Estimating Dependences and Risk between Gold Prices and S&P500: New Evidences from ARCH,GARCH, Copula and ES-VaR models

SHAHBANO AURANG ZAIB KHAN

https://orcid.org/0000-0001-5469-3146

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Abstract

This thesis examines the correlations and linkages between the stock and commodity in order to quantify the risk present for investors in financial market (stock and commodity) using the Value at Risk measure. The risk assessed in this thesis is losses on investments in stock (S&P500) and commodity (gold prices). The structure of this thesis is based on three empirical chapters. We emphasise the focus by acknowledging the risk factor which is the non-stop fluctuation in the prices of commodity and stock prices. The thesis starts by measuring volatility, then dependence which is the correlation and lastly measure the expected shortfalls and Value at risk (VaR). The research focuses on mitigating the risk using VaR measures and assessing the use of the volatility measures such as ARCH and GARCH and basic VaR calculations, we also measured the correlation using the Copula method. Since, the measures of volatility methods have limitations that they can measure single security at a time, the second empirical chapter measures the interdependence of stock and commodity (S&P500 and Gold Price Index) by investigating the risk transmission involved in investing in any of them and whether the ups and downs in the prices of one effect the prices of the other using the Time Varying copula method. Lastly, the third empirical chapter which is the last chapter, investigates the expected shortfalls and Value at Risk (VaR) between the S&P500 and Gold prices Index using the ES-VaR method proposed by Patton, Ziegel and Chen (2018). Volatility is considered to be the most popular and traditional measure of risk. For which we have used ARCH and GARCH model in our first empirical chapter. However, the problem with volatility is that it does not take into account the direction of an investments' movement: volatility of stocks is that they suddenly jump higher and investors are not distressed with gains. When we talk about investors for them the risk is about the odds of losing money, after my research and findings VaR is based on the common-sense fact. Hence, investors care about the odds of big losses, VaR answers the question, what is my worst-case scenario? Or simply how much I could lose in a

really bad month? The results of the thesis demonstrated that measuring volatility (ARCH GARCH) alone was not sufficient in measuring the risk involved in an investment therefore methodologies such as correlation and VAR demonstrates better results. In terms of measuring the interdependence, the Time Varying Copula is used since the dynamic structure of the dependence between the data can be modelled by allowing either the copula function or the dependence parameter to be time varying. Lastly, hybrid model further demonstrates the average return on a risky asset for which Expected Shortfall (ES) along with some quantile dependence and VaR (Value at risk) is utilised. Basel III Accord which is applied in coming years till 2019 focuses more on ES unlike VaR, hence there is little existing work on modelling ES. The thesis focused on the results from the model of Patton, Ziegel and Chen (2018) which is based on the statistical decision theory. Patton, Ziegel and Chen (2018), overcame the problem of elicitability for ES by using ES and VaR jointly and propose the new dynamic model of risk measure. This research adds to the contribution of knowledge that measuring risk by using volatility is not enough for measuring risk, interdependence helps in measuring the dependency of one variable over the other and estimations and inference methods proposed by Patton, Ziegel and Chen (2018) using simulations proposed in ES-VaR model further concludes that ARCH and GARCH or other rolling window models are not enough for determining the risk forecasts. The results suggest, in first empirical chapter we see volatility between Gold prices and S&P500. The second empirical chapter results suggest conditional dependence of the two indexes is strongly time varying. The correlation between the stock is high before 2008. The results further displayed slight stronger bivariate upper tail, which signifies that the conditional dependence of the indexes is influence by positive shocks. The last empirical chapter findings proposed that measuring forecasts using ES-Var model proposed by Patton, Ziegel and Chen (2018) does outer perform forecasts based on univariate GARCH model. Investors want to protect themselves from high losses and ES-VaR model discussed in last chapter would certainly help them to manage their funds properly.

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Chapter 1

Introduction

1.1 Inspiration

The thesis aims at examining the risk measurement and interdependence between the S&P500 and Gold Price index, over the period 1st of January 1992 to 1st of January 2020. The main models of volatility, risk measurement and interdependence named ARCH, GARCH, VaR calculations, Copula Quantile Approach (CQA) and ES-VaR has been utilised. Two segments have been contributed to regarding the progression of the academic exploration regarding risk measurement and interdependence of S&P500 and Gold Price Index. The initial segment has highlighted the risk measurement methods along with reliance on indices of expected volatility. This has permitted us to measure the expected volatility including current and historical volatility such as the GARCH-based methods and realised volatilities of observed cases. Such processes are of high significance to the market operative who have gained greater interest in cross-market implications involving fear proxies including the indices of volatility (Bouri et al., 2017, 2018; Badshah, 2018; Ji et al., 2018). The second segment has evaluated the CQA along with Copula approach which has assisted in assessing the non-linearity in the diversified quantiles-based relationships as well as the extreme and moderate tail dependence scenario. Variations have been observed in differential quantiles of the heterogeneous relationship of S&P500 and Gold Price Index concerning tail dependencies in the respective markets. The segment also takes into account the measurement of risk using the ES-VaR model. The model measures the expected shortfalls and Value-at-risk. Value-at-Risk (VaR) represents the maximum loss in normal market condition during the certain time period at a confidence level (Benninga and Wiener, 1998). In other words, VaR is tolerated the loss while expected shortfall (ES) may take account of a maximum loss. Expected shortfall refers to conditional VaR (cVaR) that is a statistic to be used to measure tail risk (NorthstarRisk, 2022). VaR model has some problems when there is extreme movement in price however, in order to solve the problem inherent, Artzner et al (1997, 1999) suggest the expected shortfall (Yamai, Y and Yoshiba, 2002). ES can be used to measure coherent risk and its value is greater than VaR (Rohmawati and Syuhada, 2015). According to Rockafellar and Uryasev (2000). They predict the smallest of ES can result in the best solution of the VaR due to no excess of ES. The examinations performed in this study have added to previous studies which had the following characteristics:

1: Have relied on the data of returns/prices on silver and gold without taking into account the volatility and risk measurement together (Hammoudeh et al., 2010 Hammoudeh and Yuan, 2008; Sari et al., 2009; Sensoy, 2013; Reboredo and Ugolini, 2015; Pierdzioch et al., 2015; Zhu et al., 2016; Zhu et al., 2016, 2016; Bhatia et al., 2018; Schweikert, 2018).
2: Have employed standardised models including error correction model (ECM), linear quantile regression, vector autoregression (VAR) and GARCH models (Hammoudeh et al., 2010; Sari et al., 2009; Sensoy, 2013; Lau et al., 2017; Bhatia et al., 2018). These do not account for the upper, middle and lower quantiles, tail dependency and ES-VaR model. This study will apply ARCH, GARCH, copula and ES-VaR model to measure the volatility, risk and interdependence.

The implications of this examination are efficacious for the risk managers and investors regarding implications of policies. This is particularly significant concerning the expanding demand for stock and commodities of indices of volatility which are utilised as portfolio diversification instruments and as tools for hedging against the catastrophic or tail events. Computational finance-based practitioners could exploit the empirical analyses of ours through development of strategic trading policies which could be quantile and tail dependent.

The effects of such strategies could be the successful avoidance of loss potentialities of S&P500 and Gold Price Index as well as the accounting of the heterogeneity of such markets. Such loss probabilities emerge from the inaccurate perception that S&P500 and Gold Price Index imply homogeneity. The analyses performed by us have been demonstrative of the existence of extreme asymmetric tail dependence in various upper and lower quantiles. The volatility of S&P500 on that of Gold Price Index regarding particular quantiles and systems of cross volatility have been effectively documented in terms of predictability and this has been unprecedented. This has been an effective extension to the previous studies.

VaR-based risk management systems contribute to increase financial stability, the empirical models of VaR gives the investors the opportunity to measure the risk and mitigate the loss in times of turmoil. The main message to be extracted from this thesis is that risk managers and regulators must be aware of the exogenous risk[1] and endogenous risk and the dynamics

[1] The exogenous risk these are the shocks which come outside of the financial system) – examples can be if an asteroid hit the earth- and endogenous risk (which is the interaction of market participants, each with their own biases, prejudices, abilities and resources) systematic risk is an example of endogenous risk.

potentially induced by the investments in financial markets and by VaR models, how these risks can be mitigated and act to address them. We have taken VaR incorporation with Volatility, Copula and ES-VaR method to measure the volatility, asymmetric dependence and estimated the expected shortfalls using the data of S&P500 and Gold prices index. This research has been carried out using the ARCH AGRCH, copula method and ES-VaR on the data of S&P500 and Gold price index for the analysis. Risk management systems should be combined with other types of measures, such as basic VaR and Copula VaR estimations. In any case, the adequacy of financial enhancement methodologies in investment is to date ineffectively examined (see Larsen et al., 2015). To address this, we particularly require investment dependent countries (e.g., US), this considers points to explore the utility of financial expansion in stock administration of investing, a critical portfolio management for investment (Murray and Brennan, 2009).

At present, numerous entities conduct these tests which are used in these thesis, ARCH GARCH is also used but they only focus on the individual institution and analyse if the entity, considered in isolation, would be able to withstand a shock; ARCH GARCH do not contemplate the fact that entities react to the shock and this has a ripple effect on other institutions the fragility of some stocks can be transmitted to others – and those institutions that could not stand the initial shock can end up failing. The beneficiaries of this study are the investors or the stakeholders of S&P500 and Commodity Index. This thesis is very informative and interesting for the risk management experts. However, this research will not only be beneficial for just the mentioned investors or researchers but will also give the opportunity for other research body institutions to take this research further. The essence that the data (S&P500 and Gold prices) used in this research has been used in few prior researches carried out in the field of value at risk (risk-management) dated till now.

1.2 Rationale behind choosing Gold prices and S&P500

The stock markets are in a constant change. It becomes as a determination for businesses, how they act, in terms of price setting, investing and competition. By always assessing, new competitive advantages, investments, new commodities, or values of stocks and commodities will help the investors and financial regulators to adjust in the constantly changing complex global markets.

1.2.1 Gold prices as a commodity

Gold plays an instrumental role in the global economy both as a high-value consumer good and an investment asset. In examining the centrality of gold in the global economy, World Gold Council (2021) found that gold remains the most effective commodity in an investment portfolio because of six unique characteristics. These attributes include high liquidity, a proven store of value, lower volatility, ability to outperform other commodities during periods of inflation, its higher capability for diversifying investment than other commodities, and its ability to deliver higher absolute and risk-adjusted returns over multiple time horizons than other commodities. As a liquid asset, gold can easily be exchanged for cash in physical commodity markets and gold-backed markets such as exchange-traded funds (ETFs). In periods of economic fortune, consumer expenditure on gold-based jewellery tends to increase. Secondly, gold incurs fewer storage costs, making gold futures less expensive than futures contracts on other commodities like oil that carry extremely high storage costs. McKay and Peters (2017) attribute the lower storage costs to its resistance to corrosion and oxidation.

Generally, less volatile than a most commodity and stock indices, gold makes an investment portfolio more stable and generates higher returns. Gold registers positive returns under both moderate and high inflation periods, while other commodities and stock prices register negative returns. Balcilar et al. (2019) and Hung (2022) share these sentiments while examining the linkages among financial assets. The findings revealed that the S&P 500 (an index showing the stock prices performance of the top 500 companies) index and crude oil are net transmitters of return spillovers, while gold is a net receiver. In contrast, gold is a net transmitter of volatility during crises, making it a safe haven asset.

Gold has always been a very demanding commodity all over the world. When the demand for gold increases, the price of gold as a commodity also increases. Prices of a huge number of commodities are dependent upon the price of gold (Alareeni and Hamdan, 2020). In addition to this, the steady characteristics of gold make itself a commodity that can be compared to currency. This is the reason; gold can be used as a source to hedge inflation and it always holds a significant value. Gold is something that is diversified all over the world than other commodities. It has the capability to influence the price rates of other commodities.

Lastly, the superior performance of gold over other commodity and stock indices makes it a suitable diversification asset to mitigate against systemic risk. For instance, gold has a positive correlation to stocks in periods of economic growth but a negative correlation to stocks in periods of economic downturns when investors dispose of risky stock assets. Other studies that have examined the investment role of gold have drawn the same conclusions. Šoja (2019), for instance, examined the effectiveness of a gold investment portfolio and found that gold does not carry counterparty or credit risk, nor does it lose value during financial crises – attributes that drive its inclusion in investment portfolios. In calculating the proportion of gold needed to reduce a portfolio's risk, the study recommended a 93.3% bond, 5.7% shares, and 1% gold portfolio for a risk-averse investor. on the contrary, a risk-taker will include a bigger share of gold in the portfolio.

Similarly, Shakil et al. (2018) sought to determine whether gold is a hedge (asset classes with negative correlation to another asset on average) or a haven (asset or portfolio with negative correlation in times of market crisis) using the autoregressive distributed lag model ARDL approach. After conducting relevant monthly time series analyses, the study found that gold is a hedge asset for mitigating against portfolio and inflation risks since it is not affected by the consumer prices index (CPI). Overall, the findings from these studies reiterate the prominence of gold in the stabilization of the global economy and currency markets. As a commodity the product is up for trade, commerce and is not considered as a service. Being interchangeable can be traded for money or other commodities or services. In this way it can be argued that it can be seen as a currency. Have in mind it can be used in production for services or products. Many banks, governments or financial organizations keep gold stocked in the means of future trade, wealth or as an investment (Jewellery Quarter Bullion Ltd, 2022).

As said, gold is for trading and wealth, but it is also kept as a safety. Due to the limitation of supply, and slow degree of change in value, it is a safety in inflation of other factors. The ownership will in an inflation where the value of a currency diminishes be a confidence to stay valuable in a weak economic environment as the demand increases. (Gallagher, 2020)

1.2.2 S&P 500

This is a stock market index in the United States, where a committee select businesses from specified criteria's to be included in the index. With reviewing the market capitalization of the corporations, the total value of all shares of stock a company publicized is then calculated and the market cap is found. The importance is that the index is a way to get an insight in the economy of United States, and for investors be see if investing would have a positive means-end (Amadeo, 2022). It is the one that regulates if the stock market goes up or down (Daks, 2021).

1.2.3 Importance of Gold Prices and S&P 500

In terms of the S&P 500, the relation between the gold price and Standard and Poor's 500 is negatively related to each other (Ritala et al., 2018). It has been found with the increase when the price of gold goes up, stocks go down and vice versa. However, this relationship between the gold price and S&P 500 has been debated for a long time now.
Gold as a commodity, according to new research, may be advantageous to build a portfolio with the stock market since it may be used as a hedge and diversifier in a range of scenarios. According to the World Gold Council, gold is the most popular precious metal among investors since it is the most accessible precious metal market information.

In 2010, after years of debate, the first comprehensive definition of hedging, which was based on asset correlation, was finally released. For the first and only time in history, the phrases "hedge" and "safe haven" were used to refer to financial assets, marking a watershed moment in history (uncorrelated). Another indication of this tendency is the low price of secure real estate, which has reached an all-time low and is on the verge of being extinct. It is vital in the explanations of how and why "extreme occurrences" occur at the extremities of distributions that linear correlation be used in these theories' explanations of how and why "extreme occurrences" (Gürgün and Ünalmış, 2014).

As can be seen in the accompanying image, they used a bivariate VAR-GARCH model to analyse their data to arrive at their conclusions. As a consequence of these considerations, they came to the conclusion that gold's low volatility and high rate of return may be beneficial in the revival of China's stock market (Wang, 2021).

In 2013, a group of researchers observed that there was a link between the Shanghai Composite Index and stock indexes for gold mining businesses, and they published their results in the Economic Journal in 2013. Shen et al., 2020 observed that bivariate copula GARCH models were statistically significant when compared to other models. In many cases, the price of gold is inversely proportionate to the return on an investment in the stock market.

Using data from the gold market and the Indian industrial sector, Kumar (2014) performed an analysis that was published in 2014. The findings of this study suggest that gold is an advantageous investment since it boosts risk-adjusted returns while also offering security against volatile markets and rising prices at the same time, so increasing overall returns.

If precious metals are compared to stock markets, in certain nations they are more stable, whilst in others, the contrary is true. It is possible, according to the authors, to use any metal to reduce the risk associated with investing in the stock market. According to the authors, any metal may be used to reduce the risk associated with investing in the stock market (Bauer and McDermott, 2010). The authors of Baur and McDermott (2010) state that any metal may be utilised as a hedge against the risks associated with investing in the stock market (2010).

A study carried out by Klein (2017) from January to December 2016 examines how metals are priced and how new markets are developing in the United States. Unlike other assets, gold and silver are considered permanent assets using the DCC-GARCH model, which means that they cannot be swapped as other assets may be. Because of its extreme volatility, platinum has traditionally been seen as a short-term safe-haven asset; however, this has altered in recent years. Using research carried out by He et al. (2018) it was revealed that gold is seen as a safe haven asset, regardless of whether one is in the United Kingdom or the United States of America (He, O'Connor and Thijssen, 2018). Contrary to popular belief, however, gold is not the only haven for stock markets in either the United Kingdom or the United States, despite the fact that it is often used in that capacity (Capital asset pricing model). With the support of other experts, Dutta et al. (2021) did study on the risk-hedging capacities of commodities such as gold and oil, among other topics. Because gold is utilised as a hedging tool in the stock market, it has a major advantage over oil in terms of value.

Stock exchanges around the world have proven that commodities, particularly precious metals, are effective risk-hedging and diversification techniques, with different stock exchanges around the world demonstrating the greatest success. The stock market in the United States has proven to be the most successful, with the stock market in the United Kingdom being the second most successful. Gold and other precious metals, according to data, are ideal safe-haven investments for investors in both developed and emerging stock markets (Alqaralleh and Canepa, 2022).

1.2.4 Gold is an important commodity

Gold is a very special and valuable commodity from Egyptian times, and it has been considered the symbolic value for humanity. In ancient times gold was used as a medium for exchange. Gold is a valuable and demanding commodity, and its market value always fluctuates (Yilmazkuday, 2021). It is a luxury commodity. The way it is mined, its metallic qualities, and its lustrous quality made it valuable and costly. It is an important commodity, especially for India because the price of other products of India are based on the price of gold. Gold is considered a commodity with several unique qualities which can be used for different purposes (Ma et al., 2019). This is the reason behind the necessity of investors to hold gold in their portfolios. Gold holds a good position in the monetary economy.

1.2.5 Importance of the S&P 500

S&P 500 is important and a good source for investors because when it is bought in a single security, diversified benefits can be achieved immediately. This helps in spreading out the risk of investment over different sizes and different types of industries (Alareeni and Hamdan, 2020). This benefit helps investors to play safely in the marketplace.

1.2.6 Measuring risk in commodity and stock markets

Risks in the commodity and stock markets can be measured with the help of five distinct measures that are Sharpe ratio, beta, alpha, standard deviation, and R-squared. Each of these measures can either be used individually or also together. The process of risk assessment in the stock market becomes a lot easier with the help of these measures (Wu et al., 2017). At the time of comparing two or more investments, these measures can be used to analyse the potential risks of each of the investments. The risks that are related to the market or risks related to the index of a particular benchmark can be calculated with the help of alpha. Systematic risks can be assessed through beta. R-squared can be used to calculate risks related to expect and actual movements of investment (Ritala et al., 2018). Standard deviation and Sharpe ratio are the two measures that can be used to assess risks in terms of the mean value of the set of data and calculation ROI (Return on Investment) of risk-free investments.

1.2.7 Measurement of risk

Measuring risk is a key factor for a business and its performance. The price volatility in the markets can be measured with risk management, given a holistic overview by analysing the business across the ecosystem and segments of consumers. This can be done by calculation of commodity exposure, how the prices would affect the business aligned with financials within and securing it with options as due to action performed. (Oliver Wyman, 2021)

According to Carlozo (2018), the value investors are willing to trade the S&P500 because born as an index the risks are minimised as it consists of the top 500 companies in the US. Periodically, the index is updated to insert the companies that have performed very well and eliminate those that have not carried out a good performance, so even if a company is making big losses, the investors can still be in profit because the other companies may be hiking, so there is good diversification of risks. Boyle (2021), explain how the gold price can change daily, and an important point is made based on the demand for jewellery, the production of gold, both are analysed as demand and supply, then the reserve that a central bank has in order to be a credible country, also the value of the currencies and last but not least the volatility of the markets. Different studies show that the price of gold is negatively correlated with the US equity market during the recessions period, that is because investors feel more comfortable buying commodities that are more tangible and the value will depreciate with less probability (Junttila et al,. 2018). However, the gold market is all across the world and companies that produce gold will only deliver a small fraction of annual worldwide demand, so the potential effect of the movement in the gold price and the market value of the company, and vice versa, may be non-linear and may, moreover, differ widely across gold companies, since they have different market shares and so implement different risk management strategies to protect revenues against gold price changes (Reboredo and Ugolini, 2017). Empirical evidence of risks between the gold price and S&P500 appear that investors can use gold as a substitute for stocks to hedge themselves against inflation as in the short-run the volatility of gold price has no impact over the S&P500, so for the short-run investors are not impacted, but for the long-run, this volatility can strike investors as the 14% of the S&P500 is made of materials and energy (Gokmenoglu and Fazlollahi, 2015).

Commodity risk is also aligned with the risk measurement of stock market in addition to stock prices and interest- and exchange rate. The volatility of prices and changes in markets which has exposure the risk assessment comes from identifying them and representing them as a model in portfolios. They provide information processed from financial elements. Data such as previous prices and rates (CFA Institute, 2022). In addition, changes from different market factors also play a role in, but monitoring inflation, happenings and rates will give businesses and investors information to assess the risks. A method to use is the VaR method, value- at-risk, which measures by a statistical method. Calculations of loss that will happen from a stock or portfolio and the probability. It uses price units or a percentage in the calculations. (Finance Management, 2022).

Gold has a special place of actual and symbolic importance for humans since ancient civilizations, from the Egyptians to the Inca. In addition, gold has been utilised as a medium of commerce, a store of wealth, expensive jewellery and other artefacts. For thousands of years, gold has been used to create decorative artefacts and excellent jewellery. Mineral wealth is often more extensively scattered over the globe than many industrial metals, and come in a broad range of shapes and sizes, ranging from huge and complex quartz-pebble conglomerate deposits to secondary alluvial deposits near the surface. While the former can only be mined by large corporations with a lot of money, the latter may be mined with little money and infrastructure, making it available to lesser players (Verbrugge and Geenen, 2019).

Financial markets have grown significantly in recent decades as a result of the creation of new novel financial instruments. The riskiness of underlying assets has increased as a result of the massive growth in financial markets, forcing investors to seek out a safe haven investment. Gold, the most widely held precious metal, has long served as a primary store of wealth against inflation and volatile investments. Traditional thinking is that gold has always been a secure investment option for people throughout history, and this concept still holds true now (Balcilar et al., 2021). The gold price can be influenced by different factors one of them is S&P 500.

The Standard and Poor 500 index (S&P 500) is widely regarded as a key benchmark index for the stock market. The index, which is made up of 500 large-cap businesses from a variety of industries, captures the pulse of the American corporate economy (Bennett, B. et el 2020). S&P 500 is a market capitalization-weighted index of the 500 largest publicly traded firms in the United States. The index is largely recognised as the most accurate indicator of large-cap U.S. stocks (Kieu et al., 2021). In both normal times and during stock market crises, gold and the S&P500 do not move in lockstep. As a result, gold is a poor hedge and a poor safe haven. Gold returns in the lower quantiles are inversely associated to positive S&P500 returns, while the upper quantiles are inversely related. The relationship between gold returns and moderately negative S&P500 returns, on the other hand, is positive at lower quantiles and negative at higher quantiles. This shows that changes in the price of gold are amplified by contemporaneous stock returns under severe conditions, as seen by the lower and upper conditional quantiles. Surprisingly, a negative shock in equities prices has little effect on gold return quantiles (Kuck, 2021).

Value-at-risk (VaR) is a statistical method for estimating the possible losses that an asset, portfolio, or company could suffer over time. Mean-variance analysis is used in the parametric approach to VaR to predict future events based on prior experience. It is being used to identify spillover patterns, cycles, and bursts in returns or return volatilities (or, for that matter, any return characteristic of interest) across individual assets, asset portfolios, asset markets, and so on, both within and beyond countries (Khalfaoui et al., 2022)

The economy is now so complex and integrated cross over, the knowledge on what and how to work a business with a positive outcome is key. By assessing risks and analysing, businesses will be more survivable. Commodities, such as gold, has become important to become secure in the constant change of market. The risk will always be there but knowing how to assess it and base the decision of it, is a necessity nowadays. Gold prices can be a good commodity during recession period compared to stocks, but however, considering the diversification of the S&P500, it can be argued that over the long run this index can be very profitable and less risky than commodities, which are more volatile because of the supply and demand adjustments and also gold mining company can be also in losses despite the gold price movements, moreover the reserve of central banks and the currencies play an important role on the gold price, while S&P500 have less volatility.

1.3 Relevance of Time Period 1992 to 2020

The relevance of this time period 1992 to 2020 is quite vital for this research. As, we have tried to analyse the volatility, interdependence and expected shortfall along with Value at risk during all times. The reason for choosing the extensive time period is to have a solid data analysis with good findings. In order to stress upon the fact of the relevance of the time period we have discussed the time intervals below:

1.3.1 Early 1990s Recession

The Early 1990s Recession lasted from July 1990 to March 1991. Despite being relatively short-lived and mild, its impacts were quite vital. Following the collapse of the savings-and-loan industry in the mid-1980s and the United States Federal Reserve raising interest rates in the late 1980s, this recession was caused by Iraq's invasion of Kuwait in the summer of 1990. This event increased the global price of oil, lowered consumer confidence, and exacerbated an already existing downturn (The Recession of the Early 1990s, 2015).

1.3.2 Dot-com Bubble

The Dot-com Bubble arose from a surge in investments in anything related to the Internet, as well as other technological stocks, in the 1990s. Several new firms arose during this time, the great majority of which failed to make a profit. Over an 18-month period, the Nasdaq index tripled in value, peaking in March 2000. That same index, however, had lost more than half of its value by the end of the second millennium's last year when the bubble eventually burst and would not survive until 2015 (Williams, 2022).

Enormous amount of venture cash was invested into computer and Internet firms, and investors continued to buy shares in these businesses on the premise that they would succeed. When these firms ran out of cash and new funding sources stopped up, the euphoria turned to panic. Between March and October 2002, the ensuing crash wiped approximately $5 trillion in value in the technology sector (Williams, 2022).

1.3.3 U. S. Bear Market of 2007–2009

The bear market lasted from 2007 to 2009, with a 1.5-month bull market near the conclusion. The S&P 500 index dropped by 51.9%. While this isn't a true stock market crash because of the length of the slide, the magnitude of the losses makes it worth highlighting (Quiggin, 2011).

1.3.4 Financial Crisis of 2007–08

The Financial Crisis of 2007–08, also known as the Subprime Mortgage Crisis, resulted from the collapse of the US housing market, and contributed to the Great Recession. Prior to the crisis, the Fed slowly raised the federal funds rate from 1.25% to 5.25%, leading to an increase in the number of subprime borrowers defaulting. When the resulting housing bubble burst, it set off a chain reaction that prompted even huge financial institutions to sell hedge funds investing in mortgage-backed securities, apply for government loans, merge with healthier corporations, or claim bankruptcy (Brian, 2019).

By 2008, the US Treasury Department had no choice but to nationalize Fannie Mae and Freddie Mac, the country's two largest mortgage lenders, in order to prevent their collapse. Later that year, Lehman Brothers, an investment firm, declared the largest bankruptcy in US history. The US government authorized a rescue plan in October 2008 in order to protect the financial system and foster economic growth in the United States. The economy had finally started to revive by mid-2009 (Brian, 2019).

1.3.5 2010 Flash crash

During the 36 minutes, the price of the S&P 500, the Nasdaq 100, and the Russell 2000 rapidly dropped and rose on 6 May 2010. According to the Dow Jones Industrial Average, roughly $1 trillion of market cap disappeared. Even though 70% of the share price could recoup by end of the trading day. In September 2010, the SEC and CFTC found that the numerous E-MINI S&P 500 future trading, illegal trading, and when the stock started to plunge, the electronic liquidity provider offer the price. This could lead to the Flash Crash (Brian, 2019).

1.3.6 August 2011 Stock Markets Fall

the U.S economy weakened and Investors who are unwilling and not confident increased by expending debt crisis in Europe. It Resulted in fall U.S and global stock markets. In the event of impasse, Standard & Poor's of the three most significant rating agencies gave the U.S a credit downgrade for the first time in history. Although the political matter solved however, the nation's finance of requirement has not reached the agreement of the S&P agency (Wearden and Batty, 2011).

1.3.7 2015-16 stock market selloff

The 2015-16 stock market selloff means that one year starting June 2015 shows the global selloff. According to the DJIA, it decreased 530.94 (3.1%) in August 2015. In the beginning, the market fluctuated in China. However, China could not be only blame for the crisis. China has been in turmoil and there is also crisis over the world such as a fall in petrol price, the Brexit vote, and end of quantitative easing in the U.S. in these tough situations, investors have been selling shares broadly (Williams, 2022). The U.S stock market is worth to watch because these have an impact on U.S stock market and the other countries such as China (Corbet, Dowling and Cummins, 2015).

1.3.8 2020 Coronavirus Stock Market Crash

There was a current the U.S stock market crash that happened due to the COVID-19 pandemic. On 16 March, the trading stopped many times in a day because it was all of a sudden and volatile. In the U.S. the DJAS fell the share price approximately 37% and NYSE trading halted multiple times. There were more serious impacts on transportation due to travel restrictions to prevent the spread of COVID -19 like cruise company, airlines (Mazur et al., 2021).

While the pandemic continues, there are some positive changes in stock market. As result of rapid implement with Fed, the Treasury Department and Congress. When the crisis begins, they implement a new scheme such as cutting interest rates, new lending programs, stimulus checks, and approving supplemental unemployment benefits simultaneously. It resulted in the stock market started to increase and the S&P 500 hit highest record again on 18 August. The DJAS hit over 30,000 for the first time on 24 November (Mazur et al., 2021).

Though the time period did not take into account the full year of 2020 but the purpose of providing the relevance of the time period selected is that we have also touched upon the start of the pandemic from 2019. However, the thesis is specifically not emphasising on the pandemic. The thesis takes into account the data from 1992 to 2020 to measure volatility, interdependence and ES-VaR so as to provide investors, regulators, financial analyst and policy makers with information that would help them in financial decision making.

1.4 Aims and Objectives of the Thesis

1.4.1 Research Objectives

The overall objective of the thesis is to assess the volatility, interdependence and risk factor using risk measurement that is Value at Risk (VaR), volatility measure ARCH and GARCH and Interdependence using time series copula of S&P500 and Gold price indexes in order to know the determinants that are necessary for many investment companies and fund managers investment in securities whose values are associated with the index value, these securities are known as index fund. An "index fund" is a type of mutual fund or exchange-traded fund that seeks to track the returns of a market index. The major component is the to access different methods of computing volatility, interdependence and VaR associated with index fund that is linked with the S&P500 and Gold Price index. The thesis aims to evaluate the Goodness-of-Fit (GoF) for two risk measures: value-at-risk and Expected Shortfall on gold prices and S&P500. This will be achieved by first applying a two-step estimation method using ARCH GARCH, Constant copula, Time Varying Copula and then use empirical distributions of simulated returns to estimate the VaR and ES measure. We will also check the accuracy of the proposed methods using different approaches such as bootstrap, simulations and GoF. Whereas, S&P00 index and Gold Price Index has been chosen as the main financial institution for the research.

1.4.2 Aims

1. Aim of Chapter 2 is: To measure volatility of S&P500 and Gold Price Index in order to examine the significance of volatility?
2. Aim of Chapter 3 is: To identify the interdependence between S&P500 and Gold Price Index.
3. Aim of Chapter 4 is: to measure risk and expected shortfall between S&P500 and Gold Price Index.

1.5 Research Questions

This research basically measures the volatility, correlation, value at risk and expected shortfalls of a commodity and stock to determine the relevance of risk measurement and correlation for financial investors. In order to determine the relevance of risk we prepared the thesis using the VaR model approach, comprising of 3 empirical chapters. We commenced by using some basic volatility and risk calculating methods such as the ARCH GARCH, and basic VaR calculations, this basically helps in determining the factors that are important for mitigating the risk in certain time frame when some variables are kept constant. We have also accessed that although volatility is widely used for measuring risk but it is not effective alone in measuring risk because of which we used value at risk. We further used advance measurement of Time Varying Copula along with Goodness of fit and bootstrap methods. This helped us in determining the correlation of the indexes. Lastly, we use the ES-VaR model for determining the Value at Risk and Expected Shortfalls in both S&P500 and Gold Price Index. This thesis focuses on long time period data which covers the crisis time as well. Keeping the general objectives in mind, we aim on answering vital research questions mentioned below for a systematic descriptive approach to assess the correlations and the linkages between Commodity and Stocks using VaR.

A. Our research question for chapter 2 is: What are the different kinds of volatility measures? How volatility is effective in measuring risk? What is the volatility of S&P500 and Gold Price Index? Why volatility alone is not a good indicator of risk?
   i. The questions will be explained by using univariate volatility and some risk measures ARCH GARCH, VaR calculation, Historic VaR and Expected Shortfall models.

Overall, this chapter estimates volatility and risk using measures methods (ARCH GARCH, VaR, Historic VaR and Expected Shortfall) for Gold price Index and S&P500.

B. In chapter 3, we will be determining the existence of time varying behaviour in the time series of S&P500 and Gold Price index of the estimated parameter. Bearing this in mind we will aim at answering the following questions for chapter 3 through the measurement of examination: Does the prices of S&P500 depends on the changes in the prices of Gold price? What is the correlation between the two indexes? Will sudden rises during different time intervals will affect either of the indexes? How independent are both indexes? Which market is safer choice for investing in for a profitable gain using the Time Varying copula?
   i. The relationship between S&P500 and Gold price index will be assessed from the use of the descriptive data measured in the beginning. The kurtosis will determine the sharpness of the peaks and will answer the thin tail or fat tails of the stocks and indexes used. The shocks in prices of either of the indexes and their interdependence will be assessed through Time Varying Copula method proposed by Sklar (1959). Risk importance will be determined through the theoretical aspect of the Copula model.
   ii. The chapter aims to provide all clear aspects in a systematic manner by using the goodness of fit, which will further determine the efficiency of the model as well. The Time Varying copula will determine the interdependence of both indexes.

Hence, an econometric Copula model proposed by Patton (2013) will be adopted and is applied to measure the asymmetric conditional dependence for Gold Price Index and S&P500.

C. After assessing the factors of VaR using Time Varying Copula, we investigated that the model will be more useful when used with advanced ES-VaR model proposed by Patton, Ziegel and Chen (2018). This raises further questions like: How does ES-VaR relate to investors' risk management? What is the effectiveness of value-at-risk (VaR) and Expected Shortfall (ES) in measuring the uncertainty involved in Gold prices and S&P500?

i. After the use of the Time Varying Copula and the model proposed by Patton (2013) we have assessed the relationship between the indexes. The Goodness of fit further explained the clarity of the results and the model. After determining this we will use the ES-VaR model proposed by Patton, Ziegel and Chen (2018) which will answer the effectiveness of VaR and ES in order to measure the uncertainty involved in the indexes.

Therefore, we will use ES-VaR Model proposed by Patton, Ziegel and Chen (2018) and apply that model for VaR and Expected Shortfall estimation.

1.6 Synopsis of the Thesis

The market risk refers to the chance of financial loss due to the joint movement of systematic financial variables such as interest and exchange rates. Market risk refers to a risk of losses that is shows the adverse price movement of liquid financial instruments. Companies are more likely to become exposed to market risk. Market risk includes interest rate risk, foreign exchange risk and commodity risk because of the volatility of interest rate, corporates expended to the other countries that may cause foreign exchange risks and commodity risks (Alexander, 2009). The methods of measurement of market risk can be divided into two categories. First method is to approach stochastically based on portfolio's profit and loss (P&S). Value-at-Risk (VaR)is the most popular method that this is interpreted 1 or 5 percentage Quantile of the P&L distribution. And second method is called Maximum Loss (ML) or expected shortfall which can quantify using the value of worst-case scenario. However, it does not consider correlations (Studer, 1997).Quantifying market risk is significant to regulators in assessing solvency and to risk managers in allocating scarce capital. Furthermore, market risk is often the central risk faced by financial institutions. In order to quantify the market risk, we can use a measure known as Value-at-risk (VaR). VaR is a measure which determines the risk of loss taken in any investments of stock or commodity. During the 1990's, Value-at-Risk (VaR) was widely adopted for measuring market risk in trading portfolios. Its origins can be traced back as far as 1922 to capital requirements; the New York Stock Exchange imposed on member firms. VaR also has roots in portfolio theory and a crude VaR measure published in 1945 (Holton, 2002). Value at Risk has been universally accepted as a measure of market risk in the financial institutions.

VaR is a valuable risk measure broadly used by financial institutions all over the world. VaR is admired among researchers, practitioners, regulators and risk managers of financial institutions. VaR has been widely used to measure systematic risk exposure in developed markets like of the US, Europe and Asia. A lot of research has been done in the field of Value at Risk leading to the development of differing approaches to estimate. However, each method such as historical VaR (this measure relies on historic data for the forecasts), whereas EWMA (Exponential Weighted Moving Averages) emphasise more on recent data. Therefore, each model has its own set of assumptions and there is very little consensus on the preferred method to estimate Value at Risk. Since, financial investors resume that it is very important to have knowledge about the standard variations of the annualized returns over a period of time. Therefore, for this thesis we have addressed the importance of S&P500 and Gold Index and will further discuss the relevance of measuring volatility, interdependence, expected shortfall and Value at Risk to mitigate losses and determine good investment strategy to plan during the recession times and turmoil periods using the asymmetric models and risk measuring models which is achievable to some extent by measuring correlation and risk measures simultaneously. This will not only give investors and financial analyst an insight on the performances of indexes but also allow them to prepare mitigating strategies for minimising any shocks that can arise at times of turmoil or vice versa. All existing methods involve same trade-off and simplifications, determining the best methodology for estimating Value at Risk becomes an empirical question for implementing the most suitable model. In this thesis, we have analysed the accuracy of VaR measure for America's developed stock market using daily data from the S&P500 and Gold Price index during the period January 1992 to December 2020.

This thesis proposes the use of models, which are ARCH GARCH, Constant Copula, basic VaR calculations, Time Varying Copula, Goodness of Fit, Conditional VaR, VaR Copula, Expected Shortfalls and GAS, for estimating volatility, correlation and VaR in S&P500 and Gold Price index market. It comprises of 3 empirical chapters using the models mentioned previously. The overall empirical results demonstrated that the univariate methodologies (ARCH GARCH) have estimated volatility and provided a good foundation for accessing the presence of risk. In terms of the Time Varying Copula methods and constant copula methods they have certainly estimated the correlation and interdependence of both indices and Hybrid Model ES-VaR analysed the worst case scenario and forecasts for investors and policymakers in pricing and hedging commodity prices and stock prices. In terms of conservativeness, the conditional VaR the ARCH and GARCH model, basic VaR model and some Expected Shortfall methods were used. The thesis commences with volatility models and risk models, for correlation the Copula VaR method was utilised accompanied with Time Varying Copula method, and last chapter consists of VaR Expected Shortfall (ES-VaR model) proposed by Patton, Ziegel and Chen (2018) for determining volatility, risk and correlation between the two indexes. For a detailed further insight on each empirical chapter we have provided short description of what each chapter holds below:

Chapter 2, explains the uneven prices of Gold Index and S&P500 stock index based on the volatility of both the stocks over the period of 1992-2020. For the study we have used the model of ARCH and GARCH along with basic VaR calculations. The models of measuring the volatility have been utilised for the progression of the academic exploration regarding interdependence of Gold and S&P500. The initial segments of GARCH and VaR has highlighted the reliance on indices of expected volatility implied by data gathered from Bloomberg. The utilisation of these models has permitted us to measure the volatility of the commodity and stock. Methods such as the ARCH and GARCH effectively measures the realised volatilities of both the indices. Hence, these processes are of high significance to the market investors who have gained greater interest in cross-market implications involving risk of substitutes that includes other alternative indices that consists of expected volatility implied stocks (Bouri et al., 2017; Badshah, 2017; Ji et al., 2018). The basic calculation of VaR has evaluated the multivariant factor which has assisted in assessing the non-linearity in the diversified risk measurement based on the relationship of the extreme and moderate dependence scenario. The results demonstrate the existence of volatility between the time series data. The VaR results suggest the losses in worst case scenarios. The data analysis will further clarify the results discussed in the chapter.

Chapter 3, aims at the parametric examination of the interdependence between the Gold Index and S&P500 and how efficient is Copula in measuring the interdependence in normal time and financial collapse time that occurred in the late 2000s. Since the time period covers both the period the turmoil period has been considered as well by using the Copula approach on stock and commodity market. Methods has been proposed by us primarily for optimal model selection in the meantime of creating provisional margins. Constant copula evaluated the results quite well since the use of Clayton, Gumbel along with other dependence structure performed very well. However, Constant Copula model assists the financial regulators to measure the multivariate distribution functions and measure the interdependence. The Time Varying copula model measured the shared provisional distribution, where Creal et al. (2012) generalised autoregressive score (GAS) model is utilized to demonstrate the copula parameters evaluation. Bivariate tail's upper and lower parts are assessed individually to get the results of uneven trend. The conditional dependency of both markets is Time Varying.

Since, the data also covers the crisis period prior to 2008 and post to the crisis time intervals the analysis shows that the connection increased significantly after the crisis, the presence of the risk elements involved and the relation between the two indexes which further portrays the clear presence of contamination between the two markets while the correlation decreased before the crisis which took place throughout the world. The second concern is the use of a quantitative approach to copula which helps not only to create nonlinearity between different quantities, but also copulate the interdependence and extreme copulas dependence. Also, it is suggested by upper tail of a slightly stronger bivariate tail that provisional reliance of stock returns is more drastically influenced by positive shocks in S&P500 index market which the findings of this chapter demonstrate. It is clearly visible that the difference among upper and lower of tail is significant when a test was carried to check that finding and as a result it got approved.

Chapter 4, seeks to examine the relation between discretionary volatility of Gold Price Index and S&P500 by means of ES-VaR approach. The chapter adds in the academic discussion of the Gold price index and S&P500 stocks by the use of the risk models measuring VaR estimations. The first concern is dependency on the choice of implied Gold Price Index and S&P500 Index volatility indicators, which enable us not only to account for historical and current volatility, for instance in the cases of GARCH and GAS centric volatility or processes, but the chapter focuses on Expected Shortfall and Value at Risk measurement. Expected Shortfall (ES) is more sensitive to the shape of the tail of the loss distribution Patton, Ziegel and Chen (2018). The Basel III Accord, which will be executed in the years paving the way to 2019, puts new consideration on ES, yet dissimilar to VaR, there is small existing work on displaying ES. We utilize ongoing outcomes from factual choice hypothesis to beat the issue of "elicitability for ES by demonstrating ES and VaR together, and propose the use of the new unique models for these risk measures. We give assessment and derivation techniques to the proposed models, and affirm by means of re-enactment that the strategies have great limited example properties. We apply these models to day by day returns on two financial records, and discover the proposed new ES-VaR models estimates dependent on GARCH.

Subsequently, the heterogeneous relationship between Gold price Index and S&P500 Index may differ with regards to the tail dependence of the respective Gold Price Index and S&P500 Index in various quantities. In that sense, our research adds previous studies that typically depend on Gold Price Index and S&P500 Index prices and return data to the detriment of expected future volatility data such as option induced volatility (Aloui et al., 2013; Hammoudeh et al., 2010; Sari, et al., 2010; Sensoy, 2013; Reboredo and Ugolini, 2015; Pierdzioch et al., 2015; Zhu et al., 2016; Bhatia et al., 2018; Schweikert, 2018) and utilizing standard models such as Vector Autoregression (VAR), error correction model (ECM), linear quantile regression (QR), and GARCH processes which does not account for lower, middle, and upper quantiles (i.e. different volatility regimes) tail dependency and heterogeneity (Demir et al., 2018).

CHAPTER 2

Estimation of Volatility using ARCH and GARCH Models for S&P500 and Gold Price Index

2.1 Introduction

During the last decades, financial organisations, as well as regulators, use Value-at-Risk (VaR) in terms of determining the market risk (Nieto and Ruiz, 2016). It is important for organisations to estimate the market risk to determine the overall success including the sustainability of their company. Value-at-Risk (VaR) models highlight the fact that how can the value of a portfolio be decreased over a period of time. An important volatility model which is termed as GARCH model assist the financial regulators to estimate the fluctuations of prices in the stocks and commodities. We will be using basic VaR model, Historical VaR, ARCH, GARCH model and Expected shortfall measurement in this chapter. Through analysing the daily day returns, these models assist Financial investors to understand the financial trend in the stock and commodity market which is important for operating proper transaction and financial functions in terms of investments.

Some of the literature reviews have been utilised for this paper. Reboredo and Ugolini (2015) indicates that a class of heterogeneous assets is represented through precious metals and this suggests the necessity of separate consideration of the strategic commodity and stock (Gold index and S&P500) based markets. By using ARCH and GARCH models' financial regulators are able to determine the volatility in portfolio with not only single assets, they are also able to determine the fluctuation trends associated with many assets in one portfolio (Andersen et al., 2011; Deo et al., 2006; Tauchen, 2001). However, we will be utilising univariate model of ARCH and GARCH for measuring volatility. In terms of measuring risk VaR and Historic VaR with some calculations of Expected shortfall has been utilised. Some of the literature that' involves the risk are by Zhu et al, (2016) involving strong and weak risk management (Lucey and Tully, 2006), (Pierdzioch et al., 2015), and GARCH (Schweikert, 2018) factors within such volatility and risk measurement. Financial organisation can use these models in term of analysing the financial database which will assist the financial regulators to understand how things can go bad in the financial assets of the organisation. The researches available also shows that through using proper risk management process, organisation would be able to attend proper framework in term of analysing the financial condition of the organisation.

Standardised models of ARCH, GARCH, ES and VAR have been utilised by various studies to evaluate the linkages involving volatility of returns generated by S&P500 and Gold markets. Capturing dependence has not been properly performed by the risk measuring models therefore the interdependence is measured in chapter 3 of this thesis.

Our aim is to measure volatility and risk between S&P500 and Gold index using the models VaR, Historical VaR, ARCH, GARCH and Expected Shortfall. The reason of using the volatility measuring models along with risk measurement model is because this will enable us to identify the presence of fluctuations in prices of the indexes and the risk calculations will help in mitigating losses, and also help investors in improving their forecast of stock and commodity prices evolution.

Moreover, the process of combining these models, ARCH,GARCH,VaR, Expected shortfall and Historical VaR, it is also possible to have more clearer results in measuring fluctuations of returns and the worst losses for investors in different time intervals. It can be stated that today's financial investors use these processes in terms of understanding how financial risks can impact the organisation. The concept of VaR has been adopted by regulators. VaR has been a component of both the Basel I and Basel II recommendations on keeping money laws and regulations issued by the Basel Committee on Banking Supervision.

Objectives will be achieved through using the ARCH and GARCH model, financial organisation will be able to analyse the volatility of the assets. Generalized autoregressive conditional heteroscedasticity (GARCH) is associated with estimating the financial return in an organisation. In this aspect, the financial organisation needs to understand how the GARCH model will be applied in the financial framework of the organisation in term of dealing with the volatility. Using the ARCH and GARCH model the financial investors can easily understand the possible fluctuation factors which is the volatility that are associated with the financial framework.

The paper will contribute to knowledge because the use of ARCH and GARCH model along with risk measures it is possible for the financial organisation to deal with the economic slowdown in the market by accessing volatility followed with risk measurement models. The chapter covers two methodologies used together which very few researchers have used. The time period of data used for this research is also quite extensive and there are few evident researches which have utilised these indexes together for the time period considered for this thesis.

The chapter focuses on the use of ARCH and GARCH and risk measuring model VaR between Gold Price Index and S&P500. This will be helpful for financial regulators to use these models to measure the volatility and risk. Moreover, these models also assist the Financial investors to determine proper strategies in term of dealing with risk. Several risk management models like, VaR, Historical VaR and Expected Shortfall are used by organisations and financial institution in terms of dealing with the financial crisis, in which the organisation use these models to analyse the annual financial database. The results suggest that AR-GARCH and GJR-GARCH model with t distribution is superior to AR-GARCH and GJR-GARCH with normal distribution. . The ES results indicates the worst cases within the confidence level accessed.

The results implication suggests that volatility measures have analysed each aspect of the autoregressive models and the basic calculations of risk have measured VaR for determining the least amount of risk using certain confidence levels. The result implies that the volatility of both assets provides the clear assessment of the portfolio risks[2] which again is helpful in measuring some aspect of the risk. The risk models analyse the market risk of both the indexes.

This chapter highlights the literature review and then the methodology that is associated with ARCH/GARCH, and VaR model framework. In addition to that, the paper also represents the clear understanding of the use of these models in terms of using effective volatility and risk management tools. It uses relevant resources in analysing the Gold Index and S&P500 data, which assist learner to understand the tools and process that are associated with risk management process. Finally, it represents the implication of findings of the practical field.

2.2 Literature Review

There is now a huge and increasing literature on value-at-risk, ARCH and GARCH models. Some related papers are reviewed in this study. Since, there are miscellaneous ranges of

[2] Portfolio risk is a chance that the combination of assets or units, within the investments that you own, fail to meet financial objectives. Each investment within a portfolio carries its own risk, with higher potential return typically meaning higher risk.

research papers consisting of different securities researched for different time frames having one common trait of financial volatility which makes GARCH model quite appealing due to its nature of measuring the correlations of securities. In order to address all these aspects, there are a couple of existing studies utilizing the GARCH model as well as other approaches in the literature. Getting started firstly we will examine some former studies utilizing developed and emerging economies that investigated in the stock's volatility. Hence, this would help us to understand the volatility of S&P500 and Gold index to analyse the risk involved which is our aim in this chapter.

Throughout the 1990's, Value-at-Risk (VaR) was broadly embraced for measuring market risk in exchanging portfolios. Its birthplaces could be followed once again the extent that 1922 to capital prerequisites the New York Stock Exchange. VaR likewise has established in portfolio hypothesis and an unrefined VaR measure distributed in 1945 (Holton, 2002). Darbha (2001) investigated the value-at-risk for altered pay portfolios, and looked at alternative models incorporating variance-covariance method, historical simulation method and extreme value method. He uncovered that extreme value method gives the most accurate VaR estimator as far as right disappointment ratio. Cheung (2006) looked at the force law VaR evaluation with quantile and non-direct time-changing volatility approaches. A straightforward Pareto distribution is proposed to record the heavy-tailed property in the experimental distribution of returns. The outcomes prove that the anticipated VaR under the Pareto distribution showed comparative outcomes about with the symmetric heavy-tailed long-memory ARCH model. Notwithstanding, it is discovered that just the Pareto distribution has the capacity to give a helpful for asymmetric properties in both the lower and upper tails. Kim and Koo (2010) indicate that VaR is liable to a huge positive predisposition. He demonstrates that VaR has an extensive positive inclination when utilized for a portfolio with fat-tail distribution. Loriano (2010) analysed four distinctive VaR methodologies through Monte Carlo examinations. Their effects indicate that the method dependent upon quantile relapse with ARCH impact dominates different methods that require distributional presumption. Specifically, they demonstrate that the non-vigorous methodologies have higher likelihood of foreseeing VaR's with an excess of violations.

Comparative proof for symmetric, asymmetric, and long memory GARCH models is likewise furnished. In the investigation of every day data for eight rising stock exchanges in the Asia – pacific area, notwithstanding the US and the UK benchmarks, Rachel (1999) discovered both asymmetric and long memory features to be imperative considerations in furnishing enhanced

VaR estimates. He analysed the downside risk in Asian value markets. He watches that throughout times of fiscal turmoil, deviations from the mean-variance system come to be more extreme, bringing about periods with extra downside risk to moguls and financial investors. Current risk administration procedures neglecting to consider this extra downside risk might underestimate the correct value-at-risk. Lan et al. (2007) utilized diverse combinations of resampling methods, which incorporate the bootstrap and jack-knife. Dissimilar to past studies that just consider the questionable matter of VaR emerging from the estimation of restrictive volatility, they additionally represent the lack of determination of VaR came about because of the estimation of the contingent quantile of the sifted return arrangement. The jack-knife appears to be extremely handy in enhancing conjecture accuracy.

Giannopoulos and Tunaru (2005) proposed Historical simulation, which is a standout amongst the most paramount models the extent that this study is acknowledged. Giannopoulos and Tunaru (2005) finding were striking. He discovered that parametric models contain the risk measurements of J. P. Morgan (Weller), the delta- normal (or variance-covariance) and Delta-Gamma methods that depend on ordinary distributions of returns, (Loudon et al., 2000) did research on some other parametric methodologies that utilization non-typical distributions, example, the GARCH models dependent upon Bollerslev (1985)'s study and the extreme value approach proposed by Embrechts and Schmidli (1994). Specifically, the GARCH approach first fits the GARCH-sort models for budgetary return arrangement and afterward models the GARCH-sifted residuals dependent upon parametric presumptions of the restrictive distribution of the residuals as given by Mancini and Trojani (2010).

An assortment of GARCH models is utilized and evaluated, and in addition distinctive distributional presumptions of the GARCH residuals. In the exploration paper of measuring risk measurements exhibited Angelidis et al. (2004) inspected a battery of such GARCH-sort models.

Hendricks (1996) did an exploration on a standout amongst nonparametric methodologies for historical simulation which processes the experimental quantiles of historical portfolio returns. Some refinement to historical simulation incorporates the bootstrapping simulation approach, the weighted historical simulation, the hybrid model by Richardson et al. (1998) furthermore the utilisation of nonparametric thickness estimation, for example, the kernal estimation proposed by Chen (2005). An alternate unmistakable strand of exploration by Aussenegg et al. (2011) around there was the neural system approaches.

Prior VaR demonstrates principally have a place with the first two categories, yet the semi-parametric models have turned into the standard of VaR research as of late. Semi-parametric methodologies are dependent upon a mixture of parametric and non-parametric techniques. Filtered Historical Simulation (FHS) is one of the prominent demonstrates in this category. This approach is done in two steps. In the first stage, parametric GARCH-sort models are fitted for returns utilising semi greatest probability, regularly under the suspicion of contingent ordinariness. The second stage typically utilises nonparametric bootstrap to resample institutionalised GARCH residuals. The VaR estimate is then inferred from simulated profits based for bootstrapped residuals and volatility gauges, which reflect all conceivable outcomes of current economic situations. An alternate semi-parametric methodology, GARCH-EVT, which has the same first stage as FHS, however is dependent upon the extreme value theory (EVT). This approach models the tails of the conveyance of residuals which were predominantly introduced by Morgan et al. (2011).

VaR (Value at Risk) as a measure of risk has been utilised more than the ES, which limits the range of Back-testing when compared to VaR. There is another reason for that limitation because Back-testing is more difficult as compared to VaR. Where the distribution of the stochastic loss variable (the shortfall value) is needed to test where the ES estimations are derived from the same distribution. In Acerbi and Tasche (2002) proposed a test method to test ES directly. Findings of this test were that the significance threshold or critical values of test with different assumes the distribution of the stochastic loss variable are generally the same.

Strategies which are used to quantify worst case damage include parametric and non-parametric. EWMA (exponential weighted moving average) is the more specific method of parametric which is used in many researches. The genuine historical revenues are categorised from worst to best as it is one of the methods that considers the historical data. This rearranging is also known as Historical simulation (HS) which is the used non-parametric technique. From the risk viewpoint it is expected the past will repeat itself. Another model the Monte Carlo simulation, a model must be created where numerous theoretical scenarios can be tested in relation with future stock and price returns. The fundamental procedure cannot be identified if the Monte Carlo simulation is used on its own as the simulation only produces randomly generated scenarios via the different processes. Between EWMA and HS, EWMA results were considered to be much better but HS was not far off. The maximum loss expected also known as worst-case scenario on investments can be calculated using the Value at Risk (VaR) over a certain time-scale and specified level of certainty (Xu et al., 2015).

Financial institutions, stakeholder and supervisory bodies take keen interest in evaluating the known market risk of portfolio investments. Numerous strategies are utilized and practised for risk exposure. Experts tend to prefer value-at-risk as it presents a monetary value to explain the systematic risk. It is known to be popular with experts due to its simplicity. Beta risk is another type of risk measure that is similar. Beta risk gives asset return and business return covariance, which is not easier to understand that.

The accuracy of VaR models in calculating the accuracy of risk exposure to securities in up-coming markets has only been compared in some studies. It is vital for such an input as the well-established markets are not like the emerging markets in regards to economic, financial and politic (Kumar et al., 2019).

The methods commonly used to measure VaR are the variance/covariance, historical and the Monte Carlo simulations. Despite heuristic risk model gaining a lot of popularity within the forecasting stock prices, it has not yet been related to the VaR estimation. Surprisingly, the Neural Network simulation was found not to be affected by a time series correlation.

The VaR methodologies were evaluated where he assessed two areas: accuracy and computational time. The simulation taken to assess these were the Monte Carlo stimulation and the delta and delta gamma method. As expected, the Monte Carlo simulation was not particularly fast, but the results from the delta gamma greatly supported the approaches being measured, hence increasing their accuracy (Pritsker, 2006).

For firms and individuals, assessing and managing financial risk has always been critical. Proper risk management for businesses will, among other things, increase the company's value by reducing the risk of bankruptcy, minimizing tax payments by making sales sources more constant and reducing the cost of capital by making debt servicing safer (Andersen et al., 2011). The variance or volatility of the asset is a popular method of explaining financial risk. However, this is a non-intuitive indicator since it only gives an arbitrary number and does not distinguish between positive and negative stock price movements. The risk associated with a decline in the stock price is more important knowledge for investors. There are two preferred metrics for this reason-Value at Risk and Predicted Deficiency named as Expected shortfall, both of which will be evaluated in this thesis.

Because of its understandability, Value at Risk, henceforth referred to as VaR, has been and continues to be one of the most common financial risk indicators Hull (2006) and its characteristic of highlighting the risk of loss and not the chance of benefit, but has its drawbacks when it comes to its use as a method for risk management. For this reason, when calculating market risk, the Basel Committee has agreed to phase out the VaR indicator in favour of the Anticipated Shortfall, now referred to as ES that is the expected shortfall (Basel Committee on Banking Supervision, 2013). In situations where the loss is far from the average, the calculation offers information about the tail danger, meaning the danger. In extreme cases, ES gives us the value of the predicted loss, while VaR only gives details about the threshold value. However, historical simulation (now referred to as HS), the most common way of estimating these significant steps, often yields results that are largely outperformed by more sophisticated methods (Mentel, 2013; Andersen et al., 2011). Parametric estimates using forecast volatility or through Monte Carlo simulation, better methods for the estimation of VaR and ES could be provided.

In the past it has been observed that multivariate normal distribution is inadequate when trying to provide a good in-sample fit of the joint distribution of four exchange rate returns that are under consideration. Adding onto this there are also several exceptions that are raised in back testing of VaR estimate that were significantly above average as well as this an unconditional coverage test (binomial test/ Kupiec test) and conditional coverage test (Christofferson test) have shown that the VaR estimate may be inaccurate. However, six other models produce an acceptable VaR estimate (Tsitsiklis and Roy, 2001).

Although, whilst the concept of VaR is simple and easy to understand the implementation of it is often more complicated. There is a range of different models and different model implementations that lead to considerably different risk estimates for the exact same portfolio. In the past there have been studies where the focus is how the differences between models cause variation in the VaR. However, Evaluating Value at Risk Methodologies: Accuracy versus Computational Time, 1996 considers that the differences in the implementations of the same model produce variation in VaR (Pritsker, 1996).

A number of researchers extensively studied VaR which resulted in the appliance of these newly discovered statistical techniques in order to measure the threat presented in these portfolios Danielsson et al. (1998). One particular paper that dives into this concept is the 'value of value at risk'. The economic considerations stated in these papers hugely affected the way financial institutions were run, as they gave more importance to implementing the new found techniques which will allow them to quantify the risk.

Three researchers from Denmark, did empirical research on VaR which was published in 2009 under the title of Evaluating Value-at-Risk Models with Desk-Level Data. They've used some of the methods similar to the previous research such as the Monte Carlo and other methodology which includes Hazard Rates and Test for Clustering in Violation and Effective Size of the Test (Christoffersen et al., 2009). This result has shown that the CaViaR test has performed excellently overall. Also, despite of performing best on overall test, the duration-based test also has shown sign of performing well in many cases. Finally, the research was able to finalise some of the aspects of using VaR in banking are many and varied. All the VaR application shares each other, nevertheless the need for repeated evaluation for checking the accuracy of the VaR risk measures reported by Engle and White (2021). This statement is true regardless of whether the VaR is used in a passive or active way, and whether it is in use for internal operations or externally for regulatory purpose (Berkowitzet al., 2007).

Now days, it is seen that most of the researcher are using experimental research design in order to analyse and forecast financial volatility of emerging stock markets. For instance, the research carried by Aydin (2002), Akgül and Sayyan (2008) and Gokbulut and Pekkaya (2014) in Turkey, Rashid and Shabbir (2021) in Pakistan, Goudarei and Ramanaryanan (2011) in India were found applying ARCH and GARCH models in their methodological parts. The study shows that their core findings were development of volatility cluster, non-normality, imbalance of markets in emerging economics. Furthermore, GARCH research carried by Gokbulut and Pekkaya (2014) can also be taken as the major tool for data collection. Some of the researcher like Alabed and Al-Khouri (2008) and Musa et al. (2020) in Nigeria, Su et al. (2010) in China, Rahim and Masih (2016) in Malaysia, Soumen (2012) in Saudi Arabia have already applied this model more than one time in their countries while comparing the result of these models GARCH, EGARCH and GJR GARCH; it was found that EGARCH and GJR GARCH are the wonderful models for measuring volatility, detecting, clustering effects, leptokurtosis effect.

Most of the researchers all over the world are found using ARCH and GARCH models in their study for analysing capital market of their country but it is also found some of the studies are having issues while using ARCH and GARCH model like in Jordan. The study carried by Dhaimesh and Kamel (2019) between the years 1992-2004 proves that ARCH and GARCH models are best design which provides good approximation and also captures the characteristics of Amman stock exchange. Moreover, the study applied multiple asymmetric models to follow purchase strength effect and the result indicate that the exchange rate is symmetric, hence it is proved that the good and bad news has the same magnitude. Al-Raimony and El-Nader (2012) also carried their study applying ARCH and GRACH model to measure time volatility and the effect of macro-economics, there study found that the ARCH was significantly statistic whereas GRACH was statistically insignificant from 1991 to 2010.

By applying GARCH models both symmetric and asymmetric Andersen et al. (2012) evaluated from the beginning of January 2006 to the end of November 2010 the volatility of Sudanese and Egyptian markets. Regarding those countries' presumptive volatility of returns of explosive and fairly tenacious nature have been stated. For the observation of the volatility of stock indexes from five European emerging markets which are Turkey, Bulgaria, Czech Republic, Poland and Hungary, the following models have been used: GARCH, GJR-GARCH and EGARCH by Andersen et al. (2007). In conclusion the significant impact of old information on volatility at those markets and the insistent volatility shocks found by them Andersen et al. (2011). While, we concentrate on asymmetric models these analyses apply for both symmetric and asymmetric models. For the period of 2011-2014 GARCH, EGARCH and TGARCH models have been applied by Gokbulut and Pekkaya (2014) in order to demonstrate volatility of four Borsa Istanbul sub-indexes. Although asymmetry has been displayed by the rest of sub-indices, an insignificant asymmetric impact of shocks on the volatility of banking shares were found. In the period of January 1, 1999-March 31, 1999 returns of the Nasdaq operated for the determination of intraday returns volatility (Wasiuzzama and Angabini, 2011). The most excellent model to convey the volatility of the inspected intraday returns is GARCH (1,1), as well as todays volatility can be elucidated with the past volatility which follows up over time. On trading-day basis the volatility a behaviour of NASDAQ index after IPO during the period of January 1973 until July 2001 was considered by William, (2002) and the analysis referred as giving a suitable measure for risk involved while investing in the indexes. Amid others, GARCH (1,1) model applied in order to appraise the volatility. In four US stock market indices plus Nasdaq were utilized random level shift model (incorporated into GARCH) to predict and simulate the volatility (Deo et al., 2006). Level shift model captures conditional heteroscedasticity and long-memory prosperously and surpass GARCH (1,1) model in forecasting, as their findings reveals.

According to Koirala et al. (2015), the available information and findings by researchers on the strategies and methodologies which consists of correlation coefficient and spearman's rank correlation coefficient are determined to be the two methods that are widely used in finance to find the degree of association between two variables. Those are common methods of calculating dependence for elliptical distributions but having several difficulties. According to Berkowitz et al. (2007) spikes and thick tails are major components and those incapables of meeting elliptical distribution and its modelling needs. The classical correlation analysis is not a practical theory to explain the dependence of a common nonlinear and asymmetric distribution. Variance covariance matric are the corner stone for the selection of high valuable financial assets portfolios. In a study by Hansen and Lunde (2005) they introduced GARCH multivariate to a return analysis and conduct univariate volatility analysis in the paper titled as "A forecast comparison of volatility models: does anything beat a GARCH (1,1)?". The DCC model (Dynamic Condition Correlation) widely used in 2002 reduced the use of GARCH alone (Mishra, 2019).

