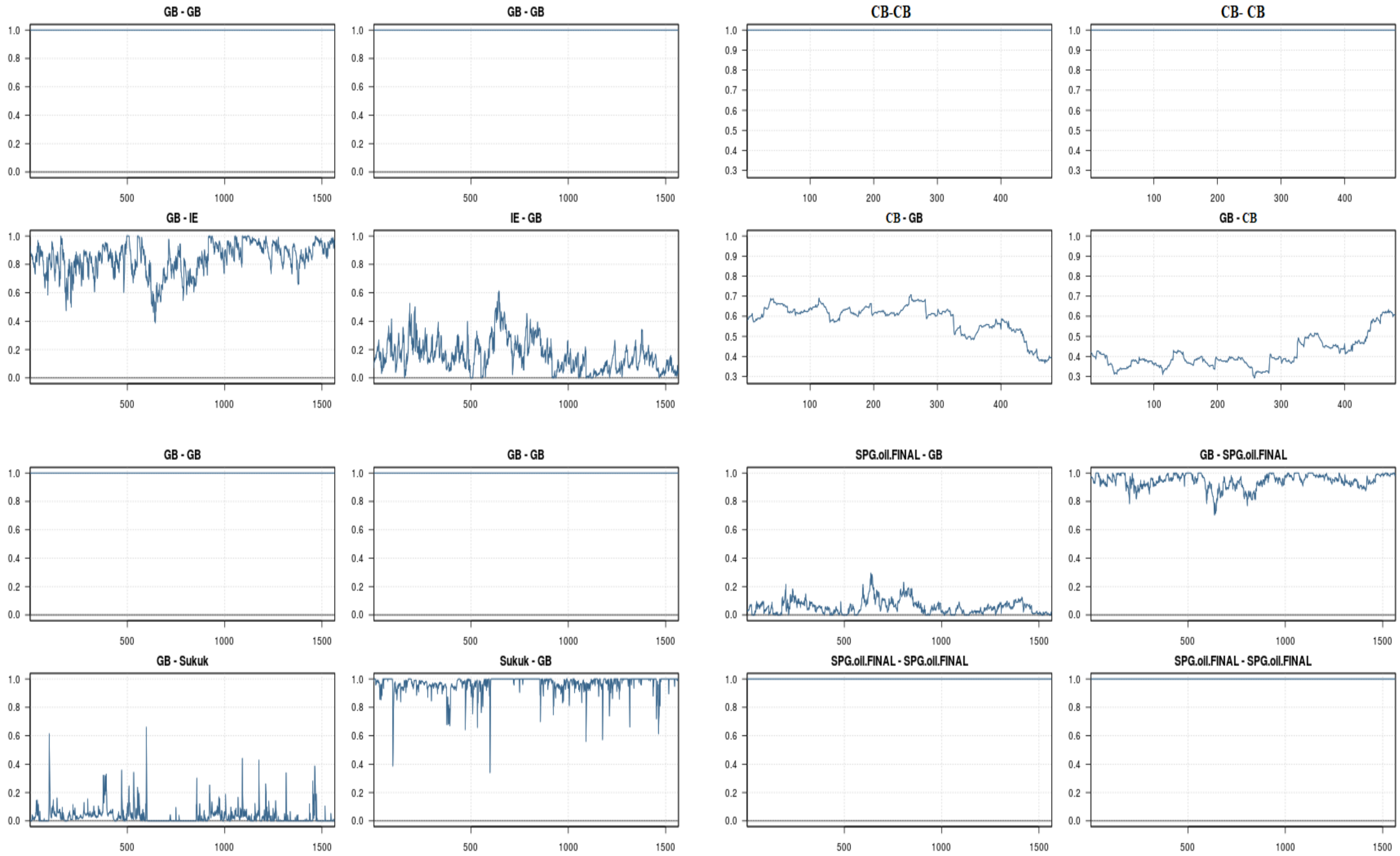

GB - GB
GB - GB
CB-CB
CB- CB
GB - IE
IE - GB
CB - GB
GB - CB
GB - GB
GB - GB
SPG.oil.FINAL - GB
GB - SPG.oil.FINAL
GB - Sukuk
Sukuk - GB
SPG.oil.FINAL - SPG.oil.FINAL
SPG.oil.FINAL - SPG.oil.FINAL