In another way, the joint modelling distribution access the dependence of financial assets. Copula is proposed by Sklar (1959) and after it gained reputation within the 1990s. Jondeau and Rockinger (2006) utilize the copula-GARCH show to analyse the relationship between financial files and measures the t-copula in the research paper titled as The Copula-GARCH model of conditional dependencies: An international stock market application. Roch and Alegre (2006) consider the relationship in Spanish stock utilizing an ARMA-GARCH demonstrate for negligible conveyance and the copula work for reliance structure. Koirala et al. (2015) archive that the reliance structure between rural product prospects costs and vitality prospects costs shows positive and quite significant. Besides, the relationship between non-financial resources has self-evident Time Varying characteristics (Koirala et al., 2015). Reboredo and Ugolini (2015) utilize the conditional value-at-risk (CoVaR) with copulas to re-examine the systemic correlation suggested findings. De Oliveira et al. (2018) apply the MGARCH-BEKK, DCC and t-Copula models to analyse the spill over impacts and channels of instability in Brazilian stock. In the process to improve, a Time Varying copula examination is exceptionally valuable to investigate active correlation relationship between factors (De Oliveira et al., 2018). For occurrence, Patton (2006) creates a Time Varying copula constraint with conditional reliance parameter. Bartram et al. (2007) develop a dynamic copula analysis and apply it to the European stock (Bartram et al., 2007). Yao and Sun (2018) utilize Markov Time Varying copula capacities to think about the energetic structures between the EPU file and a few other financial markets. Comparative works can be seen (Aepli et al., 2017; Silva Filho et al., 2012; Grossmass and Poon, 2015; Hussain and Li, 2018; Goodness and Patton, 2018) and (Salvatierra and Patton, 2015), among numerous others.

Some of the literature suggests that no matter how profitable a single security the relationship it has with other assets in a portfolio must be evaluated in order to earn successful portfolio returns, meaning that when financial assets relating to financialisaton increase in number (in commodities, currencies etc), it leads to researchers trying to find volatility between different assets. Investments in alterative assets are gaining attention from investors and market maker because of clear risk and return features (Zhang et al., 2018; Lahmiri and Bekiros, 2018). Traditional investments such as shares and bonds are being overlooked and investors are now looking for more modern ways of investment because of the turmoil current markets are facing (Cumming et al., 2012). Assets with superior hedging characteristics such as gold index and S&P500 are starting to get popular for empirical contribution on diversification of risk and return trade-off (Rahim and Masih, 2016; Kenourgios et al., 2016; Evans, 2015). S&P stock markets, and the new emerging markets have gained quite recognition because there was a need for alternative investment assets due to the financial turbulence created in markets over the past two decades (Al-Yahyaee et al., 2018). Gold Market is used as a digital investment medium of exchange and is widely accepted as it has made an innovation since early ages in the payment system from 700 BC's (Tschorsch and Scheuermann, 2016; Nakamoto, 2008; Ali et al., 2014). Since the birth of commodity market in 1933, over 100s of commodities including gold exchange markets have been introduced and offer new ways of growth (Al-Yahyaee, et al., 2018). Research has showed that the market turnover and capitalisation of Gold securities is increasing aggressively (ElBahrawy et al., 2017), so, Gold and securities like S&P500 has been classed as an asset for investors (Kawa, 2015) while also gaining the legal status of capitalisation in many countries (Kovalova and Misiura, 2019).

When Gencay and Selcuk (2004) compared the performance of extreme value theory, variance-covariance method and historical simulation method in the extreme market conditions through the data of nine emerging stock markets they understood that the extreme value theory is the best one. But there has also been some research on method improvement to make the historical simulation method work better for the financial market. When, Pritsker (2006) compared the historical simulation with the filtered historical simulation it was clear that the filtered simulation was the better one. But it needs some extra consideration with the Time Varying of financial time series When it comes to the value at risk model measure, Barone-Adesi et al. (2008) introduced a filtered historical simulation method to help measure the expected loss and the consequences of this. But Giannopoulos and Tunaru (2005) then pointed out that when using the traditional historical simulation method with the smoothing coefficient is more efficient as it also overestimates the market at its stationary period. The effects of historical simulation, weighted historical simulation and the Bootstrap method was compared by Abad and Benito (2013) to measure the interest rate risk at commercial banks. The smoothing method of historical simulation was then improved by Wong et al. (2009) to solve the issue with underestimating extreme events. When it comes to measuring the VaR method it leads to problems that people learn to adapt to in today's dynamic market. This is all because of the VaR method more than often being calculated from a static perspective. The next step in the improvement of the VaR method is to be better at reading and estimating the parameters. This is where the GARCH model comes in. Giglio et al. (2016) presented some pros and cons in their literature review about the various calculation methods and development of quantile regression in their paper titled as "Systemic risk and the macroeconomy: An empirical evaluation". Barone-Adesi et al. (2008) research clearly shows that by using the GARCH model parameters you will have the most effective calculation of VaR. However, when it comes to the tail loss the GARCH model is not the most effective. Since the GARCH model follows a normal distribution and the financial time series is usually non-normal. And the tails feature of a non-normal distribution are often different from the normal distribution, which makes the GARCH model quite undesirable in this situation when it comes to tail loss.

Jayanth (1999) applied the VaR systems in Bombay Stock Exchange and released a research paper named Value at Risk Models in the Indian Stock Market utilizing GARCH and EWMA methods. His analysis involved data of the regular values of the NSE-50 (Nifty) index of the National Stock Exchange. By using the rates on the Bombay Stock Exchange, the NSE recalculated this index for the period prior to the establishment of the NSE. The end outcome of his analysis was that Bombay stock exchange investment was relatively safe. Therefore, it is essential to obey and execute those calculations in a relevant and accurate manner (Verma, 2005). Research was conducted on the analysis of VaR, while applying the bootstrapped historical simulation method. The outcome of their analysis was 51,2312 for historical bootstrapped VaR, which was marginally higher than historical VaR, i.e., 49,935. The fitting approach suggested that the distribution in their sample was reasonable for non-normal candidate. Hence it was not useful for ordinary parametric value at risk measure, in which the corresponding expectation returns are ordinarily spread. Afterward, they implemented the Historical Simulation method, this does not have any distributional implication making it a suitable for Value. All in all, it was indicated that the primary purpose of using bootstrapped historical VaR was that it considers the need for broad data for model evaluation independently of the scale of the sample (Dutta and Bhattacharya, 2002). De Lira Salvatierra and Patton (2015) conducted a report on Estimation of Portfolio Value at Risk using Copula. The techniques he applied were the Monte Carlo method, and he used the historic and the Monte Carlo simulation under the VaR measure. In his study, he used quotidian data on four exchange rates (INR-EURO, INR-USD, INR-CHF and INRGBP) series, downloaded from the official source (www.rbi.org.in; www.federalreserve.gov). The survey period was from January 2000 to November 2010. VaR outcome in the way that the historical simulation was an appropriate method, instead the other model such as the monte Carlo were sluggish and could not achieve the optimal results in the most efficient way. The outcome was VaR results, for every one of the seven models of dependency structure, one-day portfolio VaRs were calculated for the 200 days for the theoretical portfolio based upon those four risk factors using the Monte Carlo Simulations technique (Krupskii and Genton, 2017).

The earliest studies to specify instability clustering. Leptokurtosis, and use impact of stock return in budgetary advertise was given by the taking after three studies (Mandelbrot, 1963; Fama, 1965; Jondeau and Rockinger, 2006). Measuring and evaluating the stock costs instability is a vital concept in finance in common, and in venture choices, due to its different behaviour. That driven analysts to propose numerous numerical and factual models to capture instability of stock return in money related markets around the world. The spearheading studies in this field are alluded to Engle (1982), and Bollerslev (1986) who proposed the utilization of both ARCH and GARCH models separately. This area will provide summary for the most experimental discoveries given by analysts from both created and rising markets.

Numerous analysts found that ordinary time arrangement models that works beneath the most presumption of steady fluctuation that was not exact in evaluating stock return developments. Hence, Engle (1982) study proposed the utilization of ARCH models that permits the conditional fluctuation to alter over time as a work of past mistakes clearing out the unrestricted steady change.

The ARCH model is widely utilised in characterizing time-varying financial market volatility but it does not provide a good fit in empirical applications to overcome them Bollerslev (1986) proposed an adjusted frame through Generalized ARCH (GARCH) to permit a longer memory and a more adaptable slack structure. Not as GARCH offers with the ARCH model within the primary presumption with respect to conditional fluctuation is indicated as a straight work of past test fluctuation, but also it permits slacked conditional fluctuations to enter within the demonstration as well.

More amplified forms of the ARCH demonstrate were given by numerous analysts such as Engle and Manganelli (2004) in which they presented the GARCH –M, that permits the conditional fluctuation to be determinant of the mean. In expansion of their observational discoveries underpins that risk premium are not time invariant; or maybe they change methodically. Moreover, to break the rigidness of the GARCH determinations, Nelson (1991) contributed an unused model through Exponential GARCH (EGARCH) which backed that change of return was influenced in an unexpected way by positive and negative abundance returns. Also, the observational discoveries bolster the negative relationship between both overabundance returns and stock market change.

Since at this point progressive study came with new proposed individuals to the GARCH model's family to overcome downsides of each show, for example by; Ding et al. (1993) proposed Hilter kilter Control GARCH (APGARCH), at that point Zokoian (1994) connected edge GARCH (TGARCH), and McAleer (2006) their models were Energetic Deviated (DAGARCH), Conditional Auto Backward Extend, and Quadratic GARCH (QGARCH) show, and also with more models to be connected and tried by distinctive analysts around the world.

Concerning the adequacy of the ARCH and GARCH, numerous experimental discoveries such as (Taylor, 1998; Baele et al., 2010; Aggarwal et al., 1999; Butler and Okada, 2009); found comparative conclusion that's; the most excellent models to portray the information and measure the instability is the GARCH (1,1). They all affirm the capacity of asymmetric GARCH models in capturing stock return instability.

Some of the researches using GARCH and Copula models carried for other commodities such as cryptocurrency etc are discussed because of the same model usage. Masarotto and Varin (2012) carried the research in which they applied innovative copula method to model corporate bond yield spreads, which has been freshly presented in the literature. Particularly, this study utilizes the Gaussian copula marginal regression (GCMR) combined with Weibull marginal distributions for variables see Masarotto and Varin (2012) for some references. Moreover, for testing the asymmetric tail dependencies among yield spreads and other explanatory variables, we also used more copula functions. Their finding consists of both corporate bonds callable and non-callable.

Between a Gaussian normal distribution (Gaussian) and a student's t distribution, there appears to be conflicting evidence in some researches. Financial assets returns are expected to be more effective with the student t distribution instead of the Gaussian distribution, according to Bollerslev (1986). However, no evidence was found that the student's t distribution created more productivity than the Gaussian distribution. According to the previous hypothesis that the financial data have different characteristics, to understand which of the two works better, was tested. Some researches proposed to offer a few bits of knowledge on the unpredictability determining point, by addressing two sorts of targets. The primary sort was to upgrade the instability displaying issue by proposing elective (bivariate and multivariate) models to conjecture the unpredictability of individual stocks or of various stock resources. As such it broadened a strategy proposed by Hansen et al. (2010b). It was necessary to create boundaries, due to the breadth of the field and to keep the methods reasonably easy to understand for both individuals and companies (Bollerslev, 1986). First of all, market risk is what needs to be focus on in many thesis researches, although there are many important risks to consider in financial markets. This is because it is due to the applicability and relevance of market risk for index investments, in addition it is the subject of the thesis. Secondly, the models test on equity indices, although there are different ways of investing for both individuals and companies. The accuracy of the model is relevant to a smaller number of individuals, and this is because to many people compared to single stocks. Thirdly, all the methods presented are widely used and extensively studied, so as GARCH models, however we will consider a limited number of models, as well as the Copula, although there are many alternatives.

Though the existing literature the Akaike Information Criterion (AIC) has a smaller value for the GCMR model than the traditional regression model, their examination is an improvement over the traditional linear regression analysis. In the traditional regression model, also discover that the coefficient on the coupon rate is considered positive as against to unimportance of the coefficient on the variable (Masarotto and Varin, 2013). As per, Elton et al. (2001) and Longsta et al. (2005), investigated that the positive coefficient on the Credit Default Swap Market. Since interest payments on corporate bonds are subject to state taxes as opposed to treasury bonds state tax exemption, investors with corporate bonds face tax disadvantages relative to those with treasury bonds' and they need higher rates of return, thus leading to higher yield spreads, these disadvantages are superior for greater coupon bonds. For the pairs of yield spreads and other explanatory variables, they estimate the tail dependence coefficients by using various copula functions. For instance, the sample of non- callable bonds indicates greater upper tail dependence than lower when the connection between yield spreads and equity volatility, this signifies the positive effect. When Acharya and Carpenter (2002) discover yield spreads are used to quote corporate bond prices in practice, the corporate bond investors can take benefit of this finding. To illustrate, experts should notice that equity volatility has a stronger impact on yield spreads during an economic crisis, causing inflation in yield spreads and equity volatility.

Later, they took the attention to the callable bond sample. The AIC still has a smaller value for the GCMR analysis combined with the traditional linear regression model as in the non-callable bond sample and gets the same result that their model is more appropriate than the opposing model. Contrary, the coefficient on maturity is significantly negative in their analysis of non-callable bonds. This is introduced due to the fact that the longer maturity of a bond, the more call deferral period. Furthermore, the connection between the equity volatility and yield spreads gives different findings when the tail dependence investigation occurs on the sample. For this relation, they observed in the sample of non-callable bonds that greater upper tail dependence than lower is no longer shows in this sample. Another research related to this finding to the argument which is that the exercise of the call option can be destroyed by default risk (Acharya and Carpenter, 2002). This donates, more appropriate and meaningful statistical models to the finance literature by suggested engaging. Some of the literatures review carried by other researches about other commodities is also discussed in the chapter in order to see the relevancy of the model with other stocks and commodities. Application of GARCH model was explored particularly for exploring the relation present between prices changes taking place and volatility in the market for the period 1992 and 2019. Research consisted of data gathered for the particular period which did not provide any strong insight into asymmetric relation present between volatility and yields in the bitcoin market. Increase conditional volatility as witnessed in positive shocks as compared to negative shocks. Research was carried out by Chu et al. (2017) to investigate the suitability of GARCH model in the case of several cryptocurrency such as Dash, Dogecoin, Madisafecoin, Ripple, Monero and Litecoin. Findings of the research indicate that IGARCH and GJRGARCH model provide optimal specification for modelling the volatility of most common cryptocurrencies during time of boom. Research by Beneki et al. (2019) carried out research on Ethereum and Bitcoin using the BEKK-GARCH model mainly for identifying the differences in volatility and explore its hedging capabilities. Number of significant swaps were identified in the Time Varying correlation as well as certain diversification skills in the early years of the study.

Different multivariate GARCH methodologies were applied by Guesmi et al. (2019) for the time period between January 2012 and January 2018 which mainly focused on comparing the cross-impacts present of volatility spillover present between Bitcoin and other financial indicators that provide insight into the economy. Most suitable framework to be applied in the current scenario is VARMA (1,1) - Vector Autoregressive Moving Average estimation technique. Applying hedging strategies that involve oil, gold, bitcoin and other emerging equity markets greatly helped to lower the risk present as compared to condition where bitcoin was not included. Similar sample and period were used for analysis by Charles and Darné (2019) and Balcombe and Fraser (2017) when further studies were conducted in the future. Addition made in these searches was extending the time period to march 2018 along with use of quasi maximum likelihood QML estimators for checking the data along with taking into account the jumps in bitcoin returns. Findings of the research showed that none of the six CARCH models used with short-memory and asymmetric impacts in the short-run and long-run were able to suitably mode the returns obtained from Bitcoin. Some researches using macroeconomic fluctuations displays a few kinds of procyclicality (Zhu et al., 2013; Bel and Joseph, 2015; Jiao et al., 2018). Nonetheless, the relationship between monetary market vulnerability and the carbon market is as yet muddled. Given the urgent function of budgetary business sectors in reflecting monetary execution, expecting that a steady relationship exists between the commodity market and monetary business sectors is sensible. Additionally, as recorded by the vulnerability moving mechanism proposed by Bloom (2009), money related market vulnerability is profoundly coordinated with the genuine economy however is obviously unmistakable from different vulnerabilities. Accordingly, our investigation plans to give a superior comprehension of the moving instrument between monetary market vulnerability and the stock and commodity market.

Further, applicable investigations have principally centred around the unpredictability of the commodity market as indicated by the summed up general autoregressive restrictive hetero-scedasticity (GARCH) model (Balcılar et al., 2016; Reboredo, 2014; Zhang and Sun, 2016; Zhuet al., 2013). In particular, Zhu et al. (2013) give proof that contingent Expected Shortfall (CoES) is a better measure than model danger overflow in Chinese carbon showcases by utilizing ordinary plant copula. However, these examinations have just cantered around the un-predictability overflow between the carbon and energy markets (Reboredo, 2014; Zhang and Sun, 2016) or have zeroed in on the danger overflow between the carbon and energy markets without thinking about lop-sidedness (Balcılar et al., 2016). To supplement the expanding measure of writing on hazard overflow among carbon and other monetary business sectors, our examination gives bits of knowledge into deviated hazard overflow with regards to carbon and money related market vulnerability.

Recently, in many areas like finance, biostatistics, medical research, actuarial science, and econometric, copula has been measured to be a flexible way of constructing the dependence of multivariate data. As per, Kojadinovic and Yan (2010), copula does not require independent and identical normal distribution assumptions, are the main reasons the method is in demand as well as it has no constraints on the probability distributions. Sklar's theorem states that for any continuous random variables, a copula can couple univariate marginal into dimensional distribution (Sklar, 1959). Especially, when the response variable is not commonly distributed, the copula regression is more appropriate than a traditional linear model. The financial econo-mists drew more attention to corporate bond yield spreads because the global financial system was in extreme crisis throughout 2007 – 2009. De et al. (2013) and Guidolin and Tam (2013) discover the effect of the financial crisis on yield spreads and document that bond risk premia rise during this crisis. Choudhry (2016) investigates how the global financial crisis impacts yield spreads in European markets by using the GARCH-in-mean model. De Oliveira et al. (2018) discover that correlations of a set of yield spreads are much more significant than other times by examining a set of eleven U.S. fixed-income yield spreads. They feature their findings to a dramatic increase in experiences of fixed income securities to common risk factors, which was generated by the monetary emergency.

Regarding the considers of (Balcombe and Fraser, 2017; Lu et al., 2011; Alameer et al., 2019), and (Li and Wei, 2018); their strategies depended on comparing between different asymmetric models proposed already such as TGARCH, PGARCH, EGARCH, and GARCH-M; their primary discoveries backed that deviated GARCH models plays a vital part in volatility forecast for day by day stock return totally in different nations, also they found that EGARCH models show more accuracy in estimation of instability. Hence, in comparison to the literature review discuses we can clearly see the research gap that many researches have considered using the volatility but quite few have used ARIMA, ARCH, GARCH, GJR-GARCH and VaR, measures together therefore further in-depth analysis will be discussed as theoretical demonstration relating to the chapter in the section below.

2.3 Theoretical Framework

2.3.1 Financial Asset Returns

Financial asset returns have numerous specific features that will be utilised for the expectations and choices concerning the models and specification which will be used in this paper.

2.3.2 The Leverage Effect

It was suggested that a monitored outcome in financial time series is that volatility inclines to be higher when prior periods returns have been bad. In addition, when it comes to the asymmetric effect which is usually known as leverage effect, the debts stay the same while the company's equity drops due to the falling of the share price of the company. It was also implied that this effect can be explained in equities. Furthermore, there is an indication that this will raise the debt-to-equity ratio therefore raising a central risk metric of the company and making it riskier. According to Brooks (2014) "A negative return should thus increase volatility in the equity or assets price more than a positive return should". An alternative view to the leverage effect by Bollerslev (2006) recommended that an expected rise in volatility increases the anticipated risk of the company. With the anticipated risk of the company, it was hinted that the risk-return ratio should therefore increase, and the share price needs to fall to accommodate for this. Therefore, meaning that the returns are reliant on volatility and not the other way around, as debated. To sum up, with the continuous monitoring of the leverage effect, there is no overriding explanation and does not really seem important as this type of a of analysis of measuring the asymmetry in the volatility of financial assets cannot be encountered by the volatility forecasts models.

2.3.3 Methodology

It is essential to take into consideration the possible risks that come with investing into assets. While this most concerns investors, it should always be considered by any participant in financial markets. It is also important for investors to do things such as predicting and modelling financial assets volatility in order to balance their portfolios.

Marketing dynamic models are quite important for trying to predict a financial asset future move. This is because predicting future moves of financial assets require deep analysis of historical data. Due to fluctuations in asset prices changing quickly over time predicting asset prices is quite difficult for investors and other market parties.

Volatility is the measure of the variance of returns on a time series of asset prices over a given period. This helps quantify the risk of an asset. Extended periods of high market volatility followed by a period of low market volatility is commonly characterised by Volatility clustering. Also, Thicker tails than expected under normality are often displayed when observing. Some studies have proposed that these thicker tails might be so thick as to come from distributions with infinite moments. Looking at this under linear assumptions, this may introduce errors into the analysis of financial asset prices. This being said, recent studies in the literature have still come to show that financial time series exhibit nonlinear dynamics most of the time.

2.3.4 Choice of Models

For the capability to capture the observable volatility clustering effect described in chapter in the section of literature review carried with theory, the non-linear GARCH family models were included. The asymmetric models GJR and EGARCH were included in methodology section for their ability to capture the observed leverage effect. Finally, for the sake of discussion, both the Gaussian and Student's distribution were included as the distribution of the students could catch the observed fat tails in financial asset returns, as mentioned in this chapter.

2.3.5 Financial Risk Measures

2.3.5.1 Value at Risk

As stated by Jorion (1996), VaR is a financial metric used to estimate the loss of an investment within a certain time period. Calculating VaR depends on two numerical factors which are considered to be the main parameters; the time period of which the financial item is detained by the investor and the confidence interval. This concept was then applied to assess the risks of certain investment portfolios and contrast them with other markets by Duffie and Pan (1997). This fits in well with definition which states that VaR is the value depicting the overall risk of a portfolio in comparison to different markets (Dowd, 1998).

2.3.5.1.1 Value at Risk Estimation

The VaR measure is used for estimating financial risk. There are other methods of measures however it is suggested that this method is largely used as a process for estimating financial risk. Hull (2006, p. 471) stated that "the measures is defined as the maximum loss that will occur with a probability level of 1 – p". Additionally, the repeatedly used "measure owes much of its popularity to its simplicity as it can be explained to anyone without previous knowledge in financial economics". Furthermore, Hull (2006, p. 471) added that "Mathematically, the one period VaR, VaR_{t+1}^{p}, also called the q% -VaR, is defined as the solution to Equation 1" and also " where p is probability to lose more than VaR_{t+1}^{p}, the coming time period. The VaR for period t + 1 is calculated by using the information accessible in period t. The image of the p% VaR in a Gaussian distribution can be seen in Figure 1.

$$P\,r\big(r_{t+1} < VaR_{t+1}^{p}\big) = p \tag{2.1}$$

The confidence level used for this thesis is 90%, 95%, 99% and 99.9% and the total count for the time period is 7296. Hence the formula then become as shown in equation 2.2.

$$VaR = (1 - Confidence\ level) * Total\ count \tag{2.2}$$

Which numerically for 95% will be:

$$VaR = (1 - 95\%) * 7296 \tag{2.3}$$

Therefore, the equation that we will be using for calculation VaR will be as follows:

$$VaR = (1 - p) * t \tag{2.4}$$

Where p= Confidence level

t= Total count

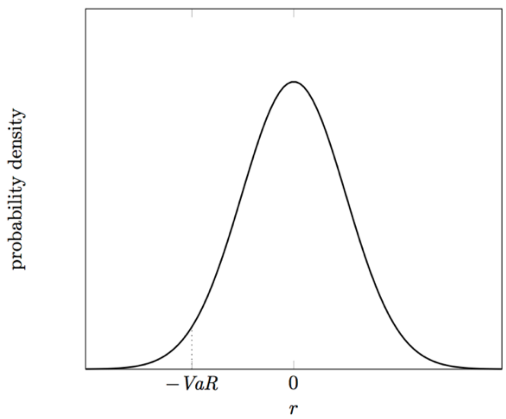

Figure 2. 1 5%-VaR in a Gaussian distribution.

2.3.5.2 Expected Shortfall

Another indicator of financial risk is the anticipated deficit or the expected shortfall, ES. Expected shortfall is also same as conditional tail expectation and even referred to the TVaR in Europe. It demonstrates the worst loss during the time period measured with the percentage used to calculate it for the period. For our thesis we took the bottom 10% and 5% of the worst period for the stock exchange and commodity index. Hence, we will define ES as,

"Estimated Shortfall is the anticipated value of the loss of the stock and commodity in the bottom 5% and 10% worst cases in 7296 days".

2.3.5.2.1 Expected Shortfall Estimations

The calculation builds on the VaR principle and discusses what can happen in situations when the loss reaches the VaR for the day. It may also be argued that ES incorporates more information than VaR, taking into account the predicated loss, and not just VaR's threshold loss (Acerbi and Tasche, 2002). Its clear description can be represented as the predicted loss, provided that the loss calculated by VaR is surpassed Andersen et al. (2011) as established by VaR in Equation 2.1 Hull and White (1998). The ES for the coming time t+1 is determined using the details provided for in the current period t. The ES in the Gaussian distribution can be seen in figure 2.2.

$$ES_{t+1}^{p} = -E\left(r_{t+1} \middle| r_{t+1} < -VaR_{t+1}^{p}\right) \tag{2.5}$$

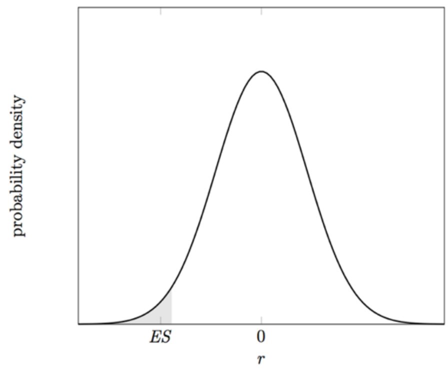

Figure 2. 2 5%-ES in a Gaussian distribution

Since, Expected Shortfall will determine the bottom worst cases, we calculated the bottom 10% and 5% worst cases in our thesis. In order to know the bottom worst cases, we will first arrange the data in ascending order to know the worst cases. After doing so we will run the equation for ES for both the indexes. Hence, equation 6 was used for calculation.

$$ES = Average\ (Bottom\ worst\ cases) \tag{2.6}$$

For instance, in case of 5% we will have the equation as follows:

$$ES = AVG(bottom\ 5\%) \tag{2.7}$$

2.3.5.3 Historical VaR (Historical Simulation)

Historical VaR is just the rearrangement of the actual historical returns, organizing them in order from worst to best. The idea behind this is that we will get an assumption that the history will repeat itself from the perspective of risk. In one of the researches, it was examined the Value at Risk by using historical simulation, variance covariance and Monte Carlo approach (Benninga and Wiener, 1999). The use of historical simulation allowed them to save up the amount of data as it wouldn't be spacious, on top of that it didn't contain enough information regarding the profit and loss distribution. Other than that, the utilisation of historical simulation was a time-consuming process but contained its own advantages. One of the advantages was that it recorded all the recent market crashes that took place in the financial world. The use of variance covariance method is the fastest. Unfortunately, it was hugely dependent on some of the information which were assumptions about the market data and linear approximation of the portfolio which question their reliability. By far, this can be considered to be the fastest method for a quick VaR estimation.

The other method that they've used was the Monte Carlo simulation. Despite being the strongest method, it is a slow pacing one. This method is considered strongest because they had the private information with historical monitoring that made them reliable to use. All the three methods used for their research produced a similar outcome by illustrating a basic information of approaching risk measurements techniques using Mathematica (Benninga and Wiener, 1999). Through using these models, financial organisational can be able to regulate the daily day and intraday financial database which assist the Financial investors to understand the financial strength and drawback of their organisation. Through analysing the practical risk measures for any organisation these models assist the organisation to analyse how they are safe in the financial condition in terms of dealing with the international financial market. Moreover, through using these models we will be able to recognise the loss and asset returns of a financial organisation.

Since, historical simulation is used in many other advance unconventional risk measuring methods. For instance, HS procedure used in the copula simulations are a multivariate strategy to the calculation of VaR and ES. The approach is generally used by financial market professionals for its usability (Perignon and Smith, 2010; Bollerslev, 2006). In addition to its flexibility, it also has a distinct benefit over more complex versions in that it contains the fat customised features of financial asset returns. The system used by Acerbi and Tasche (2002) for estimating the VaR and ES using HS with copula simulation can be represented by sorting n-day returns and selecting the return equivalent to the q: the percentile of the lowest return to display the VaR. The ES is then calculated to be the average return below the VaR. There are varying views as to the number of days used in the simulation. As per, the (Basel Committee on Banking Supervision, 2010) the minimum requirement for the use of HS in risk management is 250 days. Consequently, according to Mehta et al. (2011), one year or around 250 market days is the most common time span to remember, followed by two and four years. There's a trade-off with how many days the roller window is selected. The benefit for short windows is that they respond rapidly to changes in fluctuations.

A drawback for shorter windows is that less observations are presumed to be least representative of the actual return distribution in comparison to larger windows. Therefore, in this thesis we will utilise two forms of the simulation with Historical VaR calculation along with copula framework – a 27 years' time period. As the focus is on the VaR, using the confidence level of 95%, 99% and 99.9% the chosen market days are 7296 so an accurate percentile can be made for the value of a loss.

Despite being advantageous the simulations such as HS in copula framework method has several disadvantages. Barone-Adesi et al. (2008) highlights how it assumes that the distribution of returns remains the same over time, however, the volatility clustering in many cases makes this debatable. Furthermore, the timeframe chosen to focus on for the simulation can produce differing outcomes, raising the question of how long the time period chosen should be.

2.3.5.3.1 Historical VaR Estimations

To calculate the estimated VaR through HS, equation 2.8 can be utilised; this is where rτ is the q^{th} percentile lowest return within the assembled list of return over the previous n days.

$$\widehat{VaR_{t+1}^{p}} = r_\tau \tag{2.8}$$

Likewise, equation five calculates the estimated ES through HS where, ri is the individual return at placement i from lowest to highest and τ is the number of days the loss surpassed the VaR.

$$\widehat{ES^{q}_{t+1}} = \frac{1}{\tau}\sum_{i=1}^{r} r_i \tag{2.9}$$

Hence, we have taken the 10% and 5% percentiles for the estimation of Historical simulations and the simpler version of the formula used can be seen in the equation below:

$$t = Total\ Count \tag{2.10}$$

$$w = percentile * t \tag{2.11}$$

$$x = bottom\ 1^{st}\ Value \tag{2.12}$$

$$z = bottom\ 2^{nd}\ Value \tag{2.13}$$

The bottom values can be easily calculated using the small function in the excel for both the percentiles.

$$HS = z - x \tag{2.14}$$

Hence using the equations, the historical VaR is calculated and determining whether history will repeat itself or not which can later be seen in the data analysis.

2.3.5.4 ARCH and GARCH

Proposed by Engle (1982), says that the restrictive instability of a time arrangement can be assessed utilizing the recorded unpredictability of the arrangement just as the squared past returns. The model, for which he was later granted the Nobel prize in financial matters (Nobel Media, 2003), isn't often utilized practically speaking anymore. This is halfway because of its constraints with respect to the number of slacks are incorporated of previous returns, which means the number of past returns is relied upon to influence the present volatility (Brooks, 2014). A model that tackles this issue is the GARCH model, proposed by Bollerslev (1986). The model adds the past periods conditional volatility times a coefficient to the Curve model, in this manner catching each past periods returns in diving significance as the previous restrictive unpredictability relies upon the day before the previous contingent instability and returns, etc.

The ARCH and GARCH model, used in this thesis is designed in a way to use different effects of negative and positive shocks on conditional variability or other types of asymmetries. This type of model aims to develop a measure of variability that can be used in the financial decision-making process.

There are asymmetric dynamics in the financial ranks. Asymmetry is when the instability is higher, when the return is negative. They stem from transaction costs, market frictions, restrictions on short sales, changes in market sentiment and more. Stock prices can fall sharply, which takes a longer period to rise under the same conditions. That is, when stock prices fall, instability usually increases, and this asymmetry of volatility is called the "leverage effect" (Campbell et al., 1998). Besides stock market, asymmetry is observed in commodities Acerbi and Tasche (2002), precious metals. There are two ways to capture metric and nonlinear dynamics: autoregressive conditional models of heteroskedasticity, or with threshold models.

Financial markets often show volatile volatility, autoregression and moving average models cannot capture nonlinear dynamics.
Autoregressive conditional heteroskedasticity (ARCH) and its derivative models are widely used in modelling and forecasting asset dynamics. This is the generalized autoregressive conditional heteroscedasticity, GARCH.

2.3.5.4.1 ARCH and GARCH Estimations

The parametric VaR-estimation method assumes a distribution of probability for potential returns, and then finds the value of the VaR given the probability q defined. Nonlinearities in time series may come from conditional mean or conditional variance, or sometimes both. These nonlinear time series of conditional mean are modelled through either Threshold Autoregressive Models (TAR) or Markov switching models. However, if the nonlinearity is a result of conditional variance a series such as the autoregressive conditional heteroscedasticity (ARCH) models developed by (Engle, 1982). These models describe the variance of current error term as a function of the previous periods error terms. This model was later developed by Bollerslev (1986) into the generalized autoregressive conditional heteroscedasticity (GARCH) which allowed for changes in the time dependent volatility such as decreasing or increasing volatility in the same series.

The methodology of this research focuses on ARCH and GARCH model. Since conditional variance model has advantages that describe time series data properties, therefore in the methodology we will be using an approach that best describe each property of time series data. Its certain that the returns of asset have a positive excess kurtosis which basically determines that their probability density function peak is sharp when compared to a normal probability density function peak. The tails of returns PDF (probability density function) most of the time embodies higher PD (probability density) than the PDF shoulders hence the PDF has quite well-known fat-tails. Volatility or the Instability tends to cluster into periods with higher and lower instability. This impact implies that instability at a few times must be subordinate on its authentic values say with a few degrees of reliance. Returns fluctuations and Vacillations have topsy-turvy asymmetric effect on instability and volatility. Instability changes more after descending return move than after upward return move. Consider the common shape of conditional change variance model.

$$\alpha_t = \mu_t + e_t, e_t = \sigma_t \varepsilon_t \tag{2.15}$$

Here, α_t is a dependent variable consisting of mean μ_t and ℓ_t as innovation. However, μ_t is the conditional mean of α_t making the equation as $\mu_t = E(y_t|\Omega_{t-1}) = g(\Omega_{t-1})$ where arbitrary historical information is Ω_{t-1} which affects the value of y_t. Every μ_t is modelled by the most appropriate linear regression model by the use of the AR process. $\mu_t = 0$ is kept fixed. e_t basically, consists of the volatility which is the root of σ_t where $\sigma_t^2 = h_t = h(\Omega_{t-1}) = var(e_t|\Omega_{t-1}) = var(y_t|\Omega_{t-1})$ and the variable from t-distribution $\varepsilon_t \sim t(\nu)$ or simply $\varepsilon_t \sim N(0,1)$.

Hence, the whole equation 2.16 in the econometrics literature of the model of conditional variance can be written as:

$$\alpha_t = \mu_t + \sigma_t \varepsilon_t = \mu_{t+\sqrt{h_t \varepsilon_t} = g(\Omega_{t-1}) + \sqrt{h(\Omega_{t-1})}\varepsilon_t} \tag{2.16}$$

Where e_t is non correlated but dependent σ_t term. Where g = non-linear function making the mean non-linear in the model vice versa considering h to be non-linear in terms of the variance which mean h_t keeps on changing the non-linearly with t through the function of Ω_{t-1}. Making autoregressive conditional heteroskedasticity definition clear.

2.3.5.4.2 ARCH

The ARCH(m) model for σ_t when taking into account the equation 2.17 and specifying the conditions based on the historical information Ω_{t-1} the equation then becomes:

$$\alpha_t = \mu_t + e_t, e_t = \sigma_t \varepsilon_t \, \sigma_t{}^2 = \underbrace{\alpha_0 + \sum_{i=1}^{m} \alpha_i e_{t-1}^2}_{condition} \tag{2.17}$$

Where ε_t using the random variable and t-distribution having the mean as zero and the unit variance. Dropping the μ_t which gives the equation as:

$$\alpha_t = e_t, e_t \sigma_t \varepsilon_t \, \sigma_t{}^2 = \alpha_0 + \textstyle\sum_{i=1}^{m} \alpha_i e_{t-1}^2 \tag{2.18}$$

keeping the exogenous variables with regression mean makes the equation 2.19

$$\alpha_t = \gamma_0 + \sum_{i=1}^{k} \gamma_i x_{t,i} + e_t, \; e_t = \sigma_t \varepsilon_t, \;\; \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \, e_{t-1}^2 \tag{2.19}$$

The immense fluctuations in the historical time period makes the affect quite significant on the current volatility or the variance. In regards to the positivity and stationary variance σ_t^2 hence satisfying the coefficient of the constraints in equation 2.20 as follow:

$$\alpha_0 > 0, \alpha_1 \geq 0, \ldots., \alpha_m \geq 0, \sum_{i=1}^{m} \alpha_i < 1 \tag{2.20}$$

The Hypothesis for ARCH Test for this chapter is

H_0: The squared residuals are not autocorrelated – no ARCH effect.
H_1: : The squared residuals are autocorrelated – given time-series exhibits ARCH effect.

2.3.5.4.3 GARCH

Introduced in 1986 Robert Engle's PhD student Tim Bollerslev (1986). Both the models of ARCH and GARCH allows leptokurtic distribution of the innovations e_t and the conditional heteroskedasticity (volatility clustering) but both of them don't adjust the leverage effect in time series data. However, the ARCH model uses high order m hence parameters need to estimated which brings the need of higher computing power. The higher value order of m brings in the probability of the breaking the constraints mentioned before in equation 2.20 used for the computation further in data analysis. With this in mind and in light of the fact that the

GARCH model is more generally utilized practically speaking than the Curve model (Brooks, 2014, p. 428), just the GARCH model and not the Curve model, will be evaluated in this postulation. The numerical definition for the GARCH model can be seen in below equations.

With the estimate ()-function on individually defined arch ()-, garch ()- and gjr()-objects, the coefficient estimation for the models in the GARCH-family was produced. Matlab will be used to calculate the coefficients using maximum probability estimation, or MLE, using the logged returns. The method works by estimating the most likely coefficients to fit the data and is used as it works on non-linear models, like the GARCH family of models Brooks (2014, p. 431). New coefficient estimates for the ARCH, GARCH and GJR models with MLE (maximum likelihood estimation) were made each business day, using return data for the 7296 preceding market days. This specific number of days was chosen because it is equivalent to approximately 27 years, a satisfactory amount of time to generate statistically significant estimates of the coefficient and to include various periods of financial uncertainty in the estimates. Then the variables with their coefficient estimates were used to predict the volatility σt+1 of the following day. No coefficient estimation was performed for the simulation models in copula model and σt+1 was calculated using the fixed value λ = 0.94 instead. The Degrees of Freedom ν were also calculated using MLE for the models using the student's t-distribution.

As GARCH is upgraded than ARCH as it basically permits the current volatility to be dependent on the values lagged directly. The GARCH (m,n) is basically defined as follows in equation 2.21:

$$\alpha_t = \mu_t + e_t, e_t = \sigma_t \varepsilon_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i e_{t-1}^2 + \sum_{j=1}^{n} \beta_i \sigma_{t-j}^2 \tag{2.21}$$

This makes ε_t random variables using t - distribution and mean as zero and the unit variance. Making the parameter constraints quite similar to ARCH model:

$$\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0, \sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{n} \beta_j < 1 \tag{2.22}$$

Keeping GARCH (1, 1) with 3 parameters which describes complex volatility structures and its process for the sufficiency of applications. The volatility of the future can be forecasted $\hat{\sigma}_{t+\tau}^2$ of the GARCH (1, 1) model taking

$$\sigma_{t+r}^2 = \sigma^2 + (\alpha_1 + \beta_1)^T = (\sigma_t^2 + \sigma^2) \qquad (2.23)$$

Where

$$\sigma^2 = \frac{\alpha_0}{1 - \alpha_1 - \alpha_2} \qquad (2.24)$$

e_t is the unconditional variance of innovations. Observing $\alpha_1 + \beta_1 < 1$ as $\tau \to \infty$ which makes the equation $\hat{\sigma}_{t+\tau}^2 \to \sigma^2$. The volatility of the predication of time asymptotically to the unconditional variance.

The equation 2.24 presumes to be squared provisional volatility times an identical and independently distributed alterable following a dissemination with 0 mean and an average deviation of 1. The true distributions of index price time series are unknown however both Gaussian and students t-distributions are to be examined.

The provision volatility for the foreseeable future, number of days is exemplified as shown in the equation 2.23 above, the current is t+1 which is shown as $\hat{\sigma}_t^2$, moreover r_t^2 is the return for the current period. Coefficients is used within the model to allocate weights to the variables within the equation, based on presumed significance in the upcoming periods volatility. The coefficients are β and α assisted with a constant λ. A restraint on the coefficients is that $\alpha \geq 0$ and $\beta \geq 0$ in order to avoid an adverse conditional volatility (Brooks, 2014). In equation 2.22 the summation signs enable the inclusion of many past periods returns and conditional volatilities instead of only few, t and t therefore show the number of days included. Alternatively, Hansen and Lunde (2005) state setting t and t to anything instead of 1, will not have a significant outcome in the forecast result, therefore in order to satisfy the aim of keeping the method rationally logical it must be set to the number of returns in the data. The arithmetic definition of the GARCH (1,1), the GARCH model simplification, can be seen in Equation 2.23 The GARCH (1,1) model for the remainder of the thesis will be referred to as the GARCH.

2.3.5.5 GJR-GARCH

The inadequacy of the GARCH model is that it does not take in consideration the claimed leverage effect presents in the returns of assets, equity indices and commodity indexes. The model which consists the characteristics to combat this is GJR-GARCH model developed by Glosten et al. (1993) this adds a leverage factor to the GARCH model.

2.3.5.5.1 GJR-GARCH

GJR-GARCH was developed by Glosten et al. (1993). GJR-GARCH is also known as T-GARCH or TARCH if ARCH is used with modification along with GJR. GJR-GARCH (p, q, r) is described as follows:

$$\alpha_t = \mu_t + e_t, e_t = \sigma_t \varepsilon_t \tag{2.25}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma k \, e_{t-k}^2 I_{t-k,} = I_t = \{ \begin{matrix} 1 \\ 0 \end{matrix} \;\; if \; e_t < 0 \quad otherwise \tag{2.26}$$

Since, this adjusts for the asymmetric responses of the ups and downs that is the volatility to innovation fluctuations it is quite efficient.

For our methodology we used the above equation 2.26 in which leverage coefficients is γ_k and indicator function is I_t. For $\gamma_k > 0$ consist of the negative innovations e_t giving the additional value of the volatility σ_t^2 achieving the adjustment for the impact asymmetrically on the volatility as mentioned in the methodology in the beginning. For the $\gamma_k = 0$ getting GARCH (m = p, n = q) model now for $\gamma_k < 0$ the results are impeccable if the prices are in upward swing which can later be seen in the data analysis on the volatility than the downward moves. In our computation the GJR-GARCH (p, q) is used where the order of the leverage is o which makes it automatically equal to p. The parameters constraints are as below in equation 2.27:

$$\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0, \alpha_i + \gamma_k \geq 0, \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j + \frac{1}{2} \sum_{k=1}^{r} \gamma_k < 1 \tag{2.27}$$

Estimates of μ and σ were required to test these equations. As our own σ2 of the next cycle was calculated by various GARCH models, and these values were used as the standard deviation of the return distribution as σ = uncertainty for the next days. We used an exponentially weighted moving average of the last 7296 days for the predicted return μ. The same data was then used in the μ- and σ-estimations. Equation was then used to measure the expected return μ, where wi is the weight given by Equations. Systematic underestimation of the risk occurs if loss eclipse the VAR higher than the percentage of percentile on that specific day.

GARCH-models with corresponding distribution assumptions for the σ2-estimations were used for estimations of VaR with Gaussian- and t-distributions. Kupiec (1995) proposed a ratio test which is used to test null hypothesis. The test measures the reliability of VaR when a confidence interval is provided. Hence, a Kupiec test was used to test the validity of the estimates produced, yielding test statistics that were compared to significance levels derived from the χ2 distribution with 1 degree of freedom, which is 3.84 for the 95 % confidence interval. The degree of freedom is noted by the test statistic which belongs to a VaR - distribution, 1 is the considered as the degree of freedom in this equation 2.28.

Hence, GJR-GARCH becomes,

$$\hat{\sigma}_{t+r}^2 = \alpha_0 + \frac{\alpha_{0+\gamma_1}}{2} + \beta_1 \sigma_t^2 (r-1) \tag{2.28}$$

We have used the linear GARCH and non-linear GARCH models in the maximum likelihood MLE, quasi maximum likelihood QMLE and robust estimation method.

Equation 2.28 shows the mathematical meaning of the GJR-GARCH (1,1) this is defined in equation 2.27. The coefficient used is presumed to be in the positive accounts for the leverage effect however a negative return would have a greater effect on the conditional volatility rather than a correspondingly large positive return. The GJR-GARCH (1,1) model will be signified as the GJR for the rest of the thesis.

A critical examination of a study about values the risk methodologies. In order to measure the volatility of the portfolios, parametric, non-parametric and non-parametric density methods were used. Gómez et al. (2018), states that the performance of the parametric approach depends on the distribution of the financial returns and the volatility model that was used to estimate the conditional volatility of returns when predicting the VaR. In the study, entitled Value-at-Risk and Extreme Returns, investigation of the conditional, unconditional methods and historical simulation. The fundamental findings of this study were that historical simulation was stronger and as such that the implication of tails did not yield appropriate and desired results in the finding of the risk investors' investment. Optimal hedging, insurance, pricing of far out of the money options, and the Value-at-Risk (VaR) implementation are examples of accurate downside risk examination that is necessary for financial application. For VaR estimation, several methods have been proposed. Some rely on the use of condition volatility, such as the Risk Metric methods based on GARCH. Whereas, other rely on the historical distribution of the returns is unconditional, which includes historical simulation. Yao and Sun (2018) suggested the uses of extreme value methods, estimated tail probabilities as semi parametric methods. Conditional parametric methods were shown by GARCH with normal innovation to implement risk metrics, which was the under-predicted VaR for a sample of U.S. (Danielsson and De Vries, 2000). One of the major concerns that has been raised and critically analysed was why VaR models collapsed and could be done. Essentially, the focus was on two primary approach, conditional and unconditional empirical methodologies, which have led to indisputable evidence in all equity markets: unconditional models typically struggle to fulfil the critical test of conditional coverage. This is valid regardless of the projected distribution of return or even if the portfolio is long or short. The results of the study are based on a comprehensive back-testing study, similar to conditional (GARCH-based) VaR methods with their unconditional counterparts in the equity markets (Gokbulut and Pekkaya, 2014).

Therefore, our study will try to update all the data and information that are gather from previous studies regarding the measurement of volatility and testing leverage effect of S&P500 and Gold Price Index. In addition, it will also cover the important events that affect the economic condition regionally and globally. This kind of study will help to generalize and forecast the stock market volatility and take different decisions regarding the investment in different firms.
Further to all the research literature discussion, we will apply appropriate model proofs by using the lower AIC values, in contrast to other studies assuming normality and linearity. Moreover, our results have significant effects for practitioners like hedgers and policymakers in the commercial gold market and even in stock market.

2.4Data Analysis

The purpose of the paper is to investigate the volatility and risk between a commodity and stock exchange hence for this purpose Gold Price is taken as commodity and Standard & Poor's index S&P500 has been considered. Daily return of S&P500 and Gold Prices from the date of 01 January, 1992 to 01 January 2020, a time series data of around 27 years was obtained from S&P500 website and Historic Gold Prices from Yahoo finance. We have not considered the non-trading days as the stock exchange remained closed during weekends. The data consist of

7296 total observations for which log return expression was used as $RT = LN(\frac{P_t}{P_{t+1}})$ because the purpose is to evaluate the dependence structure of Gold prices and S&P500.

In two main strands, we study the empirical results. Firstly, using the conventional methods namely, VaR, Expected Shortfalls, Historical VaR, we create the dependency structure of the considered stock market and commodity in this thesis. Secondly, the study focuses on using volatility measures, ARCH and GARCH for both the indexes tested.

2.4.1 Programming

The programming used for the estimations in this study is basically for measuring the risk involved in the investment of the indexes used. Therefore, MATLAB has been used for the estimations because of the rigorous environment. Since, the utilization and applicability of the Econometric toolbox and being user friendly all tests were conducted in MATLAB programme (MATLAB 2014). The MATLAB code used for this chapter is proposed by (mmquant, 2016).

Table 2.1 presents the statistical measurements of prospects return of S&P500 and Gold Index which incorporate the mean, standard deviation, skewness, kurtosis, and relationship as well as the Jarque-Bera ordinariness test and the heteroscedasticity test between two prospects returns. It is clear both the two prospects return displayed negative skewness and higher kurtosis than the ordinary distribution, inferring leptokurtosis property in S&P500 and Gold Index prospects return conveyance. Other than, the JB typicality tests dismiss the typical dissemination theories for the commodities and stock prospects returns dissemination, confirming the need to utilize non- Gaussian dispersions. And the heteroscedasticity test comes about to demonstrate that the remaining arrangement shows GARCH heteroscedastic effects.

In Table 2.1, we can see the descriptive statistics of the two indexes returns. The dataset has covered an extensive period of around 27 years which includes turmoil periods for both indexes. Thus, the table provides a comprehensive analysis of the two indexes returns. The mean and mode of indexes is zero. Skewness of both is negative but Kurtosis is high positive numbers. The non-normality of both data can be monitored and seen by the Table 2.1 figures.

	S&P500	Gold-Price
Minimum	-0.0946	-0.0951
Median	0.000269	0. 000103
1^{ST} Quartile	-0.00403	-0.00425
Mean	0.020	0.028
3^{rd} Quartile	0.00526	0.00471
Mode	0	0
Std dev	0.981	1.089
Skewness	-0.110	-0.278
Kurtosis	11.371	12.512
Correl (lin/rnk)	-0.028	-0.041
Jarque-Bera (p-value)	0	0
Range	0.2042	0.1975
Maximum	0.10957	0.1024

Table 2.1 Summary Statistics of the Index Returns

Figure 2.3 demonstrates the time series plot of both the indexes. A relationship between S&P500 and Gold-Price index can be seen. Though this will be clear from further analysis. But there is a strong movement between the two markets. The returns of both indexes increased quite significantly between the period of 2013 to 2014 but there was a sudden drop in Gold Price Index during 2012-2016 which was the due to the crisis but Gold Prices return continued to increase despite the effects of Asian financial crisis. There was a fluctuation of both indexes from 2005 to 2019.

The consideration of both parametric and non-parametric model is considered. For this part, flexible and simple skewed t distribution of Hansen and Lunde (2005) see Jondeau and Rockinger (2006) was analysed. When $\lambda = 0$ the standardized Student's t distribution is recovered. Therefore, the following values when added to the equation were used results were found to be accurate according to Patton (2013).

For Skewed Normal distribution $\nu = \infty$ and the combination of $\nu = \infty$ and $\lambda = 0$ resulted in N (0; 1) distribution. For empirical distribution function $\widehat{F}_i$ of non-parametric estimation, the following function is used:

$$\widehat{F_\iota}(\varepsilon) = \frac{1}{T+1}\sum_{t=1}^{T} 1\{\widehat{\varepsilon_{\iota t}} \leq \varepsilon\} \tag{2.29}$$

In the experimental ponder, we select the S&P500 stock index prospects and the Gold Stock Index rough commodity prospects as tests, with the inspecting information of closing costs. Fig. 2.3 shows the returns of S&P500 and Gold Index, from which we can see that the two indices' prospects return have instability clusters and determination. The instability of huge prospects returns tends to be accompanied by emotional instability in this way, and the instability handle incorporates an inclination of coherence and mean-reverting.

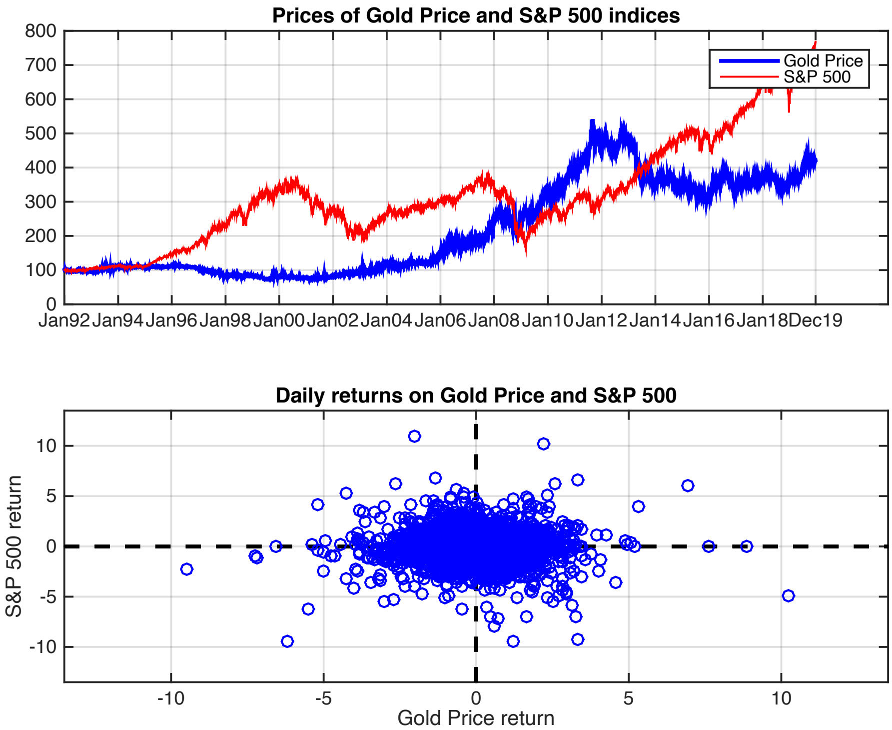

Figure 2. 3 S&P500 and Gold Price index returns

Since it can be seen from the returns and the prices figure 2.4 and 2.5 that the most volatility can be seen from the period of 2005 to 2020. We further investigated this volatility by using ARCH and GARCH on the time period of 2005 to 2020. This can be seen in the analysis below from the results and the figures.

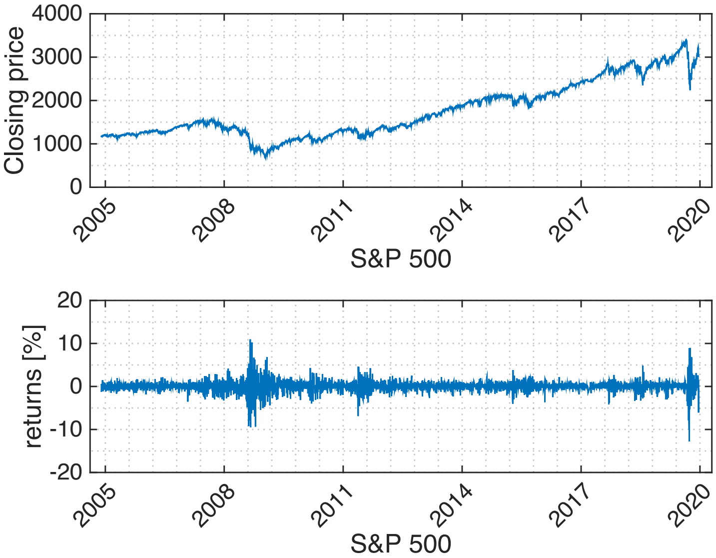

Figure 2. 5 Closing price and returns S&P500

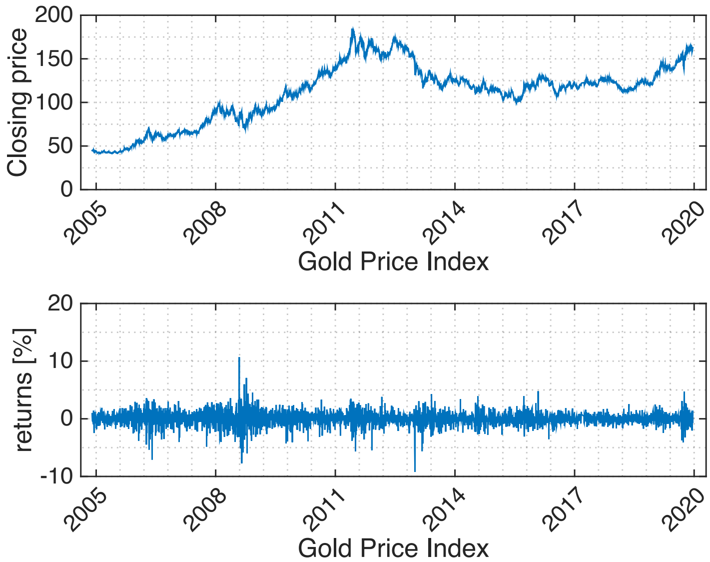

Figure 2. 4 Closing price and returns Gold Price Index

The results in Table 2.2 for overall period of the VaR method were drastic from 1992 to 2020 the VaR was highest for the 99.9 % percentile and lowest for the 95% for Gold Price index and for S&P500 VaR at 95% is highest and lowest at 99.9 % which shows that both indexes might have negative correlation. But while the concept of VaR is straightforward, its implementation is not. There are a variety of models and model implementations that produce very different estimates of the risk for the same portfolio. While previous studies have focused on how differences between models cause variation in VaR, the study "Evaluating Value at Risk Methodologies: Accuracy versus Computational Time" considers how differences in the implementations of the same model produce variation in VaR (Pritsker, 1996). This can be seen in the literature review as well from the other studies.

	VaR Model	
Confidence level	**Gold Index**	**S&P500**
VaR (90)	0.192%	-0.278%

VaR (95)	-0.530%	1.017%
VaR (99)	-0.322%	0.442%
VaR (99.9)	1.790%	-0.603%

Table 2.2 VaR Model

For Historical VaR in table 2.3, the results for the estimation were quite admirable and feasible as the consensus derived from the historical situation and data is viewed more efficient as far as the risk mechanism is considered. Hence the results for historical VaR at 10% for both indexes were quite similar within the range of -1% and even for 5% the difference was not quite high.

Historical VaR		
Historical VaR	**Gold Index**	**S&P500**
Historical VaR (10%)	-1.028%	-1.118%
Historical VaR (5%)	-1.491%	-1.703%

Table 2.3 Historical VaR

The Expected Shortfall method yielded in results shown in table 2.4 that are favourable in terms when the data is arranged in the correct manner. The results for 10% for Gold Price Index was little higher than the 5% which means that worst cases at 10% are at the level of -1.781%. However, the results for ES at 5% for both indexes is around 5.5% this demonstrates the worst case scenarios for both indexes were around the same range during the time interval used. The results of all three methods were similar and demonstrate a very basic approach to risk measurement techniques. The studies discussed in literature review also support the outcome of the analysis for the conventional methods.

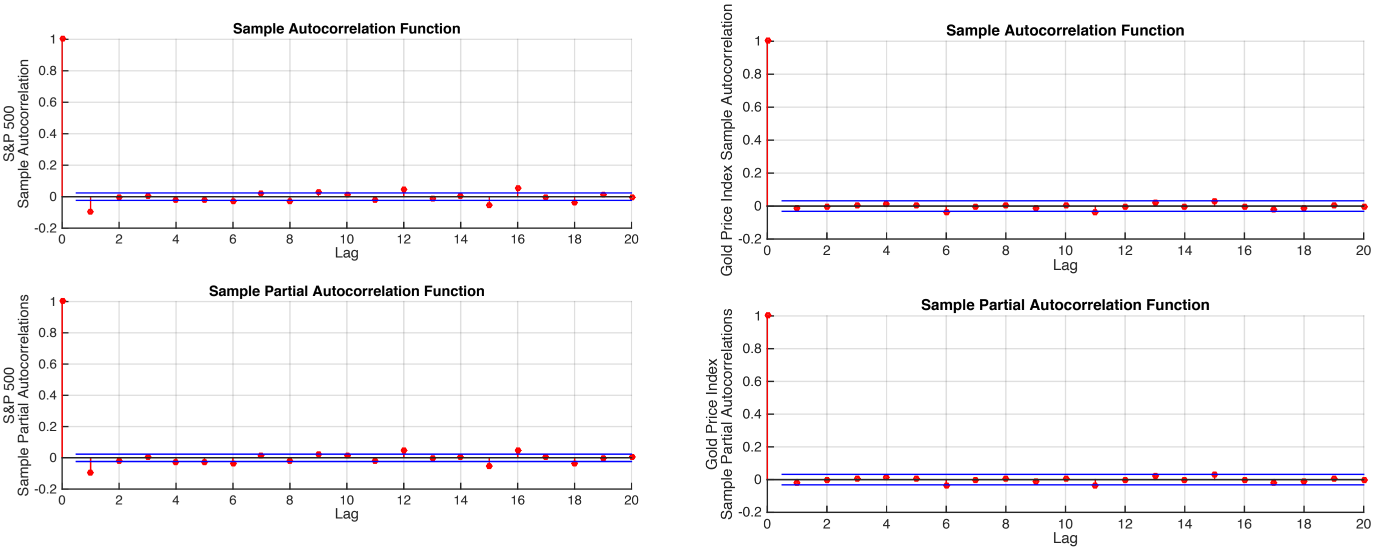

Figure 2. 6 Autocorrelation of returns Gold Price Index and S&P500

Expected Shortfall

Expected Shortfall	**Gold Price Index**	**S&P500**
Expected Shortfall (10%)	-1.781%	-5.293%
Expected Shortfall (5%)	-5.500%	-5.584%

Table 2.4 Expected Shortfall

Considering the parameter estimations being obtained for each of the model and the data set is the first step for evaluating the volatility of the asset indexes. In order to depict the estimations, the parameters are re-estimated on daily basis displaying time series over 27 years. The figure 2.6 and Figure 2.7 shows the volatility clusters clearly. The model used for the computation is as follows:

$$r_t \underbrace{c + \varphi_1 r_{t-1} + \varphi_1 r_{t-2}}_{\mu_t} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \qquad (2.30)$$

$$\sigma_t^2 = \alpha_0 + \alpha_i e_{t-1}^2 + \beta_i \sigma_{t-1}^2 \qquad (2.31)$$

Figure 2.4 showing the return prices of S&P500 it can be seen from the closing prices that the prices in the early 1990s were quite low and it gradually increased in the early 2000s but having a downfall in 2003 whereas again it continued to grow gradually but came down in 2009 and then increased gradually over the years and went quite high in 2019 but decreased quite a lot in late 2019s and again now there is an increase in the prices. However, in case of Gold Price Index the data of the returns and the closing prices is quite limited in early 1990s, seen in figure 2.5 however in early 2000s the closing prices increased quite drastically till late 2000s with slight downfalls but increasing impeccably in 2011 with ups and downs. Its peak was during the years between 2012 till 2013 with downfalls in 2014 but again the prices became quite volatile with increases and decreases till the early 2020s. Overall, both the indexes are quite volatile which is demonstrated in the return figures for both S&P500 and Gold Price Index. In case of the indexes used S&P500 and

Gold Price Index volatility is seen in clusters in periods having higher and lower volatility. The effect of the periods of volatility is considered to be dependent on the historical values to some degree of dependence in most cases. The changes in the volatility are often after the downward return move than after the upward return move.

Further the results of ARCH model for S&P500 and Gold Price Index are shown in figure 2.6. Autocorrelation function (ACF) and Partial Autocorrelation Function (PACF) show the returns are autocorrelated for both the indexes which can also reject the Ljung-Box test in which the value of p= 0.0023 hence this notifies that there is at least one figure which is non-zero correlation coefficient in p (1), p (2), p (3). The returns are exhibited at lag 2 which is L=2 for both

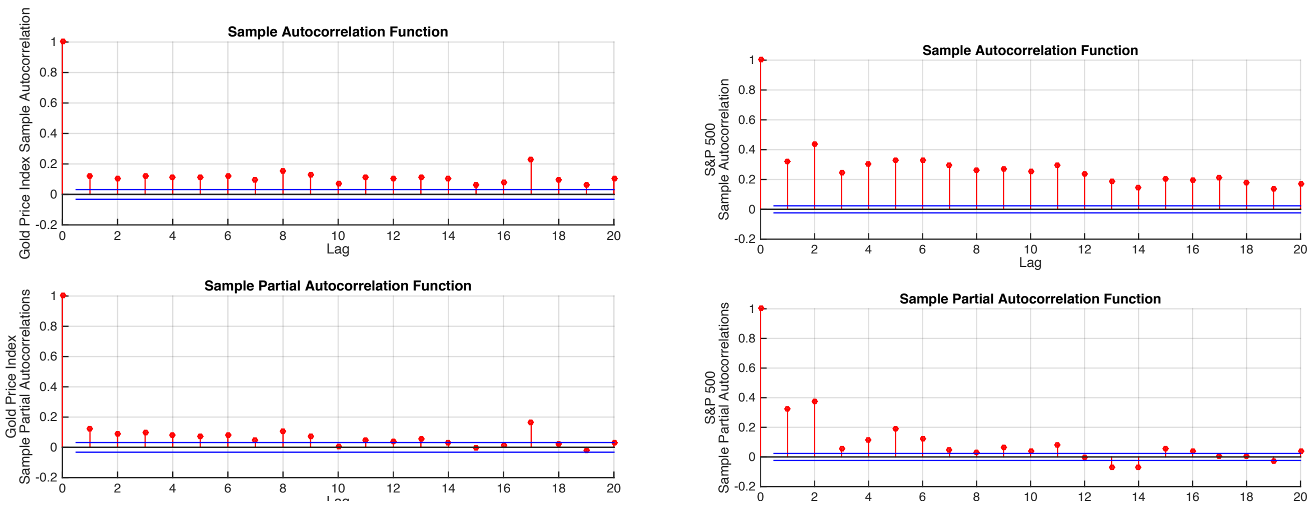

Figure 2. 8 Conditional heteroskedasticity of returns S&P500 and Gold Prices Index

the cases. In addition, under the 95% confidence, the acceptance threshold of LR figure is 3.84, which is considered suitable only if the LR is less than or equal to 3.84.as when LR is more than 3.84, it suggests that you cannot precisely predict market risks with the method used.

It has been examined that the lag properties of the figures 2.7 demonstrates that the outcome is quite based on the lag of the variances of both the stocks. The results given are in accordance with the analytical threshold. In this segment of analytical research, it is clear that both methods can be precisely predicting the potential threats in the selected gap and certainty, and the examination outcomes confirm that both methods are extremely definitive.

As ARCH and GARCH models are univariate for this chapter they do not adjust for the leverage effect they allow for the leptokurtic distribution of volatility clustering (including heteroskedasticity) in the time series data. The results of conditionally heteroskedastic portrays the variance of the returns are significantly autocorrelated which means that the returns are conditionally heteroskedastic. Since lag is 1 in this analysis therefore L=1 in this case.

$$r_t = 0.061224 - 0.00912 r_{t-2} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \tag{2.32}$$

$$\sigma_t^2 = 0.01733 + 0.11078 e_{t+1}^2 + 0.876208 \sigma_{t-1}^2 \tag{2.33}$$

In equation 2.32 and 2.33, the results for the ARCH-LM test can be located there. The results how the ARCH affects residuals and the rejection of any null hypothesis. This indicates the returns of S&P500 and Gold Index series are volatile which will be discussed further in the analysis. In Figure 2.9 and 2.8, the return series graph shows an assembling pattern on volatility. To model this conditional heteroscedasticity, we apply GARCH process which has an ARCH effect on the residuals. Subsequently, the data has not been dispersed as normal, which means they estimate the student's distribution. Using Iterating Marquardt steps to maximize the log-like function, then estimate the GARCH limitations and ARMA mean equation (1,1). In table 2.7, the estimation results can be found. The results show α0, the constant term, α1, the ARCH term and β1 which is the GARCH term are statistically substantial. The ARCH test results reject H_0 with very small p-values to favour H_1which suggests that $e_t$are autocorrelated-this further demonstrates that the returns are conditionally heteroskedastic.

$$r_t = u_t + e_t \ , e_t = \sigma_t \varepsilon_t \qquad (2.34)$$

u_t= conditional mean and $e_t = condtional\ innovation$. We describe our r_t by AR-GARCH models by setting up the ARIMA model objects. Which is displayed in equation 2.30 $r_t \underbrace{c + \varphi_1 r_{t-1} + \ \varphi_1 r_{t-2}}_{\mu_t} + \underbrace{\sigma_t \varepsilon_t}_{e_t}$ and 2.31 $\sigma_t^2 = \alpha_0 + \alpha_i e_{t-1}^2 + \beta_i \sigma_{t-1}^2$ The results are similar as with AR-GARCH approach because AR(2) plays insignificant role in AR-GARCH.

This signifies the conditional variance correlates to the lagged variance and lagged squared disturbance. The newscast about instability has expounding power for the next period of instability. This model output is available in the methodology.

$$r_t = 0.021856 + 0.01164_{t+2} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \qquad (2.35)$$

$$\sigma_t^2 = 0.009916 + 0.0533 e_{t+1}^2 + 0.9399 \sigma_{t-1}^2 \qquad (2.36)$$

The account responsible demonstrates the α1 measures to a degree into the next period instability Campbell et al. (1998). Within the sequence, S&P500 and Gold Index, the coefficient is 0.090591 which demonstrates the encumbering instability over the period of the sequence. The estimate of β1coefficient 0.906023 demonstrates long memory in the alteration. This specifies the changes in instability will affect future instabilities in the long run or the impact of instability is durable and long-lasting. To summarise the ARCH and GARCH term, α1 β1 is 0.996614 indicating instability shocks are tenacious. The Financial repercussions due to these coefficients for investors was that the S&P500 index returns instability cluttering. This authorises investors to establish future positions due to this characteristic. Subsequently, in 1993, they applied Ding et al. (1993), a trial to determine if the sequence required an asymmetric model. The trial applied the GARCH (1,1) model residual. To find the instability is a sign biased, they test for the significance of the ϕ1in equation 2.34. The test demonstrates the test results, the negative shock (ϕ1) is statistically significant. This demonstrates the positive and negative shocks have impacted asymmetrically on the conditional variance. Furthermore, the negative shock bias trial demonstrates that asymmetry originates from the negative shocks. To conclude, the combined test for both sign and size bias equations 2.31 finds ϕ2 and ϕ3 are significant.

ARIMA (2,0,0) Model			
Conditional Probability Distribution: Gaussian			
Parameter	Value	Standard Error	t Statistic
Constant	0.0612241	0.00922258	6.6385
AR {2}	-0.0091152	0.0119692	-0.761552

Table 2.5 ARIMA (2,0,0) Model S&P500

The table 2.5 above basically shows the parameter when using the conditional probability distribution: Gaussian model for S&P500 and it can be seen that the value of AR {2} is close to zero and the standard error for both cases whether the parameter is taken as constant or as a variable is quite volatile. This clearly depicts the risk involved in the S&P500 index.

ARIMA (2,0,0) Model			
Conditional Probability Distribution: Gaussian			
Parameter	Value	Standard Error	t Statistic
Constant	0.0218567	0.0146284	1.49413
AR {2}	0.011647	0.0160243	0.726831

Table 2.6 ARIMA (2,0,0) Model Gold Price Index

However, in case of Gold price index (Table 2.6) the value of AR {2} is in positive and not that close to zero as compared to table 2.6 (S&P500) there can be many factors involved in this as the volatility of a commodity is being compared to a stock index. Since volatility is driven from social, economic events (shocks), political events as the occurrence of these event lead to the significant return and fluctuation of the prices having potential of the spill over effects throughout the markets and the sectors. These effects of volatility spill over throughout the sectors and market are quite vital for examining the mounting complexity of the price index shocks to know the implications which can be local, regional or even global (Shrydeh et al., 2019). Since, the standard errors in both scenarios seems minimum whether it is S&P500 or Gold price index. The results are quite well-defined in both the table of ARIMA.

GARCH (1,1) Conditional Variance Model			
Conditional Probability Distribution: Gaussian			
Parameter	Value	Standard Error	t Statistic
Constant	0.0173387	0.00137922	12.5714
GARCH {1}	0.876208	0.00567979	154.268
ARCH {1}	0.110784	0.00530219	20.8941

Table 2.7 GARCH (1,1) Conditional Variance Model S&P500

Further, the evaluation of the GARCH model using the conditional probability distribution: Gaussian is considered to investigate the variances of S&P500 index. For instance, during the first analysis after its presentation S&P500 used the ARCH, however, it switched almost totally to the system afterwards. Descriptive statistics of all stocks scanned in the paper are shown in Table 2.1. Standard deviations and all conditional variance are reported positive. In addition, fat-tails and non-normally distributed are in all set, consistent with most financial assets. The outcome further suggests that time series are stationary. The ARCH-LM and Box-Q analysis confirm again that the null hypothesis of no ARCH effects is refused it can be seen that ridiculously small p-values rejects null hypothesis in favour of H_1. The parameters are positively asymmetric for both indexes. Since, the measure of risk is basically defined by the term of volatility of any underlying market index, commodity or security ARCH GARCH models illustrate the volatility quite efficiently. When taking ARCH GARCH with constant which are basically non-seasonable coefficient elements it can be seen that GARCH is nearby 0.8762 and ARCH is 0.1107 showing the ups and downs in the index. Though, the standard error is manageable in this respect of S&P500 index.

GARCH (1,1) Conditional Variance Model			
Conditional Probability Distribution: Gaussian			
Parameter	Value	Standard Error	t Statistic
Constant	0.0099165	0.00170018	5.83262
GARCH {1}	0.939919	0.00338827	277.404

ARCH {1}	0.0533338	0.00271372	19.6534

Table 2.8 GARCH (1,1) Conditional Variance Model Gold Price Index

The table 2.8 basically demonstrate the GARCH results for Gold Price index, the volatility of the index is seen from the values of GARCH and ARCH which shifts in the standard error and the t statistics. This demonstrates that from historical data the volatility is persistent. The prices of Gold index have significant number of fluctuations from time to time due to the volatility driven factors mentioned before.

ARIMA (2,0,0) Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.0729843	0.00845852	8.6285
AR {2}	-0.0267781	0.0119096	-2.24845
DoF	5.98367	0.429155	13.9429

Table 2.9 ARIMA (2,0,0) Model S&P500

The equation used for the computation is

$$r_t = 0.07298 - 0.0268_{t+2} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \qquad (2.37)$$

$$\sigma_t^2 = 0.01031 + 0.10368 e_{t+1}^2 + 0.8935 \sigma_{t-1}^2 \qquad (2.38)$$

In order to further measure the risk involved in the investment in the indexes ARIMA model was further used considering the conditional distribution: t factor was used and the results for S&P500 index for AR {2} (-0.0267) and DoF (5.98367) depict the variability of the index in table 2.9.

ARIMA (2,0,0) Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.0387352	0.0136677	2.83408

AR{2}	0.0109693	0.0152509	0.719256
DoF	5.27605	0.470555	11.2124

Table 2.1 ARIMA (2,0,0) Model Gold Price Index

In case of Gold Price Index, the results in table 2.10 are different for AR {2} (0.01096) which is positive as compared to that of S&P500 index. This reflects the value of Gold Index ARIMA is close to zero and same for S&P500 index as well. The volatility in both the results is complex but quite clear at the same time.

$$r_t = 0.03874 + 0.010969_{t+2} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \quad (2.39)$$

$$\sigma_t^2 = 0.006733 + 0.04522 e_{t+1}^2 + 0.95118 \sigma_{t-1}^2 \quad (2.40)$$

GARCH (1,1) Conditional Variance Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.0103138	0.00192608	5.35485
GARCH {1}	0.893591	0.00754302	118.466
ARCH {1}	0.103682	0.00808418	12.8252
DoF	5.98367	0.429155	13.9429

Table 2.2 GARCH (1,1) Conditional Variance Model S&P500

Same process is used in term of GARCH evaluation but conditional probability distribution: t is considered and the results of ARCH (0.103) and GARCH (0.893) indicate the variances which involves the risk of investment and the price fluctuations are quite volatile for the index of S&P500. Please refer to table 2.11. We have achieved acceptably standardized marginal distributions using the AR (1)-GARCH (1,1), as the base marginal design prior to modelling the dependency structure for the two indexes.

GARCH (1,1) Conditional Variance Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic

Constant	0.0067332	0.00232351	2.89786
GARCH {1}	0.951181	0.00627261	151.64
ARCH {1}	0.0452276	0.00603319	7.49646
DoF	5.27605	0.470555	11.2124

Table 2.3 GARCH (1,1) Conditional Variance Model Gold Price Index

In table 2.12, Gold price index GARCH results show similar variations and results of the GARCH are quite similar only with a difference of 0.0572 between the GARCH of S&P500 and Gold Price Index. However, the ARCH results are a bit different because in case of S&P500 is not that near to zero whereas the ARCH of Gold Price Index is quite near to zero making the index of the commodity more volatile.

ARIMA (2,0,0) Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.0485084	0.00848764	5.71518
AR {2}	-0.0151879	0.0118593	-1.28067
DoF	6.70913	0.502728	13.3454

Table 2.4 ARIMA (2,0,0) Model S&P500

Now considering AR-GJR-GARCH by adjusting for asymmetric volatility in order to compare to AR-GARCH with t-distributed for measuring the performance of each model in evaluating the volatility of the index, AIC and BIC value will be used for calculating the t-distribution. The table 2.13 show the AR value to be negatively close to zero and the value of DoF is positive as well.

ARIMA (2,0,0) Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.0441875	0.0136938	3.22682
AR {2}	0.00882935	0.0151521	0.582713
DoF	5.27461	0.464873	11.3463

Table 2.5 ARIMA (2,0,0) Model Gold Price Index

Similarly, the table 2.14 of Gold Price index shows the same variations only the AR value is in positive number and approximately zero. The volatility is clear in both the scenarios of the indexes. It is quite clear and visible that the distribution measures the right factor of volatility which supports the variances fluctuations.

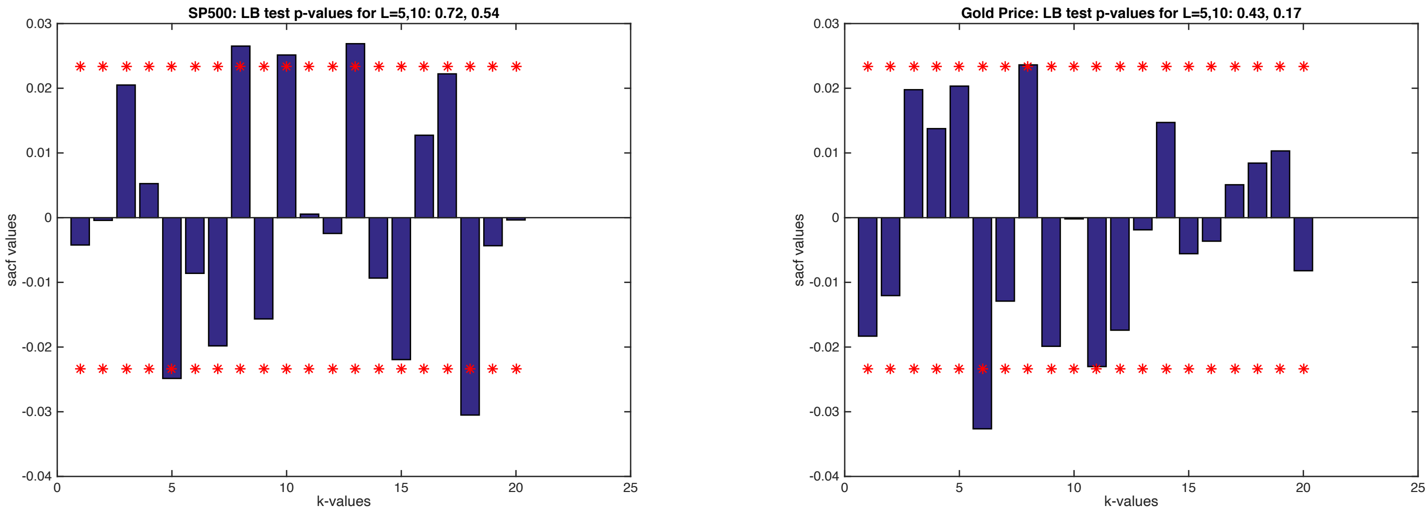

Figure 2. 8 The p values of ARMA process LB tests for S&P500 and Gold Price Index futures series.

Marginal distribution and joint distribution the ARMA process is utilized for the conditional mean condition of the commodity (Gold Price) prospects returns, and the ideal arrange concurring to the AIC Akaike information criterion (AIC) and BIC (Bayesian approach) is ultilised to determine the performance of univariate GARCH models.. Ljung-box test on whether there's a slack relationship in stock and commodity market prospects return arrangement. It finds that there's no evidence of remaining autocorrelation from ideal models for the mean. And the Ljung-Box test comes about of S&P500 returns, are shown in Fig. 2.8, which affirms the presence of autocorrelation. At that point, the GJR-GARCH model that can depict the asymmetry and heteroscedasticity of the instability prepare, utilized to demonstrate the conditional fluctuation handle, moreover with the BIC model choosing the ideal slack to arrange. To capture the leptokurtosis and fat tail property, the Skew t minimal conveyance utilized for the stock's prospects return conveyance. Moreover, the GJR-GARCH-Skew t (GGSt) model embraces negligible conveyance modelling of the prospects returns. As seen from the comes about of Table 2.13 and 2.14, the conditional cruel of gold and S&P500 index futures returns are separately in AR (2) and AR (2) shapes.

After fitting the mean condition, the Lag range multiplier test utilizes to look at whether both residuals have heteroscedasticity, and it suggests that the GARCH sort models are utilized to capture the heteroscedasticity of residuals. From the fluctuation condition of the S&P500 index returns, the returns diminish, the impact of εt-1 on h1 is α1 + δ, that is quite vital however the t-statistics is another important factor and the standard error is 0.007355 which is quite less, whereas when the returns increments, the impact ought to only be α1, that's another factor to be monitored, the leverage value came out to be 0.181, which is a few less and not times bigger than that with use impacts. At the same time, the use impact is measurably noteworthy in both gold and S&P500 index prospects return. It suggests that terrible news would cause bigger instability in stock exchange prospects markets than the impact of great news stun. Gathered from the esteem of λ, it concludes that both gold and S&P500 index prospects returns show a left-skewed phenomenon. Other than, it is clearly concluded from the esteem of ν that, the S&P500 index prospects returns display fatter tails than the Gold Price prospects returns. When surveying the exactness of Skew t dissemination, the KS test and the CvM test are utilized to analyse the fitting exhibitions of hypothetical models with actual conveyances. And the test comes about to appear that the set up marginal dispersion model is sensible, both the KS tests of the gold and S&P500 index prospects don't reject the Skew t conveyance. For comparison, we moreover compute the probability capacities with minimal distributions of GED and Understudy distribution, specifically the GJR-GARCH-GED demonstrate, and the GJR-GARCH-Student t demonstrate. From the comes about of tests, it can be confirmed that the Skew t minimal dissemination generally superior fit the commodity index prospects return information.

GJR (1,1) Conditional Variance Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.0146377	0.00171429	8.53866
GARCH {1}	0.895183	0.00735547	121.703
Leverage {1}	0.181834	0.0135938	13.3762
DoF	6.70913	0.502728	13.3454

Table 2.6 GJR (1,1) Conditional Variance Model S&P500

The original AR-GARCH in this scenario has outperformed from AR-GJR but the performance is slightly better. From the results it can be seen that the figures of leverage coefficient is insignificant statistically. Again, the values of the GARCH are not so close to zero which demonstrate the fluctuation of prices in the indexes. In Table 2.15 and 2.16, we report the parameter estimations and standard blunders of the GJR-GARCH-Skew t minimal dispersion.

GJR (1,1) Conditional Variance Model			
Conditional Probability Distribution: t			
Parameter	Value	Standard Error	t Statistic
Constant	0.00632768	0.00219543	2.88221
GARCH {1}	0.952661	0.0061062	156.015
ARCH {1}	0.0603011	0.00913382	6.60195
Leverage {1}	-0.0304046	0.0102384	-2.96966
DoF	5.27461	0.464873	11.3463

Table 2.7 GJR (1,1) Conditional Variance Model Gold Price Index

It can be seen from table 2.16 above that again the values of leverage are statistically insignificant for the results of Gold Price Index. ARCH is near zero (0.0603) whereas GARCH is 0.95 which near to the value of 1 demonstrating the poor performance of the model. The reason for ARCH to be nearly zero is due to the leverage affect which have taken away ARCH affect. However, both the indexes Gold Price index and S&P500 are very volatile.

$$r_t = -0.0268_{t+2} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \quad (2.41)$$

$$\sigma_t^2 = 0.01031 + 0.10368 e_{t+1}^2 + 0.8935 \sigma_{t-1}^2 \quad (2.42)$$

From the key study it is for shown that the conditional variance has a negative shock decrease, this basically demonstrates that the purpose of finding the connection of the two stocks in the research has been successfully achieved. The analysis further suggests that the t- distribution values have also suggested quite significant changes and connections between the stocks and have therefore presented quite good values which adds quite a lot to the meaning of the analysis. Therefore, the null hypothesis which signifies of no relation between the stocks rejected because the negative shocks are not the same as the positive shocks due to difference in magnitude.

$$r_t = 0.010969_{t+2} + \underbrace{\sigma_t \varepsilon_t}_{e_t} \qquad (2.43)$$

$$\sigma_t^2 = 0.006733 + 0.04522 e_{t+1}^2 + 0.95118 \sigma_{t-1}^2 \qquad (2.44)$$

An advantage of the EGARCH model in comparison with basic GARCH model is that the conditional variance, σ2 has a positive power which indicates that whether the variance is positive or negative the conditional variance will always be positive ((Fischer, 2006). The leverage coefficient is negative (0.0304046) signifies that the ratio results that the company has a negative net worth. Volatility is the liability to change rapidly and unpredictably, especially for the worse and that's why investors are more responsive to the negative news in comparison to positive news which implies that the volatility spill over mechanism is asymmetric and of the same magnitude. The asymmetry coefficient is positive therefore the past variance and current variance have a relationship of a positive modules. At the bottom of the QQ-plot in Fig. 2.9 the EGARCH modules has a fluctuation from normality which once again shows a higher impact of negative shocks of volatility.

From GJR-GARCH module the asymmetry term y is positive and that means the negative shocks increase volatility and the impact of shocks is asymmetric. There can be seen on the lower roles of table 2.16 that there is no ARCH effect remaining in the quantity after other things have been subtracted or allowed for in the results of the diagnostic tests

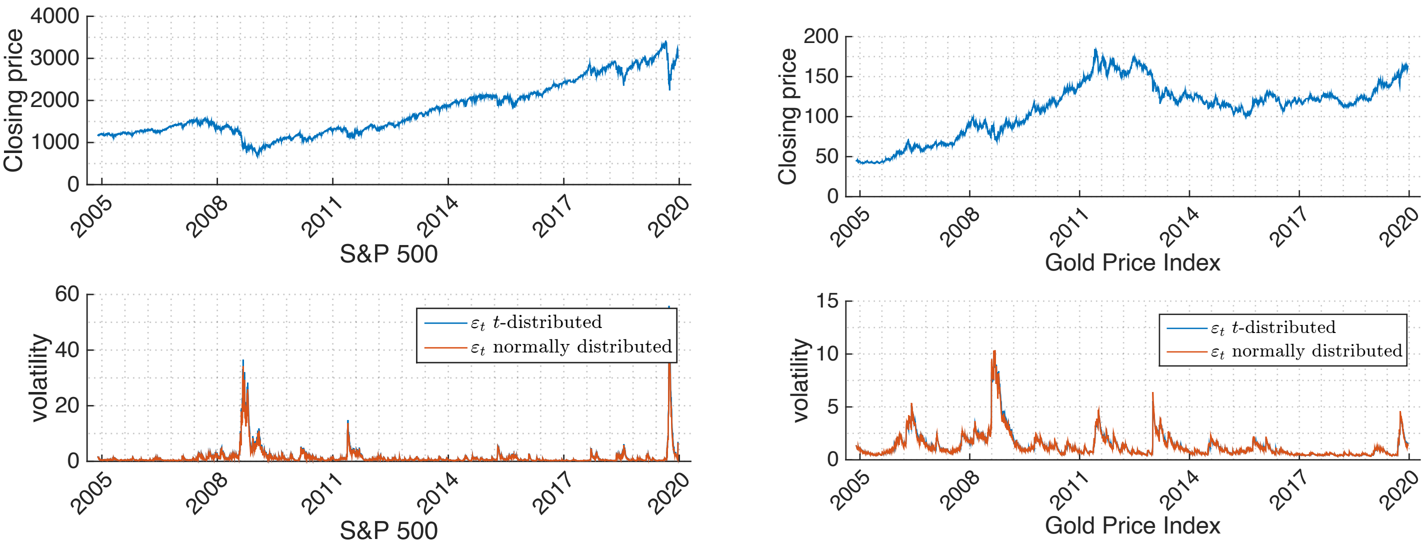

Figure 2. 9 volatility AR-GARCH t- distributed and volatility AR-GARCH normally distributed S&P500 and Gold Price Index

The figures 2.9 basically portrays the results of the t-distribution and normal t-distribution of both the indexes S&P500 and Gold Price Index and it shows the volatility of both the indexes. The figure shows both the closing prices and the distributions. The 2007 downfall can be due to Global Financial Crisis. Since the crisis is many times reported to be the most merciless after the Great Depression of the 1929. Since, the origination of the excess of volatility in the US market is broadly characterised by the 2007 Global Financial crisis which led to negative spill-over and uncertainty effects across the world's significant financial markets making the investors and the portfolio managers to be more concerned of the interrelationship of cross-market and take strict mitigating asset risk exposure actions. So, the question is which model to choose now? Model with t-distributed innovations seems to be promising. Therefor the optimal lag (p,q) is taken from the t-distribution innovation. We will examine quantitatively by AIC, BIC. In order to do so, we need to infer log-likelihood objective functions for each of the model. Another way to do is to extract final conditional variances – volatilities.

MODELS	AIC	BIC
AR-GARCH	3722.134	3762.87
	3455.11	3498.22
AR-GJR-GARCH	3413.33	3501.76
	3413.88	3512.13

Table 2.8 AIC and BIC

The results of AIC and BIC suggest that AR-GARCH with t-distribution innovations should be chosen. However, The AR-GJR-GARCH did not perform quite well therefore AR-GARCH did outperform because of the leverage coefficient in AR-GJR GARCH is statistically insignificant.

The VaR findings for the overall time period including the crisis and non-crisis time demonstrate better outcomes for the copula model followed by both GARCH criteria using both ranking measurements. Asymmetrical GARCH models yielded good performance, although a few estimates were not important. The risk measures provided the best results for the post-crisis

VaR outcomes, while the GARCH models and ARCH fared worse. This may be due to the memory problem of the historical VaR, which is a double-edged sword. Long memory raises the importance of the coefficients in GARCH models and the simulation in risk measures, yet at the same time exposing them to the risk of placing too much weight on the past. Markets may adapt and alter characteristics on a regular basis, thereby undermining a model or system that relies too much on the history of an index.

It is useful to determine the approximate GARCH models used in this study as having two kinds of memory. The lagged σ2 component is the first, and reciprocal, kind of memory, and the other is the coefficient calculation. The lagging σ2 can vary in its effect on the calculations and should not cause its precedent to intervene too much in a correctly posed model. However, the coefficient calculation, which was carried out using the maximum probability approach in this thesis, quite obviously faces past issues which is the historical simulations or Historic VaR. Using coefficient projections from a prior timeframe that varies considerably from the present day will skew the projections variance, allowing the probability to be over- or underestimated for a long time before stabilising. Both the pre and post crisis period studied were preceded by periods with different characteristics much of this is covered in chapter 3(Section 3.1). A much calmer period of stable development followed the recession, and the real crisis followed the post-crisis phase. A probable reason for which the GARCH family models consistently performed lower than the historical VaR with fixed coefficients is likely to be their historic problems which is based on the historic VaR evaluation.

The question asked at the start of the thesis was whether investors, both companies and people acting alone should use different risk measuring models to know the maximum loss along with correlation as will this be useful. The next question asked, knowing the fact that the historical simulation has effective outcomes, volatility forecasting models needed to be used – the asymmetric GARCH models. The relevance of making things easier is of course the part that is significant and is the one we leave to the reader to determine for themselves.

In the thesis we have demonstrated the adaptable nature of the volatility model and problems involved with coefficient estimation in other models. Adding this with the fact that the ARCH is an easier way to use in practice, we agreed that investors should not waste time and effort on using difficult approach and should instead be use Volatility models when assessing VaR on the stock indices for further analysis the ES (Expected shortfall is further discussed in this chapter and chapter 4 (Section 4.5). For distribution expectations, the Gaussian distribution is recommended to be used as it is evident to be better for the Copula model on average. However, as the risk measure and even GARCH produced conclusive outcome in the period pre and post crisis, for people that prefer easier ways, the GARCH can be considered as the allowable way in stable periods. Though, due to the imperfection of the GARCH in turbulent times, the VaR measure and the parametric assessment should always be used for more unstable times. Since we needed clarity in the thesis, Monte Carlo- simulation was not tested, and neither were other precise and attribute of the GARCH family models. Conclusion of these techniques and their assessment precision is left to be covered in latter chapters in the thesis.

2.5 Conclusion

The experiential findings of this study have a lot of involvement towards investors, active portfolio managers and numerous market participants and this chapter suggest that the index return volatility is asymmetric, even though investors and portfolio managers may observe the constituent stock price movements of hi-tech stock index. That situation would provide additional information for portfolio managers to adapt their positions. In conclusion of that, several different methods have been proposed. The most important ones are: HS, parametric estimation and Monte Carlo-simulation (Portmann, Siebert and Döll, 2010). Due to several reports of the HS method not being as effective as some of the other methods, should investors stick with the HS or take the time to learn the more complex estimations.

Autocorrelation and volatility were utilised for financial time series which were incompatible with the belief in traditional econometric models. When studying volatility in S&P500 and Gold Index during the period of January 01 1992 to January 01, 2020, this paper uses VaR, Historical VaR, Expected Shortfall, ARCH, GARCH and GJR-GARCH. According to sources there have been no further evidence in literature that accurately investigates the asymmetric dynamics of S&P500 Daily index return volatility, and Gold Index specifically during the period of 2005, 2008 financial crisis and the consequences along it.

S&P500 index and Gold index returns have results that show and differ from the business as usual and reveal volatility with diverse form in the residuals. To conclude the findings, show nonlinear structure in the conditional variance of the returns and this dynamic may be restorative with the GARCH (1, 1) model. The result of ARCH and GARCH show that the variance of the series has long memory and shocks on volatility are tenacious but also non-unity, this is also assisting the mean reverting process. GARCH and GJR-GARCH models represent that the series have leverage affect and the result of the shocks is asymmetric. This then leads to the result of the negative shocks of volatility are higher than positive shocks of the same size, as a result the literature is consistent with the findings.

Further developments should delve into how volatile major stock index returns compare against commodity index returns in order to see whether commodity index returns are better used in the context of risk management, rather than, for the S&P500.

2.6 Contribution to Knowledge

The contribution to knowledge of this paper to the literature is in two methods. The first is the explanation of the fluctuations of the returns using the volatility model displaying the utilization of the extensive data period used. The paper applies both ARCH and GARCH models to catch every balance and unevenness in volatility modelling. To the best of our knowledge, while there are researches at the unpredictability of progress using volatility of stock and commodity indexes inside the writing, understudies have as of now not however displayed substitute charge unpredictability bunching in S&P500 and Gold Index utilizing most recent consistently data. The second is that the chapter further contributes to knowledge because it makes the investors and financial analyst aware that when using the Volatility measures along with VaR method, investors should select the confidence level based on particular set of circumstances. For example; the investors own risk level, the conditions and consequences of the S&P500 is currently operating in, including its development ideas and the volatility of the financial markets at the relevant time etc. A higher level of confidence should be chosen if both the indexes adopt a more conservative strategy and secondly the length and quality if the samples should be given consideration when the ARCH and GARCH method is selected. On the other hand, with a limited sample size any study would not be able to find an effective analysis, but as the sample size is good therefore, the changes in the chosen sample are consistent with the expected changes in the market in the future or else it will result in instances where the predicted VaR is overly cautious or not as expected. The number of simulations should not be limited when choosing the simulation method. Factors such as policy changes, large market changes and severe losses will have an impact on the market and will lead to the inaccuracies in the VaR prediction, so it is very important to keep a close eye on these factors after the VaR value is calculated.

"Value-at-risk in S&P500 and Gold Index" analysis consider the discernment on measuring the inconstancy of S&P500 and Gold Price index portfolios. Value at risk or more commonly VaR represent primary controversy in estimating the market risk of a financial firm exposed to risk in specific situations. "Value at risk" can be easily labelled VaR, although it answers to the name of "new science of risk management". VaR is a common procedure to consider risk of investing on financial instruments. Volatility is the most conventional and appreciate units of risk. The only issue is that volatility does not involve investment variations, as it cannot predict increase or decrease in the value of stocks. Anyway, better an exceed then a decline. Regardless many different origins of financial risk, it was not considered the market risk, ergo, the prediction of inflation and deflation, as credit risk is part of it.

2.7 Discussion and Recommendations

Using the overall analysis results, a detailed comparison of the reliability of risk prediction is made and an explanation of the empirical results is given from the perspective of volitivity. In conclusion, the chapter objectives of measuring volatility and risk, VaR measure along with ARCH and GARCH has been quite significantly positive to access the worst-case scenario and volatility between S&P500 and Gold Price Index. The calculated VaR value was not exceeded by the actual loss of assets which were 95% respectively. Test results carried out later showed that the LR statistic was entirely within the accepted threshold. Looking at Fig. 2.1 and Fig.2.2 it can be noted that the volatility of the market shows major variations at different times. One example of these significant variations can be seen from the fact that data in the range of 7296 is quite stable whereas, the market is somewhat volatile in the range of this time period. The VaR method may not be capable of predicting the changes in the market during this time which from a local perspective could lead to unnoticeable test results. The reason for this can be explained by the fact that the market has changed and the analysis of future VaR values is still utilising data of the earlier interval. This is known as the "time lag" effect. This situation is not looked into now due to insufficient space, however it is important that this situation is considered impractical applications because it is important to consider market variations at any time as stated by specific volatility.

Autoregressive conditional heteroscedasticity or commonly called as ARCH model, was developed by Engle (1982). This model uses extensive analysis based on time and variance. They are commonly used methods for forecasting the changes over a time period and the intimal well-known application of this model was to identify the inflation in GB during the early seventies. This process uses mean, median, mode methods to assess the variance from predictions. Generalization of ARCH model took place later with new model called as GARCH, where the Exchange rates were used for the first time. Even though this model came up in the 70's and 80's, even today they have gained attention as they have extensive application in the commodities systems. These models have been extensively used in field of econometrics to analyse the stability of the commodities and stocks, their performances, variance and volatility. Some of the major risks were identified in use of some of the commodities such as the expensive metals for example Gold etc, like users underlying are unknown and they can be used by dark society for illegal activities. While their positive side like cutting of the brokerages in between and good for returns and investments. The process of making a transaction is much faster and reliable than the past. Security is major concern in many commodities as this can be easily stolen, and concept of private key encryption technologies and wallets can easily be hacked. Over millions of commodities like the Gold were stolen and this is only used as a medium of exchange. This might ease the process of transaction and has real physical presence like Gold. Therefore, Gold on the positive front stop loss options and degree of volatility and higher margins provide better scope for investor.

Heteroscedasticity has occurred as some of the key variables and possibilities of the outliers, has reflected in the failure in analysis of performance of the commodities. Hence the recommended use of the other types of the GARCH models like threshold or the exponential have been suggested to minimize the outliers. Application of GARCH model has proven results mainly in study of volatility. There was significant fall even though the maturity had not begun, whereas the same method also proved better results in comparison between various commodities like Gold, stocks and digital commodities. Compared to the use of symmetric analysis, the process was best in asymmetric analysis as this helped to determine the best form of investment. On the risk perspectives some of the commodities were more threat for the investment, whereas gold was less risky. But, comparisons with USD or investment in noble metals, the process of investment in Gold was found to be more fruitful in terms of returns over a long time periods. Despite the constant changes or the volatility of the prices, or the market conditions, the process of selling them for the higher prices by assessment of the risk. The best strategy would be to assess the best possible values for selling to maximize the profits based on the market forecast.

On analysis using the average trend ranges of Gold versus Stock, proves that both Gold and Stock has a tendency of yielding higher returns, profits and is more suitable for Bearish strategies when compared to Gold. Volatility of both the commodities and stocks are analysed in detailed study of them in the selected markets. Higher the volatility higher would be the options to earn using the Gold whereas the volatility levels are comparatively less for S&P500 when compared to Gold. But, on the risk prospects investment in S&P500 has a lesser risk as high-cost Gold would add-on high degree of volatility.

VaR commonly calculates a devaluation of hazardous assets or portfolio in a determinate period of time. Although there are multiple reading sources about VaR, the name "Value at risk" has been regularly used only after the mid 1990s, also if the name was introduced past in the years. The studies regarding VaR were created through hypothesis by Harry Markowitz and others scientists concerning values and portfolios of investors. In classical Markowitz mean-variance (MV) portfolio enhancement, effective portfolios are upgraded to limit their changes and to decrease in general monetary hazard (Markowitz, 1952). Thus, each portfolio along the investment for that level of return. In any case, in spite of its ubiquity, the MV strategy has limitations. This study was focused on market risk and the variations in the prices of stocks (de Gómezgil and de Gomezgil, 1967)

About 27 years of information was supplied by trusted source of Bloomberg calculated using the "Value at Risk" procedure. By a graphical representation we can clearly see that some of the results were discussed in data analysis.

It is evident that VaR is one of the major key measurements that are obligatory for risk Engle and Manganelli (2004) to be manipulated keeping into account that it's a lot more easier approach in contrast to other risk manipulation methods .Therefore there's something that's crucial to be recommended when using methods that ARCH and GARCH are well applied when having historical data whereas past isn't always an adequate predictor so alternative methods of parametric and non-parametric methods are an honest guide when just in case of unavailability of historical data . Whereas GJR GARCH could be a bit slow in contrast to the rest of the other two methods its recommended that other copula method supplies suitable and desired result and other VaR methods like delta- normal (or variance-covariance) and therefore covariance methods are good.

Within this crucial research reveals for S&P500 and Gold Index, that there were numerous amounts of parametric and non-parametric methods, exercised to estimate the risk of funds. There are four prime parametric methods, which are ‘exponentially weighted moving average’, ‘ARCH, ‘t-distribution of return distribution’, ARCH and GARCH model. The two non-parametric methods that were identified are the ‘Historical Simulation’ and the ‘VaR Calculation. Another thing that is included in VaR calculation is the quantiles of simulated returns. The 99% confidence level is used to significantly calculate all VaR cases. During 1992 to 2020, S&P500 and Gold Index have been recording the accuracy of one day VaR methods by using daily data on index returns.

The data is for 27 years, suggests that the 99% confidence level has shown authentic VaR estimates on annual basis. The parametric method used for the 99% confidence level was the ‘Historic VaR’ method. The comprehensive data that was collected is more accurate when S&P500 index return and Gold Index is estimated by ARCH GARCH. Nelson (1991) put forward an additional model which accounts for the leverage effect (EGARCH). The model makes use of the logarithm of the conditional volatility, therefore making the non-negativity constraint placed on the coefficients with inside the GARCH version obsolete as a log-function can't be negative.

Sethapramote et al. (2014), after a researching which model best forecast VaR in the Thailand, came to a similar conclusion. It was found that EGARCH, which is an asymmetric GARCH model, outperformed even more complex models. For different time periods are suitable different models and for different data sets, different models are suitable. Some researches carried period of financial crisis (December 2007 – June 2009) and the calmer post crisis period (July 2009 – December 2015) are two different periods we will therefore provide results in a category that investors need to think about hedging the risk. The peak of the depression of the financial crisis is defined by the National Bureau of Economic Research (2010) the period from December 2007 to June 2009. To conclude, the S&P500 has showed that if the VaR stock increases, the average return also increases. When a high VaR is calculated, you have a higher chance to get more money, but you also have a higher chance to lose money. This clearly shows that the investment in S&P500 and also in Gold index is not at risk so it could potentially lead up to profit.

Chapter 3

Asymmetric Conditional Dependence Modelling between S&P500 Index and Gold Price Index

3.1 Introduction

It is imperative for the international investment initiatives to establish proper linkages and correlations in between the returns generated on financial assets so as to ensure proper risk diversification. This significance also extends to the fiscal policy formulators so that the risk of financial contagion could be effectively controlled. Asymmetric Dependence in Finance examines the risks and benefits of asset correlation and provides effective strategies for more profitable stock and commodity management. During recent events like downturns in form of the financial crisis, financial regulators have lost their investments even though they had significantly diverse investments. Research of empirical nature indicates that assets are linked at a much deeper level than assumed earlier. The asymmetric model will assist in measuring the interrelation between the non-linear dependence and non-normal distribution and it will be possible for the financial organisation to use copula to analyse how much financial return would the company get in the annual term (Alcock and Satchell, 2018). Multiplicity of studies exists on the modelling of dynamic linking practices regarding the global stock management markets. The majority of these studies have concluded the purported existence of the linkages between the markets and predominant financial contagions (Kenourgios et al., 2011; Wen et al., 2012; Hui and Chan, 2013). The modelling of the tail structure based inter-market dependence has been so far undertaken by only a handful of studies. Such dependence structure could be expected to be asymmetric on account of the turmoil in the global financial scenario and this is indicative of the inter-market co-movements getting affected by the negative shocks to a greater extent in comparison to those of the positive shocks.

Adequate measure of evidence could be availed, in a relative manner, regarding the existence of this inter-market asymmetric dependence in between the returns generated by differential stock markets. Cappiello et al. (2006) have outlined the evidence pertaining to the asymmetry in the conditional volatility regarding returns on equity. Tamakoshi and Hamori (2013) have also agreed upon the fact that negative shocks significantly influence the co-movements of the stock returns. The emphasis of these studies had been on the Europe and United States of

America based developed markets and only a handful of studies have modelled the overall incremental integration of market indexes of commodities and the developed regional contender S&P500 index.

The corresponding study aims to use models encompassing the entire structure of asymmetric behaviours and dependence regarding the bivariate tails involving dual stock market and commodity indexes of US stock and Commodity markets like Gold Index. The utilisation of copula model had been performed in this chapter. The US stock market S&P500 had surpassed the commodity Gold Index market in terms of capitalisation to become the second largest stock market within the global scenario with a total worth of US$30.5 trillion (as of August 31, 2020) by the culmination of the financial year of 2005-19 in terms of capitalisation in A-shares. The study has been provided with further impetus to evaluate the dependence of the S&P500 Index on various matured financial markets concerning the unique position of it in comparison to the international competitors and the role which it played during the global financial turmoil throughout the period of 27 years.

The available literature focusing on the dynamism of dependence of the S&P500 Index is primarily technological modern in nature. The application of a multivariate GARCH model was undertaken by Gwanoya (2007) to effectively evaluate the volatile linkages between the stock markets of USA, Hong Kong, Shenzhen and Shanghai through the utilisation data of the period in between 2001-2005. This multivariate model was also employed by Fan et al. (2008) to examine the extension of volatility in between the stock markets of Shanghai and Hong Kong. Copulas are utilised to model the linkages.

Hu (2010) have discovered comparatively decreased measure of tail dependence in between the stock markets of international domain and that of the United States of America. Hsu et al. (2008) have utilised the mixture copula to model the dependence structure in between the G7 countries and some dated stocks. The analysis has been formulated on the periods of comparative stability of dated stock markets.

The literature has thus been extended to investigate the inter-stock market conditional dependence of S&P500 extending for a particular extensive period. The rationale has been the obtainment of insights of the different particularities of the individual markets through studying the dependence dynamics between the two markets. Both these markets had been affected and managed to survive by the financial crisis of 2007-09 which is also covered in the period taken for the analysis.

The international financial recession period which will be also discussed in this chapter had caused around 60% decline in the S&P500 index during 2008 after the index had registered the historic growth and it took 25 years for the stock market to get back to that position. Gold index has greater maturity in terms of internationalised functioning. Free trade of the commodity index of Gold prices within the international investors is a standard practice, however, investment of only marginal amount of stocks listed at S&P500 Index could be invested in tandem with other foreign capital. Majority of the S&P500 index listed referred entities outline technology-based investments. This had formulated particular features of distinctive association regarding both the stock and commodity indices during the extensive data taken for this thesis.

The aim of the thesis is to measure the interdependence of the two indexes and objectives are using the copula model proposed by Patton (2013) along with utilisation of Generalised Auto regressive Score (GAS) has been undertaken by Creal et al. (2012) to evaluate the transformative structure of dependence through implementation of copula approach for the additional purpose of copula parameters evolution identification. Primarily, the corresponding study analyses the structure of dependence in between the S&P500 and Gold Price index involving differential parameters. The conditional margins of variations have been defined involving both of the stock and commodity indices in a separate manner and the optimal model has been selected through introducing the subsequent methods. Next, the dependence structure along with the bivariate tails' configuration has been provided as well. The lower and upper tails had been modelled separately so that asymmetric property could be effectively highlighted. Ultimately, the tests for the identification of asymmetric dependence and structure based on time variation have been introduced.

The conditional dependence[3] of both the markets has been identified by the test results to be Time Varying extensively. The contagion in between both the markets has been identified through significant increment of the correlation for the period 1992 to 2020 which covers a fragment bit on the time before 2008 while prior to the advent of the financial crisis, it was

[3] Conditional dependence is a relationship between two or more events that are dependent when a third event occurs.

inclining. The definition provided by Forbes and Rigobon (2002) has been found to be constant with the outcomes. This definition suggests that contagion could be in existence when co-movement across the markets could expand at a post financial shock scenario which adds contribution to knowledge. The herding behaviour at the height of the time had been identified since, the correlations continued at an extensive level during 27 years. Furthermore, the marginally strong upper tail bivariate had been found which outlined asymmetric dependence and this had not been documented previously.

The outcomes and results implications could furnish accurate information to the policy formulators and investors regarding diversification of risks, managing portfolio and allocation of assets. The study has outlined that the dependency level of US markets was high prior to the crisis as opposed to greater dependency in the midst of the crisis. This is suggestive of upturns at Gold Index which had been stimulated. Since, this chapter has also touched a fragment bit on the crisis period as well, the results implications suggest that global financial crisis had influenced the bull markets and the findings have also consistently outlined the asymmetric tail dependence which previously existed in between Gold Index and S&P500 Index.

To summarise, yield spreads can be widely and practically used to quote stock and commodity prices (Acharya and Carpenter, 2002). From the global financial crisis, notable attention has been paid to commodity spreads in commodity and stock management. Especially, it has more concern from experts, researchers, and policymakers to model and forecast commodity and stocks spreads. By demonstrating that the assumptions of normality and linearity are disrupted, our findings are important and will benefit them. Additionally, we find that the degree of dependence for the pairs of (1) volatility (univariate volatility results can be seen in empirical chapter 1) and interdependence (2) returns volatility and yield spreads is greater in the upper tail than in the lower. Practically, the professionals give more attention to the effects of interdependence and volatility on returns of stocks and commodities when they face extreme changes in this from these findings.

The remaining sections of the study would be structured with the discussion and literature review of the models regarding joint and marginal distribution of copulas performed at Section 2. Marginal distributions based optimal models would be selected at Section 3. The entire dependence structure-based models would be formulated in Sections 4 and 5. Bivariate tails-based models would be structured at those sections as well with the development of the conclusion at the Section 6.

3.2 Literature Review

In this literature review, we will cover copula theory and how it can be extended to handle conditioning variables. The focuses on bivariate distributions will be discussed as copula theory applies to the more general multivariate. Financial market participants frequently manage many financial assets at the same time in the financial world. In practise, this is accomplished by diversifying across multiple stock markets or asset classes. Asymmetric Conditional Dependence aims to measure the correlation between competing stock markets to more clearly understand recent trends. In this empirical chapter, we run an asymmetrical conditional dependence analysis between the stock market and commodity index in S&P500and Gold prices. We use the time-varying copular. Patton (2006) theorized that the time-varying copula model should consider both the past and historical parameters to explain the current parameters. Once the time-varying copular parameters have been applied, the correlational coefficient can be measured. In the case of comparing the stock market in USA to that of commodity market we observe a decrease in correlation leading up to the 2008 financial crisis. This correlation can be seen as S&P500 was more open to "foreign investors" where Gold prices had fewer stock devoted toward "foreign capital." The research further signifies the importance of tail dependence. Tail dependence is a prime factor in measuring the shift of financial benefits. In the ongoing process of calculating the asymmetric dependence, it is crucial to find the upper and lower tails as these provide a more detailed report of market movement regarding the copular approach.

Copula-based multivariate energetic models have been broadly utilized to demonstrate nonlinear reliance and monetary dangers among watched and/or inactive arrangement; see, for instance (Patton, 2006; Patton, 2013; Cherubini et al. 2012; Zhao and Zhang 2018) and the references in that. In this paper, we consider estimation of semi-nonparametric energetic sifted copula models, in which the flow of person arrangement is modelled as semi-nonparametric GARCH, and the joint dispersions of the multivariate standardized developments are characterized by parametric copulas with nonparametric minimal conveyances. These models are exceptionally adaptable, permitting for use impacts, halter kilter disseminations of person time arrangement, nonlinear tail reliance among inactive stuns to diverse arrangement. Such models are valuable in hazard administrations. There are two parts of obscure limited- and infinite-dimensional parameters related with this course of models: (i) the semi-nonparametric conditional implies and volatilities (semi-nonparametric GARCH) of time series; and (ii) the semi-nonparametric joint dispersions of the idle standardized developments, which comprise of the copula parameters and the nonparametric negligible disseminations. Here the parametric copulas capture the contemporaneous reliance among the person components of the standardized developments. Chen (2013) first proposed this class of models as an extension of Chen and Fan (2006), from parametric conditional implies and volatilities of time arrangement to a semi-nonparametric partner in portion (i). This expansion is critical to capture the shapes of the "news affect curve" nonparametrically for person monetary arrangement and reduce energetic misspecification due to wrongly indicated parametric useful shapes of conditional implies and volatilities.

In stock administration, the dependence structure should be carefully considered as a means to be profitable and keep down losses which describes how the stock markets are linked in a way or another; under some economic conditions, a firm's stock price may rise or drop, as another firm's stock price increases or falls. We can say that they move synchronously with one another.

Furthermore, such correlation knowledge is required in a variety of financial applications, including asset pricing models, capital allocation, risk management, and option pricing (Jiang et al, 2016). As reported by Erb et al. (1994), Longin and Solnik (2001), and Ang and Chen (2004), one example of asymmetric dependence is when two returns exhibit greater correlation during market downturns than during market upturns. Several explanations have been proposed for the presence of asymmetric dependence between equity returns. According to Ribeiro and Veronesi (2002), correlations between international stock markets increase during market downturns because investors are more uncertain about the state of the economy (Patton, 2006). In the economic environment there will always be fluctuations cross over between different markets that will be affected by different factor as time goes. It can be in businesses in existing market, new entrants, or new markets; the demand and supply will create a template for prices and will always be in motion. For financial regulators, it is important to be updated and be aware of the financial market they are in to be able to make decisions in time for profitable outcome. There are multiple types of copulas which can be interpreted and used differently according to Burney and Ajaz (2020).

If we discuss in depth about some of these copulas then we will commence with Frechet Hoeffding – bound inequality, it is basically calculated for every copula. The union bound can be established by examining the complement of the event and applying the probability measure's sub-additivity. The Hoeffding inequality gives us an upper bound on the likelihood that the empirical mean deviates from the expected value by more than a certain amount (Burney and Ajaz, 2020).

Independent Copula – If the random variables are independent, the copula density equals the product of the random variables' marginal distributions. That is, c(u,v)=u, with v=1 (since the variables are uniform on [0,1]). As a result, copula in this context refers to the product or independent copula (Burney and Ajaz, 2020). Furthermore, there is the Sklar's Theorem – as it is the one factor needed mostly by Copulas. This theorem states that any joint distribution can be represented by its marginal distribution. In other words, According to Sklar's theorem, any multivariate joint distribution can be expressed in terms of univariate marginal distribution functions and a copula that describes the variable dependence structure (Burney and Ajaz, 2020).

The only complication introduced by extending Sklar's theorem to conditional distributions is that the conditioning variable(s), must be the same for both marginal and copula distributions. This is important when using copula theory to build conditional density models. If you fail to use the same conditioning, it will lead to failure of the function to satisfy the condition (Patton, 2006).

Asymmetric conditional dependence modelling continues to be employed in analysing variables from various fields. For instance, in assessing geotechnical engineering problems, the approach has proven crucial in analysing multivariate raw data of soil parameters. Here, as in several other domains, having accurate data and realistic statistical data is imperative. According to Wu et al. (2017), these methods prove to be beneficial to both investors as they 'diversify risk" and to monetary policy makers to risk of economic crisis. In broader terms, economists will be able to observe the cause and effect of an event on another countries market. It is important to note that the correlation is observed by employing the Copula approach. As Zhang et al. (2019) aptly observed, is essential not just for representing soil properties but also for evaluating actual soil conditions – and advanced multivariate modelling of edaphic factors has been found to be useful in improving geotechnical engineering practices. Zhang and researchers used asymmetric copulas to model and analyse geotechnical soil data. Similar to prior research that explored the use of symmetric copulas on modelling engineering data, the researchers in this study focused on capturing asymmetric dependencies on soil properties – parameters that are fundamentally essential in informing the formulation of engineering design. Here, a copula-based multivariate statistical/probabilistic model was formed guided by data from a collected sample of granite soil from Portugal (Zhang et al., 2019). Besides analysing and modelling the soil samples, the study further sought to ascertain the advantages (or lack thereof) of asymmetric copulas, including its concept. A comparison is also made with conventional copula approaches for modelling soil data. The findings are unanimous, and the outcome of the analysis revealed that asymmetric copula could generate appropriate characterizations of both the tail and asymmetric dependences in soil data. Compared to traditional modelling approaches, asymmetric copula was also found to yield more accurate predictions of empirical data, including those of extreme values (Zhang et al., 2019).

He and Hamori (2019) undertook a near-similar study. Using copula models, the researchers explored the dependence structure (or lack thereof) between West Texas Intermediate (henceforth, WYI) oil prices and foreign exchange rates of the BRICS economies. Various copulas, including Normal, rotated Gumbel, and Plackett, are used to gauge the constant dependence. The results revealed that the oil prices and exchange rate reached their lowest values when oil prices fell abruptly. The outcome of the empirical analysis further revealed that a significant and direct dependence was presented in all the foreign exchange rate and oil price pairs. This dependence was negative, implying that in BRICS economies, the oil serves as a hedge to help in moderating the potential rise in inflation. This study's findings are helpful in two regards. First, the results offer suggestions that it is critical for these countries to pay increased attention to possible exchange rate risk given the existing association between the price of oil and the exchange rate. Second, and arguably critical, is that due to the negative correlation between oil price and exchange rate, oil can be used as a hedge to mitigate against inflation in BRICS economies (He and Hamori, 2019).

A critical review of extant publications, including scholarly peer-reviewed articles, show that the technique of modelling asymmetric conditional dependence has been – and indeed continue to be used across multiple fields and disciplines, including, among others, financial and stock market performance (e.g., Wu et al., 2017; Miron and Tudor, 2010), foreign exchange and currency rate fluctuations (e.g., Patton, 2006), and international equity markets (e.g., Okimoto, 2008). Appraising and drawing insights and conclusions from this large and mounting body of literature is imperative to gain a broader and in-depth comprehension of the workings and real-life applications of modelling asymmetric conditional dependence.

Modelling asymmetric conditional dependence, stated by Wu et al. (2017), is the linkage and conditional dependence within markets. With the use of copula methods, the asymmetric tail dependence can be detected and examine the tail dependence between returns and if there are changes in volatility as explained by Echaust (2021).

The conditional dependence structure between commodities and stock markets are extremely important for the cross-asset diversity of investment portfolio since for example, changes in the oil price have demonstrated an unforeseeable influence on the direction of international oil valuation and in sequence on financial markets. Modelling correlations and relationships between monetary asset returns are crucial for international investors to extend risk, and as well for monetary policy makers to control the risk of financial contagion. Several studies have been conducted on modelling the dynamic correlations between international stock markets and most have concluded the presence of market linkages and financial contagion. In spite of that only a number of studies have modelled the tail structure of the dependence among markets. Relatively, adequate proof is found for the existence of asymmetric dependence between stock market returns. Cappiello et al. (2006) was the one who found evidence of asymmetry in conditional instability of the equality returns.

An effective and easy to use implement to describe dependant risks is given by the concept of Copula, which was presented by Sklar (1959) and then studied by numerous authors such as Deheuvels (1979), Genest and MacKay (1986). A copula is a function that combines univariate marginal distributions to set up a joint distribution with a particular dependence structure. Therefore, it provides a simple way to produce multivariate probability distributions that have a wide range of dependence and tail behaviour. Sklar's theorem states that if F is a joint distribution function with marginal distributions, F1, ..., Fn, then there exists a copula C such that: F (x1, ..., xn) = C(F1(x1), ..., Fn(xn)). Fi(xi), i=1, ..., n, has a uniform distribution assigned on the interval [0,1]. Thus, the copula can be considered as a multivariate function with standard uniform marginal distribution. In the above equation, the dependence structure is based only on the type of copula, not on the choice of marginal distribution. So, a copula function enables adaptability in the choice of marginal distribution (Sklar, 1959).

With the concept of copula, we are provided with plentiful groups of functions such as Student, Gumbel, Clayton, etc that enable us to create a richer dependence than the standard Gaussian theory; and Sklar lemma shows us how to impose one form of dependence among random variables with specified margins (Sklar, 1959).

The copula functions' main advantage is that they enable us to approach the problem of specification of marginal univariate distributions separately from the specification of market co-movement and dependence. According to Wu et al. (2017), these methods prove to be beneficial to both investors as they "diversify risk" and to monetary policy makers to manage the risk of economic crisis. In broader terms, investors will be able to observe the cause and effect of an event on another countries market. Asymmetric Conditional Dependence aims to measure the correlation between competing stock markets to more clearly understand recent trends. The copula approach is "a useful method for deriving joint distributions given the marginal distributions" (Trivedi and Zimmer, 2007). There are several other approaches such as the "linear" and "rank correlation coefficient" however these fail to take time into account as a determining variable. In the article titled Modelling Asymmetric Conditional Dependence between Shanghai and Hong Kong Stock Markets, Wu et al. (2017) runs an Asymmetrical Conditional Dependence analysis between the stock markets in Shanghai and Hong Kong. In his work, he uses time-varying copula." Patton (2006) theorized that the time-varying copula model should consider the both the past and historical parameters to explain the current parameters. Once the time-varying copular parameters have been applied, the correlational coefficient can be measured. In this case, when comparing the stock market in Hong Kong to that of Shanghai, the results suggest a decrease in correlation leading up to the 2008 financial crisis. This correlation can be seen as Hong Kong was more open to "foreign investors" where Shanghai had fewer stock devoted toward "foreign capital." The research further continues by describing the importance of "tail dependence" Wu et al. (2017). The modelling asymmetric conditional dependence is utilised to research the difference between counties financial situation. It is mostly used to signify the appreciation or depreciation of a country's currency, however since it is asymmetric, it shows that there are not many direct networks to work this out. Exchange rates are the most common to inspect, this is because it truly shows the cashflow of a country and the specific demands as well as supply needed for the country to live on. Hong Kong and China are seen to be major partners when it comes to exchange since Shanghai tends to have a lot in manufacturing goods as a way to have a high inflow towards the country. Hong Kong's exchange rate is being integrated to China which means there will be a higher balance of payments due to this.

One key example of Modelling Asymmetric Condition Dependence being used is seeing the value of the Chinese and Hong Kong currencies. The market of China and Hong Kong has been said to have been influenced more with negative shock than positive shocks which shows the asymmetric conditional dependence in their markets. The occurrence of this can be due to innovation or different trends in the countries that can change demand which will change what will be exported or imported.

Copula Methods is a smart way to collect marginal distributions of unaware variables to reunite to form a joint distribution. This will help organise the asymmetric variables to simplify the exchange rate. This will be severely effective since it will ensure a wide flexibility to model multivariate distribution, which shows the distribution of a pair of a simple random variable as well as also including triples of the random variables to (Trivedi and Zimmer, 2007).

Still one of the research of Hong Kong and China, there is a stock index return between the stock which furthermore has an amount of 3314 observations, this includes their expression '$\ln(Pt / Pt-1)$'. This formula helps comprehend how the asymmetrical conditional dependence will cause crisis periods which further allows the analysis of the turmoil period. This can lead to invalid payments outflowed from the country which can be explained to cause government expenditure to rise and be utilised incorrectly which can affect the country. This can cause more debt to rise in the country, if that's the case then it can decrease economic growth or even inflation which means the country will find it harder to make purchases abroad since they will have less purchasing power. Exchange rate is very significant for a country's financial stability. This can be linked to the UK wanting to have only a 2% inflation with a 1% increase or decrease, it isn't good for a country to inhibit a high inflation yet a deflation Wu et al. (2017).

Overall, this research is used to show linkages between differing markets affected by similar events to provide a to see their level of correlation. It is important to note that the correlation is observed by employing the copular approach. The copular approach is "a useful method for deriving joint distributions given the marginal distributions" (Trivedi and Zimmer, 2007).

There are several other approaches such as the "linear" and "rank correlation coefficient" however these fail to take time into account as a determining variable.

In simpler terms, Asymmetric Conditional Dependence is a complex method of quantifying the interdependence between many variables which "have no correlation". This trend is supported in analysis of Modelling Asymmetric Conditional Dependence seen during the decrease in correlation leading up toward the recession, followed by a strengthened correlation during the crisis. Measuring asymmetrical conditional dependence is a great tool to illustrate the nature of markets and in examining how dependent one market is in relation to another (Wiecki,2018). This correlation is then used to predict, analyse, and reflect on market trends and is shown on a scale from -1 (perfect negative correlation) to +1 (perfect positive correlation). In the article by John Edwards, he discusses the application of correlation in portfolio management to "measure the amount of diversification among assets contained in a portfolio." Investors will use this correlation to gain insight to market performance and risk factors. Tying everything together, during the 2008 financial crisis it is observed that "stocks can have a tendency to become more correlated during periods of heightened volatility" (Edwards 2021). Modelling correlations and linkages between financial asset returns are important for international investors to diversify risk, and for monetary policy makers to control for the risk of financial contagion. There are many studies on modelling the dynamic linkages between international stock markets and most have concluded the existence of market linkages and financial contagion.

First, to better understand what modelling asymmetric conditional dependence consists of, we need to make the link with the copula method. The copula theory, based on the work of Sklar in 1959, allows a flexible modelling of the dependence between two or more random variables. In recent years, the growth of interest in this theory has been phenomenal. In his book Sklar gives us his definition of the term copula "We will call a(n-dimensional) copula any continuous and non-increasing C continuous and non-decreasing -in the sense used of a n-dimension function defined on the cartesian product of n closed intervals [0;1]". Copula theory provides asset managers with a different tool that helps them to better understand the joint behaviour of financial markets. A copula deals with the dependence between the distributions of returns. The dependence measure is decoupled from the distribution function of each individual market. There is a wide variety of copulas, they fall into two main categories: meta-elliptic copulas and Archimedeans copulas are the most frequently found in the financial literature.

However, only a few studies have modelled the tail structure of the dependence between markets. Furthermore, due to the recent turmoil, one should expect such dependence to be asymmetric, as co-movements between markets will be affected by negative shocks more substantially than positive shocks. Relatively, sufficient evidence is found for the existence of asymmetric dependence between stock market returns. We can use as example the asymmetric conditional dependence between Chinese stock index returns, to assess the impact of the recent financial recession on Chinese equity markets using the Copula approach. The capitalisation of the Chinese stock market overtook Japan and became the world's second largest stock market, totalling $3,981 billion in A-share capitalisation at the end of 2010. The unique position of the Chinese stock market amongst its international competitors and its role during the recent financial crisis, has encouraged the study of its dependence with other mature financial markets during the period of turmoil. Conditional dependence is a theory based upon probability which, is when two individual variables become dependent when a third event occurs. When two things are asymmetric it is when then the two sides are not the same (Noah Webster) therefore, when modelling asymmetric conditional dependence, it is when two random independent variables become dependent due to a third event happening.

An example of this would be cyclical and defensive stocks that normally act within the stock market independent of each other due to them being opposites. Cyclical stocks are often affected by the overall trend in the economy, therefore, causing it to usually have higher volatility yet expected to have higher returns during economic strength (Young, 2021) whereas, a defensive stock is a lot more stable that provides consistent dividends and stable earnings regardless of the state of the overall stock market (Chen, 2021). However, it has been shown through history that when the CBOE Volatility Index (Vix) becomes too high- showing massive risk within the market it causes both sets of stocks to become dependent on one another and react in the same way as often investors start to panic and begin to start selling most of their stocks, causing stock prices to decline. This was demonstrated when 911 happened which caused a large amount of chaos during the stocks markets, with both cyclical and defensive stocks becoming dependent showing the clear correlation between the two that both stocks dropped in price due to a vast amount of uncertainty causing people to panic sell their stocks (Chen, 2021).

The word copula within English grammar means to link a subject with the predicate therefore when relating it in a statistical sense the copula method is a probability model used with finance which examines the dependence and helps determine the correlation between two individual variables when a third event occurs. Therefore, this can help to identify the risk sensitivity within finance to any internal or external events. They are essential as they allow us to decompose a joint probability distribution into their margins and a function that couples them together, thus specifying the correlation separately (Wiecki, 2018).

Using this method, it will correlate marginal distributions of by variables randomly chosen to form an emerged distribution. There are several methods, whereas a copula method will present a flexible model of emerged distributions, but also letting you see the both the marginal distributions as well as the dependence. It will measure the probability and risk between marginal distributions (Wiecki, 2018).

We define conditional dependence when two or more events become dependent when a third event occurs. Its function is important to see the correlation in markets during volatile period and especially during downtrends when the market is usually more correlated as a whole (Patton, 2006). The main function of the conditional dependence is to measure the correlation between events and can be applied as a technique of Portfolio management. A good personal example I can relate to is the correlation between defensive stock to cyclical stocks when the market is in a downtrend.

As the VIX Goes above 25 (Index to measure the overall volatility of the S&P500) the correlation in the Defensive stocks against cyclical stocks is more correlated. The copula Methods is a way to represent a multivariate uniform distribution which examines the dependence upon many variables potentially. It helps to find a correlation between a pair of variables that are enmeshed in a more complex multivariate system. From the copula methods we can observe correlation between assets in a complex etf that cover not only stocks but also bonds or other different assets that are nor related to the 2 companies in dependence (Kenton, 2022). A clear example was during the financial crisis in 2008 when an inappropriate assumption of gaussian dependencies between the risk of various financial instruments such as MBS (mortgage-backed securities) and CDO (collateralized debt obligations) took off and then led to the global financial crisis.

In more simple terms we can also measure the correlation of deaths for life insurance companies such as looking at the marginal distribution of a person dying after the death of its spouse.

Basically, measuring the probability of dying in succession. Another great example is found in measuring the probability of a company to fail after the leader of the industry fails. This example is interesting to analyse because the correlation in this case reveal itself as direct instead of inverse (Marsden, 2022).

As the number of assets goes above 12 the Standard deviation in the portfolio is basically the same. This is due to the fact that as the number of assets increase at some point the correlation with the S&P500 remains the same. And this is true especially during a down trend (Patton, 2006). The copula methods with the Asymmetric modelling of conditional dependence have also an accurate application in exchange rates relative to changes in the interest rates or other economic factors. In research in 1999 written by Tagaki (Patton, 2006) we observe that a desire to maintain the competitiveness of Japanese exports to the United States with German Exports to the US would lead the Bank of Japan to intervene to ensure a matching depreciation of the yen against the dollar whenever the deutsche mark depreciated against the dollar. This relation was then discovered to be Asymmetric consistent with an asymmetric central bank behaviour presented into the academic research (Patton, 2006).