Table 4.12: Portfolio Weight Table

	Mean	Std. dev	Min	Max	HE	P-value
GB/CE	0.83	0.12	0.61	0.99	0.15	0.00
CE/GB	0.17	0.12	0.01	0.39	0.91	0.00
GB/IE	0.84	0.11	0.63	0.99	0.12	0.01
IE/GB	0.16	0.11	0.01	0.37	0.90	0.00
GB/CB	0.41	0.07	0.32	0.59	0.58	0.00
CB/GB	0.59	0.07	0.41	0.68	0.43	0.00
GB/S	0.06	0.05	0.00	0.16	0.96	0.00
S/GB	0.04	0.05	0.04	1.00	0.04	0.46
GB/ O	0.06	0.05	0.00	0.16	0.96	0.00
O/GB	0.04	0.05	0.04	1.00	0.04	0.46

4.5.2 Portfolio Weight Table

Based on the hedge ratio optimal portfolio weights are calculated for creating the effective hedge with GB and other financial assets. Because we can achieve our objective of hedging against the market volatility by taking a long position in GB and a short position in CE as its hedge ratio is statistically significant (p=0.00). At a long position in GB amount which can be invested by the investor is 83% and 17% is invested in CE while taking a short position in it. To maintain this hedge variation can do in investment is 12%. At 95% confidence interval maximum amount that can be invested in GB is 99% and At 5% confidence interval minimum amount which can be invested in GB to intact this effective hedge is 61%.

For the combination of GB and IE, hedge effectiveness is 0.12 with p-value 0.01 and the amount can be invested for creating an effective hedge against the market, volatility is 84% while the rest of the amount is invested in the IE. To remain intact, the effective hedge variation in the amount invested is 11%. At extreme conditions, the maximum amount which can be invested in GB while taking a long position is 99% and the minimum level of investment at a 5% confidence interval is 63%.

Hedge effectiveness for the pair of GB and CB is 0.00 and it is statistically significant. At the long position, the level of investment by an investor in GB is 41% while the remaining 59% amount is invested in CB in the short position.