Time-varying copula where a generalized autoregressive score (GAS) from Creal et al. (2013) will capture evolution of the parameters. A study outlines the modelling asymmetrical dependence in global economics such as agriculture commodities and global oil market. Will study the actual connection in the market and the price dependency in the market. From the beginning of 2006 to the middle of 2008, global agricultural commodity prices have risen considerably. The prices of key agricultural commodities—corn, soybeans, and wheat— reached record highs in mid-2008, about the same time as oil prices peaked, and then fell down to early-2007 levels by the end of the year (Fasanya et al., 2019). In recent decades, academics have been interested in the interplay between global oil markets and agricultural raw material markets. Many studies have linked price increases in agricultural raw material markets to price increases in the global oil market. There are two primary reasons for this. On the one hand, biofuel and crude oil are both viable options. People have been rushing to create alternative energy sources such as bioethanol and biodiesel made from corn and soybeans as crude oil prices have risen in recent years. As a result, increased global oil prices may lead to higher prices for agricultural raw materials as an alternative energy source. As a result of the limited agricultural product acreage throughout time, the price of other agricultural raw material markets would eventually be higher. Agricultural raw material markets, on the other hand, are influenced by global oil markets since the agricultural product's production process, which includes fertilizers, pesticides, transportation, and processing, uses a lot of crude oil. In conclusion, it appears that the global oil and agricultural raw material markets are moving in the same direction (Jiang et al., 2018). Jiang et al. (2018) uses wavelet and copula models to investigate the dynamic interdependence of the global oil market, agricultural raw material markets, and metal markets. They discovered that the oil market trails agricultural markets but outperforms metal markets. Given the current study's aim, even though a time-varying copula is used, assuming a single regime when analysing the connection between energy and agricultural commodities may be too limited and incorrect. This emphasizes the need of distinguishing between the two regime states in the energy-agricultural commodity link. A time-varying copula model with a switching dependency is used to represent the dynamic dependences between energy and agricultural commodities markets in this section. The CoVaRs and delta CoVaRs, which are used to evaluate risk spillover across markets, are then estimated using the combined distribution of energy and agricultural commodities markets (Ji et al., 2018).

To investigate spillover effects, Reboredo and Ugolini (2016) employ copulas to capture the reliance between oil and metal prices and compute the VaR and conditional VaR. They discovered that fluctuations in the price of oil had an impact on metal pricing. The spillover effect argues that a significant shock increases the correlation of returns across all assets, not just one market. During financial crises, this effect may be magnified, with the added consequence that both volatility and correlation will move in lockstep over time (Kang et al., 2017).

According to Kenton (2021), the Copula are different mathematical functions that correlate multiple variables, and from the late '90s were introduced in the financial sector mainly to analyse the risks that is based according to Zhang (2019), on how to determine the non-parametric measure of the dependence between random variables relying on the interdependence of return of two or more assets calculating the correlation coefficient when is set a normal distribution between the data, however, if the data are skewed or asymmetric distribute this method can be used to determine the option price because the price of one security depends on the price of an underlying security, (e.g. CDO). According to the study made by Wu et al. (2017), it has been found a strong time-varying correlation between the two previously mentioned Stock Indexes, which increased particularly during the recession, suggested a financial contagion between the two Indexes. However, this work has not been cited the strong financial globalisation of nowadays and the solid correlation between the financial markets, which probably could be the reason that every country suffered this crisis started at US market. The empirical analysis made by Kayalar et al. (2017), found a very significant dependence between currencies and WTI oil prices, especially on the currencies oil exporter countries whereas the importing countries have the least dependence. This is due to the fact that importing-counties will be affected by the change in the oil prices impacting directly on the balance of payment, and so will result in a fluctuation of the exchange rate. According to Bouri et al. (2018), it has been critically analysed the correlation between Bitcoin and the GFSI finding that when Bitcoin returns are skewed to the left (deficient performance) or to the right (superior performance) the correlation became stronger, however, when the returns are normally distributed the correlation became poorer because Bitcoin on average can act as a safe-haven asset against the GFSI for approximately 60 days.

Finally, copula functions allow for a very flexible study of the dependency dynamics between different markets. At the same time, copula functions allow for a wider selection of joint distributions via an extended choice of dependence structures. This literature review has analysed how the Copula method is used in the financial sector to investigate the dependence of multiple variables and different financial products to identify the risks. It has been discussed how during a global crisis the stocks indexes became very correlated with each other, how the change in the gold price will result in a correlation with S&P500, stronger for exporters-countries and poorer for importers, and finally, the correlation between Gold and the S&p500, which confirmed that Gold prices is not quite volatile and is considered a strong financial asset.

Copula functions allow to construct flexible multivariate distribution with different margins and different dependence structure, without the constraints of the traditional joint normal distribution. Hull and White (1998) were among the first to consider this kind of modelling, even though they did not refer explicitly to copulas, but rather to mapping observations from the assumed distribution of daily changes into a standard normal distribution on a "fractile-to-fractile" basis. More recently, copula have been explicitly used for measuring portfolio Value at Risk by (Bouyé et al., 2001; Embrechts and Schmidli, 1994; Cherubini and Luciano, 2002). Glasserman et al. (2002) extended this framework to a portfolio of derivatives by considering a particular extension of the multivariate *t* distribution. Yet, the applications made so far dealt with *unconditional* distributions, only.

Incidentally, value market members will in general answer to the gold market during times of high unpredictability because of international pressures. Gold is viewed as a place of refuge as well as an elective speculation (Akbar et al., 2019). The choices of portfolio administrators and speculators rely upon dissects of the association of the gold and financial exchanges. At long last, some others work demonstrate the presence of a significance negative connection among gold and stock returns. Gold shows up as a place of refuge in speculation choices (Baur and McDermott, 2010; Tursoy and Faisal, 2018).

Covitz and Downing (2007) consciousness on industrial paper spreads and display that liquidity is the most vital element in determining a very short-time period company yield spreads. Spreads have received significant attention within the literature. Gilchrist and Zakrajšek (2012) noticed that credit score spreads can be used to expect the monetary outlook for destiny. They assemble their personal credit score unfold index and report that their index is an improvement over the spread for predicting economic pastime. Ang et al. (2011) predicted that the sudden upward thrust inside the Fed's reaction raises brief-term rates, thereby leading to growth within the time period spread. Boyarchenko et al. (2019) recommend a new model for pricing loan-sponsored securities or the mortgage-backed securities (MBS) and that they identify key determinants of variations in MBS spreads.

Specifically, the extension the models of Johannes et al., (2009) for return prediction in three directions. First, apart from the stochastic volatility (SV) models, additionally had a look at found out volatility (SV) measures and their position to return prediction. Secondly, subsequent to the dividend yield as a predictor variable use lagged returns. Sooner or later, we remember no longer only regression-type linear dependence structures. However, they additionally propose a copula-based totally model that allows for asymmetric dependencies. They allow these dependence systems to be static, dynamic, and hierarchical. By using historical statistics of 20 assets and display that an ensemble of these more capabilities improves fairness return distribution forecasts, that therefore may be used by investors in building portfolios or calculating tail risk (Johannes et al.,2009).

As mentioned in Johannes et al. (2009) volatility timing is important for reoccurrence prediction. In their paper, the authors rely upon stochastic volatility models for modelling the volatility of the returns. Instead, Andersen and Bollerslev (1998) introduced the volatility (RV) measure this is obtained the use of the high-frequency statistics. Ever for the reason that excessive frequency trading statistics became available to practitioners and researchers alike, there has been a shift in paradigm in volatility modelling. Realized that the volatility is an honestly observable volatility estimator and does not depend upon any version assumptions, consequently, RV is considered as an opportunity specification for the return volatility. Secondly, some other important feature to bear in mind in return prediction is using predictor variables. As stated in Lettau and Ludvigson (2001) it is now widely established that excess returns are predictable via variables including dividend-rate ratios, profits-rate ratios, dividend-profits ratios, and a collection of different economic indicators." A couple of empirical research has proven that the most powerful predictors have lagged returns, the dividend yield, the earnings-charge ratio. For example, do not forget the dividend yield as a predictor variable. This reveals that the gains in prediction by means of using beyond returns and dividend yield, among different variables. Therefore, in this paper, we hire lagged returns and lagged dividend yield as regressors for return prediction.

Finally, copulas had been applied in many fields in each social and natural sciences, specifically in the context of monetary time collection. Even though most of the people of the copula-related literature focuses on modelling contemporaneous dependence between more than one time series. Copulas additionally permit to version the temporal dependence of a univariate time series (Chen and Fan, 2006). Using copulas in modelling temporal dependence of univariate time series pertains to Markov procedures and has been described in Doukhan et al. (2008) as an instance. With the aid of considering numerous possible marginal distributions with exceptional copula specs, you may seize frequently found features of univariate financial time series, which include skewness and fat tails. Moreover, depending on the copula family, it is possible to model non-linear temporal dependencies, as opposed to the standard linear regression-type models.

Crucial to be aware that this work no longer pursues multivariate time series evaluation, considering the fact that it's far out of the scope of the paper. But the proposed framework may be prolonged to the multivariate case by using assuming some shape for joint modelling of the univariate procedures, mentioned in this paper. Neither do not forget the portfolio allocation exercising on advanced univariate density prediction for every asset one after the other interprets into advanced out-of-pattern portfolio overall performance. Sooner or later, model estimation is performed in a simultaneous way thru Sequential Monte Carlo strategies, allowing for immediate inference and steady version comparison through Bayes factors.

3.2.1 Relationship Between Gold and Stock Exchange

Gold, as a monetary indicator, is a standout amongst the most vital products on the planet and it is held by national banks. National banks must keep up an extent of their outside trade saves in gold, as a store of significant worth and as a confirmation to recover guarantees to pay investors, note holders, or exchanging peers, or to secure a cash. Gold is likewise utilized by goldsmiths and speculators as a supporting instrument Sari et al. (2010) At the point when monetary standards devaluate, financial specialists move to the gold market and when monetary forms revaluate speculators move far from the gold market (Ismail et al., 2020; Capie et al., 2005)

Gold influences different valuable metals. Sari et al. (2010) states: "Among the major valuable metal class, an expansion in the gold value appear to prompt parallel developments in the costs of alternate valuable metals which are considered speculation resources and in addition mechanical wares". The announcement proposes that a model satisfactorily clarifying the gold costs could likewise add to models utilized as a part of foreseeing the costs of different valuable metals. Henceforth, numerous financial analysts think about gold as a main pointer in the valuable metal pack.

The Bretton Woods framework, for which the US dollar was communicated as far as a settled gold cost, crumbled in 1971 (Capie et al., 2005). In like manner, it appears to be proper to begin our examination around this period. High expansion, indeterminate universal legislative issues and low trust in the US dollar are a portion of the primary reasons progressed for the quick increment in gold costs between September 1976 and January 1980. A blend of stresses pushed financial specialists to expand their possessions of paper monetary forms into more substantial gold (Cheung, 2006). The quick increment in gold costs amid 1980 was caused by determined exchanging the fates showcase. The gold cost achieved US$700 for eleven days amid 1980 yet then came back to around US$300 by centre 1982. Between mid-1982 and June 2002, gold was seen exchanging the US$250-US$500 territory (Capie et al., 2005).

Various researchers have given an account of the part gold plays as a swelling fence and the part expansion plays on the gold cost. In any case, as per Roy (2011) no huge relationships exist between returns on gold and changes in certain macroeconomic factors, for example, swelling, GDP and financing costs. Sjaastad and Scacciavillani (1996) revealed that gold is a store an incentive against expansion. Dowd (1998) archived that the cost of gold relies upon the future growth rate. Sherman (1983) noticed the log of the gold cost is emphatically identified with the foreseen growth.

As per Kaufmann and Winters (1989) the cost of gold depends on changes in the US rate of enlargement, and different factors. Customarily, gold has assumed a critical part amid times of political and monetary emergencies and amid value advertise crashes, whereby gold has reacted with higher costs. As per Smithson and Simkins (2005), "when the monetary condition turns out to be more indeterminate, consideration swings to exploring in gold as a place of refuge." The creator likewise noticed that following the September eleventh, 2001, assault, the FTSE All offer Index diminished by 9% while the London gold evening settling cost expanded by 7.45%. Roy (2011) announced that gold returns are less associated with returns on value and bond files than returns of different products. In accordance with gold's part as an advantage final resort, Koutsoyiannis, (1983) expressed that the cost of gold is emphatically identified with the condition of the US economy and geopolitical factor.

A few examinations have been directed the world over to research the relationship of stock costs and economy wide macroeconomic components. In setting of outside Kang et al. (2012) explore Istanbul Stock trade (ISE) and established that there is no long run connection between stock costs and macroeconomic factors incorporates loan cost, FEXR and CPI. Despite their found a long run connection between ISE stock record and IPI. Likewise, Roy (2011) analysed the relationship in setting of India and found a unidirectional relationship of stock cost with CPI, remote direct speculation (FDI), GDP, net settled capital development (GFCF). However, the stock list was found in combine savvy association with FEXRES, wide cash (M3), unrefined petroleum cost and entire value record (WPI). Also, the stock record was observed to be contrarily influenced by oil cost while decidedly influenced by adjust of exchange (BOT), loan cost, FEXRES, GDP, IPI and M3. Francis (2011) recommended that stock returns fundamentally related with swelling in securities exchange of Ghana. Singhal et al. (2019) investigated in Mexico Index stock returns association with macroeconomic factors including GDP, business rate, FEXR, expansion and cash supply. The stock return was utilized as a part of the type of portfolios and the observational examination demonstrated that GDP and FEXR affect returns of portfolios while cash supply and swelling rate have backwards association with returns of portfolios. Different investigations in a similar territory incorporate (Singhal et al., 2019; Kumar, 2011; Singhal et al., 2019; Muhammad et al., 2009). Every one of these examinations don't have similar outcomes because of the distinctions in monetary and political frameworks, contrasts in monetary and money related strategies, and contrasts in the economy wide full-scale factors all in all over the outskirts.

Roy (2017), analysed that the connection between gold costs and Indian stock trade. For this reason, they gathered the information from Feb 2001 to Jan 2012 and used the GARCH model. They had taken factors stock trade as the free factor and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there is no significant connection between Indian stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold. Cenedese et al. (2014) examines that international stock returns and foreign exchange returns using portfolio approach from period starts from November 1983 to September 2011 of sample data of 42 countries. This study revealed that exchange rates don't hamper country level equity returns in any country that were examined in this research.

Akbar et al. (2019) has undertaken the study on three countries including USA, Pakistan and India using EGARCH model and the simple period was from 1990 to 2013. Per his study, robust evidence was found that investment in gold is performing better than the investment in forex market specifically for India and Pakistan. In continuation of the above contribution in literature, Koirala et al. (2015) conducted the study on India by using GARCH model. The results have revealed that increase in oil price tends to decrease the Indian rupee and concluded that the oil prices and Indian rupee are interdependent in relationship. Baur and Lucey (2010) shown that the connection between gold costs and stock trade. For this reason, they have gathered the information from Feb 2001 to Jan 2011 and used the concurrent condition model. They had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there cannot be connection between France stock trade and gold costs. They had recommended that financial specialists ought to put resources into the gold as opposed to stock trade.

Tai (2007); Frino et al. (2017) Examined that the connection between gold costs and Asian stock trade. For this reason, they gathered the information from Feb 2005 to Jan 2014 and used the (Vector Error Correction Model- please refer to section 3.9.2)VECM model. They had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there is no significant cannot connection between Asian stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold as opposed to stock trade. Kuan-Min et al. (2016), showed that the connection between gold costs and Finland stock trade. They gathered the data from

Feb 2004 to Jan 2015 and used the co-integration model. They had taken factors to be specific, stock trade as the free factor and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there is no connection between Finland stock trade and gold costs. They had recommended that speculators ought to put resources into the gold instead of stock trade.

Smithson and Simkins (2005) observed that the connection between gold costs and Malaysia stock trade. They gathered the information from Feb 2003 to Jan 2013 and used the Johnson approach model[4]. They had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there is connection between Malaysia stock trade and gold costs. They had recommended that financial specialists ought to put resources into the gold as opposed to stock trade.

(Mishra, 2016; Koirala et al., 2015) study is based on the connection between gold costs and Denmark stock trade. For the research, they gathered the information from Feb 2007 to Jan 2015 and used the VAR model. They had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there cannot be a significant connection between Denmark stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold instead of stock trade.

Iqbal et al. (2018), showed that the connection between gold costs and Germany. Stock trade. The data was collected from Feb 2002 to Jan 2014 and used the GARCH model. They had taken factors stock trade as the autonomous variable and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there is connection between Germany stock trade and gold costs. They had proposed that speculators ought to put resources into the gold instead of stock trade. Wu et al. (2012) examined that the connection between gold costs and Japan stock trade. The data was taken from Feb 2004 to Jan 2014 and used the VAR model. They had taken factors stock trade as the autonomous variable and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there is no significant connection between Japan stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold as opposed to stock trade.

[4] This refers to enterprise risk management.

Najaf et al. (2016) saw that the connection between gold costs and Pakistan stock trade. The information was gathered from Feb 2007 to Jan 2015 and used the (Error Correct Model – refer to section 3.9.1) ECM model. They had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there is no connection between Pakistan stock trade and gold costs. Moore and Wang (2014), examined that the connection between gold costs and Hong Kong Stock trade. Data was collected from Feb 2003 to Jan 2013 and used the GARCH Model. They had taken factors specifically, stock trade as the free factor and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there is no significant connection between Hong Kong. Stock trade and gold costs. They had proposed that speculators ought to put resources into the gold as opposed to stock trade.

Ramazan et al. (2006) analysed that the connection between gold costs and Bangladesh stock trade. For this reason, they gathered the information from Feb 2001 to Jan 2014 and used the VECM model. They had taken factors to be specific, stock trade as the free factor and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there is no significant connection between Bangladesh stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold instead of stock trade. Kwon and Shin, (1999) researched that the connection between gold costs and Andorra stock trade. For this reason, they collected the data from Feb 1998 to Jan 2012 and used the co-integration and causality model. They had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the needy factors, they had demonstrated the outcomes that there is no significant connection between Andorra stock trade and gold costs. They had proposed that speculators ought to put resources into the gold as opposed to stock trade.

Samanta and Zahed (2012) demonstrated that the connection between gold costs and Bahrain stock trade. For this reason, they gathered the information from Feb 2001 to Jan 2014 and used the EARCH model, they had taken factors to be specific, stock trade as the autonomous variable and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there can't be a significant connection between Bahrain stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold as opposed to stock trade. Aktham (2003) analysed that the connection between gold costs and Korea stock trade. For this reason, they gathered the information from Feb 1999 to Jan 2011 and used the VECM model. They had taken factors stock trade as the autonomous variable and gold costs, oil costs as the reliant factors, they had demonstrated the outcomes that there is no significant connection between Andorra stock trade and gold costs. They had proposed that financial specialists ought to put resources into the gold as opposed to stock trade.

In setting of Pakistan a few examinations have been underused in the past for researching the foresaid relationship. Nishat and Shaheen (2004) analysed KSE-100 list and found that the IPI is the greatest and significant fortification component for change in the list and have positive connection with the stock file, while expansion impact the stock costs emphatically in short run and adversely in long run. Then again, Sohail (2020) recommended that there is a converse connection between stock list and expansion in long run while the three months' treasury bills have an immaterial positive association with stock list. The outcome additionally demonstrated the relationship of stock costs with M2, genuine powerful conversion scale (REER) and IPI which was sure. Abbas and Awan (2017) again applying a similar philosophy found a backwards relationship of stock costs with cash supply and here and now treasury charges rate (TBR). Akbar et al. (2019) looks at the KSE-100 list about the FEXR after the union of settled conversion standard framework into the coasting swapping scale framework. The investigation perceived a couple savvy causal connection between the two factors. So also, Najaf et al. (2016) found that there is a positive relationship exists between dark economy (underground economy) and stock costs both in short and long run, while swelling has an immediate association with stock fd costs in short run and roundabout in long run. Different examinations exploring the dynamic linkages between value advertise and macroeconomic factors incorporates (Akbar et al., 2019; Nishat and Shaheen, 2004; Ullah et al., 2011; Rafiq and Hasan, 2016; Sohail, 2020; Ali et al., 2010; Abbas and Awan, 2017; Akbar et al., 2019).

As an essential component of the downstream refined products cost, the crude oil returns have displayed volatility with full amplitude, making the crude oil futures become a vital financial instrument for hedging. For example, Reboredo (2013) analysed the nonlinear dependence structure between the crude oil market and the international gold market, finding that they have positive mutual dependence significantly. It is common knowledge that the joint tail risk mainly determined by the marginal tail risk and its corresponding dependence structure among asset variables. However, in the past, researches on the dependence of the financial future mostly assumed that futures return follow normal distributions and random walk processes. Hence, they are inconsistent with the facts and cannot explain the stylised facts in financial futures markets such as the leptokurtosis distributions, heavy tails properties, and volatility clustering effects and so on see (Fang et al., 2014).

Moreover, Daníelsson et al. (2013) have found that the oil returns frequently have leptokurtic distributions and fat tails, and were not following the normal distribution, which tended to undervalue the extreme risk. Besides, the dependency between financial futures returns tends to display nonlinear, asymmetric and Time Varying characteristics, while the traditional model can only characterise linear, symmetric or static correlations. According to the research of Patton (2012) which pointed out that there is a lack of methods in studying risks between an extensive collection of assets, but the usage of copula-based models facilitates the description of high dimensional conditional distributions. Copulas model have been used widely for risk management, portfolio optimisation, and systemic risk (Aas et al., 2009; Fei et al., 2012; Schepsmeier, 2016; Low et al., 2016; Daníelsson et al., 2013). Dependence is based on the perspective of copula models, and it refers to non-linear and asymmetric correlations among variables, including the degree of correlations between variables and the risk linkage see (Kitamura, 1998). The multivariate GARCH-copula model has been widely in used in the study of risk transmission relationships due to its flexibility and diversity in modelling (Tai, 2010; Yiu et al., 2010; Hsu et al., 2008). It enables the estimation of joint distribution in stages, then reducing the computational burden. According to Patton (2002), the interdependence of financial asset returns is Time Varying, and asset prices in different financial markets also tend to have dynamic tail dependence. Since the static copula function assumes that the correlation parameters remain constant during the sample period, it often contradicts with realities for more accurately describe the dynamic interdependence of financial assets. Scholars began to turn to the dynamic copula methods to characterise the dynamic features of risk dependence (Hu, 2010; Chang, 2012; Hafner and Manner, 2010; Patton, 2006a, 2006b), extended Sklar's theorem to construct a Time Varying conditional copula model to study the interdependence of exchange rates. After empirical researches, the dynamic copula model is significantly recognised for outperforming the static copula model when describing the related asset's structure.

Wu et al., (2012), studied the dependence of international crude oil prices on the US dollar exchange rate market and pointed out that the conclusions drawn from dynamic copula are more economical. Also, Aloui et al. (2016) concluded that constructing the copula GARCH model to dynamically examine the condition-dependent structure between the oil price and the US dollar exchange rate can improve the accuracy of the VaR prediction. And Richardson, et al. (1998), studied the time variation of copula parameters using a hybrid parameter method. Consequently, when using the copula function to analyse the interdependence of financial assets, it is necessary to analyse the dynamic changes of secondary structures through Time Varying copula parameters. Further time variation of model parameters is critical in capturing the dynamic behaviours of multivariate processes regarding how the specified parameters of the dynamic model progress, there exist stochastic copula models (see Hafner and Manner, 2010; Genest and Rémillard, 2008), that allowed parameters as latent process and the ARCH type copula models that model the settings as a function of lagged observables.

Recently, Creal et al. (2012), introduced a class of observation that based generalised autoregressive score model into the copula function to make the parameters changeable, whose mechanism is to use the scaled score of likelihood function to update settings over time. He argued that the scaled score function is a practical choice for Time Varying parameters, which has a distinctive advantage of avoiding integrating out the innovation terms. Blasques et al. (2014) showed that the GAS method could be motivated theoretically by minimising the divergence between actual density and model implied density. Based on this, Patton (2016), introduced the GAS model to characterise the dynamic changes of the copula parameters and used copula-based dynamic model for multi-dimensional distributions to measure the systemic risk.

Innovation is generally heavy-tailed in financial applications. However, the above study that considers the dynamic dependence of tail risk does not simultaneously consider the weakness and thick tail characteristics in the distribution returns. While the financial time series data exhibits abnormal features, that is, the individual returns distribution shows skewness, excessive kurtosis and asymmetry, which need to take into consideration at the same time. Recently, an increasing body of evidence of non-normality of financial returns has incorporated the copula theory. In terms of describing the fat tail attributes of financial futures returns, the Skew t-distribution, the student's t distribution, and the generalised error distribution (GED) were introduced into stochastic volatility models to capture the leptokurtosis and heavy tails properties in financial returns (Tzang et al., 2016). For example, Kang and Babbs (2012) adopted the GARCH model for distribution to characterise the marginal distribution of the overnight fund earnings and the trading returns, as well as using a dynamic copula model to describe the Time Varying dependence structure in studying the tail distribution and interdependence of profits.

Kallsen and Tankov (2006), proposed the concept of Levy copula in the binary case and utilised the Levy stochastic distribution to model the thick-tailed, asymmetrical financial variables. Although it used copula functions to model the correlation structure of the jumping part, the copula function used is still static. As to the heavy-tailed innovations in financial returns, Fan, et al. (2014), directly assume that the joint distribution of assets followed multivariate Skew t distribution to examine portfolio selection. Fan et al. (2008), also believed that the returns process follows the ARMA-GARCH process with multi-variate regular tempered stable distribution innovations to study the optimal portfolio problem. But it did not consider the non-linear correlation relationship among variables, which had significant limitations see (Reboredo, 2012). What can be seen from the previous studies is that the marginal thick-tailed nature of asset returns, volatility clustering, and the dynamic time variation non-linear dependence rarely considered at the same time.

Moreover, there is still no consensus reached for academics and practitioners on which method to choose to calculate the hedge ratio of futures covering these distributional features. Based on considering the dynamic dependent structure of asset variables, this paper combines the time variation on GAS copula method with the heavy-tailed GARCH models to investigate the magnetic dependence and the tail risk of futures returns and compares the fitting performances of the Time Varying copula models with constant copula models. The tail characteristics of marginal risk are categorised through the GJR-GARCH-Skewed-t model in addition to considering the nonlinear dependence structure between the financial asset's distribution returns, which makes up for the deficiencies of existing researches. Besides, we study the tail dependence and risk measurements of crude oil futures under the heavy-tailed condition from an empirical perspective, further calculating the dynamic hedging efficiency of crude oil futures based on Time Varying copula models. The contributions of our studies to the previous literature comprise two aspects.

On the other hand, empirically analyse show extreme tail risk, tail dependence structure and hedging effects of crude oil futures using the GJR-GARCH-Skewed-t GAS copula model, which considers the leptokurtic feature and clustering effects of financial returns distribution. The findings can provide evidence for investors and regulators to strengthen risk management. On the other hand, to improve the computation accuracy for parameter estimation, we employ the modified quasi-maximum likelihood estimator to change the two-stage estimation method for heavy-tailed GARCH model.

Significant research has been carried out in the past to explore the relation which is present between different both the stock markets. Research was carried out to find the linkage present between volatility of different markets which include Wheat, Hong Kong, Gold index, US and Shanghai by applying GARCH model test taking data mainly between 2001 and 2005 (Yu et al., 2015). Similar research was carried out by Fan et al. (2008) for examining how volatility of one market can spill-over in another market. Relation present between the stock markets present in S&P500 and Gold Index were explored for the years 1996 to 2008 using multivariate GARCH mode. Mixture copula analysis was applied by Hsu et al. (2008) which explored the dependency that is present between these markets and G7 stock markets. Hu (2010) discovered that the spill-over of Chinese markets with world markets is weak with the exception of US stock market. Somewhat low limitations are present in the researches mentioned such as exploring the relation in stable periods that do not have much change.

This represents a strong gap present in the current literature which can be filled mainly by research the interdependency presents between markets in more turbulent economic conditions. Markets selected for analysis include the S&P500 and Gold Index market, mainly because these markets have unique individual features which can provide interesting insights. Both markets are seasoned as they have passed through seven to nine subprime crisis and still stood out in the end.

Significant progress was made by the S&P500 market in 2007 it reached 6124 points but the coming years were not as favourable due to mortgage crisis in 2008 which resulted in drop of 65% in the index. Internal strength of the Gold Index market is stronger given that number of international firms are present and operating. Another major different between the S&P500 and Gold Index market is the number of stocks which can be traded by international investors. Gold Index shares have greater freedom to be traded in the international market as compared to S&P500 index due to presence of B-share stocks for which different results are expected to be seen Gold Index market has stronger relation to the overall economy given that majority of the listed stocks are invested with mainland of different portfolio management. This points out a major similarity which was present between the two markets when going through financial crisis period.

Time Varying Copula approach is planned to be applied for assessing the changing dependence structures present auto-regressive score model as developed by Creal et al. (2012) will be used for analysis. Number of other dimensions have also been focused on through which the proposed research can make valuable addition in literature. Conditional models for each stock market will be defined independently followed by introduction of methods through which the appropriate model can be selected. Tail dependence construction is done while keeping the upper and lower tails separate through which the asymmetric property can be captured. Last unique feature is the addition of tests which cater for Time Varying structure as well as the asymmetric dependence.

Results obtained from the research indicate that the presumed dependence between markets are strongly Time Varying. Correlation between the markets had decreased significantly before the crisis but strong increase in correlation was seen following the mortgage crisis of 2008 which indicate the presence of contagion between these two markets. Findings of the research are confirming the claims of Fan et al. (2008) as he had said that contagion is present between markets if co-movements are seen increasing after a shock. High correlation that was explored following the 2008 crisis shows that herding behaviour of investors grew around the crisis. New findings of the research include reporting of a stronger bivariate upper tail which had not been discovered in previous literature. Applying asymmetry analysis on the upper and lower joint tails revealed that it is statistically significant.

3.3 Theoretical Framework

The empirical chapter focuses on estimations and inference of the copula models. The model selection and the goodness of fit applicable for the copula-based models are identified. The Structure of the models is as follows:

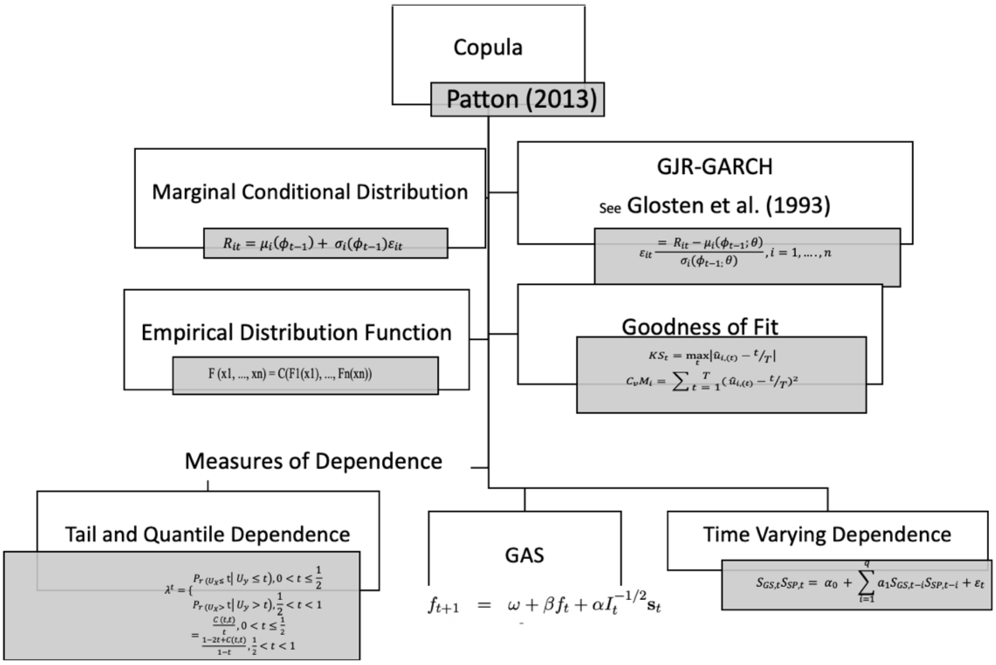

Figure 3. 1 Theoretical Structure of Patton (2013) Copula Model.

3.3.1 Copula

As stipulated over, the calculation of the CvaR using the VaR strategy requires an information of the joint conveyance of all minimal returns included within the portfolio.To fulfil this requirement, Sklar (1959) hypothesis proposes that the joint dispersion F(x1,,xn) can be communicated as:

$$F(x_1, \ldots, x_n) = C\,[F_1(x_1), \ldots, F_n(x_n)] \tag{3.1}$$

where C: [0,1] n → [0,1] could be an interesting copula work and Fi (xi) are demagogical disseminations (edges) of factors of interest. Note that Eq. 3.1 infers that the obscure joint dissemination can be developed by two partitioned parts, counting the copula work and the minimal distributions of the authentic minimal returns.

Regarding the foremost appropriate copula work, in this ponder, we have considered a few copulas that are commonly classified into diverse families based on their development strategies, comprising, but not constrained to, the circular, Archimedean, copula, experimental, extraordinary esteem, and the hybrid copulas. For more points of interest on the complete suite of copula capacities, peruses are alluded to the thinks about of (Nelsen, 2006; Bedford and Cooke, 2002).

3.3.2 GJR-GARCH

Furthermore, depending on the already specified GARCH-M demonstrate, Glosten et al. (1993) study altered the demonstration by proposing GJR GARCH, in which their model is based on the truth that there's deviated reaction of instability depending on the positive and negative stuns.

3.3.3 Marginal Conditional Distribution

If the random variables are independent, the copula density equals the product of the random variables' marginal distributions. That is, c(u,v)=u, with v=1 (since the variables are uniform on [0,1]). As a result, copula in this context refers to the product or independent copula (Burney and Ajaz, 2020). Furthermore, there is the Sklar's Theorem – as it is the one factor needed mostly by Copulas. This theorem states that any joint distribution can be represented by its marginal distribution. In other words, According to Sklar's theorem, any multivariate joint distribution can be expressed in terms of univariate marginal distribution functions and a copula that describes the variable dependence structure (Burney and Ajaz, 2020).

3.3.4 Goodness of Fit

Formed in 1973 by Hirotsugu Akaike, Akaike's Information Criteria can also be termed as goodness of fit of any estimated statistical model. Whereas Bayesian Information Criteria developed in 1978 by Gideon E. Schwarz is a type of model selection among a class of parametric models with different numbers of parameter.

3.3.5 Tail Dependence

Over the last few years, Copula has been able to explain multi-dimensional spread and tail dependency in financial strands, including bond portfolio credit risk, default mortgage risk, and contagion risk in financial markets. According to the Sklar theorem, a group of n variables $[Y_{1t}, Y_{2t}, \ldots, Y_{nt}]$ may have a marginal distribution and copula condition, namely $Y_t \sim F_t = C_t\,(F_{1t}, F_{2t}, \ldots, F_{nt})$.

3.3.6 GAS

In this article, the GAS method is presented for adjusting copula time to form a complex joint distribution. In observation-driven approaches, time variance of parameters is accomplished by making parameters function of lagged variables in addition to lagged exogenous variables, which is predictable due to historical details. The GAS approach is based on the predictive model density scaled function in time t, using the entire density structure rather than simply the highest moments.

3.3.7 Time Varying Dependence

The Time Varying copula model was introduced by Patton (2006) based on assumptions that the present dependency parameter is correlated with the past dependency parameter and the historical mean of cumulative probability integral transformations gap. A Generalized Auto-regressive Score (GAS) model was introduced by Creal et al. (2012) which expands the work of Patton (2006) on modelling Time Varying copulas.

3.4 Methodology

The use of the copula asymmetric conditional dependence is used for both the indexes S&P500 and Gold Price Index. In copula function the marginal distribution of the random variables are linked to joint distribution. Simply, the joint distribution can be known as the copula function and marginal distribution. Hence, the copula models provide flexibility in terms of the multi-variant distributions, which allows specification of marginal distributions separately from copula (dependence structure).

This chapter focuses on the conditional dependence and our interest if to apply a Sklar's (1959) theorem which is presented in the (Patton, 2006). The assumption is based on conditional variables which are represented in the information set as Rit is H (rit | Πt−1), where i = 1, ..., n. Further decomposing it to the marginal distribution the functions look as follows in equation 3.2.

$$H\left((r_{it}|\Pi_{t-i}\right) = C\left(F_i\left(r_{it}|\Pi_{t-1}\right)\right), \quad ..F_n(r_{nt}|\Pi_{t-1})|\Pi_{t-1}) \qquad (3.2)$$

The function highlights the flexibility of copula dependence models for the estimation of joint distribution and model specification. We aim to estimate the conditional distribution first and then take into account the copula models for the joint distribution. An n-dimensional model will be generated by this preventing the challenge of estimation simultaneously.

3.4.1 Models for the Conditional Marginal Distribution

We will first model the conditional margins as we aim to construct the conditional dependence model. We are using Time Varying means and variances for this chapter based on the following structure:
Rit = μi (φt−1) + σi (φt−1)εit (2) where i = 1, ..., n, φt−1 ∈ Πt−1, and εit is refereed as the standardised residuals, which can be described as follows in equation 3.3 and 3.4:

$$R_{it} = \mu_i(\phi_{t-1}) + \sigma_i(\phi_{t-1})\varepsilon_{it} \qquad (3.3)$$

$$\varepsilon_{it} \frac{= R_{it} - \mu_i(\phi_{t-1};\theta)}{\sigma_i(\phi_{t-1;}\theta)}, i = 1, \dots., n \qquad (3.4)$$

Here θ is considered as the vector of the estimation parameters of the models for conditional mean and the variance. We used the standard residuals for the calculation of the conditional marginal distribution. We will aim to adopt the parametric model for the conditional marginal distributions in which the skewed t of Hansen (1994) has been selected to estimate the distribution of standardised residuals. Though the skewed t distribution is close to the t distribution but it has additional parameter which will be captured for the asymmetry in the distribution at the same time maintaining the 0 mean and the unit variance. The skewed t distribution is as follows in equation 3.5:

$$d\ (z|n,\lambda) = \{ \begin{matrix} bc \quad (1 + \frac{1}{n-2}\left(\frac{bz+\alpha}{1-\lambda}\right)^2)^{-\frac{n+1}{2}} if z < -{}^{a}/_{b} \\ bc \quad (1 + \frac{1}{n-2}\left(\frac{bz+\alpha}{1-\lambda}\right)^2)^{-\frac{n+1}{2}} if z < -{}^{a}/_{b} \end{matrix} \qquad (3.5)$$

Equation demonstrates $a = 4\lambda\frac{n-2}{n-1}$, $b = 1 + 3\lambda^2$-a^2 and $c = \frac{r\left(\frac{n+1}{2}\right)}{\sqrt{\pi(\eta-2)}r\frac{n}{2}}$.

η and λ denote degree of freedom and asymmetric parameter, in this case 2 < η< ∞ and -1< λ <1.

3.4.2 Copula Models for the entire Dependence Structure

After modelling the conditional marginal distributions of the asset returns, we are going to get n pairs of consistently dispersed factors Uit, i = 1, ..., n, which can be utilized to appraise the copula parameter.

In this chapter, we'll give models for steady copulas as well as Time Varying copulas. In specific, the Time Varying copula will be demonstrated utilizing the Generalised autoregressive score (GAS) demonstrates of Creal et al. (2012) which expect the Time Varying copula parameters take after an advancement work of the slacked copula parameter and a "forcing variable" that's related to the scale score of the copula log-likelihood.

$$\phi_{t+1} = \omega + \alpha \frac{2}{1-p_t^2}\left[A_t - \rho_t - \rho_t \frac{B_t - 2}{1+p_t^2}\right] + \beta\emptyset_t \tag{3.6}$$

Where $\emptyset_t$ is copula parameter,p_t is correlation parameter, A_t= $\phi^{-1}(u_{1t})^{\phi-1}(u_{2t}), \beta_t = \phi^{-1}(u_{1t})^2 + \phi^{-1}(u_{2t})^2$ and ϕ^{-1} (.) is normal distribution inverse.

3.4.3 Constant Copula

As far as constant copula model is considered we used the following models:

	Parameter(s)	Parameter space	Indep	Pos & Neg dep?	Rank correlation	Kendall's τ	Lower tail dep	Upper tail dep
Normal	ρ	$(-1,1)$	0	*Yes*	$\frac{6}{\pi}\arcsin\frac{\rho}{2}$	$\frac{2}{\pi}\arcsin\rho$	0	0
Clayton	γ	$(0,\infty)$	0	*No*†	*n.a.*	$\frac{\gamma}{\gamma+2}$	$2^{-1/\gamma}$	0
Rotated Clayton	γ	$(0,\infty)$	0	*No*†	*n.a.*	$\frac{\gamma}{\gamma+2}$	0	$2^{-1/\gamma}$
Plackett	γ	$(0,\infty)$	1	*Yes*	$\frac{\gamma^2-2\gamma\log\gamma-1}{(\gamma-1)^2}$	*n.a.*	0	0
Frank	γ	$(-\infty,\infty)$	0	*Yes*	$g_\rho(\gamma)$	$g_\tau(\gamma)$	0	0
Gumbel	γ	$(1,\infty)$	1	*No*	*n.a.*	$\frac{\gamma-1}{\gamma}$	0	$2-2^{1/\gamma}$
Rotated Gumbel	γ	$(1,\infty)$	1	*No*	*n.a.*	$\frac{\gamma-1}{\gamma}$	$2-2^{1/\gamma}$	0
Sym Joe-Clayton	$\tau^L,\ \tau^U$	$[0,1)\times[0,1)$	$(0,0)$	*No*	*n.a.*	*n.a.*	τ^L	τ^U
Student's t	$\rho,\ \nu$	$(-1,1)\times(2,\infty)$	$(0,\infty)$	*Yes*	*n.a.*	$\frac{2}{\pi}\arcsin(\rho)$	$g_T(\rho,\nu)$	$g_T(\rho,\nu)$

Table 3.9 Constant Copula Models- Source Patton 2013

The consideration of copula models for dependence structure not just for tails is very vital. This determines the multi-stage estimation for several parameters.

3.4.4 Copula Models for the Tail Dependence

One of the foremost critical highlights of the structure of the relationship is the tail dependence. We consider this by to begin with looking at the quantile dependence, which is captured by the following functions, shown in equation 3.7:

$$\lambda^t = \{ \begin{matrix} P_{r\,(U_X \leq} \text{t} \big| \, U_y \leq t \big), 0 < t \leq \frac{1}{2} \\ P_{r\,(U_X >} \text{t} \big| \, U_y > t \big), \frac{1}{2} < t < 1 \end{matrix} \tag{3.7}$$

$$= \begin{matrix} \frac{C\,(t,t)}{t}, 0 < t \leq \frac{1}{2} \\ \frac{1-2t+C(t,t)}{1-t}, \frac{1}{2} < t < 1 \end{matrix}$$

The over work gives a wealthier depiction of the dependence between two arbitrary factors. As q → 0, we have the lower (cleared out) tail dependence, which is characterized as within the equation 3.8.

$$\lambda^L = \lim_{t \to 0^+} \frac{C(t,t)}{t} \tag{3.8}$$

Therefore, as t move from the centre (when t = 1/2) to the tails, by comparing the lower/left (t < 1/2) and upper/right (t > 1/ 2) tails, it gives data on the dependence structure such as asymmetric dependence.

$$\lambda^U = \lim_{t \to 0^-} \frac{1-2t+C(t,t)}{1-t} \tag{3.9}$$

Typically, amazingly valuable in cases that a deviated dependence is display, as numerous of the copula capacities, such as Gaussian copula or student's t copula, which capture as it were the symmetric dependence.

3.5 Data

This chapter examines the asymmetric conditional dependence structure between two indexes. Timer series data of everyday is taken from the time period 01 January 1992 to 01 January 2020 is taken from Bloomberg for S&P500 and Gold Index. By evacuating non-trading dates within the test period, we have in add up to 7296 perceptions. The log return is utilized using the below formula in equation 3.10:

$$RT = LN(\frac{P_t}{P_{t+1}}) \tag{3.10}$$

The dataset covers the financial crisis period as well, hence permits us to supply a comprehensive examination of the dependence structure for the calm and turmoil period. The clear insights of the two list returns are displayed in Table 2.1 in chapter 2 which describes the statistics of both the data series. As it can be seen, both arrangements have and exceptionally correlated fluctuations. Both arrangements have negative skewness and expansive positive kurtosis. In any case, the S&P500 stock file features a more negative skewness esteem, demonstrating more critical cleared out tail hazard. The Jarque Bera once more affirms the non-normality of both arrangements. The direct and Spearman's rank relationship values show a solid positive relationship between the two returns.

Since daily returns of Gold Index and S&P500 Volatility Index, is taken from Bloomberg, because of the accessibility of information, for the time frame was easily accessible. Gold index and S&P500 returns residuals can be seen in Fig. 2.3 (Chapter 2). Obviously, S&P500 returns are at more significant levels than Gold index particularly in late 2011 maybe because of the financial crisis during that time period.

Synopsis insights for both stocks are accounted for in Table 2.1 in chapter 2 (Section 2.4). S&P500 has a higher mean and standard deviation than Gold index. Both arrangements have positive skewness and abundance kurtosis, inferring deviated and fat-tail conduct (See Fig 2.3).

Additionally, the critical mean measurements show that the unlimited dispersions of the two stocks shows an indirect relationship properties of an ordinary conveyance[5].

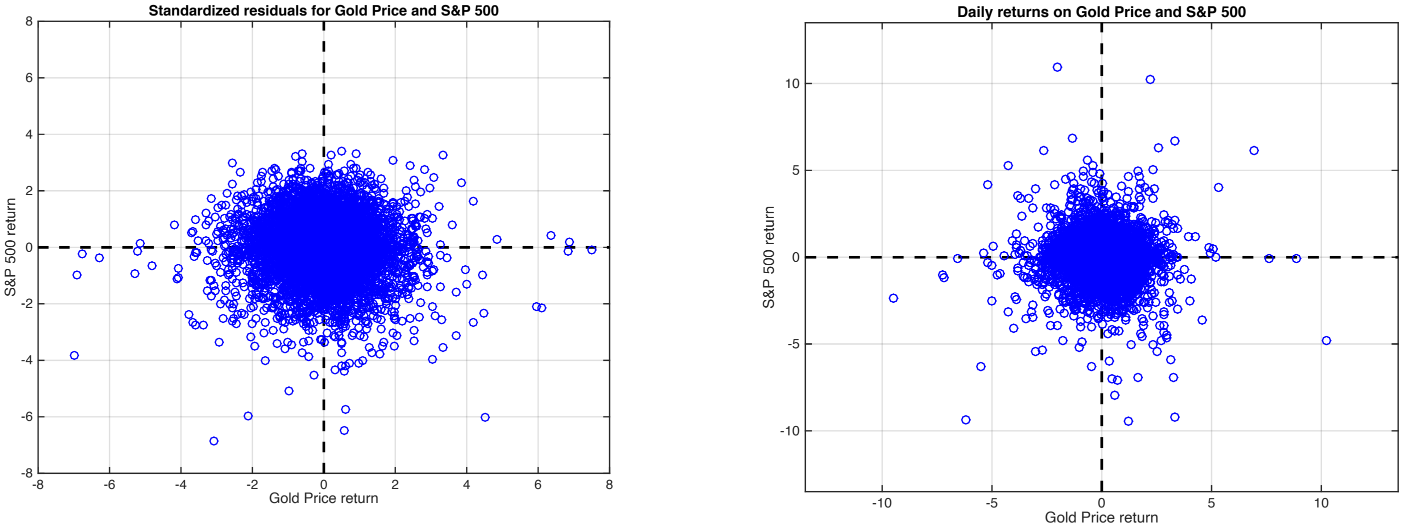

Figure 3. 2 Daily Return and Standardised Residuals for S&P500 Index and Gold Price Index.

The time-series plots of the record costs are displayed in Fig. 3.2. We see that the term structures of the two records are very comparative, which shows the presence of solid co-movements between the two markets. Both time series data expanded earlier during the period of calmness, after the financial crisis they represented less correlated relationship. Considering the period of crisis, the prices of both the series went at the highest level and after crisis they begin to drop in 2008, both series were adjusted to a level higher than the pre-crisis period. While the Gold index price continued to fluctuate around that level, the S&P500 index price was moving slowly towards a downward sloping direction after 2010 and rise significantly after 2016.

3.6 Model Selection

3.6.1 Conditional Mean

To show the conditional reliance structure of the two series related returns, we begin with appraise the conditional edges based on Eq. 3.3. That's, we accept the return arrangement has Time Varying conditional implications. Additionally, we accept that the institutionalized

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[5] Notes: the figures present expressive insights of every day esteems returns for Gold and S&P500. The example period is from 01 January, 1992 to 01 January 2020. The Jarque-Bera measurement has a circulation with two degrees of opportunity under the invalid speculation of regularly mistakes.

remaining ϵ_{it} to have a steady conditional conveyance. Subsequently, we begin to consider Autoregressive-Moving-average (ARMA) models for the conditional cruel of up to the range of (5,5), and select the ideal show by applying the Bayesian Information Criterion (BIC). We discover that AR (0) appears to be the ideal demonstrate for both Gold Price index and S&P500 returns. The Ljung- Box test on residuals recommends no remaining autocorrelation from the ideal demonstration. We moreover apply an F-test for a noteworthiness of a cross-variable slacks up to lags 5. The results suggest that there's critical across-variable connection from S&P500 and Gold Prices, but not vice-versa. This infers that the S&P500 advertise leads the Gold Price index advertise and is more vital within the cost revelation handle. The t-statistics appears that the Gold Price index list return is essentially affected by the execution of the S&P500 showcase from the past day. In this manner, we construct the taking after models for the conditional mean:

$$R_{GS,t=C_1+\epsilon_{1t}} \tag{3.11}$$

$$R_{SP,t=C_2+\varphi_1 R_{GS,t-1}+\epsilon_{2t}} \tag{3.12}$$

3.6.2 Conditional Variance

For conditional variance, we consider the Glosten–Jagannathan–Runkle-generalised auto-regressive conditional heteroscedasticity (GJR-GARCH) demonstrate of Chang (2012) for the conditional fluctuation. Models we have tried to incorporate the consistent instability demonstrate, ARCH (1), GARCH (1,1), GJR- GARCH (1,1,1), AR(2), GARCH(2,2) and GJR-GARCH (2,2,2). The general GJR-GARCH class models that have the following expression:

$$h_t = \alpha_0 + \sum_{i=1}^{n} \beta_i h_{t-i} + \sum_{i=1}^{n} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{n} \alpha_i^* \, \varepsilon_{t-i}^2 I_{t-i} \tag{3.13}$$

Where $I_t = \{ \begin{matrix} 1 if \varepsilon_{t-i} < 0 \\ 0 if \varepsilon_{t-i} \geq 0 \end{matrix}$. As can be seen, BIC-optimal models for the S&P500 composite index return and the Gold Price index and S&P500 return are both GJR- GARCH (1,1,1), which has the lowest BIC value compare to other models.

The model parameters for Time Varying means and variance from GJR-GARCH (1,1,1) specification are presented in Tables of chapter 2 (Section 2.4.1). The GJR parameter for S&P500 and Gold Price index returns mentioned in chapter 2 (Section 2.4.1), indicating that the negative error terms have a stronger effect on the future value of volatility for both stock indices.

The standardised residuals are then calculated from the optimal conditional variance models using Eq. 3.9 Fig. 3.2 plots the day by day returns and institutionalized residuals for the S&P500 and Gold Price index lists. The scramble plot for the institutionalized residuals appears as it were slight asymmetry between positive and negative institutionalized returns, which recommends that both returns reacts to stuns so also notwithstanding whether the markets are booming or smashing amid the test period.

3.6.3 Modelling Standardised Residuals

The negligible or narrow dissemination are demonstrated employing a parametric approach by the strategy Inference Function for Margins (IFM). By expecting the irregular variable takes after a particular aggregate dispersion work, the Inference Function for Margins strategy changes the arbitrary variable into a consistently dispersed variable, utilizing the likelihood fundamentally change work. In the process to avoid the misspecification issue that's commonly found in a parametric approach, we begin to test an arrangement of dispersions for the institutionalized residuals, counting Gaussian, Student's t Generalised Error Distribution (GED) the difference between expected value and observed value and skewed t distribution the family of continuous probability distributions.

While applying a Kolmogorov–Smirnov test to testing which conveyance is most near to the genuine dissemination of the institutionalized residuals. The outcomes appear that the skewed t dispersion has the most reduced p-value and consequently is the foremost fitting dissemination for the demonstration. The two parameters' gauges of Skewed t that are display in the Table 3.6. As it can be seen, both remaining arrangements have a negative skewness parameter, which proposes a left skewed dissemination. Typically, steady with the common financial condition, as there may well be more antagonistic stuns than positive stuns amid the emergency.

As shown by the upper panel fitted density appears to be reasonably provided in the empirical histogram. A few extreme observations of extreme left observation were not captured by this model for each series as presented by QQ plot inf fig. 3.3.

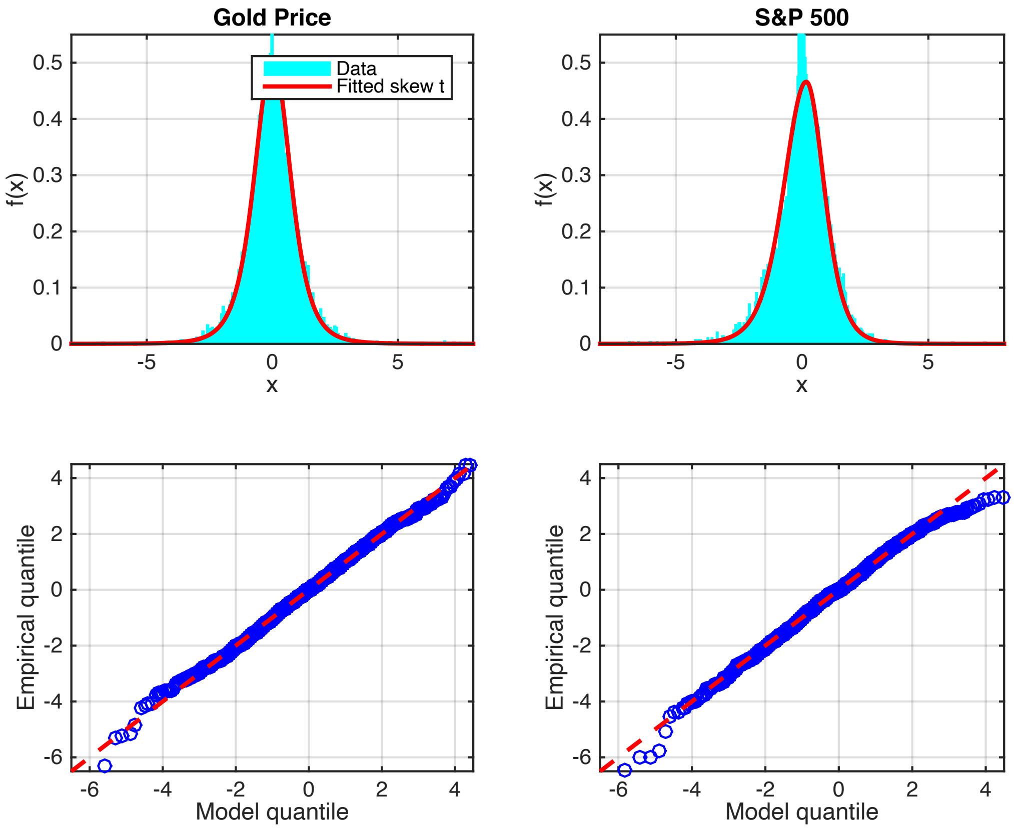

Figure 3. 3 Skewed t Distribution and the Q-Q plot.

Figure 3.3 further exhibits the skewness. As per Chen and Fan (2006) the disadvantage of the IFM model is that the dependence parameters have the tendency to be affected by mis-specified marginal distribution of the standardised residuals. In order to signify that we plotted (see figure 3.3) the fitted parametric estimates of the skewed t distribution with the histogram mentioning its empirical approximations. The density of the skewed t reveals the reliable estimates of the empirical histogram. The quantile-quantile (Q-Q) plot exhibits the right panel for skew t distribution. We can see few extreme left tail observations since that was not captured by the model for S&P500 and Gold price index.

Table 3.6 clearly shows the implementation of Gold index and S&P500 for Time Varying dependence and the standardized residuals yields the results as shown. Since the dates are not null therefore consider three break points. A p-value represents evidence of break in correlation of 0.104 whereas for the dates at the beginning there is no evidence. This concludes that the rank correlation at the beginning of time series is different as to the end of the time series. It is an autoregressive-type manner than as a discrete for the financial assets conditional volatility is plotted in figure 3.3 as one-time change.

Hence, it is monitored that there is significant evidence against constant conditional rank correlation for Gold index and S&P500 time series standardized residuals thus which is an evidence against constant copula. This provides a solid evidence and motivation for the consideration of Time Varying copulas that volatility changes through time.

	Gold Prices	SP500
$\boldsymbol{\emptyset_0}$	0.020	0.028
$\boldsymbol{\emptyset_1}$	-0.018	-
$\boldsymbol{\emptyset_2}$	-0.012	-
$\boldsymbol{\omega}$	0.002	0.018
$\boldsymbol{\alpha}$	0.045	0.003
$\boldsymbol{\delta}$	0.000	0.153
$\boldsymbol{\beta}$	0.955	0.900

Table 3. 2 Conditional mean and variance parameters

Table 3.2 demonstrated the results commencing from first three rows presents parameter estimates from AR (2) and AR (0) models for the conditional mean. The last three rows present parameter estimates from GJR-GARCH (1,1) models for the conditional variance. One of the impediments of the Inference Function for Margins (IFM) strategy, as pointed by Chen and Fan (2006), is that the reliance parameters might be influenced by a conceivably mis indicated minimal dispersion of institutionalized developments. In this manner, we encourage to plot the fitted parametric gauges of the skewed t conveyance with the histogram of its observational estimation in Fig. 3.3. As famous, the fitted thickness of skewed t is able to supply dependable gauges of the experimental histogram that are the best approach for data analysis. The correct board of Fig. 3.3 provides the quantile–quantile (Q- Q) plot for skewed t conveyance. It can be seen, there exist some extraordinary cleared out tail perceptions that are not captured by the models for the S&P500 Trade Composite list and Gold index Record.

At last, we apply a goodness-of-fit test on skewed t conveyance employing a Kolmogorov-Smirnov (KS) test and a Cramer-von Mises (CvM) test, as presented in Patton (2013), to check the goodness-of-fit of the fitted dispersion. The two equations 3.14 and 3.15 are as follows:

$$KS_t = \max_t \left| \hat{u}_{i,(t)} - {}^{t}/_{T} \right| \tag{3.14}$$

$$C_v M_i = \sum_{t=1}^{T} \left(\hat{u}_{i,(t)} - {}^{t}/_{T} \right)^2 \tag{3.15}$$

where uˆi,(t) is the tth biggest esteem of {uˆi,j}Tt=1. Uit is the likelihood necessarily changes of the institutionalized residuals based on Hansen's skewed t dissemination. KS (CvM) test measurements on the two leftovers arrangements are detailed in the table 3.1. We at that point utilize a simulation-based strategy as presented in Genest and Remillard (2008) to calculate the p-value for both tests. The test measurements and the comparing p-values are detailed in Table 3.2. Both tests recommend the dismissal of the invalid that the skewed t conveyance may be a well-specified conveyance for the institutionalized residuals. Both the tests of KS and CVM are applied in empirical copula for standard residual and also to the Rosenblatt transformation of standardized residuals. These two tests are applicable for the Rosenblatt transformation.

By the implementation of both the statistic tests on S&P500 and Gold Index standard residuals the p Values for KS (CVM) 0.29 and 0.42 (0.28 and 0.44) which clearly specifies for these two-series skew t model fail to reject the null. Which provides support for these time series data of marginal distribution favouring us to move forward with the modelling of Copula (Patton, 2013).

Furthermore, the dynamic evolution of scaled score of the likelihood function of Rotated Gumbel GAS copula and the student's t GAS copula are exhibited in Fig. 3.3. The parameter estimation consequences reveal a strong co-movement between the S&P500 and Gold returns, and thus exhibiting strong upper and lower tail correlations. For the bootstrap standard blunders. After modelling the negligible dissemination for the prospects returns with GJR- GARCH-Skew t demonstrate, the comparing standardized residuals can be extricated from the forms. To assess the fitting exhibitions with Skew t negligible dispersion for the stock exchange, prospects return thickness dispersion, a parameter estimation blunder balanced KS, and CvM goodness of fit tests for the thickness model is actualized with 1000 re-enactments. In Genest et al. (2009), the CvM measurement gives a great combination of concept effortlessness and control. These two test insights utilized for the goodness of fit test of the copula show are based on the fitted copula CDF to the Rosenblatt transform-based copula, as appeared in equations of table 3.1.

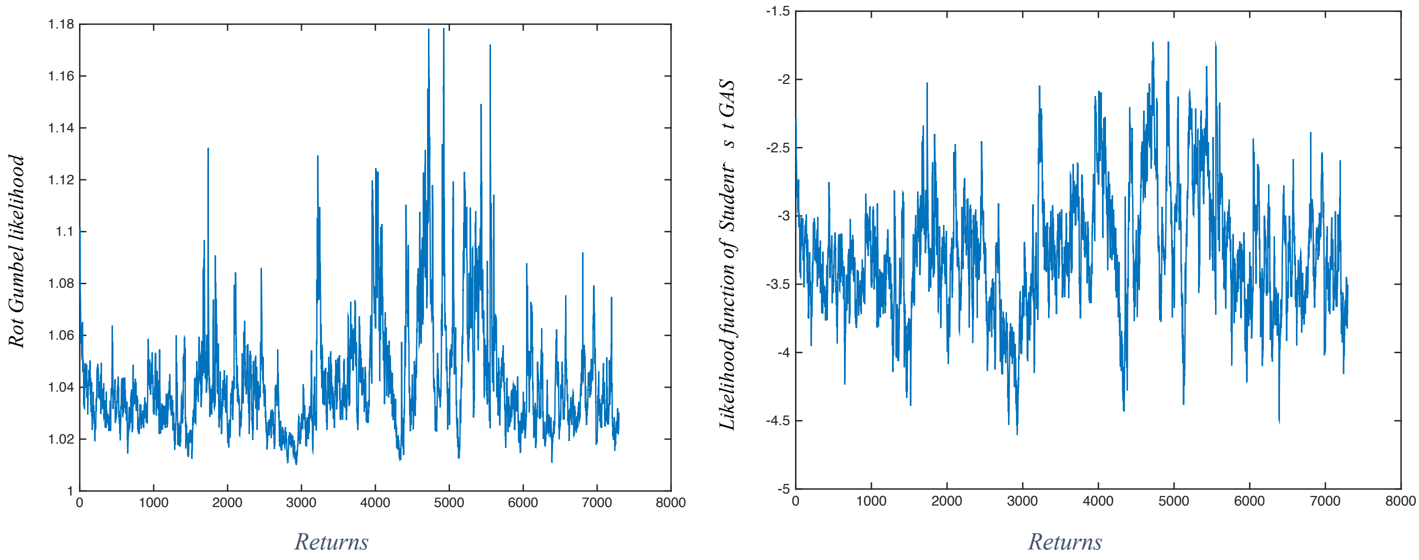

Figure 3.4 The scaled score of the likelihood function of Rot Gumbel GAS and Student's t GAS Copula

Based on the examination of the regulated residual S&P500 and Gold index futures returns, the nonlinear correlations across S&P500 and Gold Index markets can be inferred. This indicates the bases of the choice of copula function used for these returns. Having done this, the different fitting performances of constant copula and Time Varying copula will be compared. The study is to understand the constant and some of the Time Varying copula functions hence, we will only focus on four constant copula functions including the Normal copula, the Clayton copula, the Rotated Gumbel copula, and the student's t copula. For the Time Varying copula function, two varying copula functions including the Rotated Gumbel GAS copula and the student's t GAS copula will be investigated further. Table 3.2 shows the listing of the corresponding parameter estimations and some statistics of copula functions with Skew T marginal distribution in addition to the goodness of fit tests which is further analysed in this chapter for the S&P500 and Gold Price index. For the constant copula functions, it can be seen from Table 3.3 that the logarithmic likelihood value of Rot Gumbel is the highest, and the fitting effect is the best, followed by the Student T copula. However, it can be seen that the two-Time Varying copula models are better than the constant copula models. When using fat tailed GARCH model for the marginal distribution, the Time Varying copula connection functions fit high dimension asset correlations relatively superiorly. Additionally, it shows that there exists Time Varying tail dependence for the stock returns. And the Rotated Gumbel GAS copula function is suitable to be chosen in the modelling of dependence structure for fitting multivariable financial asset data. It verifies that asymmetries and excessive kurtosis are found in the dependence as well as the marginal distribution, which also illustrates that the GJR-GARCH-Skew T- Rot Gumbel GAS copula model can effectively fit the joint distribution of multivariate assets.

Additionally, in order to investigate the fitting performances of Time Varying GAS copula combining with different heavy tailed marginal distributions containing the Skew t distribution, GED distribution and Student t distribution. Several loss functions including the mean square error (MSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE) are employed to evaluate the fitting accuracy. Table 3.3 presents the evaluation results of the Rot Gumbel GAS (RGG) copula and the student's t GAS (StG) copula for the S&P500 and Gold Price index returns. The empirical results of S&P500 and Gold returns in Table 3.3 indicate that the estimation effects of GJR-GARCH-Skew t-Rot Gumbel GAS copula model is the overall best, and the worst fitting effect comes from the GJR-GARCH-Skew t- Student's t GAS copula model. It can be concluded that the combination of Rot Gumbel GAS copula model with GJR-GARCH-Skew t distribution can enhance the modelling accuracy. Moreover, the findings show that the Skew student t distribution has a better fit to the marginal distribution than others, which exhibits superior performances than other marginal distributions.

In table 3.3, we show the layout of constant copula. The chosen root node here is the one that enhances this node's number of pair-wise dependencies. We use a selection of two indexes for selection purposes, including AIC (Akaike approach) and BIC as the criterion to choose from the following copulas: Gaussian copula, Student-t copula (t-copula), Clayton copula, Gumbel copula, Frank copula, Joe copula.

	Parametric			Semiparametric		
	param1	**param2**	**LL**	**param1**	**param2**	**LL**
Normal	-0.039	-	5.5	-0.038	-	5.4
Clayton	0.010	-	0.4	0.010	-	0.5
Rot Clayton	0.000	-	-0.0	0.000	-	-0.0
Plackett	0.866	-	7.4	0.867	-	7.4
Frank	0.000	-	-0.0	0.000	-	-0.0
Gumbel	1.100	-	-107.8	1.100	-	-106.9
Rot Gumbel	1.100	-	-89.4	1.100	-	-84.9
SJC	0.000	0.000	-8.8	0.000	0.000	-8.2
Student's t	-0.042	0.125	55.5	-0.043	0.127	56.1

Table 3.3 Constant copula model parameter estimates

The table 3.3 above basically measures the constant copula and this clearly shows the likelihood of logs. The right columns show the results for semi parameters model and left for the parameter models for marginal distributions. This consists of nine specifications Normal, Clayton, Rot clayton, Plackett, Frank, Gumbel, Rot Gumble, SJC and Student's t. The worst model in them is the rotated Clayton as it imposes lower tail dependence and only upper tail is allowed. This analysis of the standardized residuals of Gold Price Index and the S&P500 returns there can be inference in the prices of Gold and S&P500 index being nonlinear correlated. The rationality of the copula returns can also be taken under consideration for the values of returns used. The Comparison of the performances of the constant copula can be seen as the core focus is on ARCH GARCH and the constant copula functions the focus for copula is majorly on the Normal copula, the Clayton copula, the Rotated Gumbel copula, and the student's t copula. The results are showing good values for loglikelihoods and for both the parametric and the semiparametric analysis of the constant copula.

3.6.4 Goodness of Fit

The problems and results of Goodness of fit (GoF) and model selection will be discussed in this section. Further the problem is traditional specification of testing the errors and determining whether the copula model is different from the true copula. The latter testing basically tries to determine the problem in each set of competing copula models in the best per the measure.

Model selection tests and GoF tests are complimentary in economic applications. GoF is considered to be very weak in some criterion as an evaluation indicator in other applications GoF application is considered very strict. However, Model selection technique helps the researches to identify the best method of from the set but again this is conditionally based on many other information.

	KS_C	**CVM_C**	**KS_R**	**CVM_R**
Normal	0.29	0.42	0.28	0.44
Clayton	0.24	0.29	1.00	1.00
Rot Gumbel	0.18	0.17	0.13	0.11
Stud t	0.40	0.57	0.36	0.58
RotGum-GAS	-	-	0.00	0.00
Studt-GAS	-	-	0.00	0.00

Table 3. 4 Goodness of fit tests for copula models – parametric margins

	KS_C	CVM_C	KS_R	CVM_R
Clayton	0.00	0.00	1.00	1.00
Stud t	0.46	0.02	0.22	0.05
RotGum-GAS	-	-	0.00	0.00
Studt-GAS	-	-	0.00	0.00

Table 3. 5 Goodness of fit tests for copula models – nonparametric margins

Patton (2013) considered two cases separately to test the inference of goodness of fit under the analysis of parametric and semiparametric model. We have focused the on the sample of Gold and S&P500 data in this case.

The code has analysed the following equation 3.16, 3.17 and 3.18 for the analysis of Goodness of fit and model selection technique.

$$\widehat{C_T}\,(u) = \frac{1}{T}\sum_{t=1}^{T}\prod_{i=1}^{n} 1\,\{\widehat{U_{it}} \leq u_i\,\} \tag{3.16}$$

$$KS_C = \max_t \left| C\,(U_t; \hat{\theta}_T) - \widehat{C_T\,(U_t)} \right| \tag{3.17}$$

$$C_v M_c = \sum_{t=1}^{T} \{\,C\,\left(U_{t;}\,\widehat{\theta_T}\right) - \widehat{C_T}(U_t)\}^2 \tag{3.18}$$

The is based on the comparison of the empirical copula model and constant copula model for non-parametric estimations for true copula model. Empirical copula can no longer be used when conditional copula is Time Varying. In order to overcome this problem, the usage of fitted copula model so as to obtain Rosenblatt which is multivariate version of probability integral transformation (Diebold and Yilmaz, 2012).

3.6.5 Dependence Structure between S&P500 and Gold Index

According to, Patton (2013), while accepting normality, the main significant statistic measurement for the dependence and reliance structure is the linear correlation coefficient, and the routinely report in empirical analysis on multivariate data of these time series. The consideration of flexible reliance and dependence structure we must consider about different proportions of reliance and dependence, to give some direction on the sorts of models that may be appropriate for the factors under examination. This area depicts some valuable reliance measures and techniques for leading surmising on evaluations of these measures.

A common degree of reliance between two irregular factors is the direct and rank relationship coefficients, both markets are interdependent and inter corelated. Which can be accessed from the statistics present in chapter 2. In addition, that we can see in any case, the straight relationship isn't univariant beneath monotonic change. Therefore, we are going to utilize copula to show the reliance structure between S&P500 and Gold stock markets.

3.6.6 Tail Dependence and GAS Approach

Various dependence estimates measures exist in the numerous literatures, see (Nelsen, 2006), for definite exchanges. A key property of a dependence measure for giving direction on the type of the copula is that it ought to be a pure measure of reliance and dependence thus ought to be unaffected by carefully expanding changes of the information and time series data.
This is proportionate to forcing that the measure can be acquired as a component of the positions of just the data, which is thus identical to it being a capacity exclusively of the copula, and not the peripheral circulations. Direct connection isn't scale invariant which is linear correlation and is affected by the peripheral conveyances of the time series data. Given its nature in financial matters, it is as yet a helpful measure to report, however we will expand it with different proportions of reliance dependence (Patton, 2013).

Although copula functions can characterize the nonlinear dependence structure among variables, typically, the constant copulas are used to assume static tail dependence of returns distributions. The tail dependence is Time Varying which requires the copula function parameters to be changeable. In this section, the GAS model will be used to update the parameters using scaled score of the likelihood function. Then the developed framework is illustrated in the stock futures markets for tail risk evaluation. This can be seen in fig. 3.4 of GAS approach.

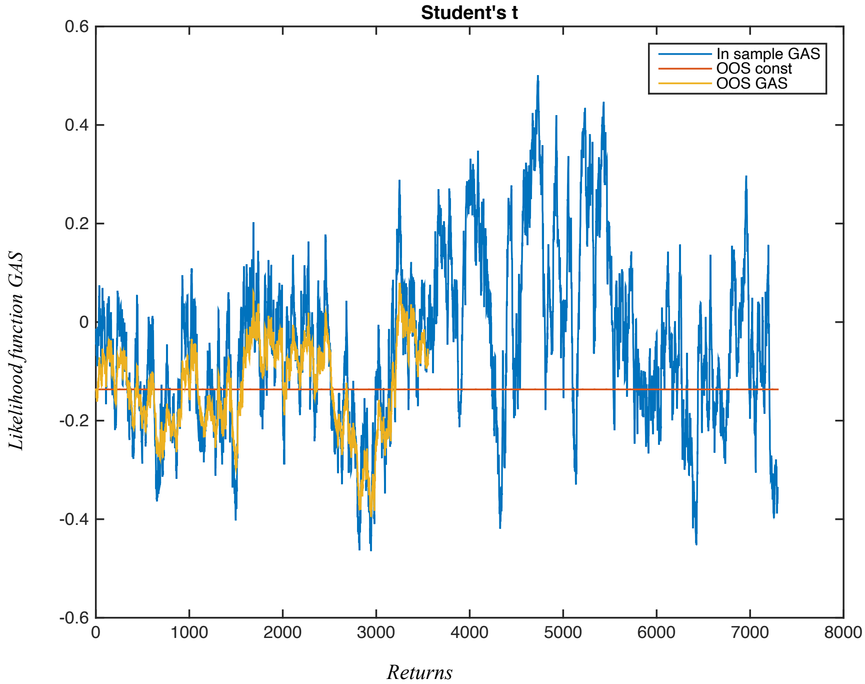

Figure 3. 5 GAS Computation for S&P500 and Gold Price Index (Student's t)

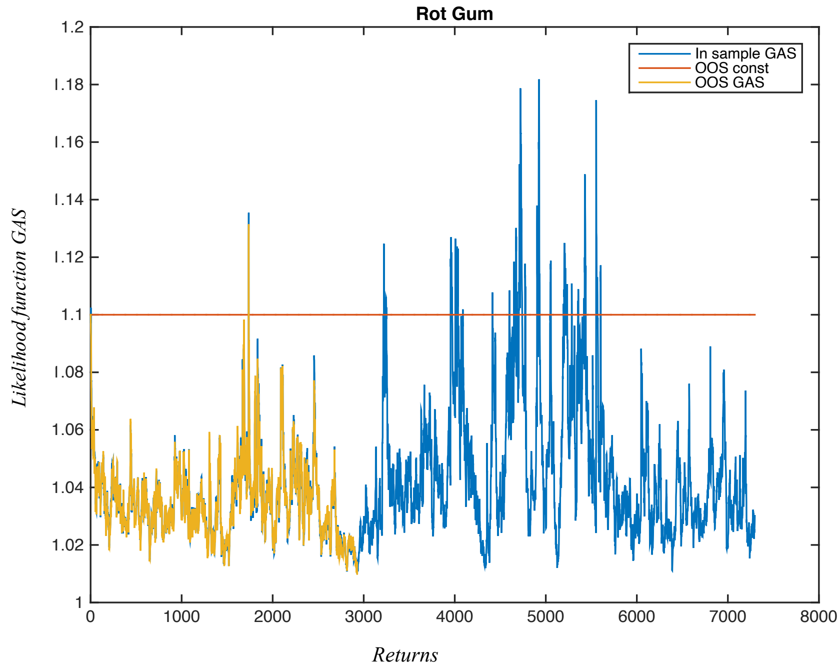

Figure 3. 6 Model Computation for S&P500 and Gold Price Index (Rot Gum)

Tail dependence describes the probability of another market encountering extreme circumstances (surge or breakdown) at the same time when one market encounters extreme circumstances, so it is an important tool to portray the tail risk contagion. Since tail correlation acts as an important role in the overall correlation structure, the Time Varying tail dependence needs to be verified before the risk measurement. The p value from tests for Time Varying rank correlation between the residuals of S&P500 and Gold returns futures series with 1000 bootstrap simulations is 0.2164, validating the suitability of Time Varying copula function. In addition, the testing for asymmetric dependence is also conducted with null hypothesis of tail dependence equality to examine the existence of asymmetric dependence. And the resulting p value of corresponding statistic is 0.0474, this indicates the existence of asymmetric tail dependence. However, for the optimal constant copula, Table 3.2 exhibits the descriptive answers and the figure 3.6 demonstrates average dynamic evolution of tail dependence containing lower tail dependence and upper tail dependence versus cut-off threshold ranging from 0 to 0.1 with 0.01 intervals and 90% confidence interval. The lower quantile dependence is computed by $\lambda L = Pr(U1 \leq q, U2 \leq q)/q$ for interval (0,0.5), and the upper quantile dependence is computed by $\lambda U=Pr(U1 > q, U2 > q)/(1-q)$. Furthermore, Fig. 3.7 gives the dynamic evolution of rank correlation between S&P500 and Gold returns.

As recommended by Hsu et al. (2008) a tall degree of perseverance in energetic conditional relationship implies crashes can thrust the relationships absent from its long-run mean and the relationships will have more unstable reactions to unused data. Fig. 3.7 further shows the plots of 60 –day rolling window rank relationships and the energetic conditional relationships between the S&P500 and Gold stock file returns. As can be seen, both time- varying relationships expanded since 2006 whereas coming to the top in early 2008. As expressed by Forbes. Andersen, et al. (2006) reported that there is a lot of research on the conditional volatility of financial factors and economics time series changes significantly through time. Figure 3.7 demonstrates a 60-day rank correlation of rolling time series data along with pointwise bootstrap standard errors.

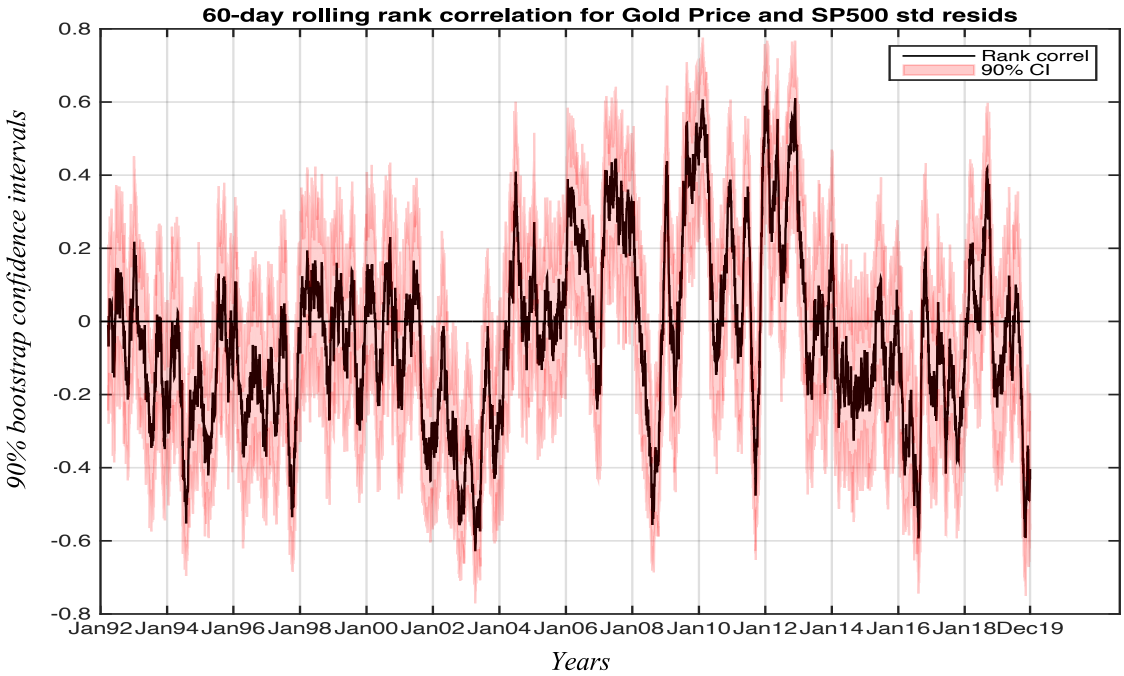

Figure 3. 7 60 day rolling correlation for Gold Price Index and S&P500 standard residuals.

For Time Varying Copula models, Fig. 3.8 displays the dynamic evolution of tail dependence from optimal Time Varying copula model for S&P500 and Gold returns. And Fig. 3.5 and 3.6 exhibits the dynamic evolution of correlation from Time Varying Rot Gumbel GAS copula model and Student's t GAS copula model for S&P500 and Gold returns.

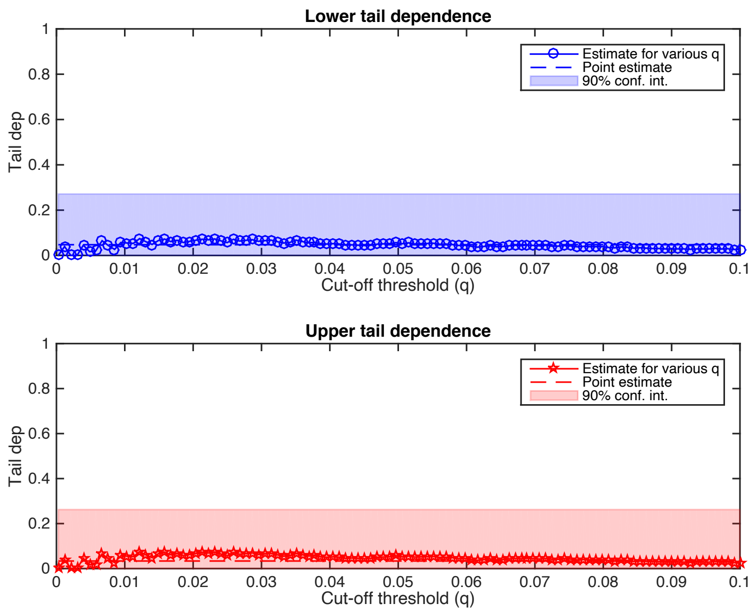

Figure 3. 8 Time Varying tail dependence of S&P500 and Gold Price Index returns.

An option in contrast to the nonparametric estimation of tail reliance coefficients examined in this section is to indicate and appraise parametric models for joint distribution of tails, see (Gwanoya, 2007). Hence, he following approach involves the parametric model of bivariate tail and the usage of fitted models so as to obtain the estimated tail dependence coefficient.

This consists of nine specifications Normal, Clayton, Rot clayton, Plackett, Frank, Gumbel, Rot Gumble, SJC and Student's t. The worst model in them is the rotated Clayton as it imposes lower tail dependence and only upper tail is allowed. In order to determine the standard error 1000 bootstrap has been used for simulated errors.

3.6.7 Conditional Copula Estimates

Conditional joint dependence with probability integral transformation uGS,t and uSP,t are the best means of defining and working with distributions for statistically dependent multivariate data. In this section we will assume both constant and Time Varying copulas. As estimation results for constant copula parameters are already discussed in table in chapter 2. For seven constant copula functions, including the usual students t, symmetrised Joe-claytons (SJC), Gumbel, Clayton, Rotated Gumbel and rotated clayton copulas, we estimate the copula parameters, the lower and upper tail dependence indicated by each copula and the value of the log likelihood. Each copula function has specific characteristics and differential abilities to grab tail dependency. The findings indicate that the t copula of the students is the best match of the entire dependency structure.

The tail reliance detailed in figure 3.8 comparisons section uncovers a few curiously highlights on these copula models. As can be seen, the student's t copula has symmetric lower and upper tail reliance. The tail reliance of the student's t copula is marginally bigger than its straight relationship parameters, recommending that the S&P500 and Gold markets are more subordinate beneath extraordinary occasions. The SJC copula has bigger lower tail reliance, showing the presence of topsy-turvy reliance. As recommended by tables of model comparison 3.3, 3.4 and 3.5, pivoted Clayton copula has the least log-likelihood esteem and consequently fails flat to capture the reliance structure. This might be related to the zero lower tail reliance forced by turned Clayton copula, which could be an erroneous reflection of the common reliance highlight amid the emergency. We too examine whether the long-run connections are not consistent over time.

Patton (2013), considered methods in the copula code for evaluating copula-based multivariate models. This is a vital aspect for the assessment of economic forecasts, Patton (2006) did a lot of research for motivation and of copula code development. In this analysis, he models use an in-sample period (of length R < T) and evaluates the remaining P = T   R observations.

Tables 3.4 clearly demonstrated the results from the time series data of Gold and S&P500. The top board of Table 3.3 reports the t-insights of pair-wise examinations. We can note that great capacity to differentiate the two models are rectified and the best model ends up to Student's t trailed by the Rotated Gumbel-GAS model. Both of these models beat the majority of the steady copula models, predictable with our prior results which are proof of time-shifting reliance, and with the GoF test outcomes talked about in the section above. Similar ends are found for pair-wise correlations of semiparametric models, exhibited in the centre board of Table 3.4.

	Normal	**Clayton**	**Rot Gumbel**	**Stud t**	**Rgum-GAS**	**Stud t-GAS**
Normal						
Clayton	4.26					
Rot Gumbel	1.86	-0.50				
Stud t	5.52	-1.30	-0.40			
Rgum-GAS	4.35.	3.94.	5.28.	2.67		
Stud t-GAS	7.55	6.06	4.58	6.55.	3.61	
log L	-52.03	2.96	-3.80	-13.41	34.84	79.07
Rank	6.00	3.00	4.00	5.00	2.00	1.00

Table 3. 6 Model comparisons of copula models – parametric margins

	Normal	**Clayton**	**Rot Gumbel**	**Stud t**	**Rgum-GAS**	**Stud t-GAS**
Log		-17.51	75.53			
Rank	3.00	4.00	5.00	2.00	6.00	1.00

Table 3. 7 Model comparisons of copula models – nonparametric margins

	Normal	**Clayton**	**Rot Gumbel**	**Stud t**	**Rgum-GAS**	**Stud t-GAS**
T-stat	0.00	0.00	0.00	-3.31	0.00	-3.31

Table 3. 8 Model comparisons of marginal models – parametric vs nonparametric margins

3.6.8 Testing for Time Varying Relationship

Since, we point to show the conditional reliance structure, it would be more reasonable to consider the reliance between two financial series changing through time. In reality, there are broad literary works that as of now account for the Time Varying nature of the conditional instability of budgetary resources. One of the basic strategies in this field is the (DCC) which is the dynamic correlation coefficient proposed by Engle (2001). Beneath a DCC system, the covariance framework is characterized as:

$$H_t = D_t R_t D_t \tag{3.19}$$

Where,

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 \\ 0 & \sqrt{h_{22t}} \end{bmatrix}, \qquad R_t = \begin{pmatrix} 1 & p_{12} \\ p_{21} & 1 \end{pmatrix} \tag{3.20}$$

And Conditional correlation R_t is given as

$$R_t = (diagQ_t)^{-1/2}\, Q_t (diagQ_t)^{-1/2}$$

And the positive symmetric matrix Q_t is given as

$$Q_t\ (1 - a - b)\psi + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \tag{3.21}$$

DCC Specification	ρ	α	β
	0.394	0.0049	0.9893

	Break				AR(p)		
	0.15	0.5	0.85	Anywhere	(1)	(5)	(10)
p-value	0.104	0.000	0.720	0.00	0.120	0.006	0.0000

Table 3.9 Testing for Time Varying Dependence.

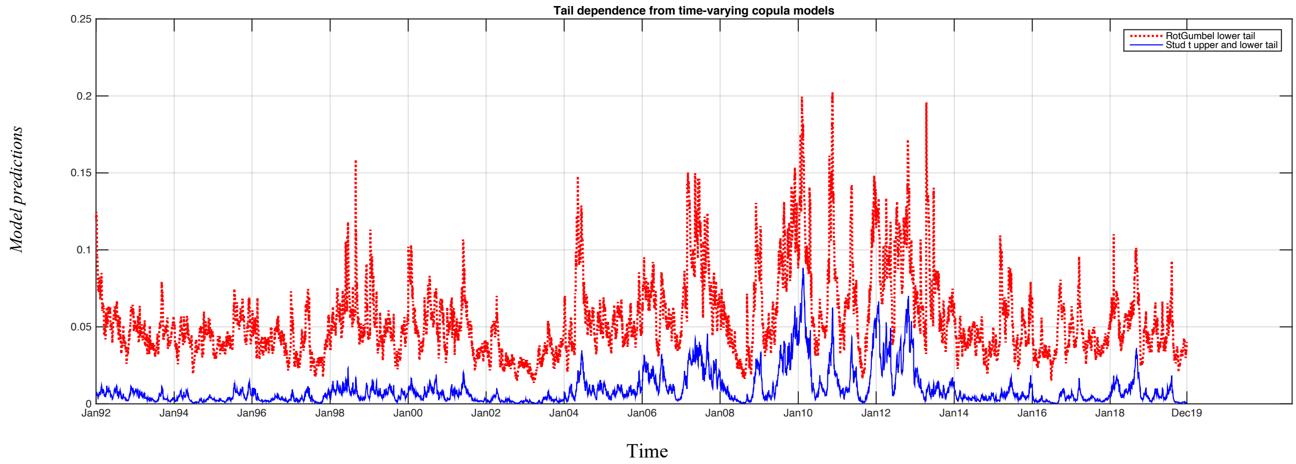

Figure 3. 9 Tail dependence from Time Varying Copula.

Since we used the GAS model by Creal et al. (2013) of time-varying copula parameter. Three time- varying copula has been analysed – which are Gaussian copula, the time varying student's t copula and the rotated Gumble copula. Figure 3.9 exhibits that dependence structure due to lowest negative log-likelihood value pointed to the fact that the heavy tail dependence exists between the S&P500 and Gold price index. The figure demonstrated that student's t distribution performed better in describing dependence. The figure 3.9 portrays the Rot Gumble tail and student t upper and lower tail dependence. The peaks demonstrated the comovements of the tail dependence of S&P500 and Gold Prices. This signifies the interdependence of the data. During the time intervals 1998, 2004, 2006, 2007, 2011 and 2013 the peaks are to the highest which shows the drastic interdependence of the stock over commodity. This could be due to the financial contagion refer to section 1.3 in chapter 1. Where Ɛit = eit/ 150it is the institutionalized residuals, ψ is the N * N unlimited relationship network of εt. Both a is positive, and b is non-negative scalar parameters fulfilling a + b<1. Table 3.6 presents the estimation comes about of the DCC show of Engle (2001), utilizing the same details for conditional implies and fluctuation as depicted prior. Our outcomes demonstrates a high degree of determination within the conditional relationship analysis, with Θ1 + Θ2 exceptionally near to one. The Time Varying dependence can be measured in various ways. In the code this test will include the changes in ranks of correlation %. Based on our literature review as proposed by Hsu et al. (2008), "a high degree of persistence in dynamic conditional correlation means crashes which are the financial turmoil etc can push the correlations away from its long-run mean and the correlations will have more volatile responses to new information". Three types of Time Varying dependence will be considered in this code. The first one is the break in rank correlation in simple form, second one in which t* keeping the null dependence measure and the third one is “ARCH LM”.

Figure 3.9 clearly shows the implementation of Gold index and S&P500 for Time Varying dependence and the standardized residuals yields the results as shown below. Since the dates are not null therefore consider three break points.

That being said, using the DCC model for the conditional correction limits the spread of the standardized residuals to an elliptical distribution. Which is also why, we consider using the Time Varying copula method to catch the changing dependency. We first add an Auto-regressive Conditional Heteroskedasticity Lagrange Multiplier (ARCH LM), which seeks autocorrelation as a calculation of dependency, before modelling the Time Varying copulas, to verify the presence of Time Varying dependency. The test is based on the following form of auto-regression:

$$S_{GS,t}S_{SP,t} = \alpha_0 + \sum_{i=1}^{q} a_1 S_{GS,t-i}S_{SP,t-i} + \varepsilon_t \tag{3.22}$$

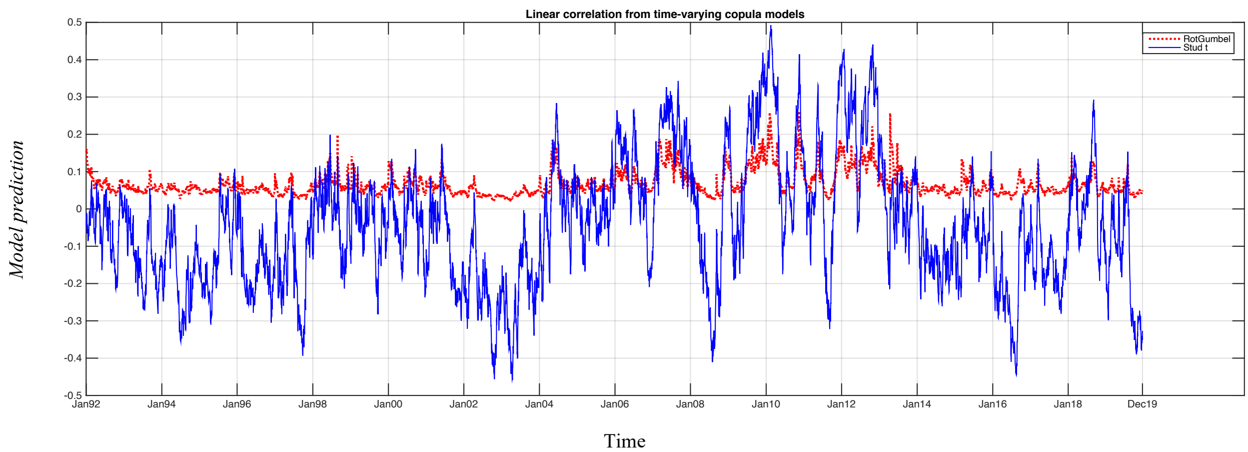

Figure 3. 10 Linear Correlation from Time Varying copula models.

Where St is the standardized residual of the same mean and variance parameters for S&P500 and Gold Index returns from the CCC-GARCH model. We could have αi = 0 for i= 1, ..., q. under the null hypothesis of a constant conditional copula. In the lower panel of Table 3.9, the test statistics and p-values are presented. As can be shown, the null for both instances are dismissed as a constant conditional correlation. We should thus assume that clear evidence exists against constant conditional correlation and therefore evidence alters a constant conditional copula.

The time varying student's t and Gumble copulas demonstrated in the figure 3.10 exhibiting the linear correlations compared the time varying rank correlations and the DCCs, some changes to the dependence structure were found. The figure depicts a decrease between the two indexes. The decrease is between 2008 to 2009. The correlation coefficient dropped from 0.3 to -0.4 this signifies that the S&P500 and gold price index was quite independent of other factors such as the financial crisis which took place during this time period. The implications of this are quite important as investors could add to the stock and commodity to diversify their risk.

Further assessing estimating dependence and reliance synopsis insights, it is regularly important to get standard mistakes and errors on these, either to furnish a thought of the exactness with which these parameters are evaluated, or to direct tests on these On the off chance that the time series data to be examined was known to as of now have Unif (0;1) edges, at that point deduction is clear, anyway when all is said in done this isn't the situation, and the information on which we figure the dependence synopsis insights will more often than not rely upon parameters assessed in a previous piece of the examination and analysis. For instance, ARCH and GARCH model of Variance and density parameters of standardised residuals. There is a difference in the method of inference on the estimated dependence depending on a parametric or non-parametric model for the distribution of standardized residuals.

The combination of parametric models with parametric marginal distribution of the standardized residuals for the variances and conditional means yields to parametric model for conditional marginal distributions.

There are two ways used in the Patton code for inference estimation of dependence statistics first is multi – stage GMM where dependence statistics are scores of marginal logs which is used for copula-based models time series data. Second, is the bootstrap method to measure each outlined in the copula equation of the code.

The usage of many other non-parametric estimate and the EDF which is the empirical distribution function for standardized residuals with combining to parametric models for the variances and the conditional means makes the model semiparametric. Inference of the dependence estimated can be conducted by using asymptotic distribution of parameters of model in case of fully parametric. Same approach of parametric is taken here using GMM to calculate each moment of time series data but EDF is used to identify any errors. Other than this bootstrap is carried in this case as well

The figure 3.10 basically demonstrate that the upper tail is less dependent than the lower tail whereas, the quantiles are dependent as high as 0.10. the confidence interval clearly demonstrates that the differences are very marginal significant at the level of 0.10 level, whereas upper-level confidence interval is as zero. Demonstrating a test of asymmetric dependence which will be explained further.

3.6.9 Time Varying Dependence Structure Captured by Copula

The Time Varying copula parameter in this paper is modelled by the GAS model of Creal, et al. (2012) as described in Eq. 3.23. Three Time Varying copulas are calculated: the Time Varying copula of Gaussian, the Time Varying copula of the student and the Time Varying rotated copula of Gumbel. In figure 3.12, corresponding parameters are presented. Due to the lowest negative log-likelihood value, the Time Varying student's t copula makes it better in defining the dependency structure, which may mean that there is strong tail dependency between the S&P500 and Gold Index stock markets.

As stated in Patton (2013), we add a simulation approximation after estimating the Time Varying copula parameters to map the Time Varying linear correlation as indicated by the t and Gumbel copulas of the student. We are particularly interested in studying the Time Varying existence of the two copulas above, as tail dependency is accounted for by both copulas. The parameter of the Gumbel copula must be in the range $(1, \infty)$, so the correlation parameter is modelled to ensure this by $\rho t = 1 + \exp(\varphi t)$, while the correlation parameter is modelled by $\rho t = [1 - \exp(-\varphi t)] / [1 + \exp(-\varphi t)]$ for the student's t copula. As investors invest in stocks to their portfolio to diversify risk, this could have some major consequences for investment management.

$$\tau_{Gumble} = \frac{\alpha - 1}{\alpha}, \tau_{student} = \frac{2}{\pi} \arcsin(\alpha) \tag{3.23}$$

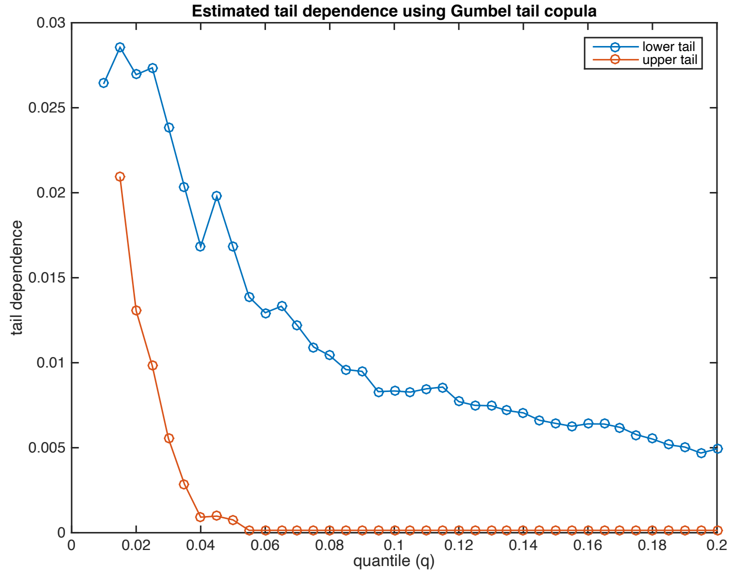

Figure 3. 1 Tail dependence captured by Gumbel Tail Copula.

As observed, the Gumbel Copula has more weightage for extreme co-movements rather than the student's T Copula implying lowered Tail Dependence. The extreme co-movements between S&P500 and Gold Index stock indices is low which can be justified by low Tail Dependence Parameters for both the Copulas.

As shown in Fig 3.11, the plot between the tail dependence captured by the Gumbel Copula and different quantile q. A clear increase in dependence as the quantile moves towards the centre of the distribution can be observed along with evidence of asymmetric tail dependence. As the quantile approaches zero, a strong bivariate upper tail is seen whereas a strong lower tail is observed when the quantile approaches the centre of distribution. However, both the bivariate tails are not seen having an immediate flat spot. While calculating the tail dependence parameters fluctuations for upper tail dependence is noticed suggesting some cut-off.

3.6.10 Copula Quantile Dependence

Prior to introducing appraisals of the copula quantiles relapse between S&P500 and Gold Index, we embrace an information driven methodology endeavouring to best fit univariate circulations by means of the copula quantile approach. This progression is significant on the grounds that both Indexes fizzled univariate ordinariness tests with overabundance kurtosis and a positive slant over the example period. Copula quantile approach-based advancement for circulation's induction was embraced more than a few groups of nonstop appropriations. We think about 11 dispersions, in particular Normal, Log-typical, Exponential, Cauchy, Gamma, Pareto 1, Inverse Gamma, Logistic, Log-Logistic, Weibull, Inverse-Weibull. Direct streamlining of the AIC was per-framed utilizing the "Nelder-Mead" strategy for dispersions described by more than one boundary and the copula quantile technique for distributions portrayed by just a single boundary.

We study the reliance structure between choice suggested volatilities of Gold and S&P500 business sectors by means of the utilization of a copula-based quantile relapse. To start with, we direct a static investigation and show that the asymptotic lower tail reliance is just articulated in the low unpredictability system of both Gold and S&P500 business sectors. Second, given the presence of a bi-directional causality between the two alternative suggested volatilities, we consider the lead-slack relationship by means of non-parametric tail reliance assessors. Results demonstrate an outrageous tail reliance in lower and upper quantiles, with proof of an awry conduct between/for low and high instability systems. Our discoveries have suggestions to speculators and danger administrators. Basically, discoveries infer proof of consistency of the likelihood of Gold inferred unpredictability dependent on the slacked S&P500 suggested instability across various quantiles. Another ramification concerns an instability based exchanging technique, particularly during couple event of high unpredictability systems, which includes the concurrent selling of an out-of-the cash call and put with various strike costs on Gold inferred unpredictability.

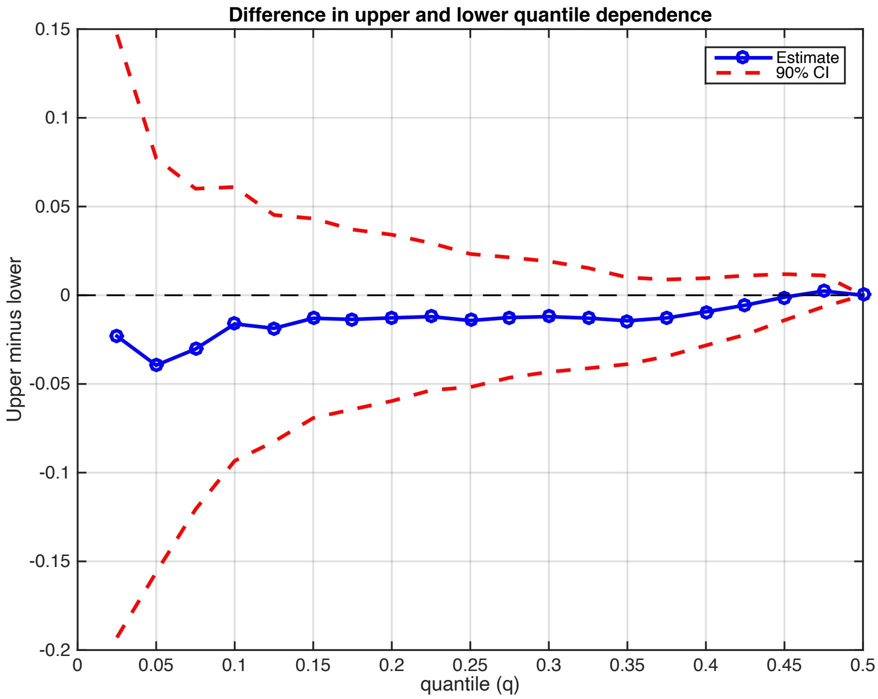

Figure 3. 12 Difference in upper and lower quantile dependence.

Figure 3.12 basically shows the results of the measurement of the quantile estimations. Since quantile estimation is quite crucial and tells the investors of the quantitative risk management. The investors can see the quantiles results and can estimate the differences in the upper and the lower quantile dependence. Which basically signifies the conditional dependence of the stock and commodity in times of distress. Greatest decency of-fit improvement uncovers that both Indexes follow an opposite gamma dispersion however with somewhat extraordinary shape and scale boundaries. Fig. 3.12 shows a line graph portrayal for both arrangement with related fitted disseminations. Actually, the state of S&P500 and Gold Index has an estimation of the quantile of around 90% confidence level keeping under consideration that whether it is upper or lower quantile the range for upper is 0.15 and 0 for the lower quantile measurement and the estimations are represented in the result which can be seen from the above figure 3.12. We likewise estimated the exact level of relationship between both the S&P500 Volatility Index and the Gold Index Volatility Index utilizing Kendall's tau coefficient.

Having decided through Copula Quantile-based fitting the best dispersion type and related boundaries for each peripheral, we will initially follow a full-parametric methodology for choosing a proper bivariate copula family for the given bivariate information. At that point, copula-based quantile relapses will be extricated and contrasted with those decided in the wake of refitting, on a quantile-by-quantile premise, for example for every tau, the boundaries of pre-set copula family. At last, parametric and non-parametric assessments of asymptotic tail reliance coefficients will be attempted, and ends will be drawn. The previously mentioned methodology will be led for both static and dynamic copula quantiles relapses

Despite the fact that the data is of greater size it is noted that the calculation of the (AIC/BIC) do not affect the measurement of the copula parameter and of the goodness of fit.

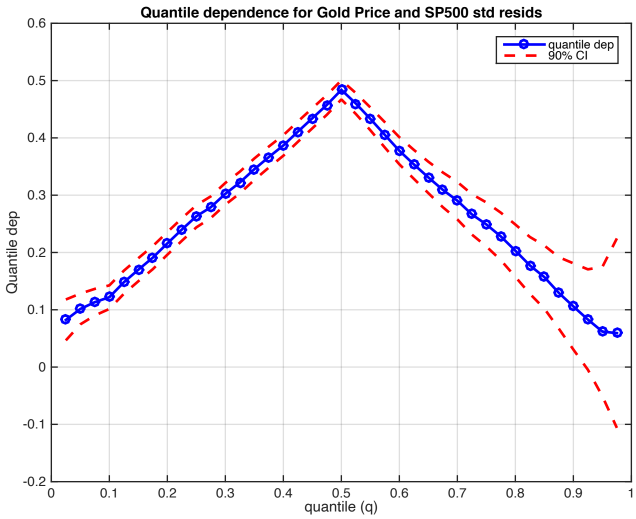

Figure 3. 13 Quantile dependence for S&P500 and Gold Price Index.

Even through, the two-boundary group of copulas prevailing in best depicting the reliance structure completely, it neglects to catch any upper or lower asymptotic tail reliance. Subsequently, refitting the boundaries of the Survival of the Bivariate copula on a quantile-by-quantile premise gets vital for catching the asymptotic reliance structure between choice suggested volatilities of Gold index and S&P500 business sectors conditions. We subsequently separate copula-based quantile relapses (see Fig. 3.13) and contrast it with those decided in the wake of refitting the boundaries of the Survival copula on a quantile-by-quantile premise, for example for every one of the likelihood levels.

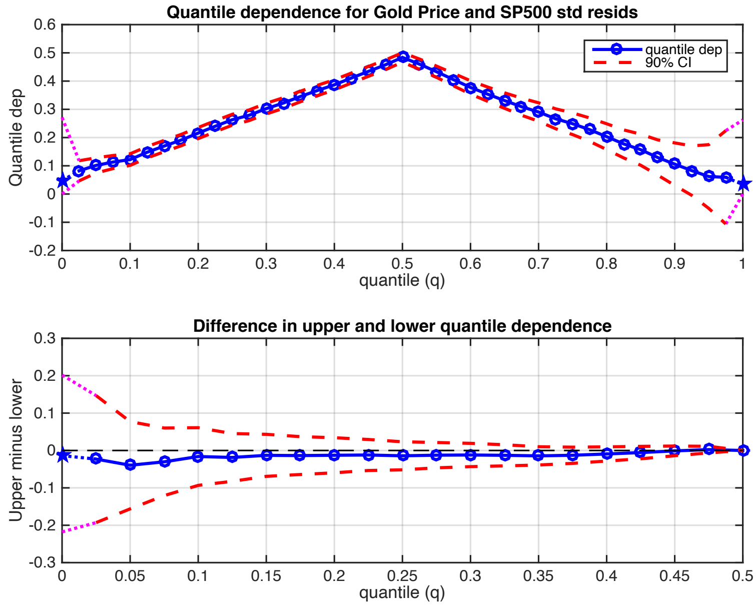

Figure 3. 2 Quantile dependence for the indexes.

It is obvious from figure 3.14 above that quantile prevailing with regards to uncovering the hilter kilter connection between the gold Index and S&P500. All the more significantly, the asymptotic lower tail reliance for the centre percentile is amazingly certain (0.90), uncovering the quality of reliance for synchronous event of moderate alternative suggested unpredictability of gold and S&P500.

3.6.11 Dynamic Copula: Boundary Assessment and Tail Reliance

We process the nonlinear dynamic quantile dependence appraisals to investigate the reliance between gold index and the slacked S&P500 and the other way around. Figure 3.15 presents copula tail reliance based assessed boundaries relating to the dynamic copulas. As indicated by AIC/BIC, the Survival Time Varying copula remains the most ideal decision.

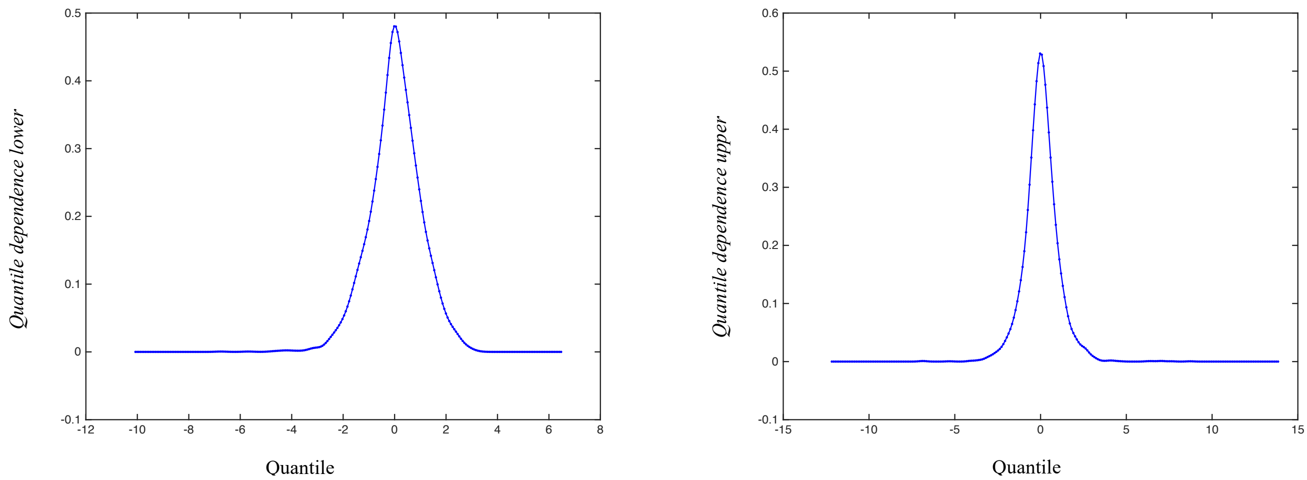

Figure 3. 3 Upper and lower Tail dependence

It shows up from results that Theta has stayed unaltered while quantile has somewhat decreased. Furthermore, the Goodness of Fit demonstrate the radiating from the lead-slacked relationship, between S&P500 and gold index, has diminished from 0.18 to 0.17.

Having chosen the two-boundary Archimedean Survival copula for the lead-slacked connection between S&P500 and gold index, we presently separate copula-based quantile relapses (see Table. 3.8) and plot them against those decided in the wake of refitting the boundaries of the Time Varying copula on a quantile-by-quantile premise, for example for every one of the likelihood levels.

	Normal	**Clayton Rot**	**Gumbel**	**Stud t**	**Rgum-GAS**	**Stud t-GAS**
Stud t-GAS	-	-	-	6.47	-	-
log L	-	-	-	-17.51	-	75.53
Rank	3.00	4.00	5.00	2.00	6.00	1.00

Table 3. 10 model comparisons of copula models – nonparametric margins

Table 3.10 shows the Survival Time Varying Copula's refitted boundaries for each quantile level, just as related constant copula results assess that depict the whole reliance structure. Moreover, hypothetical asymptotic tail reliance coefficients of the bivariate Survival Time

Varying copula for re-enhanced boundary esteems have been re-assessed. All the more critically, the asymptotic lower tail reliance for the centre quantile is amazingly certain (0.90) uncovering a similar quality of reliance for synchronous event of low choice inferred instability of gold and S&P500, as on account of static copula. Results of log likelihood likewise affirms the asymptotic lower tail autonomy when the coefficient delta is equivalent to 1, for example for fifth, tenth, 90th and 95th percentiles (further discussed in last chapter 4 (Section 4.5)). Besides, the related hypothetical Time Varying copula esteem for the centre quantile is the most noteworthy among presently assessed and is amazingly near that surveyed under no lead-slack connection between choice inferred volatilities of gold and S&P500.

	Normal	Clayton Rot	Gumbel	Stud t	RGum-GAS	Stud t-GAS
t-stat	-	-	-	-3.31	-	-3.31

Table 3. 11 model comparisons of marginal models - parametric vs nonparametric margins

3.6.12 Testing for Conditional Asymmetric Dependence

Tests are run for asymmetric dependence once parameters of upper and lower tail are gathered. Important insights on whether stronger co-relation during market downturns is exhibited by two financial asset returns. Running simple tests on the following null thesis is one way to understand this: -

$$\lambda q = \lambda 1 - q \tag{3.24}$$

λ- Quantile Dependence

For the below 'q' values, tests are run jointly to see the correlation during marketing downturns. And the quantiles are as follows: q=0.025, 0.05, 0.10, 0.975, 0.95, 0.90.

i.e

$$\lambda^q = [\lambda^{0.025}, \lambda^{0.05}, \lambda^{0.10}, \lambda^{0.975}, \lambda^{0.95}, \lambda^{0.90}] \tag{3.25}$$

And test the null hypothesis for

$$\Theta\lambda^q = 0 \tag{3.26}$$

Where: Θ = [1,1,1, -1, -1, -1].

The simplified process of producing test results for each individual quantile and interpretation of multiple test results is obtained through this test. Table 3.8 shows Student T's and Gumbel Copula's. The results for P-values of Student's T and Gumbel Copulas are consistent over various copula models. Therefore, accepting the null that the conditional dependence between S&P500 and Gold index returns is symmetric. Instead of testing different quantiles, running tests on bivariate tails is another way to see asymmetric dependence.

$$\lambda \text{ Lower} = \lambda \text{ Upper} \tag{3.27}$$

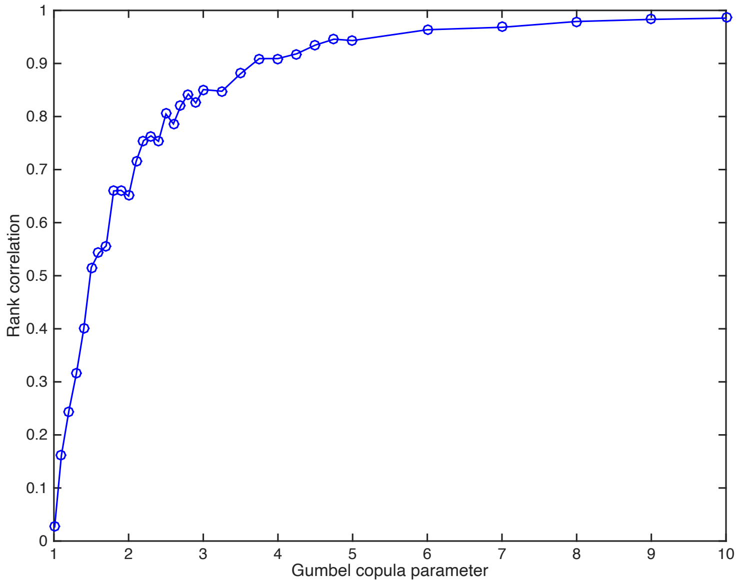

Figure 3. 4 Gumbel Copula Parameter

From the parameter of the lower and upper tail dependence used in the test are calculated. Using Student's T and Gumbel Copula significant differences between upper and lower tails are found. In conclusion, the two stock markets show more inter dependence when in bear periods than during bull periods as we have stronger lower tail parameter indicating asymmetric dependence. Therefore, market downturns witness high chances of joint extreme events rather than market upturns.

3.7 Conclusion

This paper portrays the copula approach used to examine the asymmetric dependence structure between S&P500 and Gold Price Index prices performances during 1992- 2020. The dependency during the course of greater turbulent times and common tail movements are first examined. Various copula models are then used to establish a link in dependence structure.

There is a notable correlation between the S&P500 and Gold Index markets during different time periods. There was a decrease in correlation before the crisis, but an inflation of correlation just before 2007 implies a financial contagion between the two. Since 2010, the rate this correlation has decelerated. The increase in correlation has strengthened the integration between S&P stock markets and regional developed markets since the crisis. We can predict an increase in dependence due to Gold Index markets broaden.

Dependencies can be modelled in three ways: the first is by introducing methods of selecting the most suitable models by defining the condition margins of two separate stock indices. The second way is to represent the asymmetric characteristic through separate models of upper and lower tails when composing a tail dependence. Lastly, we introduce tests for links between Time Varying structures, asymmetric dependence and Goodness of Fit.

New information regarding the portfolio management, risk diversification, and asset allocation is likely to be more up to date. Although the stock market appears to be more dependent after the crisis, it indicates the crisis caused inflation in in the Gold Index market, whereas the bull markets were a result of the global economic recession. This information aligns with the asymmetric tail dependence establish between Gold Price Index and S&P500 Index.

3.8 Contribution to Knowledge

The thesis contributes to the knowledge in quite several aspects. We first utilize a time varying copula (TVC) to examine the reliance structure among S&P500 and Gold price index through time. To be sure, not considering time-varying boundaries in the dependence distribution produces a predisposition toward proof of tail reliance. Additionally, taking into account just tail reliance may dishonestly prompt proof of awry connection between the profits. Observationally, return series are demonstrated by GARCH-type processes with reasonable minimal conveyances, and proper copula capacities are then fitted to sifted return series to check their dynamic relationship. Thusly, it is feasible to catch the possible nonlinearities in the stock and commodity connections as well as a few notable exact adapted realities of their return disseminations like unpredictability perseverance, fat tail conduct and volatility effects of return developments on unpredictability (Arouri et al., 2011, Regnier, 2007, Sadorsky, 2006), while keeping away from the disadvantages of straight proportions of reliance like Pearson relationship (Jondeau and Rockinger, 2006). We are additionally ready to look at both the degree and nature of return reliance at outrageous levels, i.e., the chance of joint outrageous varieties in the elements of Gold price index and stock returns. To wrap things up, the utilization of dataset, crossing the period from January 1, 1992 to January 1, 2020, empowers us to represent a few episodes of significant changes in gold and stock costs, over the 2007-2009 worldwide monetary emergency where outrageous co-movements are expected. An extended contribution to knowledge for the version of this study with left-behind models, methods and model specifications is left for upcoming studies and can be seen in the last final chapter of this thesis. Furthermore, we will not take into account the VaR and ES that is identified from the short sales (most of this has been covered in chapter 2 (Section 2.4.1) at the start and later in chapter 4 (Section 4.5)). Alternatively stated, when an asset is shortened by an individual, the chance of loss is not related to the asset losing value, since this would add to the value of the position. Therefore, the possibility of loss is linked to the asset gaining in value. The tail that is relevant for valuation is hence the right tail, this is because the models that operate on the left tail risk may not operate the same on the right tail risk. On the other hand, long positions are familiar than short positions by individual, as well as it being out of context for our study, we will not take this matter any beyond. Conclusively another method used to evaluate VaR is through the Monte Carlo-simulation, however this method is also out of context for our study so it will be excluded. This paper discusses the Time Varying copula which adds contribution to knowledge as risk can be evaluated by the use of the variations that can take place during any period whether normal circumstances or the turmoil period. Hence, financial researchers will find this quite useful for future further VaR investigations.

3.9 Discussion

Some of the models mentioned in literature review are discussed as follow:

3.9.1 Error Correction Model (ECM)

Cointegration, or long-term stochastic trend, is the most prevalent reason for using an error correction model (ECM) in a multiple time series model. Short- and long-term impacts of one time series on another may be estimated using ECMs, a theoretical technique. For example, a divergence from long-term equilibrium, known as error correction, has a direct impact on a system's short-term dynamics. Because of this, ECMs are able to predict the time it takes for a dependent variable's return to equilibrium after changes to other variables (Lebo et al., 2017).

Pros and Cons

3.9.1.1 Pros

- On the one hand, it is a suitable model for estimating the correction of disequilibrium from the preceding era, and on the other, it has highly positive economic implications.
- First and foremost, if we have cointegration, ECMs are stated in terms of first differences, which generally remove trends from the variables involved and the issue of false regressions.
- A significant benefit of ECMs is that they may be used in econometric modeling, which searches for the most pared-down ECM model that best fits supplied data sets. This is a third significant benefit (Kanioura et al., 2003).
- For the last and most essential property of the ECM, the disequilibrium error term is a stationary one (by definition of cointegration).

Since the two variables are cointegrated, the ECM has crucial implications: it suggests that some adjustment mechanism prevents the errors in the long-run connection from becoming more significant.

3.9.1.2 Cons

- There is little statistical power in the first stage's unit root tests.
- Granger causality dictates that Xt has to be weakly exogeneous in the first stage of the experiment in order to have a significant impact on the test findings.
- Having a tiny sample size might result in bias.
- There is no way to verify the long-run parameters in the first regression stage since the distribution of the OLS estimator of the cointegrating vector is exceedingly convoluted and non-normal.
- There can be no more than one cointegrating connection studied at any one time.

Analysis

By definition, therefore, when Yt and Xt are cointegrated $\hat{u}t \sim I(0)$. According to an ECM specification, we may represent the connection between the two variables as follows:

$Yt = a0 + b1Xt - \pi\hat{u}t{-}1 + et$

Long-term and short-term information may now be found in one place. B1 is the short-term impact multiplier (the short-run effect) that gauges the immediate impact a change in Xt will have on a change in Yt in this model. However, the feedback effect, or the adjustment effect, reveals how much of the disequilibrium is being addressed – that is, how much of any disequilibrium in the preceding period influences any adjustment of Yt. Ut1 = Yt1 + 1 + 2Xt1 = u2; hence, the long-term reaction is u2 as well.

3.9.2 Vector Error Correct Model (VECM)

Nonstationary series that are known to be cointegrated may be modelled using a vector error correction (VEC) model. An estimated VAR object, an equation object estimated through non-stationary regression techniques, or a Group object may all be used to determine if it exhibits cointegration (Liao et al., 2015).

Pros and Cons

3.9.2.1 Pros

- VECM's primary benefit is that it can be used to both long- and short-term equations with ease. Cointegrated VAR is the theoretical basis for VECM. As a result of Granger's representation theorem. As a result, if you have a cointegrated VAR, you have a VECM representation of it.

3.9.2.2 Cons

- Because the VECM model does not enable us to determine the direction of causation between the variables, it has a drawback. Granger causality's Toda and Yamamoto version is used to pinpoint the direction of causation.

Analysis

Models that represent the dynamic interaction between stationary variables are known as vector autoregressive (VAR). As a result, the initial step in time-series analysis should be to identify whether the data represent stationary levels. If it doesn't work, have a look at the first differences in the series and see if that helps. For time series with non-stationary levels (or log levels), the initial differences tend to be.

The VAR framework must be adjusted if the time series are not stationary in order to consistently estimate the connections among the series. Models for stationary differences (i.e., I (1)) include vector error correction (VEC), which is a specific instance of the VAR. As a result, the VEC may also take into consideration any cointegrating correlations between variables.

Consider t y and.t x, two time-series variables. A system of equations is formed by generalizing the idea of dynamic interactions to these two connected variables.

For the system, each variable is a function of both its own lag as well as another variable in the system's lag (the equations). y and x are the two variables that make up this system. It is called a vector autoregression when the equations are combined (VAR). We have a VAR in this case since the greatest latency is just one order of magnitude (1).

The system may be approximated using least squares applied to each equation if y and x are stationary. The difference between the levels of y and x (i.e., I(1)) may be used to evaluate whether the differences are stable. For I (1) variables that are cointegrated, the system of equations has to be reworked such that it can accommodate the cointegrating connection. The vector error correction (VEC) model is the result of including the cointegrating connection.

3.9.3 Vector autoregressive model (VAR)

VARs are multivariate time series models that link present observations of a variable to observations of that variable in the past, as well as to observations of other variables in the system from the past.

Univariate autoregressive models, on the other hand, do not have the ability to provide for feedback between variables in the model. Different procedures have been utilized to research the overflow impact among energy and carbon markets, for example, vector autoregressive (Cai and Wang, 2018; (Liu et al., 2017; Yu et al., 2015) and multivariate summed up autoregressive contingent heteroskedasticity (GARCH) models (Balcılar et al., 2016; Zhang and Sun, 2016). For instance, by utilizing the connectedness proportion of (Diebold and Yilmaz, 2012; Ji et al., 2019) give proof that the carbon market is a net data collector from power companies. Besides, a few examinations have recorded the overflow impact among vulnerabilities and the energy market (Yang, 2019). Notwithstanding, these examinations have neglected to consider overflow impacts in extraordinary economic situations just as the moving component of vulnerabilities to the carbon market. To illustrate the relationship between real GDP and the policy rate, we may construct a VAR model to demonstrate how the policy rate is a function of real GDP (Lütkepohl, 2013).

Complete VAR analysis is a multi-step procedure that includes:

- Making a VAR model specification and estimation.
- Analyzing and improving a model using inferences (as needed).

- Forecasting.
- Analyse the structure.

3.9.3.1 Pros

- Easy Implementations

Using ordinary least squares (OLS) to analyze each VAR equation independently allows us to estimate the coefficients of the overall system, which are given by the right-hand side of each equation having the same number of variables as on the left. The asymptotic characteristics of the OLS estimator are as expected. The asymptotically normal distribution of the OLS estimator is consistent and as big samples as possible (kilan, 2013).

- Classical interference

Any linear limitation may be tested using t and F statistics since the OLS estimator has the same asymptotic features as the conventional t and F statistics. What if the second lag is of relevance, but the first equation doesn't include it? The null hypothesis is written as H0: 12 = 12 = 0. Restrictions are imposed on just the first equation in this case. Testing for constraints using several equations is also an option. One may ask, "Does H0:12:22 correspond to the same coefficients in each of the following equations?" and the answer would be yes. An F-statistic will be adequate in both circumstances.

3.9.3.2 Cons

- Ad hoc specification - AR models have been criticized for failing to reveal the true structure of the economy. Criticizing VAR for predicting isn't relevant if you're trying to identify causal relationships between macroeconomic variables, though. A structural VAR is a set of simultaneous equations used to investigate the underlying causes of a set of observed phenomena. There is an equation for each variable in the system that takes into account the simultaneous and dynamic interactions of the whole collection of variables.

Analysis

The number of prior time periods a VAR model uses is one way to identify a VAR model. 5th order VAR would represent the wheat price as a linear summation of all previous five year's wheat prices. The value of a variable at a prior point in time is known as a lag. Pth-order VARs, in general, are VAR models in which lag times are included for the last p time periods. The term "VAR(p)" is used to refer to a pth-order VAR, which is also known as "a VAR with p delays. A pth-order VAR model is expressed in this manner:

y_{t}=c+A_{1}y_{{t-1}} +A_{2}y_{{t-2}} +……….. +A_{p}y_{{t-p}} +e{t}

Economists may use vector auto-regression (VAR) time series model to anticipate the development and interdependencies of numerous time-series. An equation for each variable is included for each of the variables in the model to describe how it evolved through time, taking into account all of the other variables in that model and their delays as well. This is what we would refer to as a scientific process for developing trading strategies.

Investor globally feels that it is important to make connections and linkages among financial assets return to vary risk, also for control the risk of financial contagion by monetary policy makers. The active linkages of international stock markets modelling can be found on a lot of studies and the conclusion came of as existence of market linkages and financial contagion in most studies (see, for example, (Kenourgios et al., 2011; Wen et al., 2012; Hui and Chan, 2013). Fluid markets, for example, banks and portfolio managers regularly uncover their portfolio change dramatically starting with one day then onto the next, and so consider a one-day holding period to be appropriate. Important aspects that are associated with risk management models are determining the risk, dealing with the development of proper risk assessment strategy in terms of preventing these risks by the use of proper mitigation techniques. It can be stated that risk management process is one of the important processes that each financial institution needs to conduct in terms of analysing the current financial condition of that stock market. Through using different models, the Financial investors of organisations are able to understand the risk that is associated with the organisation.

Though, the tail structure of dependence on markets was modelled by a few studies. Additionally, it is expected by one that such dependency to be uneven due to the recent turmoil, as negative shocks can more substantially affect co-movements between markets than positive shocks. Moderately, the uneven dependence between stock market return is exist which sufficient evidence is found. Evidence of asymmetry in conditional volatility of the equality returns was found by Cappiello et al. (2006). Negative shocks are influence co-movements of stock return more drastically found by Tamakoshi and Hamori (2013) amongst others. However, Euro areas and the United States developed markets become highlighted with these studies. On the other hand, regional developed contender has increased integration among them which was modelled by few.

This paper intends to present asymmetric behaviour in bivariate tails using conditional copula models for two stock markets S&P500 and Gold Index along with model for the entire dependence structure. At the end of 2019 the S&P500 Index overtook Gold by capitalisation and became first largest stock market globally, totalling $22,923 billion in share capitalisation. S&P500 Index positioning uniquely between its international competitors encouraged study of other mature financial markets along with its dependence while its role during the recent financial crisis help to encouraging during the period of turmoil.

Chapter 4

Value at Risk and Expected Shortfall Estimation for S&P500 Index and Gold Price Index

4.1 Introduction

Volatilities of S&P500 and Gold Price have essential impacts on the steady and durable development of world economy because if volatility is extremely high, the organisations will rise the wages and as a result companies will hire less people or not undertake new capital investment. Then corporations may have to pay higher rates to raise capital (Brincks, 2020). Hence its of significant academic and practical importance to measure the volatility and risk of Gold price index and S&P500 markets precisely. This paper attempts to measure the Value-at-Risk (VaR) and Expected Shortfall (ES) of S&P500 and Gold Price Index using GARCH-type models, hybrid GAS copulas and ES-VaR model. The back testing results suggest that the mixture of GARCH-type-GAS models (most of the GARCH is covered in chapter 2 (Section 2.3.5.4.3)) and GAS copula methods can produce accurate risk measures. Mixed hybrid copula is more adaptable and superior to other copulas. Different GARCH-type models, which may portray the long-memory and leverage effect of S&P500 and Gold Prices index volatilities but offer similar marginal distributions of the stock returns.

The financial crisis of 2007-08 and its consequence prompted various changes in money related market guideline and banking management. One significant change shows up in the Third Basel Accord (Basel Committee, 2010), where new accentuation is set on "Anticipated Shortfall which is the expected shortfall (ES) as a proportion of danger, supplementing, and in parts subbing, the more-recognizable Value-at-Risk (VaR) measure. Expected Shortfall (ES) is the normal profit for an advantage restrictive on the return being under a given quantile of its circulation, to be specific its VaR. Financial inconstancy essentially impacts developing countries stock markets and the ensuing incomes gotten from the deal of different commodities. Nevertheless, later extraordinary political occasions have been connected to huge misfortunes in investing generations, in both under developed and developed economies (Barriopedro et al., 2011; Coumou and Rahmstorf, 2012; Herold et al., 2018). For occurrence, approximately one-quarter of the investors generation in creating financial markets has been related with extraordinary financial catastrophes. In expansion, the think about of Lesk et al. (2016) detailed that extraordinary recession and turmoil occasions have too caused a critical decrease in investment extending around 2.5% fall in the economy. To relieve and possibly, to decrease investment yields and the related money related misfortunes and losses that may well be activated by extraordinary turmoil occasions, copula adaptation methodologies are required.

As Basel III is executed around the world (using the data from January 1992 to January 2020), ES will definitely pick up, and require, expanding consideration from hazard directors and banking managers and controllers. The new “market discipline parts of Basel III imply that ES and VaR will be consistently unveiled by banks, thus an information on these measures will likewise hold any importance with these banks’ financial specialists and counter-parties. There is, however, a scarcity of analytical models ’or the predicted shortfall as the Expected Shortfall is quite vital. The comprehensive literature on Volatility Models see (Artzner et al., 1999) for a review) and VaR Models (Komunjer, 2005; Süss, 2006) offered a variety of useful models for these risk measures. However, although ES has long been considered to be a “coherent indicator of risk” Artzner et al. (1999), in comparison to VaR, the literature includes comparatively few models for ES, some exceptions are discussed below.