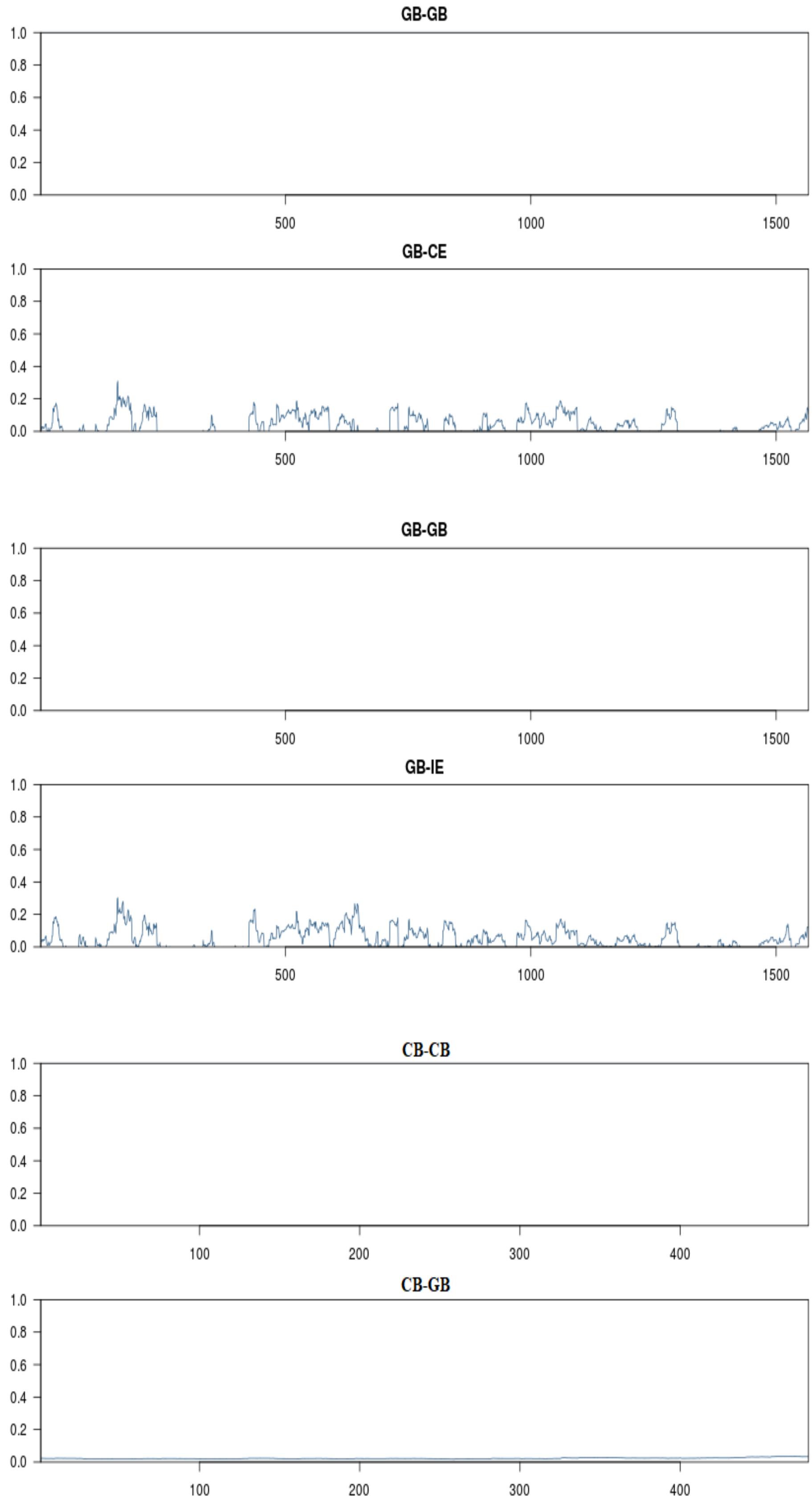
Based on market volatility change in the investment amount is 7% in GB for hedging the risk. The maximum amount of investment at a 95% confidence interval in GB is 59% and at a 5% confidence interval, the minimum level of investment in GB is 32% while investing the rest of the amount in CE at a short position.

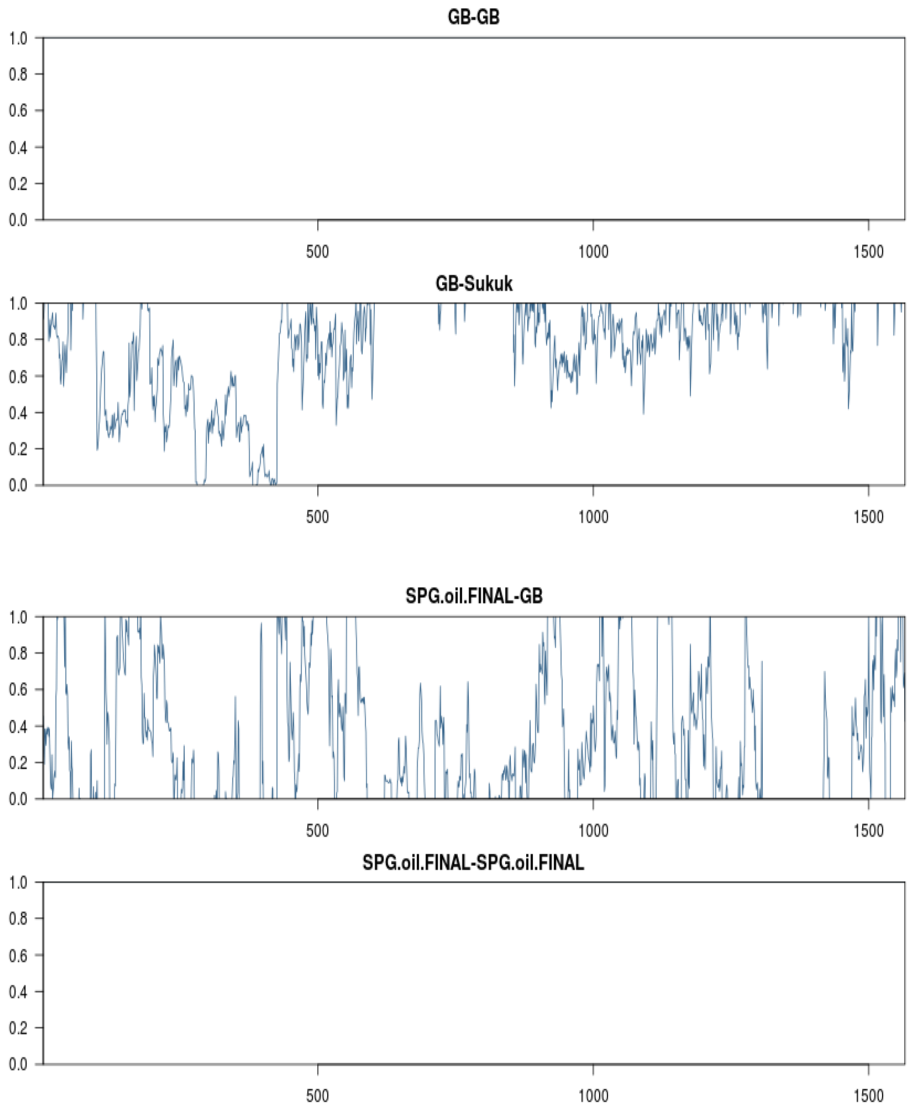
For the combination of GB and S, hedge effectiveness is 0.04 with a p-value of 0.00. For creating an optimal portfolio, the amount which can be invested for creating an effective hedge against the volatility of the market is 6% at a long position while the rest of the amount is invested in the S. To remain intact, the effective hedge variation in the amount invested is 5%. At extreme conditions, the maximum amount which can be invested in GB while taking a long position is 16%, and the minimum no amount is invested in GB at 5%, and all amount is invested in S.

Hedging against the market volatility can be achieved by taking a long position in GB and a short position in O as its hedge ratio is 0.96 and it statistically significant (p=0.00). At a long position in GB amount which can be invested by the investor is 6% and 94% is invested in O while taking a short position in it. To maintain this hedge variation can do in investment is 5%. At 95% confidence interval maximum amount that can be invested in GB is 16% and at 5% confidence interval minimum amount which can be invested in GB to intact, this effective hedge is 0%.

Graphical representation of portfolio weight for green bonds and all financial assets is given below as figure 3.

Figure 4.4: Portfolio weight




GB-GB
GB-Sukuk
SPG.oil.FINAL-GB
SPG.oil.FINAL-SPG.oil.FINAL
1.0
0.8
0.6
0.4
0.2
0.0
500
1000
1500

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

Volatility of financial assets are the most important factor while considering the investment due to the reason they give information regarding the information spillover and volatility transmission which affect future returns. An in-depth understanding of volatility dynamics helps an investor to explore opportunities for profit-maximizing while constructing the portfolio of multiple financial assets. Because the existence of information spillover leads towards the comprehensive understanding of multiple important factors necessary for portfolio diversification such as persistence of volatility, time-varying correlation, market risk of the financial asset, co-movement dynamics, etc.

The purpose of this study is to find out the volatility dynamics, market risk, dependence structure of green bonds, and the possibility of portfolio diversification with the green bond. To achieve the objective of the study daily returns of the global conventional equity, global Islamic equity, global conventional bond, Sukuk, global green bond, and oil market for the period of July 2014 to May 2020 are used. For estimating the results, analysis of data is divided into seven stages which are GARCH modeling, application of DCC, estimation of VaR, an application of copula, estimating the copula VaR, comparison of the copula, and copula-VaR and estimating the hedge ratio and optimal portfolio weights.