We aim at measuring the risk and expected shortfall with the objective of using the ES-VaR model along with GAS method in this document as well we took the everyday periodicity from January 1992- January 2020 to represent the co-dependence and portfolio value-at- risk (VaR) of commodity and stock. The research chapter focuses on significance of ES-Var to investors in risk management. We found concrete results for solid dependencies between the S&P500 and Gold Price using a dynamic dependency formation. Utilizing the effective frontier, Gold price index offered the greatest optimal and economically risk-reward trade-off subject to a no-shorting restriction for portfolio investors. Since there is only a limited number of empirical researches on the commodity markets, this document provided new understandings on this topic. This paper could be beneficial for emerging dependence and risk policies for investment and hedging purposes, especially during periods of financial turmoil.

This is perhaps partially due to the fact that the regulatory interest in this risk measure is only recent, and may also be due to the fact that this measure is not “eligible.” The risk measure (or objectively more generally) is said to be “eligible” if there is a loss function such that the risk measure is the solution to minimise the predicted loss. For illustration, the mean is elicitable using the quadratic loss function, and VaR is elicitable using the non-linear or “fuzz loss” function. Getting such a loss function is a step in creating complex models for these quantities.

Recent findings from Fissler and Ziegel (2021), which show that ES is jointly elicitable with VaR and also used to construct new dynamic models for ES and VaR. This paper provides three main contributions. First, the use of ES and Var together for estimating risk. Second by the use of copula built in the model and last is proposing the use of the ES-VaR model proposed by Patton, Ziegel and Chen (2018).

Our objectives is that first, we introduce several dynamic models for ES and VaR, based on the GAS system for Creal et al. (2012), as well as active models in the Volatility Literature, see Andersen et a1. (2006). The objectives will be achieved by implementing the models that we propose are semiparametric in that they impose parametric structures for the dynamics of ES and VaR, but are fully agnostic in terms of the conditional distribution of returns (apart from the regularity conditions needed for estimation and inference). The models proposed in this paper also include 'CvaR' models proposed by Rockafellar and Uryasev (2000) in that we explicitly parameterize risk measure that are of concern and eliminate the need to define a conditional distribution of returns. This chapter add to contribution to knowledge because the models we consider make estimation and prediction quick and easy to execute. Our semi-parametric approach removes the need to define and approximate the conditional density, thereby reducing the probability that such a model could be improperly defined, but at the cost of a loss of efficiency relative to the correctly specified density model.

The results suggest that main difficulties arise in using these two models such as (Value at Risk) VaR and (Conditional Value at risk) CVaR models[6] in terms of estimating the financial assets while the portfolio has many assets. Expected shortfall refers to conditional VaR (CVaR) that is a statistic to be used to measure tail risk (NorthstarRisk, 2022). On the other hand, while the portfolio has single asset there is no difficulties in using these two models in analysing the financial database of company. In this aspect, several financial databases suggest that through using the two models financial organisational can understand and estimate the single asset of a portfolio by analysing its financial records. While using several return series and assets, it is difficult for the regulators to determine the individual financial database for each asset and return (Engle and Russell, 1998). This is the reason, why today's investors and the financial

[6] Value-at-Risk (VaR) represents the maximum loss in normal market condition during the certain time period at a confidence level (Benninga and Wiener, 1998). In other words, VaR is tolerated the loss while Conditional VaR may take account of a maximum loss.
Conditional VaR (CVaR) that is a statistic to be used to measure tail risk (NorthstarRisk, 2022).

organisation focuses on using these two models only why they want to estimate single asset in the portfolio. In addition to this, these two models can be used in analysing the Pearson's correlation coefficient, which is used in analysing linear relationship between assets. Through using Pearson's correlation coefficient, the VaR and CvaR model assumes the relationship of different assets is linear and independent of time. On the contrary results implications suggests that several recent studies on the financial framework implies, that the relationship among assets in the financial framework is non-linear as well as they are Time Varying. Moreover, the studies also suggest that relationship between the return distributions are asymmetric which are associated with the upside and downside movements. In this paper, the primary three families counting the circular, VaR, and copula are tested and Expected Shortfall. The estimation and utilization of these capacities are depicted within the following area. The construction of a multi-variate distribution is essentially a combination of an individual marginal distribution and a suitable copula.

The rest of the paper is organized as follows. In Section 2 we present the literature review along with the discussion of some new unique semiparametric models for ES and VaR and contrast them and the fundamental existing models for ES and VaR. In Section 3 we present asymptotic appropriation hypothesis for a conventional dynamic semiparametric model for ES and VaR, and in Section 4 we study the limited example properties of the assessors in some sensible CvaR, hybrid copula models and ES-VaR model. In Section 5 we apply the new models to day-by-day information on two markets data, and analyse these models with existing models. Segment 6 closes the verifications and extra specialized subtleties are introduced in the reference section, and a supplemental web index contains definite confirmations and extra examinations along with the discussion on the contribution of knowledge.

4.2 Literature Review

People's lives are uncertain in terms of the financial assets they possess. "Rainy days" or uncertain circumstances are too common and more than one expects, which is the reason people tend to save money in many forms of financial investment. The savings or investments they have prevents them from experiencing crisis situations to a considerable extent. Technically, investment defines the purchase of goods and commodities that is aimed at a better future value. Before investing, it is important to ensure that the financial aspects of the investment are planned adequately to obtain maximum returns. Careful analysis of the market and the opportunities is necessary before investing. Understanding the right investment plans available and managing the investments or appointing the right manager for the investment is important, as much as understanding the necessity of diversifying portfolios of investment (Artzner et al., 1997, 1999).

Mutual funds, FDs, bonds, stock, gold, and other forms of investment exist for people to choose from when investing in assets. When a person's investment portfolio is being analyzed, one of the main aspects that are evaluated is the Risk that the investments of the said investor carry. Two important factors that are used during risk assessment are Value at Risk (VaR) and Expected Shortfall. While they are not two different factors in the general sense, they are not similar either. In layman's terms, the value at Risk determines the amount of investment that is at Risk or what part of an investment portfolio is at Risk. On the other hand, the expected Shortfall is a term that quantifies the possible loss; in other words, if the predicted bad event were to occur, what would be the financial loss that can be expected? This paper focuses on understanding the terms in-depth, how various market conditions affect the values of VaR and ES, and the interrelation between the two concepts (Benninga and Wiener, 1998).

Value at Risk is defined as the statistical term that defines the extent of the possible financial decline for the investment portfolio, i.e., it shows the probability of the potential losses that the investor may experience. For instance, say a firm declares that its assets are at 3% VaR of 2% over a duration of one month. This means that there is a 3% chance that the value of the firm's investments may decline at a rate of 2% per month for a duration of one month. The VaR actually refers to the worst performing set of investments of a firm in a normal distribution of its assets.

On the other hand, the Expected Shortfall, or the Conditional VaR, is a term that quantifies the amount of financial loss that can happen from the extreme end of the normal distribution of the returns that a company is expecting from the market. CvaR provides a way to optimize the portfolio of investment by a company in an asset (Fissler, et al., 2015). It is a measure that companies or individuals use to overcome the shortage that they feel when using just VaR as a risk assessment strategy or model.

While it is true that most investment firms use VaR as a primary risk assessment tool or measure, there are numerous shortcomings that have been identified in the measure, over many years of study. One of the main drawbacks of the measure is the fact that it does not consider the assets beyond the tail risk as being risky. This method of risk assessment is one of the reasons behind the 2008 financial crisis, though not the sole reason for it (Degiannakis, et al., 2012). The use of VaR does not provide high accuracy in the risk measure that exists within a portfolio of investment. Since the measure only takes into account the least performing assets within the tail risk category, during the 2008 crisis, the subprime stocks were never identified as being risky as the market crashed, leading to billions in financial losses to institutions as they kept lending mortgages recklessly (Corporate Finance Institute, 2022). However, studies conducted that try to understand the market conditions before and after the crisis indicate that the crisis was not solely the fault of the risk measurement tool but human error as well, because even though the subprime mortgages were not under the tail, risk category, they were still risky. The fact is, VaR does not provide the worst-case scenario. For instance, 99% VaR implies that with 99% confidence, a particular amount of asset value is at Risk in a given duration of time. However, the 1% of the time that remains can have significant negative effects on the company or the financial institution, enough to liquidate the company (Macroption, 2022). In addition to this condition, the fact that the nature of input on the market is a highly important factor, and the confidence of the risk measure depends on the accuracy of the information that is available on the market and the fact that the calculations are done based on normal distribution assumption.

Value-at-Risk has been generally acknowledged as a measure of market risk in the financial establishments. It is important to note that VaR has recently been the object of discussion and criticism, mainly because it may be not sub-additive and non-coherent for heavy-tailed loss distributions, see discussion in (Daníelsson et al., 2013; Ibragimov and Walden, 2010). Hence other risk measures have been proposed as well, making the choice of the right risk measure a problem of theoretical interest of its own (Cherubini and Luciano, 2002). In any case, the Basel III accords recommend complementing the VaR with the Expected Shortfall (ES), owing to the guaranteed coherence of the latter. Hence estimation methods for the conditional Expected Shortfall have been suggested and investigated (Cai and Wang, 2018; Chen, 2005; Kato, 2012; Linton and Xiao, 2013; Xu, 2014); see (Nadarajah et al., 2013) for a review, for same level α, the (conditional) ES.

According to Birz and Lott (2011), in the previous twenty years the quantification of risk has become a major concern due to its important role in modern financial areas, as centre business tasks are predicated on commonly beneficial exchanges of this risk. One of the most popular and widespread methodologies of quantifying risk is Value-at-Risk (here- after: VaR) despite the prevalence of alternative ones. VaR turned into a urgent methods for financial risk management after the stock market crash of 1987, and it is presently internationally acknowledged as benchmark for risk management through its consideration in the mandatory Basel II Banking standard in 2004. Basically, VaR is the measure of capital that a firm needs to tie down aside to oppose far-fetched however not impossible adverse events while participating in dangerous exchanging exercises. Refer to (Duffie and Pan, 1997; Jorion, 2001; Birz and Lott, 2011) for the financial background and applications. In statistics terms, VaR is only an upper quantile of the distribution FX of some random loss X, potentially looked by the firm over a given period while participating in those exercises.

A great deal of research mainly along with EVT (extreme value theory) for risk measures has been done in the field of Value at Risk prompting to the advancement of varying methodologies to deal with the estimation of Value-at-Risk. However, EVT for risk measures on vital areas where extreme observations of time series data are of vital interest such as finance, insurance, hydrology, engineering and climatology. Various researches in commodity and finance markets have been led using EVT including (Gilli and këllezi, 2006; Embrechts and Schmidli, 1994), and (Gençay and Selçuk, 2004). The application of EVT in the case of extreme large electricity prices were a good fit with the generalized Pareto distribution and the GDP (gross domestic products) (Byström, 2005). Bali (2003) determined the sort of asymptotic distribution for showing the absurd changes in US treasury yields. He discovered that the thin-tailed Gumbel and exponential distributions execute poorer than the fat-tailed Fréchet and Pareto distributions. Marohn (2005) examined the tail index because generalised order statistics and decided the asymptotic properties of the Fréchet distribution. In any case, to the best of my insight, there are limited researches on the use of EVT to the gold market, which counts as a pivotal commodity to the world economy. The main concern in the field of financial risk are large losses. For instance, it might mean the circumstance of stock exchange crash. While a huge and increasing literature mainly focuses on value at risk, extreme losses and gains in financial returns in gold prices, on contrary the focus is also on financial leverage in the likes of security options, mutual funds and hedge funds (Balcılar et al.,2016).What we do in this work is to implement a Monte Carlo methodology for measuring portfolio Value at Risk by performing simulations from different *conditional* multivariate distributions, in order to evaluate what are the main determinants when doing VaR forecasts for a portfolio of assets. We compare different distribution assumptions for the margins, as well as different dynamic specifications for their moments, to understand whether the proper modelling of the latter is more important than the type of distribution. The focus of this thesis is on ES-VaR method. To find out the parametric estimations we will use sample conditional volatility and the expected loss as variable. ES-VaR model- the volatility prediction is what is going to be a big factor coming to conclusion about if the estimation value is best for VaR or ES. Because of this another question arises. Which is the best volatility forecast model is best for which specifications? This has been addressed in chapter 2 (refer to section 2.4).

It has always been vital to count and manage financial risk for both businesses and people. For company's risk management is crucial alongside other things, this grows the value of the company by reducing the risk of bankruptcy, reduce tax payments by making revenue streams more continuous and decrease the cost of capital by making debt servicing more reliable. (Christoffersen et al., 2012). A popular method of demonstrating financial risk is the variance or volatility of the asset. However, this is a non-intuitive measure this is because it only supplies a random number and does not change between positive and negative movements in regards to stock prices. More applicable details for investors are the risk connected with a drop in the stock price. For this aim there are two common measures value at risk and expected shortfall, both of which have been evaluated in this thesis.

Value at risk, henceforth referred to as VaR has been, and at present is one of the most favoured measures for financial risk because of its understandability Hull (2006, p.472) and its element for highlighting the danger of loss and not the change of increase but has its flaws when it comes to its usage as a risk management tool. Due to this, the Basel committee has decided to dismiss the VaR measure in favour of the expected shortfall, from now on knows as ES, when calculating market risk (Basel committee on banking supervision, 2013 p.3). The measure provides details about the tail risk, defining the risk in cases where the loss is far from the mean. ES gives us a value of expected loss in utmost cases compared to VaR only provides details about the threshold value. However, the most used way of estimating these vital measures, historical simulation (from now on referred to as HS), often yields results which are largely outperformed by more complicated techniques (Mentel, 2013; Christoffersen et al., 2012). Improved measures for the estimation of VaR and ES might be commanded by so called parametric estimations using forecasted volatility or through Monte Carlo-simulation.

No matter how profitable a single security the relationship it has with other assets in a portfolio must be evaluated in order to earn successful portfolio returns, meaning that when financial assets relating to financialisaton increase in number (in commodities, currencies etc), it leads to researchers trying to find patterns between different asset classes. Investments in alterative assets are gaining attention from investors and market maker because of clear risk and return features (Lahmiri and Bekiros, 2018). Traditional investments such as shares and bonds are being overlooked investors are now looking for more modern ways of investment due to the turmoil current markets are facing (Cumming et al., 2012). Assets with superior hedging characteristics such as gold, crypto currencies and Islamic equites are starting to get popular for empirical contribution on diversification of risk and return trade-off (Jaffar et al., 2018; Kenourgios et al., 2016; Evans, 2015). Islamic stock markets, the formation of crypto currency market as well as others finally gained some recognition because there was a need for alternative investment assets due to the financial turbulence created in markets over the past two decades whereas, gold has been there as a trade commodity from several centuries (Al-Yahyaee et al., 2018). Crypto currency is used as a digital investment medium of exchange and is widely accepted as it was an innovation in the payment system in the 80's (Tschorsch and Scheuermann, 2016; Nakamoto, 2008; Ali et al., 2014). Since the birth of some of the digital currencies in the form of commodities such as Bitcoin in 2009, over 1500 new crypto currencies have been introduced and offer new ways of growth but gold as a commodity holds the same place in the commodity market (Al-Yahyaee et al., 2018). Research has showed that the market turnover and capitalisation of digital commodities is increasing aggressively but gold fortunately holds its own place ElBahrawy et al. (2017), so, Bitcoin has been classed as a commodity asset in the US Fang et al (2014) while also gaining the legal status of currency in Japan.

The capability of stocks and commodities is to discover an important place in the financial market stays debateable. Although the results show a strong increase. Some experts advocate that the speedy growth of commodity markets will become a new asset of investors (Corbet et al., 2018). Gold has become the most precious commodity in the world. It just spiked \$1392.50/troy oz in 2019. The Gold market was valued at around \$60,758.80/kg in November 2020. In point of truth, the CNBC billionaire investor Marc Larsry who is a major financial market participator hypothesized that the price of gold could attain US\$40,000 but it has attained more in value.

Despite the fact that the GARCH model can deal with most measurable properties of volatile returns, for example, autocorrelation and heteroscedasticity, it experiences challenges in assessing unbounded unrestricted minutes while dissecting substantial followed distributions. As proposed by Adrian and Brunnermeier (2016), CoVaR is touchy to skewness and hefty followed negligible circulations, and any adjustments in these qualities differ the level of CoVaR. Hence, a viable econometric apparatus to quantify the distribution of volatile return costs is needed to represent the previously mentioned qualities from the viewpoints of market members and strategy producers. Likewise, to show the tail appropriation without the presence of unqualified or contingent minutes, they utilize the dynamic contingent score (DCS) model of Thiele (2019) for limiting the boundary space.1 Because the incentive in danger (VaR) is profoundly subject to the dissemination of carbon value returns, they fuse Zhu et al. (2016) deviated Student-t distribution into the DCS model to portray the upper tail and lower tail in an unexpected way. As such, they consider the lop-sidedness of the tail conveyance in their analysis. Moreover, by considering both potential gain and drawback hazard, they found the highlights of danger overflow under various economic situations, particularly when vulnerability pointers are applied.

In the research of Jaffar et al. (2018), experimental outcomes uncover a lopsided tail dispersion of profits on budgetary market vulnerability and the stock market. In particular, for the oil market, the upper tail is heavier than the lower tail. Paradoxically, for monetary market vulnerability, the lower tail is heavier than the upper tail. Besides, the level of unevenness is extensively higher for budgetary market vulnerability than for the commodity market. These outcomes affirm the upside of our proposed GAS-DCC-Copula model. They additionally find that the connection between budgetary market vulnerability and the market is negative as a rule. As such, a serious level of monetary market vulnerability is related with a diminishing in the commodity cost. This outcome affirms the procyclicality of the commodity market. Additionally, we likewise find deviation in the danger overflow from money related market vulnerability to the commodity market. Specifically, potential gain hazard overflow is bigger than disadvantage hazard overflow as far as supreme worth, which recommends that market gets more danger from the money related market during times of high vulnerability or monetary downturn than it gets during times of low vulnerability or periods of prosperity. These outcomes give additional proof that the stock market is procyclical.

The methodology of Jaffar et al. (2018) varies marginally from (Aloui et al., 2013; Hammoudeh et al., 2014) who utilized monetary, money related and political danger appraisals on BRICS nations. Utilizing a MTAR and an ADRL structure they estimated the transmission of danger by these variables. Other than the distinction in the models utilized, these writers are depending in hazard evaluations files as components of danger, though in contrast to (Jaffar et al. (2018) article usually utilized resources, wares or monetary items fill in as drivers of in-development among business sectors. Thusly, the danger transmission between business sectors are absolutely interpreted as costs wavering – even political or financial ones.

Ding et al. (1993) is fundamental while with respect to transmission impacts, qualifying the unpredictability cycle as lying in a nimble response to a contemporary data or in a lazy data valuing by the market. Engle and Bollerslev (1986) set up an instinctive scientific categorization, yet in addition a way to deal with decipher transmission impacts in an Efficient Market system displaying Yen/USD, to a wide gathering of business sectors. The creators tried the theory of Heat Waves and Meteor Shower. The previous 180dentifyes with monetary fundamentals, whose must not broad to different business sectors. Conversely, the Meteor Shower speculation proposes the inclination of less productive business sectors to inescapable data.

The word 'conditional Value-at-Risk' is seen being used in different methods in past literature, e.g., in (Stoimenov, 2009; Rockafellar and Uryasev, 2002) which is now usually called the Expected Shortfall (ES).

Attempts to get an estimate of VaR have always been centred on parametric models due to their traditional and accessible nature. One the most used approach is the industry-benchmark Risk-Metrics Morgan et al. (2011), which characterises returns in the future through normal distribution which is scaled by Exponentially Weighted Moving Average (EWMA) estimate of the market volatility. Despite that pragmatic research discloses the lack to fit of ordinary assumption in the financial data, which normally show considerable skewness and kurtosis. This encouraged on the development of EWMA-models replacing the old implementations with new ones from t-distribution So and Yu (2006), the Laplace distribution Guermat and Harris (2002) the asymmetric Laplace-distribution Ciaian et al. (2016), or other advanced parametric distributions. Despite that, Risk Metrics has kept the industry since 1996. Risk Metrics is developed around the volatility that has been embedded in the continuous returns via an integrated GARCH model with Ordinary inventions, which belong to a broader class of time series of models. Beyond the mention of the integrated GARCH (iGARCH) model Engle and Bollerslev (1986), one can quote the Exponential GARCH model (EGARCH) Nelson (1991) and the Asymetric Power ARCH model (APARCH) Ding et al. (1993), with the GJR-GARCH specification of Chang (2012) as a unique case, each of which are normally known Normal, Student or skew-Student innovations. Another group is developed by the Generalised Auto-regressive Score models recently suggested in (Creal et al., 2012; Harvey, 2013), while other optional parametric models for estimating the VaR finally included methods based on Extreme-Value-Theory, such as Block Maxima Model Demarta and McNeil (2007) or Peak over Threshold models (POT, (Aloui et al., 2013; Chang, 2012) or on quantile regression such as CaViaR Engle (2004). Adrian and Brunnermeier (2016) offers a recent thorough review.

Another paper that utilised VaR and Copula by Ciaian et al. (2018) is the sole framework that has accounted for the formational correlations and interdependencies among the range of cryptocurrencies. In order for investors to obtain a varied portfolio and understand the microstructure of the cryptocurrency market, they must be able to fully comprehend the interlinks between numerous cryptocurrencies. Price dependency relationships, portfolio value-at-risk of Bitcoin and the five key altcoins (Dash, Ethereum, Litecoin, Ripple and Stellar) are all reviewed by the paper using regular vine (R-vine) copulas to analyse the risks of financial assets in order to fill any knowledge gaps. The paper also addresses specific questions about cryptocurrencies, with answers provided in order to understand the potential effect of one on another.

Both our empirical papers have slight differences since our study focuses on Gold and S&P500 and contrary to Ciaian et al. (2018) directly compares the relationship and dependence between Bitcoins and altcoins via the use of an autoregressive distributed lag model (ARDL), which analyses 17 virtual currencies against two altcoin price indices between the years 2013 and 2017. On the other hand, our application of the R-vine copula method is broader and more holistic as it examines multiple possible dependencies by quantifying the value-at-risk of six cryptocurrency indices. This model implies that there is more co-dependency stated by Al-Yahyaee (2018) between Bitcoins and altcoins through the use of both C-vine and R-vine measures. These contrasting theories allow multiple dependency structures to be formed which will allow the portfolio to be viewed in different ways.

4.2.1 Research Papers Focusing on Commodity and Stock Exchange

Further we discuss about papers that take gold and silver as commodity market into account suing the copula and VaR. The perceptions of current and future uncertainty are concerned with by market participants. This indicator of potential uncertainty is option-implied volatility, which has drawn much attention in academia (Balcilar et al., 2017; Badshah, 2017; Ji et al., 2018). Currently, the availability of the option-implemented volatility indices and their tradability have become a key feature of the financial markets. This applies particularly to gold and inferior silver, which are important measures for measuring and signalling repeated stress market times. In order to hedge systemic risk and uncertainty and as a form of financial diversification, these option-implied volatility indexes have been used in the precious metals market. Much recently, Dutta (2018) uses optional volatility in a bivariate VAR-GARCH model from the gold-silver markets and claims that these markets are prone to return and volatility shocks. However, his method fails into consideration for tail dependency and potential heterogeneity across various quantiles. This is not the case with the copula quantile regression in upper, medium and lower amounts of tail dependence in high, moderate or low volatility.

The discovering of the structure of dependency between financial variables at a given quantile is critical for risk management, pricing and asset prediction. This refers to the price metal markets, which also shine during times of stress (Baur and Lucey, 2009). Hammoudehet al. (2014) show the heterogeneity of precious metals, which mean that the two strategic resources, gold and silver, should not be regarded separately. Relevant, there was considerable attention to the nature of gold-silver relations, but contentious Zhu et al. (2016), showing both weak and strong Lucey and Tully (2006), nonlinear Schweikert (2018), Time Varying Pierdzioch et al. (2015) and quantile and tail-dependency in relationship relations (Zhu et al., 2016; Bhatia et al., 2018).

Some studies have analysed the volatility ties between gold-silver returns using standard models like VAR, ECM, Quantile and GARCH. However, these models often fail to properly capture tail dependence, especially if the gold-silver joint distribution is non-elliptical and exhibits fat tails. The presence of a reliance on thickness is not inherently related to conventional correlation behaviour. As with copula dependency, traditional quantile analysis does not have enough information. This is especially significant if the two markets under investigation are not beneficially causally dependent at their extremes. Non-linear dependency on quantity is necessary to discover where the copulation form and shape connecting the two markets show

how quantiles are reduced (Bouyé and Salmon, 2009). In this respect, a copula-quantile regression is used to detect the rich and complex relation of the implicated CBOE volatility indicators of gold-silver.

Just like VaR and ES estimations volatility forecasting has been heavily studied. Engle (1982) was the first to consider using the heteroskedasticity as volatility when presenting the ARCH-model. Since then, a lot of different models has been proposed, such as the univariate and multivariate GARCH type models but also simpler models like the EWMA models (Brooks 2014). Of the proposed methods, the GARCH type models, including the EWMA model is the most used (Brooks, 2014, p 428). Even though most of the GARCH type models were introduced in the early 1980s they are still very relevant in volatility forecasting today (Engle and Bollerslev, 1986; Portmann et al., 2010; Nelson, 1991). In example, Hansen and Lunde (2005) found out that none of 330 other volatility forecasting methods where as useful as the GARCH (1,1) when testing on DM/$ exchange rate data and IBM stock prices. But when they updated their research method to researching the data set of realized volatility GARCH (1,1) was outperformed by its asymmetric cousins (Hansen and Lunde, 2005). Yet this realization, drew no conclusions about which model was the most suitable after all. They just suggested that different models do not set different data sets equally well (Hansen and Lunde, 2001).

It isn't fundamental to recognise the fact that the optimistic predictions of the virtual commodity market that is developing rapidly has a potential to become cheaper and replace the traditional market. Commodities not only attracted the consideration of investors and other key players of the financial markets sector, but also researchers (Demir et al., 2018). The current research on commodities and cryptocurrencies includes the formation of Bitcoin e.g. (Al-Yahyaee et al, 2018; Balcilar et al., 2017; Bariviera, 2017; Moore and Stephen, 2016); (Bouoiyour et al., 2015; Kristoufek, 2015; Ciaian et al., 2018), the information of information transmission across commodity and many stock and commodity markets(e.g. (Corbet et al., 2018)) technical aspects and stylized facts of commodity markets (e.g. (Blau, 2018; Bariviera, 2017) the hedging and safe haven properties of commodities, stocks and cryptocurrencies (e.g. (Blau, 2018; Ji et al., 2018),the relationship of the volume of return (e.g. (Bouoiyour et al., 2015), speculation e.g., (Yermack, 2013; Ciaian et al., 2016; Blau, 2018; Corbet et al., 2018), the unpredictability of stock returns Katsiampa (2017), market effectiveness e.g., (Urquhart, 2016; Bariviera, 2017; Nadarajah and Chu, 2017), and its transaction expense Szakmary et al. (2003).

During the past, researches on the financial futures dependence mostly assumed that futures return follows normal distributions and follows random walk processes. And in contrast Hammoudeh et al. (2014) research the nonlinear dependence structure between the crude oil market and the international gold market, finding that they have positive mutual dependence significantly. It is well known that the joint tail risk is mainly determined by the marginal tail risk and the corresponding dependence structure among asset variables.

However, they cannot explain the stylized facts in financial futures markets such as the leptokurtosis distributions, heavy tails properties, and volatility clustering effects and so on (see Allen et al. (2013) as they don't have actual facts and figures. Moreover, Fang et al. (2014) have found that there is extreme risk as oil returns often have leptokurtic distributions and fat tails, and were not in accordance with the normal distribution.

Moreover, the dependences between financial futures returns tend to display nonlinear, asymmetric and Time Varying characteristics, while the traditional model can only characterize linear, symmetric or static correlations. Patton (2012) have pointed out that there is a paucity of methods in studying risks between a large collection of assets, but the usage of copula-based models facilitates the description of high dimensional conditional distributions. Copulas have been widely used in risk management, portfolio optimization, and systemic risk (Aas et al., 2009; Fei et al., 2012; Schepsmeier, 2016; Low et al., 2016; Allen et al., 2013).

The dependence here is based on the perspective of copula models, and it refers to nonlinear and asymmetric correlations among variables, including the degree of correlations between variables and the risk linkage (see (Aas et al, 2009)). The multivariate GARCH-copula model has been widely used in the study of risk transmission relationships due to its flexibility and diversity in modelling stated by (Tai, 2010; Choi, 2010; Wang et al., 2013).

It enables the estimation of joint distribution in stages, then reducing the computational burden. Since the static copula function assumes that the correlation parameters remain constant during the sample period, which often contradicts with realities. In order to more accurately describe the dynamic interdependence of financial assets, scholars began to turn to dynamic copula methods to characterize the dynamic features of risk dependence (Hu, 2006; Chang, 2012; Hafner and Manner, 2010). Patton (2006) extended Sklar's theorem to construct a Time

Varying conditional copula model to study the interdependence of exchange rates. As observed, it was found that the dynamic copula model generally outperformed the static copula model when describing the related asset's structure. Wang et al. (2013) studied the dependence of international commodity prices on the US dollar exchange rate market, and pointed out that the conclusions drawn from dynamic copula are more economical. In addition, Aloui et al. (2016) concluded that constructing the copula GARCH model to dynamically examine the condition dependent structure between the commodity price and the US dollar exchange rate can improve the accuracy of the VaR prediction. Aas et al. (2009) studied the time variation of copula parameters using a hybrid parameter method. Consequently, when using the copula function to analyse the interdependence of financial assets, it is necessary to analyse the dynamic changes of dependent structures through Time Varying copula parameters.

In addition, in capturing the complex behaviours of multivariate systems, time variance of model parameters is important. There are stochastic copula models with regard to how the specified parameters of the dynamic model evolve over time (see (Hafner and Manner, 2010; Guermat and Harris, 2002) that allow latent process parameters and copula models of the ARCH form that model the parameters as a function of lagging observables. Creal et al. (2012) recently implemented a class of observation-driven generalised auto-regressive score model into the copula function to make the parameters changeable, the mechanism of which is to adjust parameters over time by using the scaled probability score function. He argued that the role of the scaled score is an appropriate option for Time Varying parameters, which has a distinctive advantage in preventing the terms of innovation from being integrated. Patton (2016) showed that the GAS method can be motivated theoretically through minimizing the divergence between true density and model implied density. On the basis of this, Oh and Patton, (2016) introduced the GAS model to characterize the dynamic changes of the copula parameters, and used copula based dynamic model for multi-dimensional distributions to measure the systemic risk. It is understood that in financial applications, the true innovation is normally heavily tailed. However, the above analysis, which takes into account the complex dependency of tail risk, does not simultaneously take into account the peak and thick tail characteristics in the distribution of returns. Although the financial time series data actually exhibits peculiar characteristics, that is, the distribution of individual returns displays skewness, extreme kurtosis and asymmetry, which must be taken into account at the same time.

Lately an increasing body of proof, studies and literature review of the non-normality of financial returns has recently been integrated into the theory of copula. The Skew t distribution, the Student t distribution, and the generalised error distribution (GED) were introduced into stochastic volatility models in order to capture the leptokurtosis and heavy tails properties in financial returns in terms of defining the fat tail attributes of financial future returns (Tzang, et al., 2016; Rockafellar and Uryasev, 2002), For example , in order to characterise the marginal distribution of the fund's overnight earnings and trading returns, Thiele (2019) adopted the GARCH-t distribution, as well as using a dynamic copula model to characterise the Time Varying dependency structure in the analysis of tail distribution and return interdependence. In the binary case, Kresta and Tichy (2012) suggested the Levy copula principle and used the Levy stochastic distribution to model the thick-tailed, asymmetrical financial variables. While copula functions were used to model the jumping part correlation structure, the copula function used is still a static copula function. As for the heavy-tailed financial returns developments, Bouyé and Salmon (2009) explicitly assumed that multivariate Skew t distribution accompanied the joint distribution of assets to analyse portfolio selection. Francq and Zakoïan (2013) proposed that the mechanism of returns follows the ARMA-GARCH mechanism with multi-varying normal tempered stable distribution developments to research the optimal problem of the portfolio. But the nonlinear correlation relationship between variables, which had great limitations, was not considered (see (Mensi et al., 2015). What can be shown from previous studies is that asset returns, uncertainty clustering, and dynamic Time Varying nonlinear dependence are seldom considered at the same time as the marginal thick-tailed nature. In addition, there is still no consensus about what approach should be selected for academics and practitioners to determine the hedge ratio of futures that cover these distributional features. Based on this, this paper combines the Time Varying GAS copula approach with the heavy tailed GARCH models to analyse the dynamic dependency and tail risk of future returns, taking into account the dynamic dependent structure of asset variables, and compares the fitting performance of the Time Varying copula models with constant copula models. Through the GJR-GARCH-Skewed-t model, the tail characteristics of the marginal risk are described in addition to the consideration of the nonlinear dependency structure between the distribution of returns on financial assets, which compensates for the shortcomings of current studies. In addition, from an analytical perspective, we study tail dependence and risk measurements of Gold – S&P500 futures under the heavy tailed condition, further calculating the dynamic hedging effectiveness of Gold – S&P500 futures on the basis of Time Varying copula models (refer to chapter 3 section 3.6.9)

The contributions of our studies to the previous literature include two aspects. On the one hand, using the GJR-GARCH-Skewed-t GAS copula model, which considers the leptokurtic function and clustering effects (most of this is discussed in chapter 2 - Section 2.3.5.5) of the distribution of financial returns, we empirically analyse the extreme tail risk, tail dependency structure and hedging effects of Gold- S&P500 futures. Evidence for investors and regulators to improve risk management can be generated by the results. On the other hand, we use the modified quasi-maximum probability estimator to adjust the two-stage estimation method for the heavy tailed GARCH model in order to increase the computational accuracy for parameter estimation. Rockafellar and Uryasev (2002) have suggested CVaR as a degree of elective hazard that's favored to the common VaR concept. A CVaR-based upgraded portfolio as it were punishing for the misfortune (i.e., the drawback chance), and not the pickup (i.e., upside chance) within the portfolio return dissemination. It is related to but is prevalent to the VaR for optimisation applications for a few reasons. Firstly, the VaR tends to fulfil the four properties of a coherent hazard degree; interpretation in- change, monotonicity, subadditivity and positive homogeneity (Larsen et al., 2015). Besides, the VaR is able to portray a misfortune of X or more noteworthy than this, and in this way, this final clause tends to be overlooked in most cases when individuals cite the VaR. VaR, on the opposite, is a gauge of the estimate of the tail misfortune, which gives a more exact gauge of the related hazard. Within the existing writing, common strategies of calculating the VaR regularly comprises of the variance-covariance, chronicled and the Monte Carlo re-enactment (Chernozhukov and Umantsev, 2001; Zhu et al., 2016). Calculating VaR too includes an estimation of the tails of the joint dispersion among the minimal returns (i.e., the profit of each farm that's considered within the issue). Nevertheless, the change- covariance and chronicled recreation strategy have a few degrees of restrictions, which might not be continuously sensible, and essentially genuine. For illustration, the variance-covariance strategy expects the returns to be ordinarily distributed, which can be risky from a common-sense point of see. This is often since numerous budgetary returns have stretched and broadened tails within the dataset so a typical conveyance presumption can truly think little of the measure (and the urgent part) of the tail conclusion of the information (Allen et al., 2013; Süss, 2006; Bouyé and Salmon, 2009). Recreations based on chronicled information too expect that the disseminations of the returns within the future are similar to those within the past. Moreover, in most cases, there are generally few information focuses that are display in, for case, the 0–5th percentile, or extraordinary tail of the dissemination. The Monte Carlo strategy is hence favoured in such circumstances since it is able to calculate the VaR in a comparative mould to chronicled recreation, whereas too being based on the arbitrarily producing scenarios from a show whose parameters are procured from the chronicled information.

According to Sklar (1959), marginal distribution which analyse all series in part and a copula, the connection between them, are the elements of multivariate distribution function. Copula is a unique tool that can connect the edge points and create vulnerability in every section of the chain (Delatte and Lopez, 2013). Nelson (2006) completed, copula represents a constant line with slight deformation at the edges repeated in certain gap of time or position. Copula's functionality requests a vector of any X variables with marginal distribution functions using diagram algorithm, Bhatia et al. (2018) creates the R-vine to deal with incapability of the C-vine pair copula when coping with complex models, that has a different issue, static essence.

Another problem is the calculating power needed to extract the details of the model. The problem may be solved by dividing the model to a simple form. Allen et al. (2013) suggests a level K, where by passing it, the R-vine will be simplified due to replacing pair-copulas in a single separate one. The formed copulas are much efficient in terms of reading and analysing and are called Gaussian copulas. Masarotto and Varin (2012) divided the useful data can be Alkaike information criteria (AIC), Bayesian information criterion (BIC), and likelihood-ratio based tests.

As specified over, the non-linear interdependency at the tails between the minimal returns have to be captured more viably relative to routine approaches in arrange to get exact estimation of CVaR. This requires a strong multivariate expectation show that's competent of completely capturing the joint reliance structure among the related factors. A customary approach commonly depends on the utilization of a multivariate-normal conveyance that accept ordinariness of the considered variable(s). In any case, there's no question that the agrarian costs and crop yields have been appeared to be non- ordinarily disseminated (e.g., (Goodwin and Hungerford, 2014)), and so, any approach that does not consider this critical information impediment perspective can lead to incorrect conclusions. Luckily, copula capacities (that can dissect non-linearity in multivariate information) is able to supply an elective measurable approach to displaying the joint dispersion of multivariate datasets, permitting one to indicate the marginal conveyance among the tried variable and their reliance structures independently. Due to their particular merits in displaying multivariate joint conveyances, copula-based models have been connected broadly in numerous areas such as protections and monetary chance displaying

(Hu, 2006; Kole et al., 2007), hydrology and water assets (Chowdhary et al., 2011; Favre et al., 2004), dry season ponders, rural and precipitation determining (Bessa et al., 2012; Janga et al., 2011; Janga et al., 2011; Nguyen-Huy et al., 2017; Vergniet al., 2015; Nguyen-Huy et al., 2018).

Another study demonstrates the moving instrument between monetary market vulnerability the utilization the contingent worth in danger (CoVaR) approach proposed by Adrian and Brunnermeier (2016) to uncover the size and bearing of time-fluctuating deviated hazard overflow. To all the more completely understand the moving system between monetary market vulnerability and the market, the researchers basically thought about two proportions of monetary market vulnerability: the EURO STOXX 50 Volatility Index (VIX) and the Chicago Board Options Exchange raw petroleum instability file (OVX). Basically, these vulnerability pointers reflect information about recorded unpredictability and furthermore reflect speculator sentiment (Liu et al.,2017; Maghyereh and Al-Zoubi, 2006). Since the market is exceptionally related with the energy market (Aatola et al., 2013; Kim and Koo, 2010; Seifert and Uhrig-Homburg, 2006; Tian et al., 2011), an examination is needed to decide the distinctions in the unassurance moving systems of these two vulnerability pointers.

Some of the other researches show examinations have archived hazard overflow between unsureness's and energy advertises by utilizing copula EGARCH-based CoVaR approaches (Aloui et al., 2016; Liu et al., 2017; Ji et al., 2019). In any case, these examinations have neglected to explore the function of vulnerabilities in the danger overflow system in the commodity market. For instance, Aloui et al. (2016) give proof that an expansion in financial exchange and monetary arrangement vulnerability (EPU) builds unrefined petroleum returns. Conversely, by utilizing EPU, VIX, and OVX, Ji et al. (2019) show that the energy cost diminishes as vulnerabilities increment. As shown in the investigations of (Pástor and Veronesi, 2013; Jurado et al., 2015), monetary vulnerabilities assume a focal part in macroeconomic vacillations, which considerably influence the business cycle. Since the commodity market value displays procyclicality, examining deviated hazard overflow gives improved comprehension of vulnerability move systems as well as a successful danger the board instrument.

But there are several studies which have different findings. Pérignon and Smith (2010) in an exceedingly study on US using cointegration and Granger Causality found a rather inverse relation between the stock price and gold prices. in an exceedingly related study on Europe and

Japan, using cointegration and Granger Causality Pérignon and Smith (2010) found that within a short duration there was a negative relation between gold prices and also the securities market within the short run, but within the long term the connection wasn't significant.

While the degree and direction of relationship remains arguable, another important dimension from which this relationship should be seen through is from the attitude of relatively abundant oil exporting countries because the country of interest during this study is Asian country. Commodity prices have an inclination to manoeuvre together as they're driven by general macroeconomic factors like interest rates, exchange rates and inflation (Hammoudeh et al., 2010). Gold has a vital place among the most valuable and is even taken to be the leader of precious metals as there's a parallel movement between gold and other precious metals (Sari et al., 2010). Investors from advanced and emerging markets frequently move between gold and oil and also combine them to diversify their portfolios (Sari et al., 2010). Nguyen (2010) found that oil prices have an inclination to in hence various sectors like, oil and gas, financials, industrials and utilities, although but, the degree and also the direction of the effect was different for various sectors. during this respect the effect of oil prices for oil exporting countries becomes interesting.

The increase in the prices of commodities such as an increase in oil price will have a positive effect in an oil-exporting country, because the income of the country increases which might cause a rise in expenditure and investments, enhancing productivity and employment. As a results of all of those the stock markets respond positively. Szakmary et al. (2003) are of the opinion that gold and oil function substitutes to investments in US dollar value as they're safer. Arouri et al. (2012) found that oil prices don't have a bent of affecting GCC stock markets and hence can't be used as predictors. Li and Wei (2018) found that oil price shocks of positive nature had a positive impact on the stock exchange performance of GCC countries. (Aloui et al., 2013; Mishra, 2019) found a bidirectional relationship between stock markets and oil prices, in oil exporting countries. Hammoudeh et al. (2014) opined that major event that result in changes in oil prices have a propensity to extend the volatility of securities market in GCC countries.

Precious metals especially gold is also expressed in US Dollar. Shrydeh et al. (2019) which assess the role of gold as a hedge against the US dollar by estimating elasticities for a model of the responsiveness of gold to changes within the rate. Shrydeh et al. (2019) find that gold has within the past acted as an efficient hedge. However, their approach takes the shape of a single-equation model during which the independent variable, the rate of exchange, is assumed to be unaffected by the time path of the variable quantity, the worth of gold. Both oil price, gold is leading economic variables, which drive the evolution of the globe economy. Their changes profoundly affect international trade and economic activity all told countries. Li and Wei (2018), using annual data, examine the pass-through of crude oil rates changes to the worth of 35 internationally traded primary commodities. He finds that the value of precious metals, in particular, gold, responded strongly to the crude price. Through three volatility models from the generalized autoregressive conditional heteroskedasticity (GARCH) family, Hammoudeh et al. (2010) studied the impact of oil prices and charge per unit shocks on gold returns and therefore the volatility of gold returns. For daily data and using an exponential general auto-regressive exponential heteroskedasticity (EGARCH) model, they find that oil price shocks had an insignificant effect on gold returns and reduced the volatility of gold returns. Sari et al. (2010) study, for Turkey, the link between oil prices and gold, silver and other macroeconomic variables using a vector autoregressive model to look at the short-run and long-run relationships between metal prices and therefore the oil price. They report that the globe oil price had no predictive power over precious metal prices within the Turkish economy.

In spite of the fact that copula strategy may be a prevalent tool in monetary chance writing in common additionally in portfolio examination (Boubaker and Sghaier, 2013; Huang et al., 2009; Kresta and Tichy, 2012), its application in agri- social hazard administration and trim protections angles are generally later (Goodwin and Hungerford, 2014; Nguyen-Huy et al., 2018; Okhrin et al., 2012; Vedenov, 2008). Moreover, the distributed writing in this region appears restricted inquire about has been undertaken with respect to the application of copulas in geologically diversifying dangers in horticulture. In show disdain toward of this, a few ponders are particularly outstanding, for case, Larsen et al. (2015) proposed a copula- based mean-CVaR model to examine the potential benefits of chance reduction employing a geological broadening procedure for the case of a US wheat cultivating situation. The creators connected multivariate Archimedean copula show and compared it with a conventional multivariate-normal demonstrate as a benchmark device. The mean-CVaR enhancement comes about indicated the adequacy of topographical enhancement in hazard management procedure from a farm's negligible return perspective. It was not shocking to note that the multivariate-normal show driven to an under estimation of the least level of related hazard confronted by the wheat rancher at a given level of rural benefit. Vitally, the think about concluded the copula- based demonstrate performed more appropriately for extraordinary misfortunes of the cultivate productivity. Be that as it may, the multivariate Archimedean copulas accept the same reliance parameter among the combine of factors. This sort of presumption is unreasonable in down to earth situation (Hao and Singh, 2016; Zhang and Singh, 2014; Nguyen-Huy et al., 2018). The volatility of the S&P500 Index is not significantly dependant on spill-over from the gold market as results have previously shown. Research methods such as VAR, the multivariate GARCH model and the Granger causality test are often used when researching multi-market relativity. Non the less, these methods cannot provide accuracy when it comes to describing the non-linear dependence of financial markets. Moreover, studies from specific multivariate distribution are required for the multivariate GARCH model. Copula methods have now been introduced in new studies in order to describe the nonlinear dependence among financial assets. The traditional binary copula is regarded as a "dimensional disaster" whereas the multivariate copula still has flaws such as the lack of flexibility and accuracy. Ringrose and Joe (1998) address the problems discussed above by proposing that some pair-copula construction modules can be composed from a multi-variable joint distribution.

In this paper, we centre on Gold and S&P500, gold considered to be an essential commodity in the world. Be that as it may, gold is for the most part developed and undeveloped countries, apart from commodities like wheat in drylands in Australia (i.e., as a rain- bolstered trim) that shows one of the world's most extraordinary variable climate conditions (Portmann et al., 2010; Turner, 2004). Be that as it may, to the leading of the authors' information, the adequacy of geological diversification counting the mean CVaR enhancement in hazard administration procedure has not been inspected in Australian and other parts of the world cultivating settings. The display hence, uses the modern vine copula strategy in Monte Carlo recreation approach for calculating the comparing esteem of CVaR. This approach permits to arbitrarily produce the scenarios of the negligible returns of gold commodity based on their joint dispersion. The essential justify of vine copula demonstrate (Nguyen-Huy et al., 2017, 2018) (in comparison to the other sorts of multivariate copulas) is that it permits the integration of diverse bivariate copulas for the displaying of the adaptable reliance among the pairwise variable neglecting the minimal choices contrasts (Bedford and Cooke, 2002).

To answer this challenge, scholars incorporate utmost value theory, copula function and other methods into VaR. In the example, the tail loss is added. In recent years, the use of quantile regression tactics has improved the applicability of the VaR method. Schweikert (2018) used the quantile regression technique to measure the daytime VaR of various securities and gained back test results supporting the method. Bouyé and Salmon (2009) combines quantile regression with nuclear estimation for extreme quantile prediction Okhrin et al. (2012) believe that the holding period and volatility will affect the measurement effect of multi- period VaR, and a nonlinear quantile regression model is proposed. Also, the current research has different effects on the risk measurement of historical simulation methods, and there is also a lack of strong explanation for the findings.

Different investigations have zeroed in on dissecting the factual qualities of other commodity returns. On this point, the writing takes note of that Bitcoin's return likelihood dispersion is different from the conventional money dissemination, which is more like the ordinary circulation. Nonetheless, Bitcoin's return likelihood dissemination is slanted and shows a serious level of kurtosis. In this sense, the Bitcoin dissemination is more like the appropriation of conventional resources (stocks, bonds, and wares), in spite of the fact that it displays a higher normal return, higher instability, and fatter tail, which implies that putting resources into Bitcoin includes more serious danger than putting resources into customary resources (European Central Bank (ECB), 2012).

There is likewise a gathering of studies that have examined the connections between the different commodities market and the securities exchanges. These examinations have delivered two strands of the writing. The first strand sets the solid connection between the Bitcoin and securities exchanges (Bouri et al., 2017). The second strand of the writing depicts a frail connection among Bitcoin and securities exchanges, with the goal that Bitcoin may go about as a support resource against the stock value developments (Al-Yahyaee et al., 2018; Barber, 2015; Bouri et al., 2017; Beneki et al., 2019). Thusly, as contended by (Bouoiyour et al., 2015) the writing to this respect is not just youthful yet in addition not definitive.

In this chapter, we investigate the capacity of Gold index and S&P500 to go about as a diverse cation resource and support against stock resources hazard. The inspiration for this investigation is that, as the writing calls attention to, securities exchanges are presented to macroeconomics factors, for example, government or financial strategy. In any case, Gold and S&P500 return probably will not rely upon such factors, but instead by theoretical and gracefully and request factors. The way that these business sectors rely upon factors so different opens the opportunities for the Gold index and S&P500 market to be a wellspring of diverse cation against the danger of the financial exchanges.

The above-referred to papers study the capacity of Gold index and S&P500 to go about as an enhancing or supporting resource utilizing the Dynamic Conditional Correlation (DCC)- GAS Copula model. This model probably will not be suitable for estimating reliance on whether the bivariate ordinariness assumption on the joint circulation does not hold. Furthermore, this strategy encourages us in inspecting the reliance structure between business sectors when there exists a direct connection between the marginals of the arrangement under investigation. Be that as it may, when the connection between the marginals is not direct, this model will not have the option to restore the right outcomes. Considering, we lead our examination through a copula investigation that suitably portrays the reliance structure (also discussed in chapter 3) between financial resources (e.g., (McNeil and Frey, 2000; Jondeau and Rockinger, 2006; Frahm et al., 2005). Besides, we direct a steady and time-changing copula model, which permits us to survey the time-fluctuating nature of the diverse and fence properties of Gold index and S&P500.

There are in any event three preferences to utilizing copulas for investigating the reliance (the copula technique can catch the complex and non-straight reliance structure of a multivariate circulation; 2) the minor conduct and the reliance structure are isolated by the system of copulas, facilizing both the model specification and the model assessment (the assessment can be acted in independent strides for the peripheral models and copula capacities); and 3) copulas are invariant to expanding and ceaseless changes (De Lira et al., 2015) for example, the scaling of logarithm returns, which are generally utilized in financial matters and examines.

The targets of the investigation are: 1st, to comprehend the relationship, assuming any, of the Gold index and S&P500 market with the significant securities exchanges on the market; second, to build up the significance of copula capacities regarding direct connection in understanding this relationship; and third, to examine the conceivable outcomes of diverse cation and support that Gold and S&P500 market to financial specialists.

Our paper adds to the writing in a few different ways. This paper is one of the studies to utilize time-fluctuating copula models for surveying the properties of Gold and S&P500 as a diverse and support resource. Further, the investigation is exceptionally extensive data and the use of the ES-VaR model.

The overall class of factor copula models proposed by De Oliveira et al. (2018) clarifies the reliance structure (for further details refer to chapter 3 section 3.1) of high dimensional factors regarding a couple of dormant factors. Because of the adaptability of copula capacities, factor copulas can catch well the connection alongside the tail co-development in outrageous functions. Since the Gaussian factor copula model by Hull and White (2004), factor copulas have been stretched out to fit with various qualities of information, for instance, spatial reliance of temperatures in De Oliveira et al. (2018) spatio-transient reliance information in De Oliveira et al. (2018) mortality reliance of different populaces in Andersen (2001) conduct reliance of thing reaction in Abad and Benito (2013) extraordinary reliance of waterway streams , and money related time arrangement reliance in (De Michele et al., 2013; Creal et al., 2012; Oh and Patton, 2017; Nguyen et al., 2019) among others. In contrast with the shortened plant copulas proposed by Brechmann and Czado (2014) the factor copula model is an elective copula model which gives closefisted and interpretable financial implications.

Bouri et al. (2017) looked into the dependence of a number of the global charges for gold, crude oil, the USD–INR alternate price, and the inventory market in India. The dynamic contemporary linkages have analysed the usage of popular, exponential, and beginning models, and also the lead-lag linkages have tested the usage of ordinary and uneven Non-Linear causality assessments. Empirical analyses show a decline in gold fees and crude oil charges purpose a decline within the fee of the Indian Rupee and Sensex.

Mensi et al. (2017) explore co-actions among three commodities implied volatility indexes such as oil, wheat, and corn. For this objective, they comprise the wavelet and copula method to analyse the moves of the tail dependence at diverse scales or funding horizons. Their finding helps the affirmation of time-various asymmetric tail dependence among oil and the two forms of cereal in addition to among the pair of cereals at exclusive time horizons. Long time horizon, medium-term horizon, and brief-time period horizon offering that the dependence shape is sensitive to time horizons. Mishra (2019) explores the Time Varying relation between commodity shares by means of introducing a brand-new empirical technique that incorporates generalized autoregressive score copula capabilities with high-frequency statistics.

Exploration of the dynamic dependence amongst agricultural markets, international oil and steel markets is the work of Mishra (2019). For this reason, the wavelet squared coherence method is hired to inspect the interdependence stage and lag–lead relationship of three markets throughout time at exclusive horizons. Additionally, they include wavelet and copula to observe tail dependence among three markets at numerous time-frequencies. Their finding shows that the global commodity oil market leads metallic markets in parallel with agricultural raw fabric markets. He also explored the dynamic dependence among the worldwide oil marketplace and China's commodity market on the industry level through the usage of a DCC-GJR-GARCH model. Their finding suggests the lengthy-term time-various courting in volatility between the worldwide oil market and China's commodity sectors. They discovered evidence that diverse portfolios can help us to decrease dangers correctly, and the performances of portfolio diversification strategies range throughout specific time frequencies. Ma and Wang discover the co-moves between charges of crude oil, steam coal, herbal fuel and iron ore, the Chinese RMB, and the Australian dollar alternate rates. Dependence systems are tested and in comparison, using copula features. Their locating shows that the upward push in commodity fees coincides with an upward push in the Australian greenback and a drop inside the Chinese language.

Ji et al. (2018) examined the dynamic dependence among WTI crude oil and the exchange quotes of the U.S. and China, thinking about structural adjustments of dependence with the aid of using six Time Varying copula fashions. Drawback and upside conditional Values-at-Risk are proposed exactly to measure the downward and upward risk dependencies among oil expenses and alternate costs. Their consequences show that a structural wreck-point of dependence exists between weekly or day by day commodity market prices and the U.S. dollar index. similarly, they determined extreme dependence between crude oil and change prices and proof of sizable danger spill-over from crude oil to Chinese language alternate charges is located. Further investigations on how oil as an international economic factor influences the charged conduct of agricultural commodities consisting of maize, wheat, rice, and soybeans, below terrible and desirable market situations. They determined proof of symmetry in the tail dependence among variables, and of asymmetry in the spill overs from oil to agricultural commodities that increase all through the monetary disaster.

The research demanding situations of efficient market speculation in the context of Dow Jones quarter ETFs indices. For this reason, they appointed the generalized Hurst exponent and multifractal de-trended fluctuation analysis (MF-DFA) techniques, to evaluate zone ETF indices in phrases of market efficiency, the usage of everyday records ranges from 2000 to 2015 (Tiwari et al., 2017). Aloui et al. (2016) check out the volatility forecasting for crude oil and gasoline alternate-traded finances. Their examination employed the unique volatility forecast of crude oil or natural gas raised by means of the averaging model as an alternative consisting of facts handiest.

Dependence between Gold index and S&P500 and different stock and commodity market has been defined in a great deal by using different methodologies such as GARCH and Copula methodologies. However, the copula method has not been used for exploring the connection among Gold and S&P500 costs. We have recognized that the research on Gold and S&P500 costs has no longer been discussed up to now. therefore, exploration of this relationship together with using the GARCH-Copula GAS hybrid method along with the use of ES-VaR model is novel to this observation as there's no take a look at which deals with the effect of Gold index and S&P500.

The Bayesian method can also help to retrieve the hidden structure in factor ES-VaR and copula models which indicates an advantage over the proposed maximum likelihood estimation. Starting with arbitrary bivariate connections, we obtain the posterior modes of the latent factors. Then, we seek for the best bivariate copula functions between the measurable variables and the latent variables considering that the values of the latent variables are set at their posterior modes. We apply the new dependency structure to the results, estimate the factor model and conduct the copula selection until the bivariate copula linkages remain the same. We produce simulation experiments in various contexts to prove that the procedures of bivariate copula selection may be very effective. We also used the Hybrid Copula and ES-VaR model to make it easier to estimate the factor copula models.

For the cross-asset diversification of investment portfolios, the pattern of dependency and risk-sharing arrangement among commodities and international stock markets are extremely significant. Indeed, while countries may be partly affected by global economy volatility, reliance on country-specific stock markets and global commodity prices may be minor, particularly when share markets have not a substantial weighting composition of the particular commodity.

The structure of dependency between stock exchanges and gold returns is discussed in this document (tail versus average). Traditionally, gold is seen as a strong choice for savings with a long-term portfolio. The gold is distinguished by its clear negative relations between stock and Gold in times of highly volatile market conditions, by (Baur and Lucey, 2010; Boako and Alagidede, 2016). Although the literature about economics confirms that gold will be secure during stock-market downturns (Baur and Lucey, 2009; Baur and Lucey, 2010; Boako and Alagidede, 2016; Nguyen et al., 2016; Bouri et al., 2017; Troster et al., 2019) literature is quiet about how an investor tries to maximise the gold and equity portfolio. Understanding how the gold equity fund can allow literature to deepen and advise decisions on future investment.

Several experiments have been conducted over time for multivariable GARCH models on dependency in foreign capital markets (Yang and Hamori, 2013; Syllignakis and Kouretas, 2011; Boako and Alagidede, 2016; Mensi et al., 2017). A significant drawback of this method however is its assumption of a symmetric regular multivariate distribution or Student-t (Patton, 2006; Garcia and Tsafack, 2011) as the return patterns on properties. The multivariate GARCH models can become unreliable if the distribution of financial returns is heavy, non-linear and asymmetric (Huang et al., 2009).

In comparison to linear correlations in the multivariate analysis, the copula approach offers two main benefits. First, the marginal distributions can be modelled independently and their dependency arrangement can promote the differentiation of their respective factors. Second, the copula feature completely captures variability interaction between them (Jondeau and Rockinger, 2006; Basher et al., 2014; Aloui et al., 2016; Boako and Alagidede, 2016; Boako and Alagidede, 2018).

Although these studies were successfully conducted to investigate certain types of addiction, the types of copula model used are based on the Gaussian properties that empirically lack a sufficient tail dependence (Bouyé and Salmon, 2009). The total tail dependency improves on current copulas, which can only model asymptotic dependency or asymptotic freedom. It calls, however, for a modern approach that models the upper and lower sides in a similar manner (Okimoto, 2008).

The research discusses, in addition to the Stochastic copulas derived from Hafner and Manner, the dependency mechanism between the stock market returns and gold returns in eight countries. In both lower and upper tails and asymmetry of tail, our full range copula models a broad range of tail dependency. We use two newly-developed complete tail dependencies, in particular. Firstly, one based on Hua (2017) built on the combination of two random gamma and two exponential variables. A random vector, the margin of which is combined with four independent Pareto mixture of a random variable, induces (Su and Hua, 2017).

It is, nonetheless, obvious that the risk that some exchanging exercises differs to changes according to the market conditions. Thus, it is crucial to survey that risk conditionally on some extra factors, reflecting the most recent accessible data about the financial climate (Chernozhukov and Umantsev, 2001; McNeil and Frey, 2000; Huang et al., 2009).

Our research adds significantly to the literature. In the best of our understanding, this is the first research to explore empirically the structure of depending on full-scope tail dependency between S&P500 and gold index since it was adopted in 2017 and to look at Hafner and Manner's stochastic copula models (2012). The implementation of mixed copulas first helps ensure the modelling dependency, as copulas make marginal distributions (MD) modelling separately and the resulting dependence structure. So, we can model every MD and then use it in a particular copula to diagnose the dependence, so that dynamic non-normal distributions can catch addiction and probably show co-movements between financial variables. Second, Clayton, Frank and Gumbel 's findings in chapter 3 strengthen the degree and composition of the dependency that means that the variables step together through a slowdown and / or upturn in the economy. Third, the functions of copulas are invariant under data transformation, which ensures that under some kind of transformation the dependency structure does not change, whilst linear correlation cannot do the necessary work. The Hybrid copula and ES-VaR models can also examine the stochastic functional dependency between the effects of gold index and S&P500.

By expanding past thinks about within the setting of agrarian abdicate displaying and regular precipitation determining thinks about in the world (Nguyen-Huy et al., 2017, 2018), the points of the show ponder are as takes after. (1) To explore the viability of the GARCH diversification procedure in diminishing dangers in Gold index and S&P500. (2) To illustrate a vigorous factual strategy, the copula-based VaR show, for measuring ideal sum of expansion required for given level of chance. (3) To compare the conventional multivariate-ordinary, multivariate GAS copula demonstrate in re-enacting the extraordinary misfortunes. The copula-based

VaR approach is expected to perform way better and give encourage experiences into moving forward customary multivariate-normal models that belittle the least hazard levels at a given target of benefit.

This chapter will assess the market risk measurement effect of GAS Copula when the market volatility changes and try to describe the test results from the perspective of volatility change. The first part is the introduction of this paper, expounding the two main development directions of the VaR method. The second part introduces the literature review on VaR and the discussion on calculation process of GAS Copula and Expected Shortfall ES replication method. The third part discusses the calculation principle of VaR and the calculation process of GAS Copula and Expected Shortfall ES replication method and the conducts a back testing test on the risk measurement effect of the hybrid Copula method under the three conditions of constant market volatility, market volatility and market volatility, and infers the empirical results from the perspective of volatility change. The last part gives the decision of the study.

This paper selects the 7296 returns of Gold Price Index and S&P500 from the start of 1992 to the start of January 2020. The VaR value is calculated by the GAS Copula and the Expected Shortfall ES process for the two market. Then the probability ratio test method is used to confirm the risk of the two methods. The dependability of the forecast is compared in more detail, and the empirical results are explained from the view of volatility changes.

Our methodology has certain advantages. First, it is known for their variety and asymmetric properties that a wide range of copula group, such as the two-parameter family of GAS copulas is collected. Second, it allows the study of the entire conditional distribution at different amounts instead of limiting the analysis of the intermarket reliance structure to standard tail region dependence tests. Third, it explores the static as well as the dynamic connexions, which show precisely possible extreme tail dependencies in asymmetrical quantities. Our starting point is the combined distribution of the non-Gaussian gold index and S&P500 implied volatility (see the data section). The next segment explains the theoretical framework.

4.3 Theoretical Framework and Estimation Method

VaR depends on the extreme value theory, which focuses on understanding the possibility of the extreme deviations from the median value of a given scenario. The EV (extreme value)[7] theory generally takes the scenario into account under the normal distribution, with the Gaussian curve describing the probabilities of the deviation. The tail risk, which is the left extreme with the negative deviation, is taken into account, but the rest of the deviation on the negative side, which indicates loss, is ignored. This dependency of the VaR value on a theory that depends on normal distribution is a drawback, as normal distribution fails to describe the scenarios adequately all the time.

ES-VaR (Patton, Ziegel and Chen (2018))	
Models incorporated in the code	Equations
Consistent scoring rule for ES and VaR (Fissler and Ziegel (2016)	1. $L_{FZ}(Y, v, e; \alpha, G_{1,} G_2) = (1\{Y \leq v\} - \alpha) \left(G_1(v) - G_1(Y) + \frac{1}{\alpha} G_2(e)v\right)$ $= -G_2(e)\left(\frac{1}{\alpha} 1\{Y \leq v\} Y - e\right) - G_2(e)$ 2. $(\text{Va}R_t, ES_t) = \text{argmin}_{(V,e)} \mathbb{E}_{t-1}[L_{FZ}(Y_t, v, e;\ \alpha, G_1, G_2)]$ 3. $(\text{Va}R_t, ES_t) = (\text{v}(\text{Z}_{t-1};\ \theta), \text{e}(\text{Z}_{t-1};\ \theta))$ 4. $\hat{\theta}_T = \text{argmin}_\theta \frac{1}{T} \sum_{t=1}^{T} L_{FZ0}(Y_{t,v}(\text{Z}_{t-1};\ \theta), \text{e}(\text{Z}_{t-1};\ \theta);\ \alpha)$
A GAS model for ES VaR	1. $\begin{bmatrix} v_{t+1} \\ e_{t+1} \end{bmatrix} = \mathbf{w} + \mathbf{B} \begin{bmatrix} v_t \\ e_t \end{bmatrix} + \mathbf{A}\mathbf{H}_t^{-1} \nabla_t$
A one-factor GAS model for ES and VaR	1. $f_{t+1} = w + \sum_{i=1}^{p} A_i S_{t-i+1} + \sum_{j=1}^{q} \beta_j f_{t-j+1}$ 2. $s_t = S_{(t, f_t};\ \theta). \frac{\partial \ln p(y_t \| f_t; \theta)}{\partial f_t}$ 3. $S_t = E_{t-1}^{-1}[\frac{\partial \ln p(y_t \| f_t; \theta)}{\partial f_t}. \left(\frac{\partial \ln p(y_t \| f_t; \theta)}{\partial f_t}\right)']$ 4. $\kappa_t = \omega + \beta\kappa_{t-1} + \gamma \frac{1}{e_{t-1}} \left(\frac{1}{\alpha} \mathbf{1}\{Y_{t-1} \leq v_{t-1}\} Y_{t-1} - e_{t-1}\right) + \delta \log \|Y_{t-1}\|$
Existing dynamic models for ES and VaR	1. $\widehat{VaR_t} = \widehat{Quantile}\{Y_s\}_{s=t-m}^{t}$ 2. $\widehat{ES_t} = \frac{1}{am} \sum_{s=t-m}^{t-1} Y_S 1\{Y_s \leq \widehat{VaR_s}$
GARCH and ES/VaR estimation	1. $Y_t = \sigma_t \eta_{t,}\ \eta_{t,} \sim iid\ F_n(0,1)$ 2. $\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \gamma Y_{t-1}^2$
Hybrid GAS/GARCH model	1. $Y_t = \exp\{\kappa_t\}\eta_t, \quad \eta_t \sim iid\ F_\eta(0,1)$ 2. $\kappa_t = \omega + \beta\kappa_{t-1} + \gamma \frac{1}{e_{t-1}} \left(\frac{1}{\alpha} \mathbf{1}\{Y_{t-1} \leq v_{t-1}\} Y_{t-1} - e_{t-1}\right) + \delta \log \|Y_{t-1}\|$

Table 4. 1 Structure of ES-VaR model by Patton, Ziegel and Chen (2018)

4.3.1 Data

In this study, we utilized the data from two of indexes Gold Index and S&P500 index from the period of 1992–2020. The broad indexes of gold index and S&P500 portfolio management by investors throughout the world, where the gap appear in different financial crisis situation for

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Extreme value theory (EVT) is a tool used to determine probabilities (Risks) associated with extreme events. It is used by Investors in situations where there is/expected to occur higher stress on investment portfolios each of the individual investor regardless of the Economies. In many other research papers, some commodities are analysed which are not found in all countries and economies (Nguyen-Huy et al., 2017, 2018) and unmistakable crossing are anticipated to uncover the diverse dangers at distinctive times. But since Gold is one such commodity that it can be found in any country and is traded and plays vital role in fluctuation of many other stocks and commodities (as discussed in chapter 1 under the relevance and importance of gold as a commodity section 1.2) and on the other hand S&P500 stock can be traded from any part of the world.

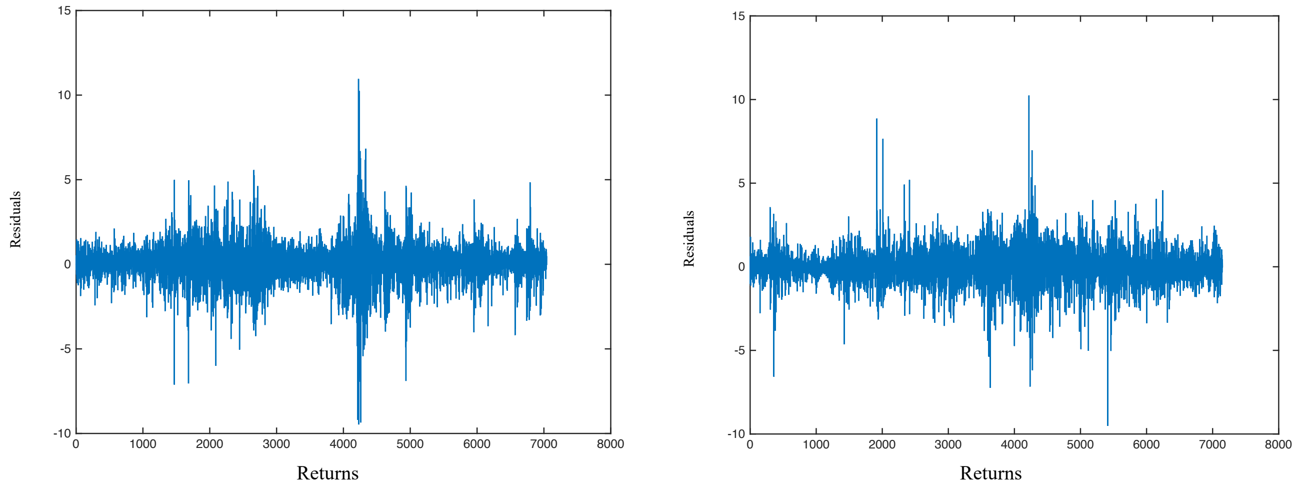

Figure 4. 1 S&P500 and Gold Price Index Returns.

Figure 4.1 demonstrates the return of both the indexes which can be seen in detail in chapter 2. The reason for discussing the returns here is to acknowledge the existence of volatility in the data. As discussed in chapter 2 (Section 2.4.1) about the data it can be seen that the information as per midpoints, counting the Gold and the S&P500. The overall fetched comprises of the political, social, intrigued paid, economical, legal, financial, protections, and a few of the other related returns issue which are considered when gold is being considered as the main commodity in the formation of a portfolio.

4.3.2 The benefit of CVaR as a measurement tool

CvaR or ES is a strong adversary to VaR as a risk assessment tool or measure. The fact that the ES value is a measure that is derived from superior mathematical functions ensures that the ES value provides better risk assessment as compared to VaR, and the quantified results provide better support for financial institutions. The ES value provides the information on the return value at a particular percent level of performance of the investment, which enables the investor to make appropriate choices of whether to buy or sell the assets. Further, ES needs a much larger sample size of data on the market to provide results as accurate as of that of VaR. While this may seem like a disadvantage, it isn't one. A larger data set for similar accuracy means that the reliability of the result increases drastically as compared to that of the VaR measure.

Both VaR and ES have their benefits and limitations when it comes to assessing Risk. Therefore, studies indicate that the performance of risk assessment which accounts for both VaR and ES as a combined measure of the Risk in the investment, could help in the development of portfolios that are better equipped against Risk from the market fluctuations. Ensuring that back testing is done provides higher safety to an investment portfolio (Fissler et al., 2015). Apart from just assessing the portfolio for Risk, it is important to ensure that the investment is diversified. Equity, gold, real estate, cryptocurrency, etc. must be some elements in which investment has to be made such that market fluctuation does not affect the total value of the assets and the Risk is minimized (Gobler, 2022).

4.3.3 Expected Shortfall (ES) and Value at Risk (VaR)

Value at Risk and Expected Shortfall are two important risk assessment measures that financial institutions use to assess their investment portfolios and the Risk that is present concerning the assets they have invested in. VaR is an intuitive measure to some extent and relies on lesser data to predict the risk value based on a normal distribution of the value of the assets and their return using the extreme value theory. However, the EV theory doesn't account for the complete Risk that is present and only takes extreme values into account, which partly led to the 2008 crisis and market crash. Since then, risk assessment measures have evolved, and ES is one of the important tools that currently exist. Using larger data set wit' a better mathematical foundation provides better and more reliable results through ES. Along with ES, VaR can be used for back testing the results to ensure congruency and satisfaction of knowing that there is a particular amount of risk, or the lack thereof.

The section 4.4 of Methodology will further discuss the estimations and the theory behind the models.

4.4 Methodology

Value-at-risk, suppose that confidence level taking away the percentage will signify a misfortune work depending upon the choice for example 95% is the confidence level then the risk will be 5%, to be chosen from a doable set of a chosen practical portfolio which in this case are the Gold Price Index and the S&P500, and an irregular measurement of the circumstances in the interval taken into account involving both the crisis and non-crisis time period. In this chapter we will be measuring the Conditional Value at risk (CvaR) as we have measured the VaR previously in chapter 2 (Section 2.4.1). Considering the equation below the probability of density is measured with the distribution and the break-down of the VaR has been set. And it can be related to the CVaR work αβ (x), which is the percentile of the misfortune dissemination at the certainty level β, proposed by Rockafellar and Uryasev (2000):

$$\text{VaR} = (1 - \text{Confidence level}) * \text{Total count} \qquad (4.1)$$

$$CVaR = \frac{1}{1-c}\int_{-1}^{VaR} xp\ (x)\ dx \qquad (4.2)$$

The formula in Equation 4.2 represents that the p(x)dx= to the probability density of getting the return along the x value, and c is the cut-off point for the distribution on which the VaR is set at the break point and lastly VaR is the set level of confidence.

By this definition, VaR is able to degree the expectation of the misfortunes more noteworthy than that sum α. In this manner, the VaR work φβ (x) is characterized scientifically as takes after Rockafellar and Uryasev (2000): ri = net income – add up to fetched net income. Where p(y) is the likelihood thickness work of the arbitrary vector y. It is evident that the VaR may be a more prominent bound for the VaR at the same certainty level.

$$\emptyset_{\beta}(\chi) = (1-\beta)^{-1}\int f(x,y) > \alpha_{\beta(x)} f(x,y)P(y)dy \qquad (4.3)$$

Also, with numerous focal points expressed within the past data, VaR offers a steadier chance degree than VaR and generally results more proficient within the setting of portfolio advancement (Mulvey and Erkan, 2006).

In expansion, CvaR can be communicated as an arched work permitting the development of the portfolio enhancement issue which can be productively illuminated by direct programming techniques as appeared in Rockafellar and Uryasev (2000) and will be described within the pending strategy area. In spite of the fact that VaR plays a part within the ideal portfolio approach, it uncovered a few characteristic restrictions as said over (Rockafellar and Uryasev, 2000).

4.4.1 Dynamic Models for ES and VaR

In this part we propose some new powerful models for ES and Value-at-Risk (VaR). We do as such by using ongoing work in Fissler and Ziegel (2016) which shows that these factors are elicitable joint, notwithstanding the way that ES was known to be not elicitable all alone, see (Gneiting, 2011a). The models we propose depend on the GAS system of (Creal et a1., 2013; Harvey, 2013), which we will discuss briefly while discussing the GAS model along with VaR and ES.

4.4.2 A Consistent Scoring Rule for ES and VaR

(Fissler and Ziegel, 2016) show that the accompanying class of misfortune capacities (or "scoring rule), recorded by the capacities $G_1$and G_2, is steady for VaR and ES. That is, limiting the normal misfortune utilizing any of these misfortune capacities restores the genuine VaR and ES. In the capacities beneath shown in Equation 4.6, we utilize the documentation v and e for VaR and ES.

$$L_{FZ}\left(Y, v, e; \alpha, G_{1,} G_2\right) = (1\{Y \leq v\} - \alpha)\left(G_1(v) - G_1(Y) + \frac{1}{\alpha} G_2(e)v\right) \qquad (4.4)$$
$$= -G_2(e)\left(\frac{1}{\alpha} 1\{Y \leq v\} Y - e\right) - G_2(e)$$

where G_1 is weakly increasing, G_2 is strictly increasing and strictly positive, and $g'_2 = G_2$. We will refer to the above class as" FZ loss functions. Minimizing any member of this class yields VaR and ES:

$$(\mathrm{Va}R_t, ES_t) = \mathrm{argmin}_{(V,e)} \mathbb{E}_{t-1}[\, L_{FZ}\,(Y_t, v, e;\ \alpha, G_1, G_2)] \qquad (4.5)$$

Using the FZ loss function for estimation and forecast evaluation requires choosing G_1 and G_2. To do so, first define $OG\ (Yt, vfit, efit, vXt, eXt)\ \div\ G\ (Yt, vfit, efit)$ — $G\ (Yt, vXt, eXt)$ as the loss difference for two forecasts $(vj, t, ej, t),\ \ j\ \ c\ (fi, 2)$. We choose G_1 and G_2 so that the loss function generates OG that is homogeneous of degree zero, a property that has been shown in volatility forecasting applications to lead to higher power in Diebold-Mariano (1995) tests, see (Patton and Sheppard, 2009).

The semiparametric dynamic model will be used for ES and VaR, having solved for the FZ0 loss function.

$$(\mathrm{Va}R_t, ES_t) = (\mathrm{v}\ (\mathrm{Z}_{t-1};\ \theta), \mathrm{e}\ (\mathrm{Z}_{t-1};\ \theta)) \tag{4.6}$$

$Et—fi\ c\ 7t—fi$ should be used where the true VaR and ES are specified parametric function of elements of the information set. The parameters of this model are given as follows:

$$\hat{\theta}_T = \mathrm{argmin}_\theta\ \frac{1}{T}\sum_{t=1}^{T} L_{FZ0}\ (\ Y_{t,v}(\mathrm{Z}_{t-1};\ \theta), \mathrm{e}\ (\mathrm{Z}_{t-1};\ \theta);\ \alpha) \tag{4.7}$$

To gain some insight into how past returns influence current ES and VaR predic-
tions in this model, consider this model's "news impact curve TM, which presents Yt as a function of Yt via its effect on $Zt\ \div\ [Zv,\ t,\ Z\ e,\ t]j$ keeping all other variables constant. These two curves for alpha = 0.05 are shown in data analysis, using the approximate parameters for this model when applied to daily returns on the Gold Index and the S&p500. For the current TM value of $(v,\ e)$ two values are assumed (1:64; 2:06).

4.4.3 Construction of the Copula-Based Model

We utilize the hybrid copula approach that is the extended version already used in our prior distributed work but its more advanced to create copula-based models for this think about. Here, we briefly depict the most steps of the copula model development method.

The primary step in developing the copula model and show choose the hypothetical distribution capacities that are able to around depict the historical negligible returns. This consider adopts the parametric approach to fit the authentic marginal returns since afterward within the re-enacting prepare, the turnaround dissemination work should be utilized to convert the copula- demonstrated information back to the genuine scale values. A set of twenty-seven hypothetical likelihood disseminations are fitted to the negligible return information, which takes after prior thinks about (Nguyen-Huy et al., 2017, 2018). The candidate dissemination is chosen based on a factual appraisal of the goodness-of-fit test, i.e., the Kolmogorov-Smirnov measurement (KS) this is additionally calculated in chapter 3(Section 3.6.3).

On the off chance that the p-value of the KS test is more noteworthy than 0.05, we cannot dismiss the invalid theory that the watched information takes after that specific conveyance. At that point, the dispersion with a lower Akaike In- arrangement Basis (AIC) is chosen for that information. Advance, the graphical investigation is additionally performed to back selecting the foremost appropriate dissemination work as in some of studies by (Nguyen-Huy et al., 2017, 2018). In the moment step, the copula parameters are evaluated utilizing the greatest pseudo-likelihood strategy Chowdhary et al. (2011) requiring the minimal return information to be changed within the unit hypercube. In common, this transformation can be performed by Favre et al. (2004) to guarantee that the reliance structure between the pairwise information is free of the minimal conveyances. In this way, the negligible returns are changed into the pseudo-data utilizing the comparing experimental conveyance work F (.) as ui = F (ri). From now on, the copula parameters θ are assessed through the most extreme pseudo likelihood estimation strategy (Chowdhary et al., 2011).

$$\hat{\theta} = \arg\max_{\theta \epsilon \theta} \sum_{t=1}^{T} \ln c\ (u_{1t}, \ldots\ldots, u_{nt};\ \theta) \tag{4.8}$$

In this, the copula density is denoted by c(.). The Akaike Information Criterion AIC = −2 ln(llmax) + 2k is constructed based on the majority of fitted copula model as the system of the most of the log-likelihood value (llmax) and the quantity of parameters are denoted by k.

Later, a random vector $(r_1, \ldots, r_n) = [F_1^{-1}(u_1), \ldots, F_n^{-1}(u_n)]$ by making use of the selected copulas marginal distribution can bring out the marginal distribution. For acquiring data and samples from a fitted copulas process can be created. At last, with the help of inverse transformation the simulated understanding of every marginal return can be gathered by following the functions of six famous copula and for proper scanning rotated functions were involved as well as Gaussian, Student's t (symmetric but heavier tails), Clayton, Gumbel, Frank, and Joe. In building multivariate Archimedean and Hybrid copula models both copula functions were worked and used. To gather more information on the multivariate elliptical and Archimedean copulas, as well as on copulas readers may opt for old issued books of (Zhang and Singh, 2014). The computations can carry out with help of various packages of the copula Yang and Hamori, (2013) and Copula Schepsmeier (2016) and can also be accessed in R software (R Core Team, 2016).

4.4.4 GARCH and ES and VaR Estimation

In this segment, we consider two expansions of the models displayed over in an endeavour to combine the victory and niggardliness of GARCH models with this paper ‘s centre on ES and VaR estimating.

4.4.5 Estimating a GARCH Model via FZ Minimization

On the off chance that an ARMA-GARCH model also discussed in chapter 2 (Section 2.4.1), counting the determination for the conveyance of standardized residuals, is accurately indicated for the conditional dispersion of an asset return, at that point, the most extreme probability is the foremost proficient estimation strategy and ought to be received. In case, on the other hand, we consider an ARMA-GARCH model as it were as a valuable estimation to the genuine conditional dispersion, at that point, it is not clear that MLE is ideal. In specific studies and research by Francq and Zakoïan (2013), on the off chance that the application of the model is to ES and VaR forecasting, then we may well be able to move forward the fitted ARMA-GARCH demonstrate by evaluating the parameters of that model utilizing FZ loss minimization.

Model below demonstrates for asset returns:

$$Y_t = \sigma_t \eta_{t,} \;\; \eta_{t,} \sim iid\ F_n\ (0,1) \tag{4.9}$$

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \gamma Y_{t-1}^2 \tag{4.10}$$

The variable σ_t^2 is the conditional change expected to take after a GARCH (1, 1) handle. This model infers a structure closely resembling the one-factor GAS model displayed as we discover:

$$v_t = \alpha . \sigma_{t,}\ where\ \alpha = F_\eta^{-1}(\alpha) \tag{4.11}$$

$$e_t = b . \sigma_{t,}\ where\ b = \mathbb{E}\left[\eta | \eta \le \alpha\right] \tag{4.12}$$

$$k_t = \omega . \beta_{kt-1} + \gamma H_{t-1}^{-1} S_{t-1}) \tag{4.13}$$

A few assists come about on VaR and ES in dynamic location-scale. To apply this model to VaR and ES estimating, we need to gauge the VaR and ES of the standardized leftover, indicated (a, b). Instead of evaluating the parameters of this model utilizing Q MLE, we consider here evaluating through FZ loss minimization. As within the one-factor GAS show, ω is unidentified, and we set it to one, so the parameter vector to be estimated is (β, γ, a, b). This estimation approach leads to a suited GARCH model that's custom-made to provide the best-fitting ES and VaR estimate instead of the best-fitting instability figures.

4.4.6 Gas Formula

When filtering financial returns using such routine models, the cumulus of underlying assets does not differ. We used a total of six copula versions, including a two time-different copula model, i.e., the GAS copula rotated and the GAS copula t student, with four constant copula versions including regular copula, the copula student and the copula Gumbel rotated. For this reason, we used a total of six copula models. Creal et al (2012) can be used to widely adjust time-length parameters for dynamic volatility and correlations by generalised auto-regressive score dynamics. The GAS model specification that uses the lagged density model score as driving variables for Time Varying copula functions is added. Let yt denote the vector of dependent variables, ft denotes the vector of time-changed parameters, xt represents the exogenous covariates, and x is a fixed parameter vector. In view of the available knowledge collection, yt is assumed to be created by the observation density p (yt ft, Δ). In addition, the update of the time shift parameter ft is accomplished by the following auto-regressive update equation.

$$f_{t+1} = w + \sum_{i=1}^{p} A_i S_{t-i+1} + \sum\nolimits_{j=1}^{q} \beta_j f_{t-j+1} \qquad (4.14)$$

Where Ai and Bj denote the metric coefficient, respectively. And st is set as a suitable feature of historical records, with the unidentified coefficient being the feature of st = st(yt, ft;θ).
In the case of GAS (1,1), a restriction of 0 < A1 < B1 < 1 is enforced when estimating the variable. When conducting Yt measurements, the Time Varying vector ft parameter is modified to the next time t+1 by the following theorem of equation 4.17.

$$s_t = S_{(t,f_t;\ \theta)}.\frac{\partial \ln p\ (y_t|f_t;\ \theta)}{\partial f_t} \tag{4.15}$$

Where Et-1 represents the expectation with respect to p (yt ft, Δ). As a multivariate distribution function with a median uniform, the copula function ties the marginal distribution to the marginal distribution. Multivariate distribution by the theorem of Sklar. The GAS system introduces a new model specification to modify the constant copula parameter. Eqs 4.18, Formulate the Gumbel copula and the student t copula distribution functions, respectively, where the Student t copula is the copula function of the Student t distribution.

CGumbel (u,v;δ) = exp(−((−ln u)δ + (−ln v)δ)1/δ), 1 ≤ δ < + ∞

$$S_t = E_{t-1}^{-1}[\frac{\partial \ln p\ (y_t|f_t;\ \theta)}{\partial f_t}.\left(\frac{\partial \ln p\ (y_t|f_t;\ \theta)}{\partial f_t}\right)'] \tag{4.16}$$

Demonstrates a variety of typical static copula distribution functions in contour plots. The Gaussian copula has symmetrical tails with student copula.

The Gaussian copula is, among other aspects, insensitive to changes in upper and lower tails correlation and can only represent models of symmetric correspondence. While the student t copula is stronger and vulnerable to modification of variable structures related to tail, it can only explain the symmetric association of tail. The asymmetrical tail reliance is on Clayton and Gumbel copulas. Gumbel copula may describe, among them, the great dependences of the top tail, while the changes of the lower tail dependency cannot be represented, while copula Clayton is the opposite. Gumbel copula can then be used to identify correlations of high tail dependency in financial markets and to characterise correlations of lower tail dependency in financial markets by using Clayton copula.

And with the numerous upper tail parameters and lower tail, SJC copula is able to capture the asymmetric tail dependency separately. In particular, it was found that non-elliptic copulas would catch patterns of varied tail dependency by measuring and checking of tail dependency and risks distributed through various capital markets (Su, 2016).

Since, monetary resource returns arrangement will in general show certain common attributes, including sequential connection, thick tail circulation, and unpredictability grouping. The GARCH model is broadly perceived as an incredible asset for monetary time arrangement investigation and displaying (McNeil and Frey, 2000). The current written works Huang et al. (2009) indicated that the contingent conveyance of budgetary resource returns is likewise anomalous, with a fatter tail than that of the typical dispersion. It is suitable to pick hefty followed conveyance in returns peripheral demonstrating for hazard the executives examines. Su et al. (2011) have discovered that the GJR-GARCH model functions admirably in the VaR expectation. Chang et al. (2010) introduced proof of unpredictability overflow impacts and unbalanced property on the contingent fluctuations for significant unrefined petroleum markets. Henceforth, the Skew t appropriation is utilized to fit the Gold and S&P500 prospects development circulation in this paper, and is contrasted and the student's t dispersion and the summed-up blunder GED dissemination. The prospects returns measure following the ARMA(p,q)- GJR-GARCH(p,q) cycle to portray the minimal distribution, which is set in the accompanying.

$$C_{Gumble\ (u,v;\ \delta)} = \exp(-((-\ln u)^{\delta})^{\frac{1}{\delta}}),\ 1\leq\ \delta < +\infty \qquad (4.17)$$

$$C_T(U,V;P,V) = \frac{1}{2_\pi\sqrt{1-P^2}}\int_{-\infty}^{t_v^{-1}(u)}\int_{-\infty}^{t_v^{-1}(u)}(1 + \frac{s^2 - 2_{pst} + t^2}{v\,(1-p^2)})^{-\frac{v+1}{2}}dsdt$$

where p and q are non-negative whole numbers, which separately speak to the autoregressive and moving normal request; It-s signifies the demonstrative capacity, when εt-s < 0 is esteem one, in any case zero. αi > 0, βj > 0 for the difference to stay positive, and α + β < 1 for the fluctuation cycle to be covariance fixed for the instance of p = q = 1. The slack request of the mean and difference successions is chosen by the BIC standard. The GJR model has imbalance, which means uplifting news has an impact on the instability of α, while terrible news has an effect on the unpredictability of α + δ. When δ ≠ 0, the influence impact exists, if δ > 0, it implies that the negative returns of the past period will prompt higher unpredictability in the current time frame contrasted and the positive returns of a similar greatness in past period. The proper circulation setting of the development in GJR model and GARCH model depends on the KS test and Cramér–von Mises (CvM) test.

The normalized residuals are demonstrated parametrically, and there exist mellow presumption that the negligible dispersion boundaries are reliably respectable. Assume that the development term ηt individually follows the Skew t appropriation, Student t circulation and GED conveyance to depict the leptokurtic properties of profits.

The Skew t dissemination has two shape boundaries, that is, the skewness boundary λ controlling the lop-sidedness degree, and the opportunity boundary ν controlling the thickness of the tails. When $\lambda = 0$, it prompts the normalized Student's t circulation. The more modest the opportunity boundary ν is, the more grounded the proof of high weakness the profits circulation shows. When $\lambda < 1(\lambda > 1)$, the likelihood that the arbitrary variable acknowledgment esteem is lower than the dispersion mean is bigger (more modest), that is, the Skew t appropriation has a negative (positive) skewness.

4.4.7 GAS Model for ES and VaR

A major challenge faced when choosing a dynamic model for risk measurement or any other quantity is the mapping the current value of the variable from the lagged information available. A proposed solution to VaR and ES lapses dates back to the work of (Creal et al., 2012; Harvey, 2013), who proposed a general class of models called" generalized autoregressive score (GAS) models by the former authors, and" dynamic conditional score models by the latter author. The similarity between the two models is in their assumption. They both assumes that the target variable has some parametric conditional distribution where the parameter (vector) of that distribution follows a GARCH-like equation which is further used in hybrid GAS/GARCH model.

$$\begin{bmatrix} v_{t+1} \\ e_{t+1} \end{bmatrix} = \mathbf{w} + \mathbf{B} \begin{bmatrix} v_t \\ e_t \end{bmatrix} + \mathbf{A}\mathbf{H}_t^{-1}\boldsymbol{\nabla}_t \tag{4.18}$$

In the model, the forcing component is the lagging score of the log-likelihood, scaled by a certain fixed-point matrix, for which the inverse Hessian is a common approach. Plenty of well-known models, including ARMA, GARCH Bollerslev (1986), and ACD (Engle and Russell, 1998) models, are perched within this specification. Refer to Creal et al. (2012) for a GAS (Generalized Autoregressive Score) and associated models summary.

We consider this to modelling and implement it to our issue of M-estimation. In this request, the forcing variable is a function, rather than a log probability of the derivative and Hessian of the GT 7O loss function. For the following GAS (1, 1) model for ES and VaR, we can consider.

This empirical study is mainly based on the VaR model and ES, is represented to the formula:

$$\widehat{VaR}_t = \widehat{Quantile\,\{Y_s\}}_{s=t-m}^{t} \tag{4.19}$$

$$\widehat{ES_t} = \frac{1}{am}\sum_{s=t-m}^{t-1} Y_S 1\ \{Y_s \leq \widehat{VaR}_s \tag{4.20}$$

The equation 4.20 represented in the formula is the confidential level, VaR is the combinations of the in-risk value and the loss suffered by the combination in the future holding period

To calculate the VaR we need first to use the statistical distribution of the value in other to analyse the assets. In this distribution statistic the value that is equal to the confidence range represent the lowest value of the assets that will held during the holding period.

$$Y_t = \mu_t + \sigma_t \eta_t \tag{4.21}$$

$$\eta_t \sim iid\ F_\eta (0, 1) \tag{4.22}$$

For example, if an asset from the start of time and the yield represented by the end of the holding period assets, the assets value is given by the following formula in equation 4.23 and 4.24.

$$v_t = \mu_t + a\sigma_t, \quad \text{where} \quad a = F_\eta^{-1}(\alpha) \tag{4.23}$$

$$e_t = \mu_t + b\sigma_t, \quad \text{where} \quad b = \mathbb{E}\left[\eta_t | \eta_t \leq a\right] \tag{4.24}$$

The real application of ARMA GARCH will be a set of discrete distribution. With that method it can be found the minimum possible return of the asset, under confidence. Similarly, with the formula, we can have the result of the lowest possible value of the asset under confidence.

One type of VaR is the absolute VaR which is the full loss of finance assets. The second one is the relative ES which consisted to the VaR of the asset relative to its expected value the formula in Equation 4.24 and 4.25. the VaR of the calculate asset is given by the lowest value and the Skewness. The VaR can be determined if we have the equation below.

$$\eta_t \sim iid\ N(0,1) \tag{4.25}$$

$$\eta_t \sim iid\ Skew\ t(0,1,\nu,\lambda) \tag{4.26}$$

4.4.8 A One-Factor GAS Model for ES and VaR

In Section 4.3.9, the specification enables ES and VaR to develop as two independents, correlated, processes. A useful, simplified model for many risk forecasting applications is one focused on a framework with only one Time Varying risk measure, e.g., volatility.

In this section, we will assume a one-factor model, and will call the model a two-factor-GAS model in further sections. Consider the following one-factor GAS model for ES and VaR, where both risk measures are driven by a single variable, kt

$$vt = a\ exp\ (kt\} \tag{4.27}$$

$$et = b\ exp\ (kt\}, where\ b < a < 0 \tag{4.28}$$

And

$kt = c\ Ønt—fi\ ‡\ çHt—fi\ st—fi$

The forcing variable, $Ht—fi\ st—fi$, in the evolution equation for kt is obtained from the FZ0 loss function, plugging in $(a\ exp\ (nt\}, b\ exp\ (nt\})\ for\ (vt, et)$.

$$st\ 70\ (Yt,\ a\ exp\ (nt\},\ b\ exp\ (nt\}\ ¡\ \alpha)\ =\ —\ fi\ .\ fi\ 1\ (Y\ \leq\ v\}\ Y\ —\ e\ \Sigma(fi8)$$

And

$$It \div\ 6XEt—fi\ [GT\ 70\ (Yt,\ a\ exp\ (nt\},\ b\ exp\ (nt\}\ ¡\ \alpha)]\ \ 6nX\ =\ \alpha —\ h\alpha a\alpha(fi9)\ \alpha$$

Where $k\ al$ is a negative constant and between zero and one lies in all[8].

[8] Note: In this example, the Hessian, It, turns out to be a constant, and since we estimate a fre

4.4.9 A Hybrid GAS/GARCH Model

At last, we consider a coordinate combination of the constraining variable proposed by a GAS structure for a one-factor model of returns, depicted in condition of GARCH/ES Model with the valid GARCH model for instability. We specify:

$$Y_t = \exp\{\kappa_t\}\eta_t, \quad \eta_t \sim iid\ F_\eta(0,1) \tag{4.29}$$

$$\kappa_t = \omega + \beta\kappa_{t-1} + \gamma\frac{1}{e_{t-1}}\left(\frac{1}{\alpha}\mathbf{1}\{Y_{t-1} \leq v_{t-1}\}Y_{t-1} - e_{t-1}\right) + \delta\log|Y_{t-1}| \tag{4.30}$$

The variable κ_t is the log-volatility, distinguished up to scale. As the idle variable in this model is log-volatility, we utilize the slacked log outright return instead of the slacked squared return so that the units stay in line for the advancement equation for κ_t. There are five parameters in this model $(\beta, \gamma, \delta, a, b)$, and we gauge them utilizing FZ loss minimization.

4.4.10 Adjusted Assessment Strategy

On account of the copula based multivariate model, it permits to determine the peripheral appropriation and reliance structure independently, giving a lot more prominent level of adaptability in assessing the model boundary independently. Fang et al. (2014) proposed a novel semi most extreme probability assessment strategy with non-Gaussian probability capacities for catching weighty followed returns, which gives better chance to the assessment of mix of non-linear reliance with substantial followed instability. By and large, the multi-stage most extreme probability assessment empowers the assessment of joint dispersion for high dimensional circulation in stages, subsequently enormously diminishing the calculation weight, and subtleties can be seen in Patton (2006). Characterize Θc the boundary vector of copula work, Θi, I = 1,2, ...n speaks to the boundary vector of peripheral capacity Fn, c(u1,u2, ...,un) means the thickness capacity of copula work, at that point the thickness capacity of joint dispersion capacity can be communicated.

---

coefficient on our forcing variable, we can set the scaling matrix, Ht, to one of any positive constants.

$$f(x_1, x_2, \ldots x_n; \Theta) = c(u_1, u_2, \ldots, u_n; \Theta_c) \prod_{i=1}^{n} f_i(x_i; \Theta_i) \tag{4.31}$$

The two-venture most extreme probability assessment technique looks at the negligible conveyance work and the association work independently. The boundary Θi of the minimal appropriation is assessed basically, and afterward the likelihood basic change of the standard leftover is determined dependent on the assessment of the got negligible conveyance boundary. At last, the most extreme probability strategy is utilized to gauge the copula work boundary Θc as per the accompanying recipe. Also, the semi-Newton calculation is iteratively used until the ideal boundaries are gotten.

In spite of the fact that the non-Gaussian most extreme probability assessor is generally utilized in the GARCH model with weighty tails, the assessor won't be reliable except if the thickness misspecification predisposition is amended. Luckily, Fang et al (2014) researched on another semi greatest probability (QML) system when the GARCH development has substantial tails, which has been demonstrated predictable and asymptotic.

The model boundaries are summed up as Θ = {θ, γ}, where θ indicates the scale boundary, and γ signifies the heteroscedastic boundary. Assume κ is used to change the size of the semi probability, at that point the boundary κf as for a particular probability work f limits the contrast between the genuine development thickness g and the semi probability in the event of Kullback-Leibler data separation. Upon given κf, the non-Gaussian QMLE can be characterized through augmenting the adjusted semi probability with boundary κf. It has been demonstrated that fusing the inclination remedy factor κf into the probability can encourage the recognizable proof of instability scale boundaries θ notwithstanding revising the predisposition for basic non-Gaussian QMLE of the scale boundary. So as to gauge κf, the Gaussian QMLE is essentially directed, and afterward the comparing κf is acquired with assessed residuals.

$$\widehat{\Theta} = \arg\max \sum_{t=1}^{T} C\ \left(F_1(x_{1t;}\widehat{\Theta_1}), F_2(x_{2t;}\widehat{\Theta_2}), \ldots F_n(x_{nt;}\widehat{\Theta_n}),\ ;\ \Theta_c\ \right) \tag{4.32}$$

Along these lines, the non-Gaussian semi probability with amendment factor κf is expanded, subsequently acquiring the non-Gaussian semi probability assessor τ as follows.

$$K_f = arg \max \frac{1}{T} \sum_{t=1}^{T} l\,(r_t, \quad \varpi, \quad k\,) \tag{4.33}$$

$$= arg \max \tfrac{1}{T} \textstyle\sum_{t=1}^{T} \left(-\log(x) + \log f\,(\tfrac{\varepsilon_t}{k}\right))$$

Incidentally, the weighty followed QLE assessor τ has unmistakable bit of leeway over the Gaussian partner, indicating lower change when the genuine development is substantial followed. Its qualities can be concluded by the substantiable of the tails of assorted advancement mistakes deftly. In particular, the heavier the tails of the advancement mistake, the more modest worth the κf is. Also, the inclination revision factor κf doesn't fluctuate if changing distinctive contingent heteroscedastic models.

Note that the probability assessment of GAS model for boundary assessment is clear because of the helpful property of perception driven in GAS model. Through using the standard forecast blunder deterioration, the augmentation issue of l = ln p (yt | ft, θ) can be communicated. It just includes the usage of the update condition of GAS model. On account of GAS detail, the inclination is determined through the accompanying chain rule.

$$\tau = \; arg \max \frac{1}{T} \sum_{t=1}^{T} -log\,\left(k_f \Theta h_t\right) + logf\,(\frac{r_t}{k_f \Theta h_t}) \tag{4.34}$$

where represents the vector with stacked section of framework A, and denotes the Kronecker item. After the accessibility of boundaries, the tail reliance would then be able to be estimated to evaluate the disease chances.

4.4.11 Back Testing Value at Risk

The Kupiec test basically measures the order to determine the accuracy of the VaR. The initial measures introduced by Kupiec (1995) basically measures the amount of the exceptions of probability level. If the loss does not surpass the estimated VaR, the estimation is systematically over estimating the threat in the market, to conclude it is an inaccurate estimation.

In prior learning commodity yield simulation can be studied in the papers by (e.g. (Nguyen-Huy et al., 2017; Nguyen-Huy et al., 2018) and copula model usage and results these studies can be taken into consideration.

4.4.12 Portfolio Optimisation Problem

Suppose a portfolio comprises of n Stock and commodity with an irregular rate of the minimal returns r1, ..., rn, the marginal expected return E [ri] and wi could be a share of the overall gold and stock distributed to the investment (i.e., the choice vector or weight). The investor's portfolio enhancement issue, within the setting of the different segment, is to expand the anticipated returns (whole of all negligible anticipated returns increase with the comparing weights) of the portfolio given a specified hazard level β. The portfolio advancement issue can at that point be defined as (Larsen et al., 2015).

$$\text{Maximise} -- \sum_{i=1}^{n} w_i E[n] \tag{4.35}$$

$$\textit{Subject, to} - \begin{cases} \phi_\beta\ (w_i) \leq \phi \\ \sum_{i=1}^{n} w_i = 1 \end{cases}$$

4.5 Results and Discussion

This segment covers the outcome of Gold and S&P500 optimisation based on optimal copula-statistical model problems that can be solved with help of physical interpretation based on the idea of the applied models and the cause of the problem. Firstly, in extreme volatile conditions variations are regarded as marginal returns. With the help of ES-VaR and hybrid copulas and GAS copula function outcomes of the copula, model selection can be determined. With help of multivariate copulas, hybrid copula and ES-VaR models, the conventional multivariate-normal model is evolved for the outcome of a comparison. In last, we talk about optimal portfolio allocation outcomes generated from distinct confidence levels models and the meaning of VaR optimisations.

4.5.1 Variations in the Marginal Return

The historical marginal returns of Gold index and S&P500 are displayed in Fig 4.1 and 4.2 in data section. Except from 2007 to 2008 (financial crisis) the design marginal return Gold and S&P500 seems to be most appropriate. The prime financial crisis and losses in throughout the world during the year 2006-2007. It is been observed that the marginal return of every stock mostly moves in a different direction than that of in later years. This can be clearly noted in the

2006-2007 period of the financial crisis, and also observed that the S&P500 fluctuating marginal returns are increased and the Gold index and S&P500 margins are decreased extremely. In the 27 successive years of 1992–2020 of the financial boom, the marginal returns of Gold and S&P500 are noted to be varying every year. While the marginal return is seen increased or steady of Gold and S&P500 in the same years. In Table 4.1 it is seen that the low correlation coefficients indicate the distinct degrees of the dependence of every study which basically demonstrates the VaR values for the returns co-movement. The marginal returns stochastic nature of these stock and commodity that to minimize the risk and losses of investors can be possible by using diversification strategy.

The stock index indicates multiple chosen indexes in the market helping you to view stock change at a wide-scale. The stock index can be more thorough and general to minor specific weighting activity and adjustments to the market. The market share of the market is near the real business portion of the index. In USA this stock index is most typically used on the stock market, which can have a heavy impact when adjustments are made to the index. From the past 27 years January 1, 1992 to January 1, 2020 the similar investigation shows the index development when analysing the use of 7296 daily logs data. To measure the stock market the use of VaR data is taken from the Bloomberg providing you with the risk outcomes. Prior to figuring the VaR value, we have to surmise the dissemination of the information collected. Preferably, the pace of return ought to be ordinary dispersion, yet the genuine issue will be influenced by market changes and by the policy aspect.

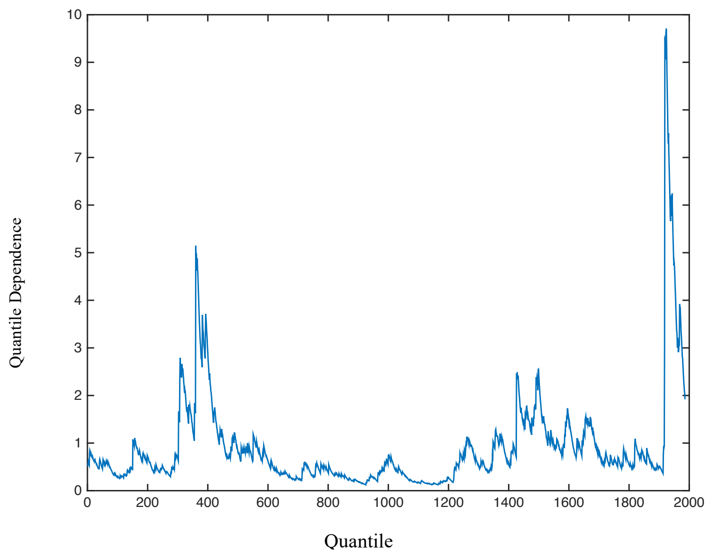

Figure 4. 2 Quantile Dependence of Gold Price Index.

Fig. 4.2 and 4.3 shows the calculation of ordinary dispersal on chosen data. The diagram shown suggests the positioning of the data does not fit the quantile line and is remarkably different, implying the dispersal does not stay in the original quantile line.

The distribution data within a Table 4.2, communicating a broad and clear distribution which fails to correspond. The kurtosis is fundamentally bigger than 0, demonstrating that the information is more extreme than the ordinary distribution and is a "spike" distribution. The skewness esteem Skewness is under 0, demonstrating that the information is marginally portrayed by a left-one-sided distribution.

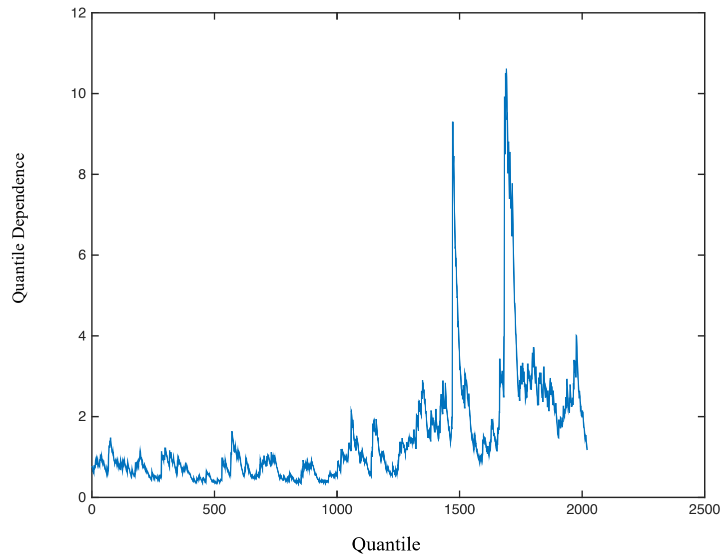

Figure 4. 3 Quantile Dependence of S&P500.

In Fig. 4.4 copula-based frontiers are presented with the single portfolios of each stock relative to the CVaR. How the variation strategy can reduce risk is reveals in this figure 4.4. It's clearly visible that farmer's profitability for S&P500 are on the frontier curve on the other hand Gold index are under efficient limits and at S&P500 profitability currently growing investments. For a given degree of downside risk, profitability in likely to increase in both the S&P500 and Gold index. Therefore, rise in S&P500 may face the greatest risk as it is located at the highest point of the curve, but it also has the potential to achieve the highest profitability.

Descriptive	S&P500	Gold Prices
Mean	7.297	5.071
StdDev	17.604	15.730
Skew	-0.276	-0.110
Kurt	12.077	11.143
VaR-0.01	-3.132	-2.725
VaR-0.025	-2.324	-2.050
VaR-0.05	-1.728	-1.499
VaR-0.10	-1.143	-1.039
ES-0.01	-4.510	-3.870
ES-0.025	-3.396	-2.957
ES-0.05	-2.694	-2.352
ES-0.10	-2.055	-1.797

Table 4. 2 Descriptive Summary of S&P500 and Gold Price Index

Table 4.2 elaborate the descriptive analysis along with VaR and ES calculations. The Basel Committee recommends confidence level of 99% should be used over a 10-day horizon. Since, this research is for a long-time interval hence measuring with different confidence level has been utilised. The results demonstrate the loss for S&P500 and Gold prices during a time interval of 27 years which suggests the maximum loss during that time. For Expected Shortfall we can see the worst-case scenarios.

Moreover, under the circumstances, through diversifying, investors may decide to be slightly less profitable in order to reduce the relatively large downside risk. For instance, by allocating about 10 percent of the investment to Gold index, S&P500 can change their expected profitability. The VaR-0.01 is -3.132 for S&P500 and -2.725 for gold prices and ES-0.01 is -4.510 for S&P500 and -3.870 is for gold Prices. This has happened due in S&P500, the average marginal return (and the usual deviation) is 17.604 for S&P500 and 15.730 for Gold Prices (Gold standard deviation is 1.874 lower than S&P500) all the information can be seen in the (Table 4.2). By definition, the kurtosis factor is capable of measuring whether, compared to normal distribution, the data are heavy-tailed or light-tailed. We therefore deduce that in the lower tail, the S&P500 area is likely to have higher heavy tails or outliers (extreme losses) because the high negative skewness means the asymmetry of its marginal return distribution to the left.

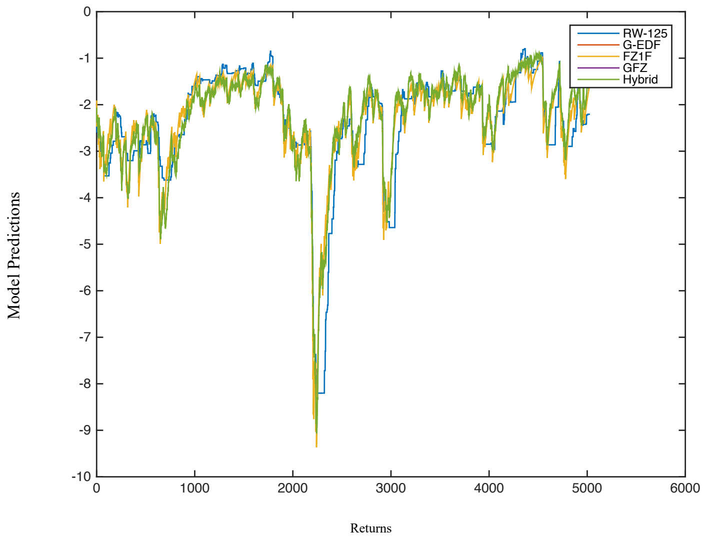

Figure 4. 4 Hybrid ES-VaR Approach for S&P500.

Figure 4.4 demonstrated that ES-VaR hybrid approach. The dips in the figure shows the worst-case scenarios along with the maximum losses. This shows that S&P500 returns were quite low during the time of financial crisis which will be further discussed later in the analysis. The effect of this model is the parametric structure it imposes on VaR and ES dynamics because of its connection with insulated information. There are certain assumptions made based on the information gathered which are not beyond the ordered condition stated for using this model, that is the conditional distribution of returns. Hence, this model is seen as semiparametric to a large extent. With the application of the theory for M-estimators see Hull and White (1998) for example. We establish figures 4.5 and 4.6 the asymptotic properties of such estimators. A new dynamic specification for VaR and ES will be considered.

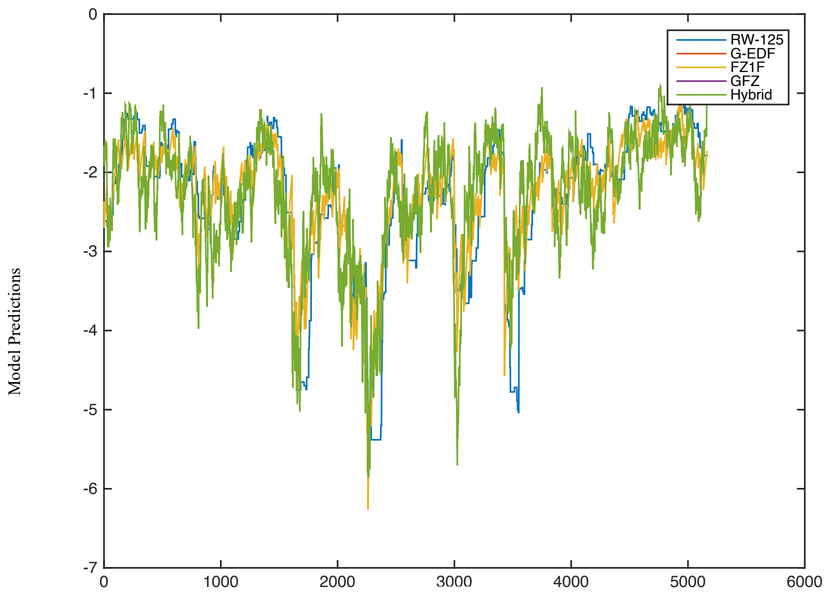

Figure 4. 5 Hybrid ES-VaR Approach for Gold Price Index

Figure 4.5 demonstrated the ups and downs of the Gold prices. It can be seen that the Hybrid ES-VaR model represents the volatility of the commodity prices. In the early 1990's we can see dips and a major dip during mid of 2000s. Primarily, figures 4.5 and 4.6 shows that most FZ loss of the back testing are more extensive than 5%, signifying that the models based on the combination of GARCH-type models, EVT and GAS copulas can measure the risk of S&P500 and Gold portfolio accurately. GARCH-GPD, RIN- 125, G-EDF, FZ1F, GFZ and Hybrid are the marginal distributions reported in figures as the results in S&P500 and Gold Price Index showing the back testing results for risk models also demonstrated in table 4.4 and 4.5.

Nolde and Ziegel (2017) demonstrate that there is usually no FZ loss function that produces degree zero homogeneous loss differences, but we demonstrate in Proposition 1 below that zero-degree homogeneity can be achieved by taking advantage of the fact that we can achieve a homogeneity for the values of a that are of interest in risk management applications (namely, values ranging from about 0.01 to 0.10). We may assume that HAS < 0 a.s. Vt. Proposition 1 shows that if VaR < 0 a.s.Vt. is further enforced by us, V t, then, there is only one FZ loss function that produces loss variations that are degree zero homogeneous up to irrelevant position and scale variables. Of course, the uniqueness of the loss function described in Proposition 1 means that it also has the added advantage of not having to specify any remaining shape or tuning parameters.

Proposition 1: Define the FZ loss difference for two forecasts (Vit, et) and (v2t, €21) as LFz (Y: Vit, eit; a, G1, G2) LFz (Y_1, v2, €2t; a, G1, G2). Under the assumption that VaR and ES are both strictly negative, the loss differences generated by a FZ loss function are homogeneous of degree zero iff G (2) = 0 and G2(x) = -1/r. The resulting "FZ0" loss function is:
1{Y < v} Y) + + Lezo (Y, v, e; a) = -1{Y <v} {v = + log (-e) – 1

In further analysis, all evidence is provided. Lezo is plotted in Figure 4.4 and 4.5 when Y = -1. We fix e = -2.06 in the left panel and change v, and we fix v = -1.64 in the right panel and change e. (These values for (v, e) are a = 0.05 VaR and ES from a regular Normal distribution.) The left panel shows that from quantile estimation, the implied VaR loss function resembles the 'tick' loss function, see, for example, (Komunjer, 2005).

S&P500	AVG LOSS	MZ-VaR	MZ-ES
RW-125	0.907	0.004	0.024
RW-250	0.935	0.001	0.035
RW-500	1.011	0.000	0.003
GCH-n	NaN	NaN	NaN
GCH-skt	NaN	NaN	NaN
GCH-edf	NaN	NaN	NaN
FZ2F	0.860	0.000	0.398
FZ1F	0.838	0.000	0.001
GCH-FZ	NaN	NaN	NaN
Hybrid	0.855	0.000	0.001

Table 4. 3 Average losses and goodness-of-fit tests for S&P500.

GOLD INDEX	AVG LOSS	MZ-VAR	MZ-ES
RW-125	0.853	0.066	0.050
RW-250	0.887	0.029	0.026
RW-500	0.876	0.127	0.097
GCH-N	NAN	NAN	NAN
GCH-SKT	NAN	NAN	NAN
GCH-EDF	NAN	NAN	NAN
FZ2F	0.904	0.000	0.000
FZ1F	0.837	0.000	0.002
GCH-FZ	NAN	NAN	NAN
HYBRID	0.815	0.264	0.380

Table 4. 4 Average losses and goodness-of-fit tests for Gold Index

Determined from the dependence structure of S&P500 and Gold Index markets measured by copulas, the portfolio VaR and ES are calculated by hybrid GAS Copula conveyed in section of methodology. The data sample examined endured a sharp decrease in Gold price from more than quite a decent amount, the cost of gold then increased at a steady pace with a small chance of another large drop. Therefore, the short-position risk (upper-tail risk) is the leading market risk for Gold index investors in the near future. Tables 4.3 and 4.4 shows the values of average losses for the gold index and S&P500 portfolio the larger the p values, the better risk measuring precision is achieved.

Mixed hybrid copula archives two out of four best performances among different hybrid copulas, as indicated in the figures. Mixed model of copulas is also found to be superior to the other two copulas in three out of four cases in both the data set used. This data firmly implies that mixed copula approach is very flexible and can be used as a powerful tool in describing the complex dependence structures of Gold index and S&P 500.

The figures 4.6 and 4.7 imply that there is no large difference of measurement accuracy across different marginal distribution models, i.e., GAS Copula, GARCH and ES. This result may indicate that the dependence modelling of S&P500 and Gold Prices assets instead of the marginal distribution is the other factor determining risk measurement. It should also be noted that a special case of portfolio investment is the portfolio with equal-weighted assets.

To guarantee the precision of the findings, it is conjectured another new set of asset weights for S&P500 and Gold Prices to be between the range of 0 to -10, respectively. Figures 4.6 and 4.7 demonstrates the back testing results under the new weights, and present similar results.

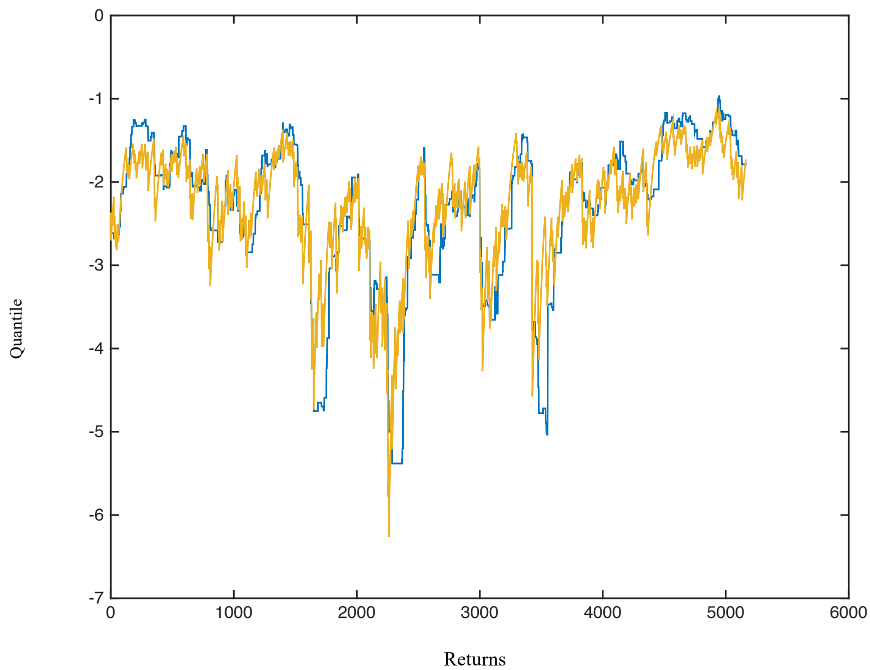

Figure 4. 6 GARCH FZ parameters for Gold Price Index

Often, basing VaR and ES measurements on Hybrid copula are more precise than other copulas. No apparent differences are performed under VaR and ES measurements within the technique's different marginal distributions, with 0.99 and 0.975 quantile.

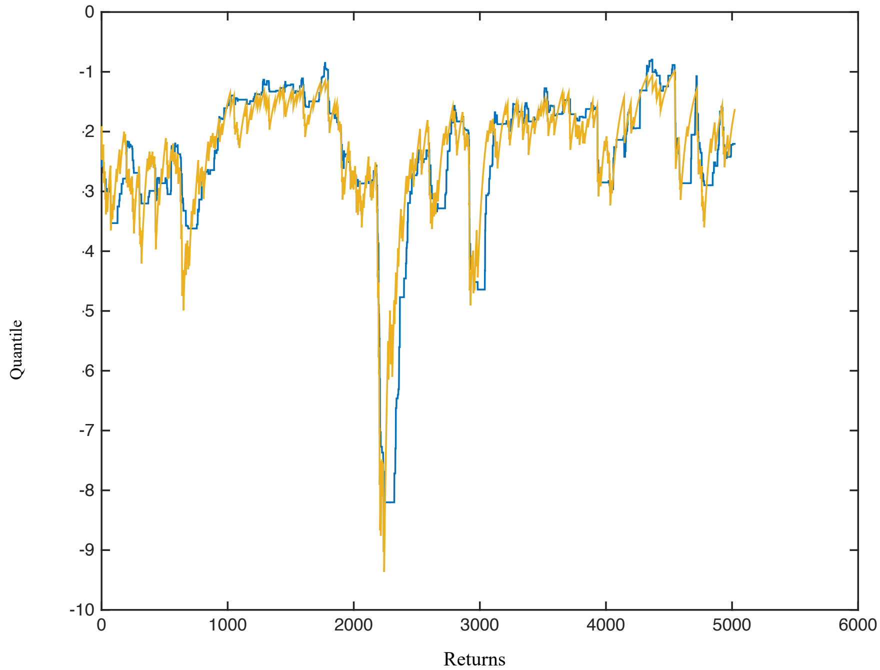

Figure 4. 7 GARCH FZ parameters for S&P500

The implied ES loss function is identical to the "QLIK" loss function from volatility forecasting in the right panel, see, for example, Patton (2011). The values of (v, e) in both panels, where v < e is presented with a dashed line, as described by ES, are below VaR, and so are those values that would never be considered in practise. For a regular Normal random variable, we plot the contours of the predicted FZ0 loss in Figure 4.7."The minimum value that is reached when (v, e) = (-1.64, -2.06), and we see that the implied ES loss function resembles the" volatility forecast LIKETM loss function, see, for example, (Patton, 2017).

Values of (v, e) in both panels, where v c e is presented with a dashed line, as ESt is below VaRt by definition, and so such values can never be considered in practise. For a regular normal random variable, we plot the contours of the predicted FZ0 loss in Figure 4.7. The minimum value reached when (v, e) = (-fi.64, -2.06) is marked with a star, and we see that the star is marked the limits of convex sets are the iso- expected loss TM contours (that is, the level sets) of the expected loss function. (Fissler and Ziegel, 2021) shows that under any distribution with finite first moments, unique alpha-quantiles, continuous densities, and negative ES, convexity of sublevel sets holds more generally for the FZ0 loss function.

The trade-off ratios between the goal risks and the anticipated returns change along the successful frontiers in line with the results. In comparison to the high expected return targets, portfolio investments are able to increase their expected returns without placing themselves at higher risk by geographically spreading wheat farms to lower expected profitability levels. The balancing of the hectares allocated to the S&P500 and Gold Index. This result is anticipated between the S&P500 and Gold Index for the reasons described above. Importantly, S&P500 has the lowest marginal average return and the highest (absolute) skewness and kurtosis. The key advantages of Gold Index development are therefore essentially de-derived from the low relationship (or opposite co-movement) of the marginal returns with S&P500 and Gold Index (see Figs. 4.6 and 4.7).

4.5.2 Optimal Allocation using Hybrid FZ

We examine the optimal percentage allocation between the S&P500 and Gold Index in this chapter. Firstly, the variations between a feasible asset allocation of equal weight (i.e., the total equally divided into two assets) and an effective portfolio of VaR are examined. This comparison is carried out by determining the estimated return goal and then optimising the portfolio for both cases with the lowest risk. The findings illustrated in Table 4.5 and 4.6 show that for the same target return, the risk of the optimised effective VaR was reduced since this is based on simulation results for Normal innovations which are defined in the tables below.

	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{b_\alpha}$
True	0.9420	0.0129	72.8394
Median	0.0000	0.0019	0.0000
Avg bias	0.0489	0.0048	10.3018
St Dev	-3.0214	1.9964	-1.5134
Coverage	-4.2524	2.7324	-1.5563

Table 4. 5 Hybrid FZ Parameters for Gold Price Index

	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{b_\alpha}$
True	0.9773	0.0051	192.4852
Median	0.0025	0.0019	1.3216
Avg bia	0.0168	0.0015	11.3206

St Dev	-2.5133	3.9522	-0.6359
Coverage	-3.7415	5.9449	-0.6294

Table 4. 6 Hybrid FZ Parameters for S&P500

We are further investigating the optimum allocation with efficient Hybrid Copula boundaries. Figure 4.8 shows the efficient allocation (i.e., optimal weight) (a), the weighted returns (b) and the covariance risk budgets (c) for the copula-based portfolios corresponding to the various VaR-mean effective border goals (95 % confidence level). Since the weighted yield is the product of the optimum weight and the corresponding marginal yield, its value represents the proportion of each index contributing to the estimated marginal yield. These figures therefore tend to display a pattern similar to the figure (4.6 and 4.7).

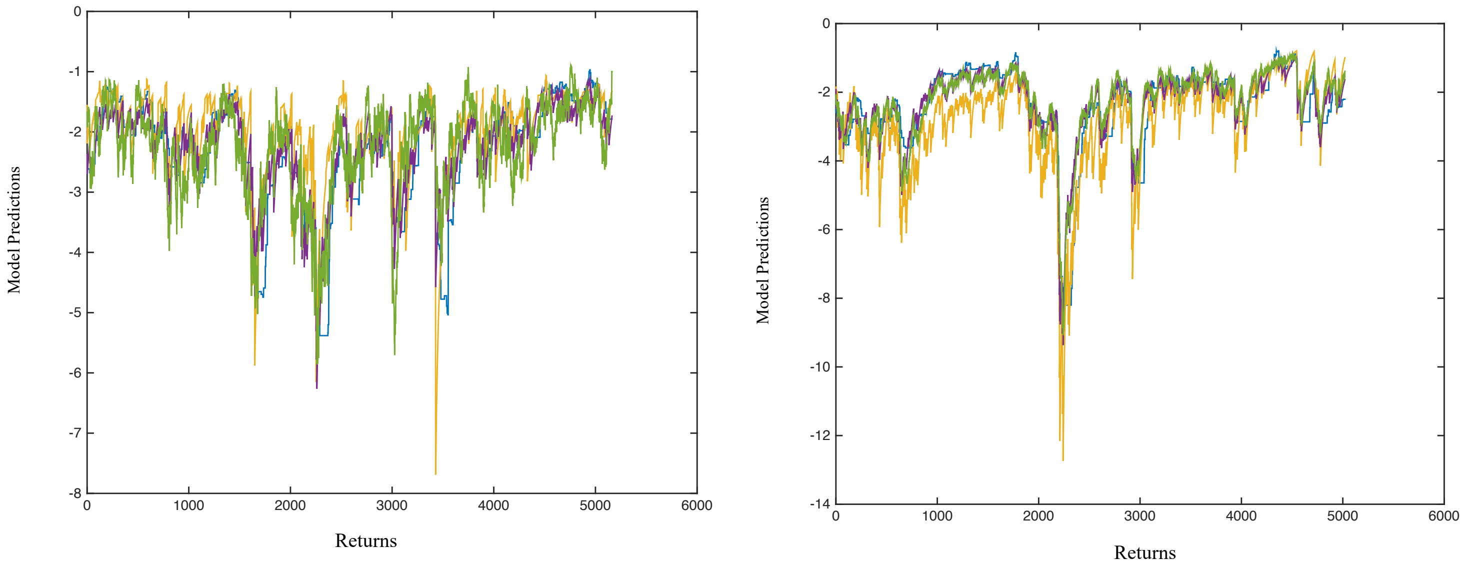

Figure 4. 8 Hybrid Parameter for Gold Price Index and S&P500

The historical marginal returns are adapted to the theoretical distribution curves as the first step of the model construction (Nguyen-Huy et al., 2017, 2018). All 2 historical marginal return data are capable of being. The generalized logistic distribution with the estimated parameters shown in Tables 4.6 and 4.7. The graphical evaluation includes the plots of density, cumulative distribution function, quantile-quantile, and probability-probability, which are analysed to validate the effects of the marginal distribution. Fig. 4.8 shows the density and quantile-quantile graphs while the graphical analysis of the hybrid copula in combination with the statistical FZ tests supports the selection of the generalized logistic distribution in Gold and S&P500 to fit the returns. The summary results of the multivariate copula functions with the corresponding parameters, maximum log likelihood (llmax), and AIC are represented the results show that with regard to the case of multivariate copulas, the Gumbel copula is the most suitable copula model. For copula growth, the same set of copula functions are used, and the selected model of Hybrid copula is illustrated in Table 4.5 and 4.6.

In this analysis, we have applied hybrid copula to help the selection of the most acceptable copula, similar to the procedure adopted for fitting the marginal distributions. Fig 4.8 plots the contours of the chosen bivariate copulas, superimposed on empirical observations and simulated data extracted from the corresponding copulas, for each pair of returns. Fig. 4.8 further plots the contours of the chosen multivariate copulas, superimposed on empirical observations and simulated data extracted from the corresponding copulas, for each pair of returns. It is necessary to create three unique drawable and canonical copulas Aas et al., (2009) since there are two indexes in this analysis. Among the three measures used, the copula with the construction data of the Gold and S&P500 combinations is selected as this construction yields the lowest AIC. It is notable that the nodes of the copula model with the corresponding order are implied by the indexes, while the symbols denote the edges of the copula model constructions. Following the creation of optimal copula-statistical models, from the chosen Gumbel and copula models, we apply the copula-based GAS measure and obtain 1000 bootstrap simulations (i.e., simulation is repeated in 100 times for the sample size of 7296 points) of the marginal returns for each index (Nguyen-Huy et al., 2017, 2018). For the purpose of comparison, this analysis also uses the standard multivariate-normal distribution to produce another collection of simulated data using the simulation technique of ARCHGARCH. In this case, a multivariate-normal distribution (i.e., the individual marginal return distributions and their dependencies are presumed to be normal) is presumed to obey the marginal returns. These Gold and S&P500 sets of randomly simulated data (transformed back to the actual values) are used in the following study and interpretation of portfolio diversification VaR efficient frontiers

	Gold Index	**S&P 500**
CVaR (95)	0.021%	0.023%
CVaR (99)	-0.040%	-0.037%
CVaR (99.9)	0.271%	-0.071%

Table 4.7 CVaR For Gold Price Index and S&P500

This section describes the mean optimizations of CVaR where the ex-pegged return of the portfolio of Gold index and S& 500 is maximized subject to the restriction of the target risk (CVaR). Examples of optimal portfolios at three common confidence levels (i.e. 95%, 99% and 99.9%) from copula-based and traditional multivariate normal models are shown in table 4.7. It is found that, by definition, the CVaR risk measure measures the out-comes versus the zero and, therefore, it is likely to have positive and negative values. The recorded values of the positive or greater than zero CVaR (similar to the positive VaR) applies to the certain negative outcomes (i.e., losses), and the negative CVaR correspond to certain positive outcomes (i.e., the gains or the returns). For example, a 95 percent CVaR value of 0.10(a positive value) refers to the scenario in which the expected return of the worst scenarios (i.e., 5 percent * 7296) is equal to -10 percent, and conversely, a 95 percent CVaR value of -0.10 (a negative value) refers to the scenarios in which the expected return of the -0.021% for gold and 0.023 for S&P500 worst scenarios is equal to 10 percent. In order to compare the optimized mean CVaR values under different distribution assumptions, for each confidence level, the same targets of the expected returns are chosen. A higher mean-CVaR value than the traditional multivariate-normal portfolio is provided by the two copula-based portfolios.