The first stage of the study deals intending to explore the volatility dynamics of the green bond. GARCH modeling is used to achieve this objective. GARCH, E-GARCH, and T-GARCH are used to measure the linear and exponential lag-variance relationship. Based on the lowest AIC E-GARCH selected for global conventional equity, global Islamic equity, and global oil market. T-GARCH is selected for exploring the volatility dynamics of world conventional bond and global Sukuk and GARCH is employed for measuring the dynamics of the volatility of global green bond.

The second stage includes the data analysis of green bonds and international financial markets to find out the time-varying conditional correctional among the series. Best fitted models are selected based on the lowest AIC which are-GARCH and E-GARCH. Past residual shock is statistically significant for all the pair except for the pair of green bond and world conventional bond. Lagged dynamic correlation is statistically significant and positive for all pairs.

The third stage of the study includes information about measuring the market risk of all the selected six financial assets. VaR and CVaR are used to achieve the objective of estimating the market risk of green bonds and all financial assets. Based on the results of VaR at 95% and 99% confidence interval oil is the riskiest asset among all of the financial assets, global conventional equity is the second-highest risky asset, global Islamic equity is less risky than oil and conventional equity but riskier then global green bond, world conventional bond and Sukuk, a global green bond is riskier than world conventional bond market and Sukuk but less risky oil, conventional and Islamic equity and world conventional bond have market risk greater than Sukuk but having less market risk than oil, conventional and Islamic equity and global green bond. Sukuk is the least risky among all of the selected financial assets for the portfolio.

The fourth stage of this study is linked to the third objective to explore the dependence structure of green bonds with international financial markets. To find the dependence structure copula family is used. Tail dependence is measured by the Gaussian, t-student, Gumbel, Clayton, and frank copula, and the best-fitted model is selected from among the copula family is based on AIC. The T-student copula is selected for all the pairs of global green bonds with international financial markets due to asymmetrical financial data except for the pair of global green bond and world conventional bond.

Moreover, the t-student copula explains the common marginal behavior of series at both the upper and lower tail. Frank copula is selected based on the lowest AIC for green bond and world conventional bond for measuring the dependence structure. The highest upper and lower tail dependence is shown by the pair of global green bond and Sukuk. Upper tail dependence is 0.1981584 and lower tail dependence is 0.1981584. The lowest tail dependence is shown by the global green bond and world conventional bond because the values of upper and lower tail dependence are 0.

The fifth stage of this study is based on the Copula-VaR and Tail-VaR which describe the market risk of the green bond with international financial markets that is measured by employing Copula-Garch at 95% and 99% confidence interval. Based on copula-VaR at 95% and 99% risk of the financial asset is increased by combining it with the global green bond.

Based on the results of VaR and Copula-VaR sixth stage of this study deals with the comparison of the impact on risk on a pair of financial assets by adding it with the green bond. At both quartiles, 95% and 99% in VaR and T-VaR risk is increased of all the series by combining them with the global green bond.

In the last stage of the study, impact of green bonds on the portfolio, diversification is measured by using a hedge ratio and calculating the optimal portfolio weights. In this section, our objective to find out the possibility of risk diversification with the help of a global green bond for the investor is explored. Based on the results of the hedge ratio combination of the global green bond with oil and Sukuk provides an opportunity for creating the optimal hedge against the market volatility. In this section maximum, minimum, and average level of investment is also calculated by taking a long position in global green bond and a short position in the rest of the financial assets in the portfolio.

Based on the results of GARCH modeling of global green bond, it is concluded that past residual impact on volatility is statistically significant persistence of volatility is in the long run and DCC outputs of global green bond with international financial markets depict that lagged dynamic correlation is significant and positive. Market risk of the global green bond is less than oil, global conventional equity, and global Islamic equity on both confidence intervals at 95% and 99% according to Table 4.5. But combine risk of the pair global green bond with oil, global conventional equity, and global Islamic equity increased instead of decreasing because the green bond is a young financial instrument and it is risky but with time when it becomes mature green bond becomes a very good investment opportunity. The dependence structure represents that the global green bond shows upper and lower tail dependence with the international financial markets except for the world conventional bond that shows no upper and lower tail dependence. The hedge ratio optimal portfolio weights enable investor to hedge against the volatility of the market. And in last the green bond is riskier than sukuk and conventional bond but less riskier than oil, global conventional equity, and global Islamic equity.

5.2 Recommendations

Based on the current study on global green bonds and international financial markets following recommendations are presented. All these recommendations are linked with the multiple dimension such as implementing the global green bond as a good investment opportunity, to build the more comprehensive literature on the dynamics of global green bond with other financial markets, for its legalization in multiple economies and increase the liquidity position by launching it on multiple stock exchanges.

Recommendations for an investor-related using the global green bond as a good investment are based on the results of multiple econometric models such as Garch modelling shows that lag variance relationship exists in global green bond and international financial markets. So, the investor should consider this persistence of volatility while hedging against the market risk because the persistence of volatility eliminates or decrease the opportunity of hedging. The output of the DCC shows the existence of time-varying correlation among all pairs of green bond and international financial markets which eliminates the clear cut benefit of diversification except for the pair of green bond and conventional bond market because of its lagged dynamic correlation is statistically insignificant. So, the investor can use the pair of green bonds and conventional bonds for diversifying their portfolio.

Results of VaR and CoVaR rank all the asset classes based on riskiness for using them in the construction of a portfolio. Among all the asset classes oil is the highest riskiest asset. The second and third riskiest assets are conventional and Islamic equity. After oil and equities, a global green bond is at the fourth rank which is riskier than conventional bond and Sukuk but less risky than oil, conventional, and Islamic equity. According to the ranking of VaR and CoVaR Sukuk secures the fifth rank and the conventional bond is at a sixth rank makes it the least risky asset. Therefore, the investor will use assets in their portfolio based on their risk profile. So, it is recommended that a risk-taker investor should use high-risk assets such as oil, conventional and Islamic equity, etc while constructing their portfolio while risk-averse investors should use sukuk, conventional bonds, and green bonds in their portfolio for diversifying based on their risk appetite.

Dependence structure shows the common marginal behavior among the pair of financial assets which help investor for the selection of assets to achieve the objective of constructing the optimal portfolio and hedge their position against the market volatility. Based on the results of copula it is recommended that green bond with the conventional bond can be used by the investor in the portfolio because this combination of green bond with conventional bond shows no upper and lower tail dependence. Maximum upper and lower and upper tail dependence among all the pairs exhibits by the pair of green bond and Sukuk and eliminates the opportunity of diversification. Pair of green bond and Islamic equity, oil, and conventional equity exhibits lower and upper tail dependence so, it is recommended that investors should carefully use these combinations of assets with green bond while the construction of portfolio and relocation of resources in their portfolio.

According to Table 4.10 for measuring the risk of combined pair of green bonds with international financial markets results of Copula-VaR exhibit an increase in the riskiness of the pair at both quartiles in VaR and Co-VaR. The ranking order of the pair of green bonds with the international financial market based on riskiness is green bond and oil, then green bond and Sukuk. At the third level green bond and Islamic equity comes and at the fourth level green bond and conventional bond comes and at last level green bond and conventional equity comes which is the least risky pair. Based on these ranking it is recommended according to risk appetite investors should use these combinations in their portfolio.

Results of optimal portfolio weights also explain the maximum and minimum amount of investment in the long position in the global green bond. The hedge ratio indicates that the optimal hedge can created by the global green bond with oil and Sukuk against the market volatility. So, it is recommended for taking an effective hedge position by the fund manager and trader green bond can be used with the combination of oil and Sukuk for maximizing the return.

A limited number of studies are available on the green bond which creates a research gap in the literature. Therefore, on the basis of understanding of the co-movement, volatility, return dynamics of the green bond it is recommended to academic researchers for exploring the relationship of global green bonds with other financial markets such as Bitcoin, commodity, green Sukuk, and metal, etc. Finally, the outcomes of this study are used by the regulatory authorities for designing the policies of legalizing the green bond in their stock exchanges, for developing the strategies of macro stabilization, efficient and effective allocation of resources, and for achieving risk management. For diversifying the risk fund manager and an investor can use the outcomes of this study for hedging,profit-optimization, and construction of the portfolio.

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