It is obvious that, depending on the different expected marginal returns and risk levels, the optimal share assigned to each asset. The optimal decision, as expected, is to assign to the highest expected marginal return, i.e., S&P500 in this case, resulting in the maximum level of risk. Operating in both S&P500 and Gold Index with the highest proportion of rising investment allocated to S&P500 (50 percent) is the optimal option for the minimum CVaR portfolio. Investment should be grown mainly in S&P500 and not at all in Gold, in order to achieve a medium to high level of planned profitability. When targeting low to medium levels of profitability and risk, it is also desirable to assign most of the stock return to S&P500 and Gold Index.

However, for the 90 percent and 99 percent confidence rate, refer Table 4.8. It can be easily seen that the patterns of allocation S&P500 and Gold Price index returns. To maximise the minimum risk, for the very worst cases (i.e. at the 99 percent trust level), the ES measured the worst cases in S&P500 (55 percent) and less in Gold Index (5 percent) because S&P500 has the lowest standard deviation.

Accordingly, the findings in Table 4.7show that Gold and S&P500 are likely to underestimate the minimum level of risk calculated by CVaR for a given expected return using the multivariate-normal method if the joint distribution of marginal returns is properly followed by a non-normal distribution modelled as a copula. Underestimation of the risk under the multivariate-normal distribution assumption can be detected by the CVaR results. The CVaR efficient boundary acquired from the standard multivariate-normal portfolio is plotted for different levels of trust against those from the copula-based portfolios. As one can see from Table 4.6, 4.7 and 4.8, from copula-based models, substantially higher frontier values can be observed compared to the multivariate-normal model. This is because the copula-based models are able to account for the dependence of the tails, while the multivariate-normal distribution assumes that the tail dependency coefficient is zero, and thus ignores the co-movement of the joint distributions in the tail. As such, the portfolio optimisation approach relying on the traditional multivariate-normal assumption may be less defensive, while copula-based models are more suitable for investors who are concerned with the extreme losses of their index's profitability.

We now turn to forecast performance of the models discussed above, as well as some competitor models from the existing literature. We will focus initially on the results for that in all of the one-factor models, the intercept (c) in the GAS equation is unidentified. We fix it at zero for the GAS-fiF and Hybrid models, and at one for the GARCH-FZ model. This has no impact on the fit of these models for VaR and ES, but it means that we cannot interpret the estimated (a, b) parameters as the VaR and ES of the standardized residuals, and we no longer expect the estimated values to match the sample estimates in Tables 4.8 and 4.9.

	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{b_\alpha}$
True	0.9420	0.0554	17.0187
Median	0.1036	0.0326	3.1770
Avg bias	-1.1900	0.1102	-10.7970
St dev	-1.7504	0.2618	-6.6859

Table 4. 8 GARCH FZ Parameter for S&P500

	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{b_{\alpha}}$
True	0.9484	0.0472	20.0774
Median	0.0835	0.0213	3.9256
Avg bias	-1.2598	0.1123	-11.2180
St dev	-1.8129	0.2399	-7.5556

Table 4. 9 GARCH FZ Parameter for Gold Price Index

α = 0.05, given the focus on that percentile in the extant VaR literature. (Results for other values of α are considered below, with details provided in this detailed analysis.) We will consider a total of ten models for forecasting ES and VaR. Firstly, we consider three rolling window methods, using window lengths of FZ1Fand 500 days. We next consider ARMA-GARCH models, with the ARMA model orders selected using the BIC, and assuming that the distribution of the innovations is standard Normal or skew t, or estimating it nonparametrically using the sample ES and VaR of the estimated standardized residuals. Finally, we consider four new semiparametric dynamic models for ES and VaR: the two-factor GAS model presented in methodology section 4.3.9, the one-factor GAS model presented in methodology section 4.3.7, a GARCH model estimated using FZ loss minimization, and the hybrid GAS/GARCH model presented in methodology section 4.3.11. We estimate these models using the first ten years as our in-sample period, and retain those parameter estimates throughout the OOS period.

In Figure 4.10 below we plot the fitted 5% ES and VaR for the S&P500 and Gold Index return series, using three models: the rolling window model using a window of 125 days, the GARCH-EDF model, and the one-factor GAS model. This figure 4.12 covers both the in-sample periods. The figure shows that the average ES was estimated at around -2%, rising as high as around -1% in the mid 90s and mid 00s, and falling to its most extreme values of around -10% during the financial crisis in late 2008. Thus, like volatility, ES fluctuates substantially over time.

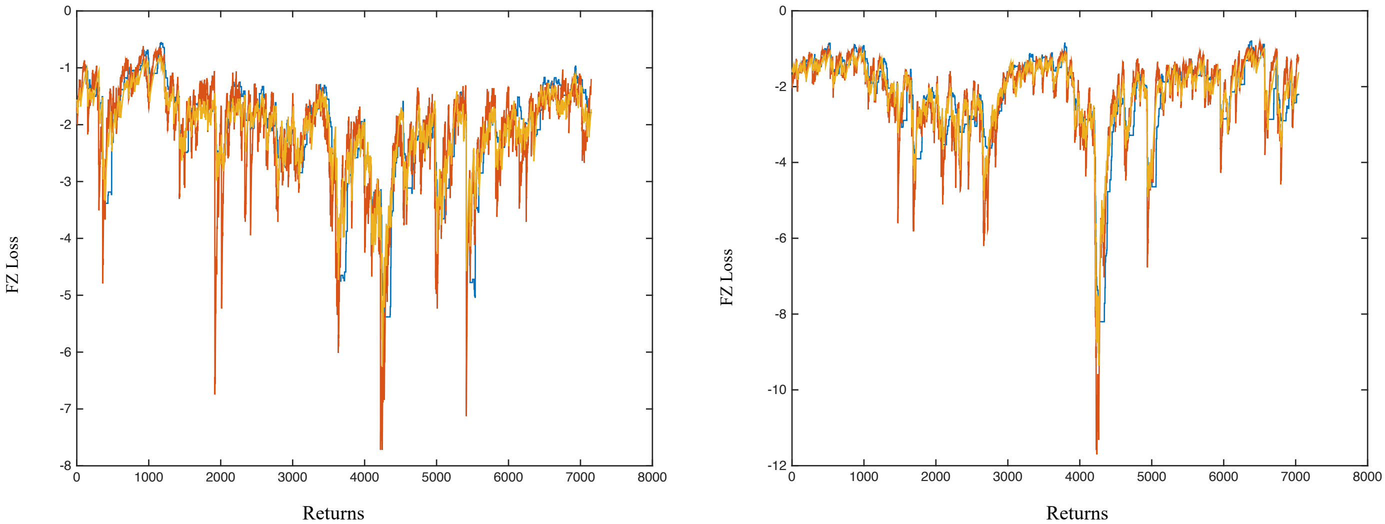

Figure 4. 9 The Hybrid Copula along with GAS, GARCH, CVaR, FZ loss estimations for Gold Price Index and S&P500

The copula mutually attached evaluates for S&P500 and Gold Index prices portray. Powerful admiring involving reliance among subsets of the episodes are specified the life by the entrance from lowest row. The outcome generated by Ciaian et al. (2016) or Corbet et al. (2018) are comparable. An intense mutually attached among stock and commodities is discussed in the analysis. The reliance is all great with the significant maintenance everywhere, founded among S&P500 and Gold Index. Developing proof of dominant equivalence between them the non-astonishing fact.

We at the moment think hybrid copulas more detailed compare of the two options, since GAS copulas present more flexibility than Constant copulas. It is known that GAS copula frameworks outstand the constant structures. The two categories of markets are analysed quite closely.

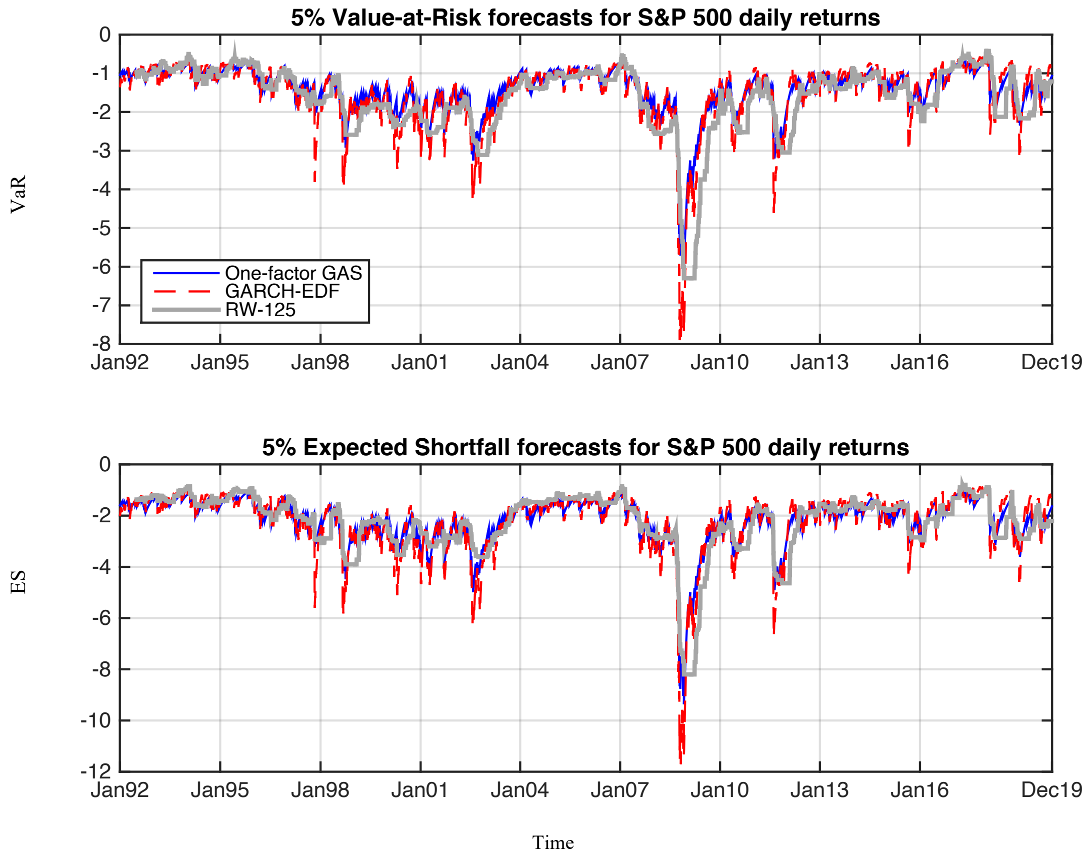

Figure 4. 10 5% VaR and ES forecasts for S&P500 daily returns.

Figure 4.10 demonstrated the VaR and ES results of the past 27 years. We can see the downfalls during 2008 and 2009 which could be because of the financial crisis during that time. The results show that S&P500 was highly affected by the financial turmoil. Other than this other dips and ups are not quite significant but another thing that can be well noted is that it recovered in 2010. Companies of finance, use risk measuring method Ciaian et al. (2016) for the investors. Ciaian et al. (2016) have mentioned that some of the practical notes use hybrid system copula mechanisms. As the hybrid approach of copula used in this study the GAS mechanism for the original gold distribution to investors, the hybrid system based on the copula strategy will fix the question of the initial investment on commodity related risk. Later, the GAS mechanism is eventually taken over the Copula along with VaR mechanism. Therefore, combining the strategies to rectify the risk when reducing the total expense of the investors to invest in much safer and secure financial market.

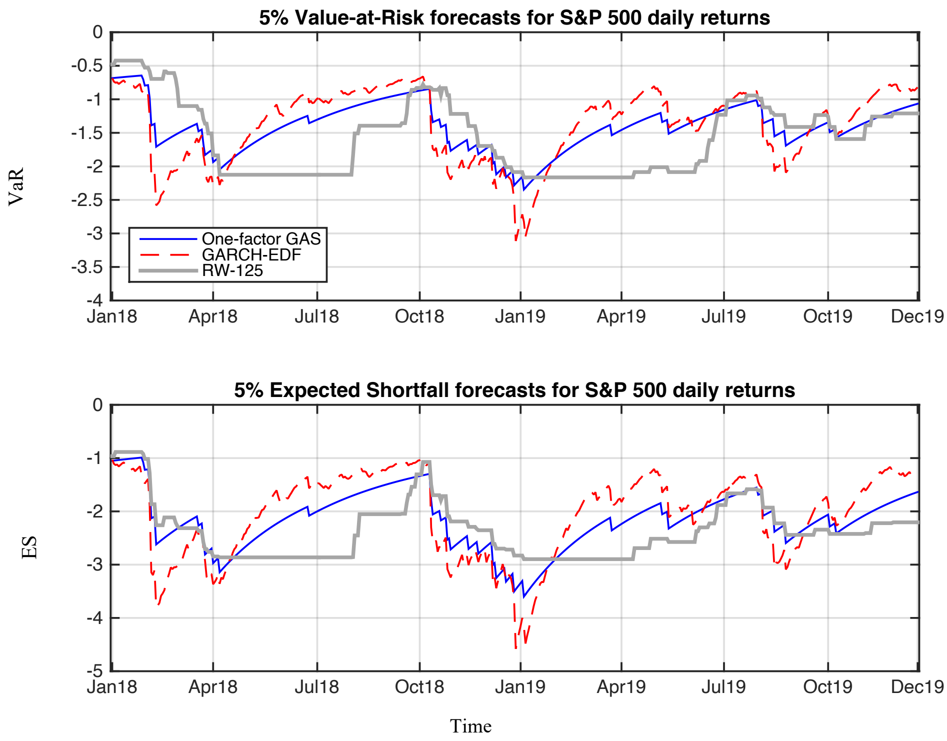

Figure 4. 11 *VaR and ES for S&P500*

Figure 4.11 focuses on the last two years of our sample period, to better reveal the differences in the estimates from these models. We observe the usual step-like movements in the rolling window estimate of VaR and ES, as the more extreme observations enter and leave the estimation window. Comparing the GARCH and GAS estimates, we see how they differ in reacting to returns: the GARCH estimates are driven by lagged squared returns, and thus move stochastically each day. The GAS estimates, on the other hand, only use information from returns when the VaR is violated, and on other days the estimates revert deterministically to the long-run mean. This generates a smoother time series of VaR and ES estimates. We investigate below which of these estimates provides a better fit to the data.

Respectively, the Hybrid ES-VaR model outline and identification form is displayed figure 4.11. We talk about outcome which tell of the kind of copula suited to get the reliance among diverse couples, for compactness. And so forth, we monitor column 1 from deep down that the Clayton copula (number3) suits to get the reliance diverse S&P500 and Gold Prices, provided by returns, which in contact with Clayton. Just half of the copula line is consumed with the main copula clan overall turned up 4 times: shoving up 5 timer, existing 3(Clayton) and supervened by Frank (5). Using the techniques above supplies forecasts to the VaR (Value at Risk) which is time-invariant. This also has the benefit of the commodities in the portfolio having co-dependency. This framework is used as a manifestation of a practical application of the co-dependencies which are then captured by the flexible VaR Copula approach. This is applied so that VaR forecasts can be confirmed. Fig. 4.11 portrays the 5% VaR forecasts and Estimated shortfall. It also portrays original portfolio return series which are taken from the procedure which shows a 7296-day rolling window sample in full. Judging by the plot, it shows us that the VaR forecasts closely follow the daily returns from January 1992- January 2020 to the early days.

For a much better contrast on how the copula VaR forecasts perform, we use a series of S&P500 and gold returns. We also join this with an equally-weighted portfolio. This is to create a simulation and would give a suitable analysis on the use of GARCH (1,1) model presenting 200 daily rolling windows. The violation number which is most relevant of the VaR set at 5% shows us that our copula approach captures the complex structure of dependencies more effectively and would be the best option for a VaR analysis.

We also use these instructions here. First of all, change the sample data so it's in log returns form. Then select 7296 returns as the moving window. The second step would be to fit normal innovation into the GARCH (1,1). This would lead to a change of the log returns into an IID series. Thirdly, after extracting the fit from the previous step, we would then simulate 1000 returns per asset. Once this is completed, the fourth step is to repeat the process of fitting the GARCH, converting the log returns and extracting the fit for all the stocks and Gold Index. Following this step, we then complete the calculations of the portfolio return from the simulated series. Step five is to generate a series of simulated daily portfolio returns which would forecast 5% VaR (Value at Risk) and estimated shortfalls (ES). The sixth and final step would be to then repeat from the first step to the fifth step for a moving window. There are study reports that show the plots (Fig. 4.9) use of the GARCH model has led to numerous violations of the VaR 5% and Estimated Shortfall 5% in comparison of the forecasts of VaR constructed on the application of copulas. Thus, our copula GAS models are more suitable to calculate the portfolio VaR for the selected time frame.

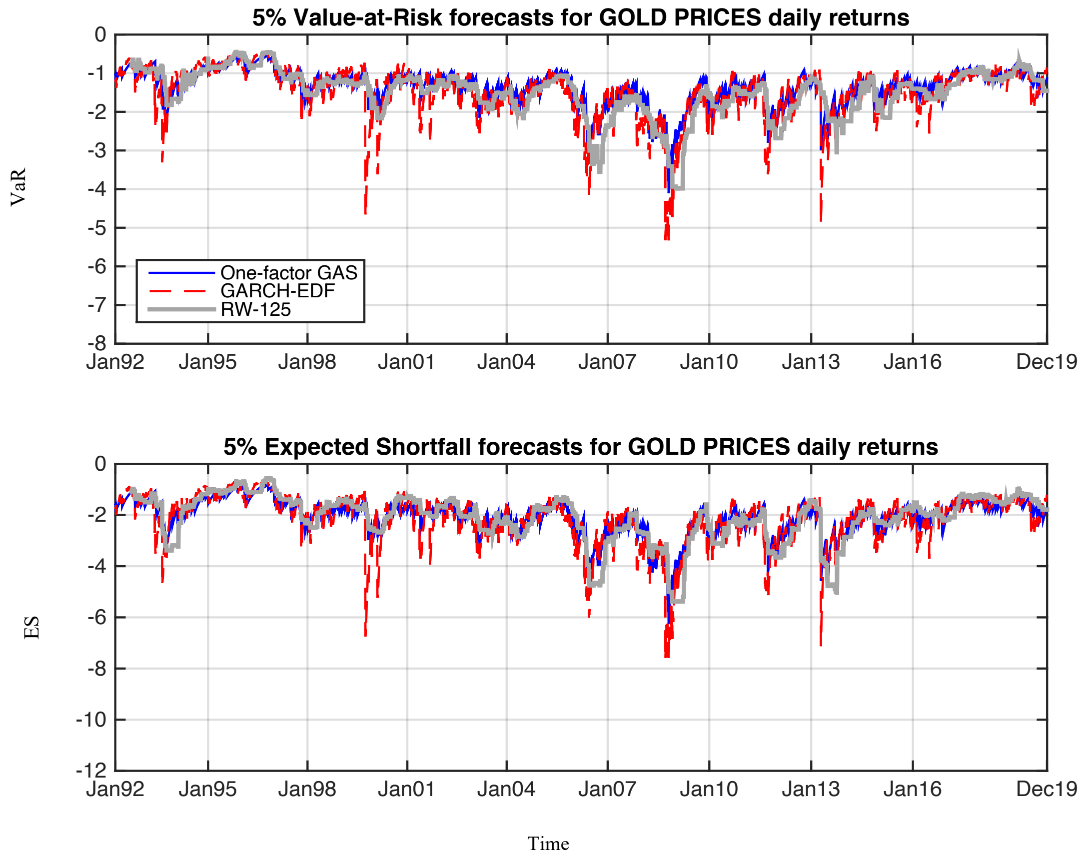

Figure 4. 12 5% VaR and ES forecasts for Gold Price Index daily returns.

In figure 4.12 we track Ciaian et al. (2016) to display the main aspect of cash. Similar to Gold, highest returns own a fixed higher distribution of the Gold conceivably rich (put in circulation). The slight supply growth of produced gold cutdown over the stage and meets to zero when it comes to peak, the acceleration differs from commodity to commodity. With respect to the transaction performance/proof mechanism, various commodities have distinctive generating mechanisms. The Value at risk figure is used for practical demonstration, S&P500 risk measurement. Investors who complete the measure the risk by using the measurement of VaR earn compensation in shape of that they can forecast the risk involved in the asset that they wish to invest in. The ethic of VaR and ES, is that it is that these both are inter connected with the computing power, but on the other hand, straightforward to be identified by network participants. The investment in commodities fulfil the risk first, for the network to allow their proposed block of transaction. In other words, an investor must consider the risk factor, so that a new block can be added with the order of investment. The limitation of identifying a risk investment system is that it results in a significant expenditure in computing power and energy usage, with its only benefit of checking risk involved in the investment of the asset (Chowdhary et al., 2011).

The average sample losses, using the FZ0 loss function for each of the ten models, for the two equity return series. The lowest values in each column are highlighted in bold, and the second-lowest are in italics. We observe that the one-factor GAS model, labelled FZ1Fis the preferred model for the one US equity indices, while the Hybrid model is the preferred model for the S&P500 and Gold Index. The worst model is the rolling window with a window length of 7296 days.

	RW-125	**RW-250**	**RW-500**	**FZ2F**	**FZ1F**	**Hybrid**
RW-125	-	-1.364	-3.432	2.133	4.193	3.569
RW-250	1.364	-	-3.501	2.403	3.861	3.388
RW-500	3.432	3.501	-	4.005	5.365	5.048
FZ2F	-2.133	-2.403	-4.005	-	1.762	0.334
FZ1F	-4.193	-3.861	-5.365	-1.762	-	- 1.784
Hybrid	-3.569	-3.388	-5.048	-0.334	1.784	-

Table 4. 10 Diebold-Mariano t-statistics on average loss differences alpha=0.05, S&P500 returns

.	**RW-125**	**RW-250**	**RW-500**	**FZ2F**	**FZ1F**	**Hybrid**
RW-125	-	-2.823	-1.185	-2.579	1.617	2.161
RW-250	2.823	-	0.754	-0.776	3.520	3.693
RW-500	1.185	-0.754	-	-1.124	2.191	2.642
FZ2F	2.579	0.776	1.124	-	4.086	3.807
FZ1F	-1.617	-3.520	-2.191	-4.086	-	1.400
Hybrid	-2.161	-3.693	-2.642	-3.807	-1.400	-

Table 4. 11 Diebold-Mariano t-statistics on average loss differences alpha=0.05, Gold Price Index returns

While average losses are useful for an initial look at sample forecast performance, they do not reveal whether the gains are statistically significant. Table 4.10 and 4.11 presents Diebold-Mariano (1995) t-statistics on the loss differences, for the Gold Index and S&P500 index. Corresponding tables for the other equity return series are presented in Table 4.4 and 4.5 of the supplemental. The tests are conducted as row model minus column model and so a positive number indicates that the column model outperforms the row model. The column FZ1F corresponding to the one-factor GAS model contains all positive entries, revealing that this model out-performed all competing models. This outperformance is strongly significant for the comparisons to the rolling window forecasts, as well as the GARCH model with Normal innovations. The gains relative to the GARCH model with skew t or nonparametric innovations are not significant, with DM t-statistics 1.79 and 1.53 respectively. Similar results are found for the best models for each of the equity return series. Thus, the worst models are easily separated from the better models, but the best few models are generally not significantly different. The supplemental results analogous in both the table, but with alpha=0.025, which is the value for ES that is the focus of the Basel III accord. The rankings and results are qualitatively similar to those for alpha=0.05 discussed here.

From the outcomes in the table 4.9 and 4.10, it tends to be seen that the Rotated Gumbel GAS copula model presentations higher support proficiency than the student t GAS copula model, in which the RGG-Skew t model accomplishes the supporting productivity as high as 90.6%. While the utilization of the student t GAS copula model joined with various peripheral models doesn't show huge danger decrease. Among them, the StG-Student t model gets the most minimal positioning of supporting impact, that is, 75%. It shows that there is uneven unique reliance between unrefined gold index and S&P500 fates, and the thick-followed prospects returns circulation is deviated. The supporting technique considering the above qualities of Gold Price index and S&P500 prospects returns can accomplish higher fence proficiency.

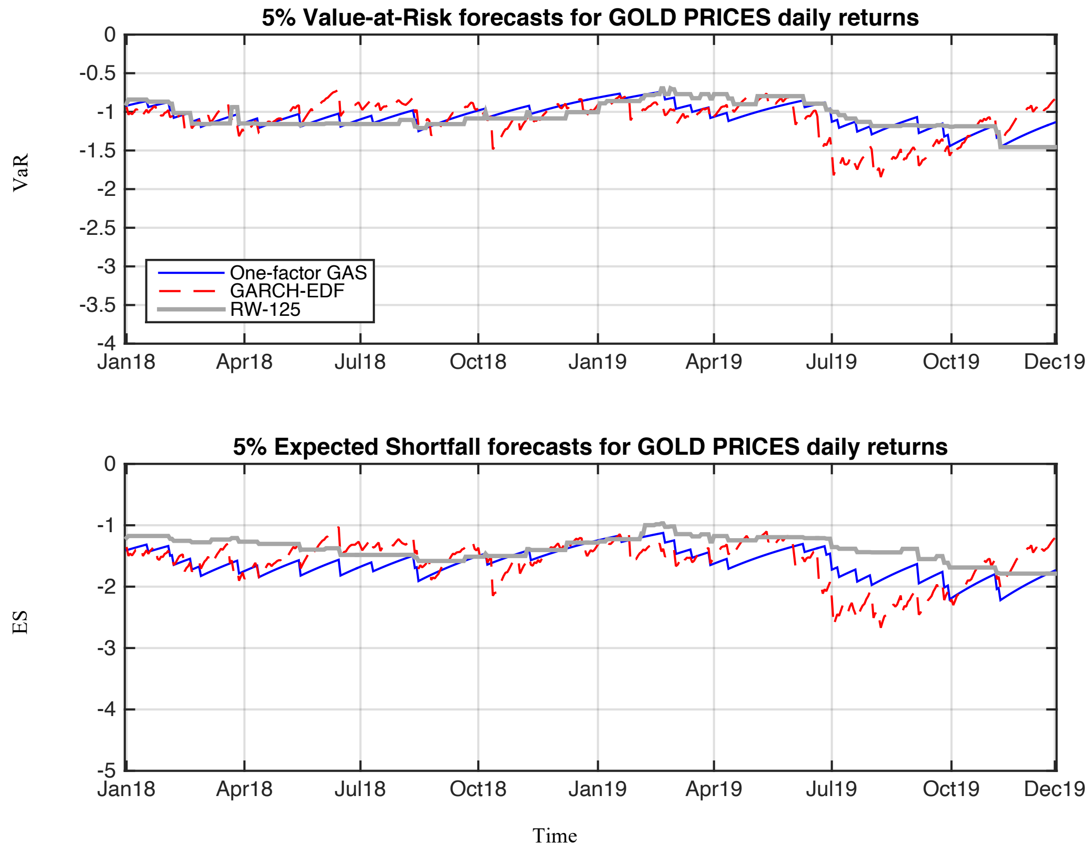

Figure 4. 13 VaR and ES for Gold Price Index

Figure 4.13 puts light on the last two years of VaR and ES results for Gold prices. It can be observed that the gold prices have remained quite stagnant during the last years. We can see that the maximum losses during the time interval is not quite significant and the worst-case scenario seems good as well.

From fig 4.9, it is instinctively observed that the tail dependence between Gold and S&P500 has commerce dramatically in addition to nonlinear dependence over time. On the other hand, the indexes confirm a strong correlation at the tail and in extreme events, it shows a strong Time Varying spill-over effect between the Gold and S&P500. The probability of synchronous slump between the markets gets greater due to the existence of tail dependence which also indicates that the tail risk is getting more contagious between markets. Therefore, it also explains that when conducting tail risk management, investors need to take in mind the impacts of extreme events on risk assessment.

4.5.3 Tail Risk Evaluation

In this section, we are going to evaluate the one-day-ahead VaR and ES of an equally weighted portfolio consist of Gold and S&P500 returns as our objective. It requires investigating the joint distribution of returns to estimate the portfolio risk. And since the best choice for capturing the heaviness of tail is skew t marginal distribution. Thereafter we will calculate the VaR and ES risk measurement with the help of the Rotated Gumbel GAS copula model and the Student GAS copula model with skew t marginal distribution for index returns on average. Fig 4.16 shows the risk variation trend. The copula simulation method is utilized to forecast risk measurements as there is no analytic formula to switch from.

At the beginning of the sample, it can be seen that the VaR ranges from about -5% to about -02% in financial crisis. At the beginning of the sample, the ES ranges about -7% and at the height of financial crisis it ranges as low as -20%. The risk estimated by Rotated Gumbel GAS copula model are lower than that which was estimated from Student GAS copula model on average for indexes return, which is stable with lower tail dependence implied from this GAS copula. Furthermore, we found from our analysis that the VaR means of S&P500 at the same confidence levels are larger than that of Gold Index no matter the returns increase or goes down. Therefore, it reveals that more risk reserves should be prepared by S&P500 market.

The coverage degree of the actual losses by the model risk value should be examined to assess the prediction accuracy under different models. Prediction performance of VaR which are estimated from different models are compared by using backtesting. The Christoffersen Likelihood Ratio Test (CLR) and the Berkowitz Likelihood Ratio Test (BLR) are used in VaR backtesting. The number of violations where true loss exceeds the predicted VaR are calculated by CLR test which includes unconditional coverage of the CLR test (CLRuc), CLR independence test (CLRind), and the joint test CLRcc. The BLR test which is based on the density calculation performs the BLR independence test (BLRind) and the tail distribution prediction (BLRtail) by calculating the inverse function of the cumulative distribution functions. Using the out-of-sample dataset at 99% confidence level, table depicts the statistical result and the corresponding p-value of forecasting performances with different models.

From Table 4.5 and 4,6 , it is clear that the StG-GED model does not pass the CLRuc test, the CLRcc test, and the BLRind test at the 1% confidence level. And also, the StG-Student t model does not pass the CLRuc test and BLRtail test at the 1% confidence level. Whereas the RGG-

Skew t model and the RGG-GED model pass both the CLR test and the BLR test. According to consequences of number of violations it is clear that the estimated effect of the Rot Gumbel copula model is considerably better than that of the student t copula model, therefore it verifies that the Rot Gumbel copula model is suitable for measuring financial risks which was the conclusion procured in the previous section.

4.5.4 Hedging for Indexes Return with GJR-GARCH-Skew t-GAS-Copula Model

Hedging is one of the key functionalities of the financial future in terms to avoid price risk. Due to the derivative products and their complexity, hedging strategy is critical and its effectivity depends upon the accurate estimation of the hedging ratio. As known the effect of hedging depends on the changes of basis and hedging of future is mainly conducted on the basis. Hedging strategy is perfect only if the basis is zero or the expected basis is achieved. The existence of perfect hedging is very rare because in real trading the basis is variable. Changes in the investment profits and losses are caused by the small probability events in the futures investment field or the thick-tailed phenomenon. Therefore, it is necessary to consider the aforementioned financial stylized phenomenon while constructing a hedging portfolio.

The joint distribution of assets is Time Varying, and the static hedging is no longer appropriate with the introduction of new information shocks. Adopting hedge strategies can lead to better risk aversion efficiency based on dynamic dependence to characterize relationships between spot and futures (Bhatia et al., 2018) Presently there is a small amount of research done on future hedging based on Time Varying copula models. Brandtner (2013) stated that the advantage of Time Varying hedging strategy is achieved from accommodating the changing joint distribution of spot and futures returns. In this section to investigate the hedge ratio and the efficiency of both indexes in the circumstances of dynamic copula based nonlinear dependence structure, leptokurtic, and asymmetric marginal distribution we will examine the performances of the GJR-GARCH-Skew t-GAS-copula model for hedging both indexes.

As per the definition of hedge ratio, the dynamic risk ratio (HR) taking into consideration the conditional variance-covariance matrix can be defined as HR = ρtσsσf/(σf). For the GAS copula models, instead of ρt; the mean value of dynamic tail correlation is used to calculate HR. Here we define the hedging efficiency (HE) as the reduction percentage of the spot variance after entering the futures hedge. It can be seen that HE is larger values correspond to higher hedging efficiency and more risks reduction of the spot variance, with a positive number between 0 and 1. The results of hedge ratio and the hedge efficiency of both the assets is been depicted in Tables 4.4 and 4.5.

This study focuses out a few challenges in copula development that seem shape the subject of encourage examination to address these impediments. One such challenge is that basic instabilities within the demonstration that may influence of results when estimating copula parameters, counting the potential sources of blunder that are inferred from information administration and model structures created by absolutely factual approach. This might lead to major issues, where a few of the copula parameters may equally fit the factual goodness-of-fit test Schepsmeier, (2016) but may in truth carry mistakes inside them to confound the overall and precision of the recreated information. This issue seems to influence the method of finding an interesting combi- country of copula parameters that are significantly prevalent to the others. Moreover, one combination of copula parameters may be either be superior than the others based on the goodness-of-fit degree or it may be more regrettable in regard to another parameter. For instance, in case a copula family is chosen agreeing to the Bayesian Data Criteria (BIC), the punishment for a two-parameter copula (e.g., student's t, BB1, BB6, etc.) might be more prominent than that based on the AIC esteem (Schepsmeier, 2016).

It is additionally worth noticing that the estimation of copula parameters depends on the period of watched information (Nguyen-Huy et al., 2018; Schepsmeier, 2016). This implies that the reliance structure between any perceptions seem change with the time calculate, resulting in diverse selection of copula for demonstrating the relationship between same objects. For instance, in our past study (chapter 2 and 3), the copula combination was distinctive in each k-fold cross-validation prepare where the dataset was split into distinctive preparing and testing subsamples. In this manner, the utilize of a satisfactory gather of tests to reflect more information about the framework behaviour is energized rather than finding the leading parameter combination which is inferred as the true representative of the framework (Schepsmeier, 2016). In expansion, according to Schepsmeier (2016) choosing the most excellent copula parameter combination may lead to an underestimation of the vulnerabilities of the complete framework. At long last, the constrained length of the data can conceivably influence the precision of the parameter estimation by expanding the uncertainties (Francq and Zakoïan, 2015). All these reasons, and others, war-rage an encourage examination to moderate the complications in selecting the most excellent copula demonstrate as well as the best parameters of the ideal copula function.

The current study too comes with common presumptions that have been detailed in distributed writing. To begin with, this thought does not account for the taken a toll of developing in investment stocks (Larsen et al., 2015). Moment, it is accepted that the minimal conveyance does not alter over the entry of time (Schepsmeier, 2016). At last, since the measurable demonstrate was developed utilizing verifiable information, this information isn't able to account for the scenarios which have not been happened some time recently. This implies the show cannot be effortlessly balanced to suit for the changes in factors such as financial changes, innovation, and development of new techniques. In this manner, in arrange to attain more strongness diversification benefits, it is imperative to join the impacts of all the costs which will happen in geological conveying the portfolio management on the basis of stocks and commodities as well as performing the show with beneath numerous anticipated scenarios.

Effectiveness of applying portfolio diversification strategy has been mainly explored in the current research for risk management in the commodity and stock sector. It has revealed that mean-CVaR is among the most famous methods for measuring down side risks that occur, which was calculated through the use of copula-based approach. Comparing the performance of the copula-statistical mode with the traditional multivariate-normal model, the former was able to carrying out modelling of joint distribution for various type of datasets in a flexible manner and even include account the non-normal distributions. Study also revealed that the hybrid copula statistical model was able to successful capture of variety of dependencies structures that were present, especially in the case where joint distribution of marginal returns exhibited a dependence of tails which were pointed out in the studies carried out earlier relating to perception and forecasting relating to Gold Price Index and S&P500 (Nguyem-Huy et al, 2017, 2018).

Also, on our investigation of commodities and stock, we concluded that VaR is the best option as it is the one that will provide the ideal economical risk-reward trade-off for those who utilize efficient frontier portfolios. This research will be a useful revelation for investors who are considering to speculate or hedge positions using commodities and stocks, and is based on the shortage of a posteriori research on the stock and commodity market. However, this document does not analyse the price breaks of 1992/2020, so we suggest that any potential structural breaks are considered in prospective studies. Our methods isolate parameters that would be of use in drawing up dependence risk and investment risk strategies aimed at potential investors, in particular when the markets are heavily fluctuating. Policymakers who wish to contribute to the decrease of systemic risks and regulators such as financial market authorities or central banks rely on such dependence and relations.

In this chapter, conductive frontier of the both the assets under the short-selling pressure is used to explore the mean-variance portfolio expansion framework. Two largest liquid and highly capitalized stock and commodity, are based on the profitable frontier, showing the maximum and minimum predicted returns among all the stock and commodities considered, respectively, are observed in Fig 4.12. Over logical asset allocation across the virtual funds, the highest Sharpe scale and highest utility can be accomplished on the profitable frontier in Fig. 4.12. In Fig. 4.13 and 4.14, we take out the short-selling constraints and conspire the profitable frontier again. The figure 4.12 represents that none of the stock now lie on the frontier.

Results of the research showed important implication for two important investment aspects in S&P500 and Gold Index, dividing the indexes carefully keeping under consideration even the external factors such as recession, financial turmoil and political aspects but the findings of the research can also be extended to other basis of stable economical and unstable economical countries. Feature of the model to calculate joint dependencies as well as analysing the potential investment stocks where diversification of portfolio can be offered to investors in optimizing their mapping of getting greater return which will result in reduction of risks. Such approach has gained importance as a broad modelling method mainly due to its multivariate joint distribution ability and the marginal return which is generated by the copula function, and then for comparison persons, evaluated with the multivariate-normal approach. CVaR criteria was calculated by using scenarios form the copula simulation methods for achieving optimization of this method. Maximizing the expected marginal return at the target levels as specific by CVaR helped to achieve portfolio optimization.

Using daily data from January 1992 to January 2020, we cover hybrid copula surrounds to model the co-dependence and portfolio value-at-risk (VaR) of commodity and stock in this paper. Evidence of strong dependencies was established among the commodity and the stock exchange with a dependency format that changes in a problematic manner. Gold index allows the best optimal and economically risk-reward trade-off substance to a no-shorting constraint for portfolio investors using the profitable frontier was found among the class of commodity and stock examined. The findings imply capable dependencies between Gold Index and S&P500, which represent the highly substance and most capitalized virtual currency. S&P500 and Gold Index are most connected to commodity with stock having the only direct dependence with Gold are observed.

Commodities are related to Stock in terms of supply characteristics and type of valuation mechanism, this paradox can partly be explained by the fact that among the category of commodities in our fragment Ciaian et al. (2018) We create portfolio VaR based on the dependencies obtained, relying on the resilience of the hybrid copula approach and the prevalence of the Student-t copula family in modelling dependence. As results show the VaR calculations closely follow the periodic returns with few violations. By matching these with results given from the same data using GARCH (1,1) distribution, we conclude that our GAS copula models and estimated shortfalls are best suited to gauge the VaR during the considered time period.

Use of portfolio distribution to downside the risk is deemed as valuable as indicated through the optimization of CVaR results as described by the corresponding efficient frontier and optimal stock allocation. Findings of the research and application in risk reduction is particular applicable for investors present in S&P500 and Gold Index given that these are located below efficient frontiers. S&P500 investors at the frontier curve was taken for explaining this phenomenon, which was able to generate significant benefit from portfolio diversification. Two optimal portfolio models were used in the current study for showing the benefit which can be derived from diversification strategy, which is an achievable tool for risk modelling and management. Portfolio allocation for stock was not the same but depended on the profitability which investors expected and the target amount of risk that was desired to be taken up.

Ability of the copula method for addressing the lower tail dependence on joint return distribution was found to be advantageous. In the case where marginal returns are not normally distributed, as was shown the case, multivariate normal model holds potential for pointing out the minimum level of downside risk that can be expected at a given target, mainly through discounting of the existence present at lower tail dependencies. Results clearly show that the hybrid copula and GAS has outperformed the Gumbel copula, given that it had allowed different variable pairs to be modelled by different copula functions. Based on the results that have been achieved and their discussion made, it can be said that yield of investors can be significantly enhanced at the same level of risk by dividing index in two that is Gold Index and S&P500 that have been identified. Results have been discussed mainly at a portfolio diversification but the method can be extended further at different levels such as other stocks and commodities. Few drawbacks are also present in the research such as failing to take into account the cost associated with brokers that are working at different places to sell the stocks to investors, which could significantly influence the modelling strategy mentioned in this paper. Need is also present to explore the cost related components that are associated with different stocks and can be explored for different indexes diversification strategy. Last potential value that can be derived for future research is exploring the spatiotemporal impact which political conditions have on marginal returns across different countries.

4.5.5 Ranking of Models:

Two comparative techniques have been used to rate and measure the variables after the results were achieved. Firstly, the rate of the best evaluation on the index, were used similarly, for both VaR and ES results. The purpose of the calculation is to determine the most efficient model with the most indices. This ranking system may, however, ignore models that regularly have decent estimates, but hardly produce the best index estimates. The second method-the average results-has been used to address this problem. Under VaR, the sum of every LR in the duration, not only for LR, was calculated while for ES the sum of actual values was calculated from Z, [Z], since the overview of external and internal factors may produce confusing outcomes. The evaluation should be capable of capturing that model being represented in individual indices, and also on average using all these attributes for both VaR and ES. To evaluate which distributions are most useful, every variant belonging to a particular distribution has statistics indicated for each duration as LR and |Z|. In order to demonstrate the absolute reliability of the models. Models in which all results are appropriate as statistically valid at a 5% confidence level were found to be more trustworthy than those which did not. The crucial significance for LR statistics at the 5% level of confidence is 3.84; for LR, it is 10.

18.31. 18.31 is extracted from $\chi210$ – allocation, since LRi ~ $\chi21 \Rightarrow$ LRi ~ $\chi210$. The value of LR i=1 was not checked but used only for specific contrast. The Z-statists were compared to the crucial 5%-confidence standard −0.7 as (Acerbi and Szekely, 2014) suggested, while |Z| and |Z| and have no critical value and function simply as resources to compare the precision of the model internally.

Regarding the copula-based portfolios, we can conclude that for all considered confidence levels, the copula is able to calculate the risk much better than the Gumbel copula. This is because the hybrid copula models the dependencies of each variable pair more flexibly than the multivariate Archimedean copula by the construction approach (Bedford and Cooke, 2002; Zhang and Singh, 2014). We also analyse the preservative ability of the two models to model the dependencies between variable pairs in order to examine this. For the three models, a comparison of simulated and observed rank-based correlation coefficients (Kendall's τ). It is obvious that, compared with the multivariate Gumbel and multivariate-normal model, the Hybrid method is able to reserve the dependencies of all variable pairs. Therefore, provided the same target expected returns relative to the copula model, the Gumbel model could overestimate the risks. Please refer to figure 4.9.

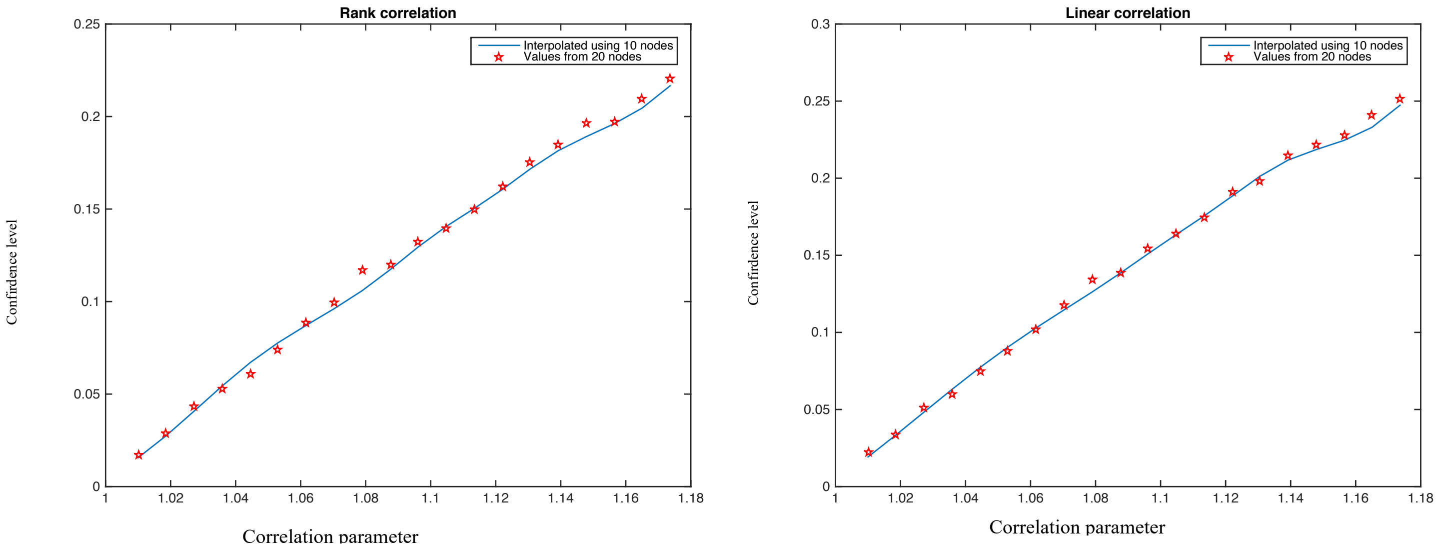

Figure 4. 14 Rank Correlation and Linear Correlation of Gold Price Index and S&P500

There's modern talk about among the specialists with respect to the enhancement of efficiency of diversification strategies in finance industry. In the worst case when an arrangement of financial turmoil occasions is exceedingly connected, it is apparent there may be no advantage of broadening. Agreeing Li (2011), we cannot broaden systematic hazard on the off chance that normal fiascos happen concurrently among an expansive number of financial losses. Some significant ideas may be drawn from the study of Xu et al. (2010) in German, expressing those systematic risks shifts of investment are not conceivable to be broadened at recession basis. Based on a study within United States, Wang and Zhang (2003) expressed that an investment system can be broadened at the international level. In the same manner, the behaviour of systematic risks of investments may be different over a worldwide scale since of the contrasts in economically stable and unstable countries (Okhrin et al., 2012). In this study, investment broadening has been inspected as a possibly compelling technique for an unsystematic system. This study is critical since risk along with correlation methodology can accomplish a suitable measure with specially required target dangers and expected returns through the proposed copula-based CVaR approach. This may be performed by altering the extent of the proportion to developing portfolio management to obtain an ideal return-risk trade-off.

In respects to the strategy, the copula- based ES-VaR model is found to be prevalent to the ordinary multivariate normal approach. It is anticipated since the distribution of the negligible returns isn't normal and our results about are in understanding with the study of (Larsen et al., 2015). However, whereas the author connected only the multivariate copulas with lower tail, our study is about utilizing copula capacities that have either lower tail or upper tail for more adaptable and appropriate depiction of information dependences. Moreover, the hybrid copula is found to be way better than the multivariate copula (as used within the ponder of Larsen et al. (2015) in demonstrating the reliance structures of the joint dissemination by reserving the dependences among variable sets. This finding reconfirms the focal points of the copulas expressed in Brechmann (2010) and found by Zhang and Singh (2014).

4.6 Conclusion

In this paper, the GJR-GARCH-Skew t model, Hybrid Copula, GAS estimations and Expected Shortfall (ES-VaR model) is utilized for catching the deviation and hefty tail impacts of the negligible returns' appropriation of the Gold Price Index and S&P500. So as to at the same time fuse the uneven and dynamic reliance structure of advantages, the GAS strategy is acquainted into copula capacities with make the boundaries time fluctuating for tail reliance of prospects returns in high measurements. In this way, we give a bound together and reliable structure by consolidating dynamic GAS copula model with fat tail followed model for describing the joint appropriation. Also, the traditional two-stage most extreme probability assessment technique is adjusted with the non-Gaussian QML assessor for hefty followed advancement mistakes. Further, under the recently developed model structure, the tail risk dependence of financial assets (Gold Price index and S&P500) market is investigated. At that point we process the time changing supporting proficiency of stock and commodity prospects under the GAS copula model with the thick tail followed minimal dispersion.

The examinations have discovered that the S&P500 and Gold Price index prospects display solid tail reliance, which demonstrates that there exist time differing overflow impacts between the volatility of S&P500 and Gold Prices in outrageous functions. A further investigation of the dynamic tail dependence between the two financial sectors uncovers that the tail reliance is unbalanced. It tends to be discovered that the time shifting copulas show improvement over the consistent copulas, which suggests that there exist dynamic copula boundaries and it creates significant consequences for the GOF of copula for both the indexes. The assessment of integrity of fit trial of GAS copula and the Skew t minimal appropriation find that the GJR-GARCH-Skew t-Rot Gumbel GAS copula model can successfully fit the multivariate joint conveyance, with the fitting exactness getting higher than that of other time changing copula models and thick-followed dissemination detail structures. Upon this premise, the VaR and ES patterns of the danger of stock and commodity portfolio and the supporting effectiveness of returns of both markets on spot are introduced. The outcomes acquired give proposals to speculators and administrators: when performing supporting technique, the GJR-GARCH-Skew t-Rot Gumbel GAS copula model can be utilized to direct the computation of supporting proportion and the execution of supporting methodologies so as to get higher productivity.

4.7 Contribution to Knowledge

The findings of this study contribute to the existing body of knowledge in three distinct ways. To get started, we are going to discuss a variety of modelling methodologies that are tailored to ES and VaR. in particular. These systems depend on the GAS system that was established by Creal et al. (2013), in addition to excellent concepts that can be found in the literature relevant to instability. Creal et al. (for additional details about this topic, check Andersen et al., 2006). in the sense that they impose parametric frameworks for the dynamics of ES and VaR., the techniques that we provide fall into the category of being semi-parametric. On the other hand, these models are totally indifferent to the dependent variable, which is a collection of return probabilities. We explicitly fine-tune the probability density function (pdf) of risks that are of concern, and as a result, we eliminate the need to express a conditional probability for return outcomes. The models that are offered in this research have a connection to the category of CAViaR models that Engle and Manganelli first presented (2004a). Because of the models that we are looking at, estimating and forecasting can now be done in a way that is both fast and straightforward. Because our method of curve fitting does not need the user to specify and compute a contingent density, we are able to remove the possibility that such a model is constructed in an incorrect manner. On the other hand, this results in a decrease in quality when compared to a density model that has been given in the correct format.

The exponential growth theory for a broad category of lively semi-parametric designs for ES and VaR is our second contribution to the area and forms our second effect. This theory is a component of the outcomes for VaR. that were proposed in Weiss (1991) and Engle and Manganelli (2004a), and it makes an attempt to draw on the recognizing results found in Fissler and Ziegel (2016) as well as the results found in Newey and McFadden's research on M-estimators. This theory is a component of the outcomes for VaR. that were proposed in Weiss (1991) and Engle and Manganelli (2004, 1994). We provide the conditions that need to be satisfied for the model coefficients of the VaR. and ES models to be consistent with one another and to be approximation normal. This is done so that the approximation normality may be achieved. In addition, we propose an estimate that is compatible with the covariance matrix for exponential growth. Through the use of a thorough Monte Carlo research that we carried out, we were able to demonstrate that the asymptotic findings do, in fact, yield realistic approximations when applied to robust modelling designs. The asymptotic theory that we existing not only has implementations for the new designs that we propose, but it also provides a basic outline that other researchers can use to design, guesstimate, and examine new models for value at risk and expected shortfall. We present this theory because it not only has requests for the new models that we recommend, but also because it is applicable to the new models that designers propose. Additionally, the asymptotic theory that we provide has applicability for the newer products that we suggest, which is something else that we have to mention.

Our biggest accomplishment is an expanded use of innovative concepts and estimating approaches in this assessment of prognostications of ES and VaR. S&P500 and Gold price indexes were used throughout the span of time beginning in January 1992 and 01 in January 2020. This analysis covers the entire period of time from 1992 to 2020. This inquiry was carried out continuously over the course of twenty-seven years, during which time it encompassed. In comparison to more conventional methods that have been gleaned from the research literature, we evaluate the efficacy of these novel models over a broad spectrum of terminal odds ratios that are relevant to risk management. We determine the best concepts for ES and VaR. by making use of tests that were published by Diebold and Mariano (1995), and we back test the ES predictions by making use of simple linear extrapolation techniques. These techniques are comparable to those developed by Engle and Manganelli (2004a) and Nolde and Ziegel (2017). These scholars' previous work provided as a source of motivation for the development of these different tactics.

As a main element of the downstream refined products cost, the Gold index and S&P500 returns have displayed volatility with extensive volume, making the Gold Index and S&P500 returns become an important financial instrument for risk evaluation used in this thesis. The study of both indexes' volatility is one of the significant importance for related companies and investors in the financial markets. The large volatility in financial markets is caused by linkage effects among Gold Index and various stocks hence markets tend to cause risks transmission.

The research gives three commitments to the writing. To begin with, our investigation gives another comprehension of the danger overflow between budgetary market vulnerability and the gold market by considering securities exchange and stock market vulnerability contrast. Consequently, they can comprehend their unmistakable impacts on the market by recognizing the danger and risk involved in moving component. Second, as opposed to utilizing the GARCH model, they offered another econometric apparatus to address the tail circulation imbalance that exists in monetary market vulnerability and the S&P500 and the Gold Price market alongside a direct assessment measure. Third, by stretching out the CVaR way to deal with potential gain and drawback hazard overflow, they further investigated extraordinary vulnerability development in both the market. Rather than past investigations, they distinguish the greatness and direction of danger overflow by utilizing the Kolmogorov Smirnov test. The research along these lines gives the main hybrid copula model of overflow between vulnerability changes and both returns as far as outrageous economic situations.

The monetary fates market is a nonlinear complex unique framework and the outrageous tail between two indexes shows solid co-developments. Examining the extraordinary tail between index markets and the risk reliance structure between finance sectors is of incredible hugeness for speculators and controllers to fortify risk the board, maintaining a strategic distance from the event of money related emergency. Finding the proper model that precisely portrays the connections of these factors is likewise an essential for leading nonlinear tail dependence.

The ongoing writing on transmission impacts is as yet worried about the effect of functions in financial factors, or about the distinguishing proof of components that spread risk among existing indexes investment and with the emergency, too. In any case, this examination grows the writing giving uncovering answers to a perplexing period. It is imperative to fortify the period examined speaks to a characteristic investigation to contemplate the time priority and association of political, monetary and, worldwide functions in a single market.

4.8 Discussion

Stock markets play a vital role in the economic growth and development of any country. It organizes and collects the surplus money from investor party and channels them into productive means. An efficient market works as an escalation towards industrialization and economic development. Investors has always showed interest in gold prices investments that play a vital role and therefore many arguments have been raised for the analysis of investment in the commodity markets. The S&P500 Index data was one of the unique data which has been analysed by most of the researchers therefore this research will be beneficial for people investing in the international Financial Markets. There are economy wide factors such as interest rates, tax rates, laws, policies, wages, and governmental activities that affect the stock market by most and cannot be ignored. However, there are some macroeconomic variables such as Inflation, gross domestic product (GDP), national income, and unemployment levels that affects the stock prices in one way or the other and continuously challenging Efficient Market Hypothesis (EMH). Therefore, the area remains favourite for the researchers and has spaces for organizing such studies.

The first stock market was formed in 1773 in London and after industrial revolution in 1800s and in late 1860's commodity market was evolved in America. When the industries increased there was felt a need for high level of capital provision, for which the concept of stock exchange was developed. In the same way the need for trading of commodities like Gold, Wheat, Silver and Corn took place in 1864 through the standard instruments on the Chicago Board of Trade (CBOT). Hereafter the stock market and commodity markets were developed and are considered as an economic and financial indicator in most of developed and developing countries (Al-Raimony and El-Nader, 2012). To use the word stock index as a financial indicator is subject to controversy. Per Fama (1965) an efficient market is that market in which the stock prices reflect all the available information in the market.

In this thesis, we are remitting the research on the prices of stock and index market, called S&P500 and Gold Price Index, the one common trait of all stocks and index is the volatility of their prices which makes the investors to take certain actions such as to hedge against downside losses and to forecasts losses using volatility measures such ARCH/GARCH, expected shortfalls and Value at risk (VaR) to minimise the risk of loss. Since we are using stock and index both in this research, we commence by explaining S&P500 which is a stock market index, created to bring trading online which focuses mainly on technological, retail and healthcare-based companies but not financial business like commercial or financial banks. S&P500 is also known as the second largest stock exchange in the world with more than 83% of the total domestic U.S. equity market capitalization enriched with a predominant technological set of layouts, which helps in making the companies more organised and well productive (spglobal, 2022). On one hand, S&P500 is the modern modified index which is used for the capitalization of the stock in a very technologically accurate manner. Whereas, on the other hand Gold index is one of the biggest market in commodities. The prices of the Gold have always been of quite surprise for the investors. Gold is one of the oldest commodities which has been used as one of the common trading tools since quite a long time. This commodity has been of great interest due to its exclusivity and value. Since, stock and indexes restore their volatility to operate in different types of conditions. Measuring the conditional heteroscedasticity is a good way of measuring the basic risk involved in the stocks and commodity indexes since it demonstrates volatility which is signifies about the fluctuations of indexes' prices. The presence of volatility further identifies risk.

During the last decades, financial organisations, as well as regulators, use Value-at-Risk (VaR) in terms of determining the market risk that is associated with any financial framework (Nieto & Ruiz, 2016). It is important for the financial organisations to estimate the proper market risk to determine the overall success as well as sustainability of their stock investments. Value-at-Risk (VaR) models highlight the fact that how can the value of a portfolio be decreased over a period of time. VaR summarizes the worst expected loss over a target horizon and within a given confidence interval (Jorion, 1996). The risk management models termed as ARCH GARCH, constant Copula, Time Varying Copula and VaR model assists the financial regulators to estimate the proper loss in the assets. Financial organisations can use the models in term of analysing the financial database which will assist the financial regulators to understand how things can go bad in the financial assets of the stocks and indexes. Through using these models, financial markets can be able to regulate the daily day and intraday financial database which assist the Financial investors to understand the financial strength and drawback of their choice of investment markets. By the analysation of the practical risk measures for any investments these models assist the organisation to analyse how they are safe in the financial condition in terms of dealing with the international financial market. Moreover, the use of these models' adept to recognise the loss and asset returns of an organisation. The rectification of the daily day portfolio, enables the models to assist financial investors to understand the financial trend in the stock market which is important for operating proper transaction and financial functions.

Chapter 5

Conclusion and Further research

5.1 Conclusion

We conclude that the research is based on three empirical chapters. First chapter measures volatility of commodity gold index along with the stocks S&P500. The results suggest the existence of volatility and predict the most realistic and meaningful outcomes for the investors, policy makers and financial regulators. The chapter provides with good basis of measuring the risk for further assessment. The use of the model ARCH and GARCH along with some basic measurement of VaR suggest that investors and regulators can measure volatility using these models to capture the existence of fluctuation between Gold index and S&P500. The optimal results are from t distribution of ARCH and GARCH. The second empirical chapter measures time varying copula. Correlation gives an estimate that if one asset will go down will the other one goes down or up. Correlation helps in identifying risk further as two variables are negatively correlated one variable decreases as the other increases and vice versa. Negative correlation between two investments determines the risk management to diversify, mitigate the risk associated with a stock or commodity. From the time interval of 1992 to 2006 it can be seen that the correlation decreased. However, prior to 2008 the correlation increased which suggest that during financial turmoil the commodity and stock were correlated. Again, this could be dependent on the financial crisis. After 2009, there was again a decline in the correlation. Finally, the last empirical chapter measure the ES-VaR model. Financial investment for individuals or banks needs to be balanced adequately to ensure better returns for the invested amount. More necessary is the fact that the investment must be made in such a way that the Risk in the assets invested must be minimal. Market conditions have a large effect on the Risk associated with investments, and therefore, understanding the market conditions for various forms of assets and investments must be understood, along with the Risk associated with the elements in the stocks and commodities. This chapter is beneficial for investors and financial regulators as they would be able to answer the question of the worst-case scenario and losses.

5.2 Further Research

This part briefly reviews the important studies that have been carried where applied methods are being highlighted and gold is kept as a major domain asset. The study carried by Alameer et al. (2019) entitled “the effect of fluctuation of gold price on stock prices” found that ARCH effect is in both Gold price and stock market and moreover, both the variables were affected by the shock of their own assets. GARCH model used in different multivariate by Arouri et al. (2012) shows that there is significant return and volatility cross effects between gold prices and stock prices in China. More specifically in order to predict future stock return of Chinese market past GR should be used to explain the dynamics of conditional return and volatility of Chinese stock market. The study of gold into a portfolio Chinese stock market improves the risk-adjusted return which proves that amongst BEKK-CCC/DCC, diagonal BEKK and VAR-GARCH, the VAR-GARCH model works better than the other. In addition, the study carried by Mishra (2010) using Granger Causality test found that there is a casual relationship between the gold price and stock market return in India and also it can be used for predicting each other's assets. EWMA/Risk-metrics (1996) presented a less complex approach to volatility forecasting. The version, referred to as both EWMA or Risk-metrics after its authors, it is an easier version to comprehend the GARCH which eliminates the need for coefficient estimations.

Barone-Adesi et al. (2008) carried out analysis from another viewpoint by applying the Vector Autoregressive VAR (1)-Bekk-AGARCH (Baba, Engle, Kraft, and Kroner) specifications when examining the spill overs that arose from Bitcoin particularly focusing on technology and energy companies precisely in the period August 2011 to February 2018. This proves that spill over effect is present in the technology companies on bitcoin market. Bidirectional asymmetric shock spill overs were also found between equity indices and bitcoin. Weak linkage that is present between bitcoin and stock indices present opportunity of profitable trading.

The use of high-frequency data could be expanded to other classes of models as well as to other measures of intraday volatility (such as bi-power variation, quadratic variance, and Markov chains). Using Monte Carlo simulation methods, intra-night volatility measurements can be simulated and incorporated into new realized volatility models. Several types of data could be used in the studies, such as commodity data (oil, gold, etc.) or exchange rates, as well as multi-period horizon forecasts.

Head part augmentations might be considered to bigger classes of stocks, that might be controlled to fewer factors as per the most noteworthy pertinent head parts. In that capacity, a potential application is considering the 500 stocks intensifying the S&P list, to apply the PC calculation to every one of the 500 factors, finding the 500 symmetrical head parts and afterward choosing just those with the most noteworthy effect on the underlying factors. Thusly, it might acquire another file, with many less factors than S&P500, however close concerning importance, with which it could be additionally worked. It could be shaped another arrangement of stocks with the new factors to which the new PC-models might be applied to track down their change covariance lattice, and thusly to track down their instability.

Added intranight volatility measures to bivariate modelling can enhance it. Some new models may be proposed, such as models that include day and night, as well as estimates of intranight and intraday volatility. At long last, the ongoing work could be reached out by assessing different univariate and multivariate GARCH models with Bayesian insights methods. Further exploration could likewise incorporate expansions of utilizing high-recurrence data, or of night instability data to other multivariate GARCH models, as VEC, BEKK, CCC, TVC and DCC models, and the work of new improvements like semi-parametric assessment, more adaptable DCC and factor models, limited combinations of GARCH models.

Frequency dependence approach, DCC-GARCH and CCC-GARCH was applied by Chan et al. (2019) for checking the hedging capabilities in the period between October 2010 to October 2017. Bitcoin proved to be a strong hedging tool against the Euro-Index, Shanghai A-Share, TSX Index and Nikkei Index (Beneki et al., 2019). Contrary researches are also present as indicated by Al-Yahyaee et al. (2018) that Bitcoin is not a safe-have due to its weak correlation with stocks, commodities and bonds in normal as well as distressed periods. Statistical properties of Bitcoin were explored by Lahmiri and Bekiros (2018) through the use of 1-min data between January 2014 to December 2106 through the use of MF-DFA, GARCH and RGARCH model. Results obtained from the research indicate that prices of Bitcoin indicate a multifractality that emerges from temporal correlation as well as fat-tailed distribution which indicated several inefficiencies present in the Bitcoin market. Little impact was seen on the Brexit incident on bitcoin. Heavy tailed GARCH and GAS models were used by Troster et al. (2019) on predictive conditional density for measuring returns earned from Bitcoins. Several benefits were discovered in the heavy-tailed GAS models such as the coverage of risk derived from bitcoin as well as goodness-of-fit. Chan et al. (2019) explored the hedging capabilities of bitcoin which revealed that hedging capabilities of Bitcoin s strong aged Euro Index, Shanghai Index, S&P, TSX index and Nikkei.

Chapter 6

Summary and Contribution to Knowledge

6.1 Summary

The thesis proposed to offer some insights on the volatility forecasting topic, by addressing to three main objectives. The first is to measure the volatility of commodity and stock by utilising univariate ARCH and GARCH model. The purpose of measuring the volatility in the first empirical chapter is to identify the ups and downs in the Gold prices and S&P500 which will identify the volatility of both the indexes. Volatility is one of basic measure to identify the existence of risk. The first empirical chapter also include some of calculations of basic VaR. This is to further stress the existence of risk and some measures to mitigate the worst-case scenario. The second chapter establishes the interdependence between the two variable which is the bivariate time series modelling. This chapter focuses on the investigation of asymmetric conditional dependence between gold prices and S&P500 to access the impact of the indices on each other using Copula approach. The chapter begins with proposing methods for the optimal model selection while constructing the conditional margins. By the use of time-varying copula the join conditional distribution is modelled, where generalised autoregressive score (GAS) model of Creal et al. (2013) is utilised to measure the evolution of copula parameters. Upper and lower parts of bivariate tail is estimated to capture the asymmetric property. The results suggest that conditional dependence between the two variables is strongly time-varying.

Though the chapter does not cater of measuring the pre and post crisis but the results clearly demonstrate the existence of financial contagion between the two markets during the time period prior to 2008. Results also demonstrates slightly stronger bivariate upper tail, which further suggests the conditional dependence of the variables return is more significantly influences by positive shocks in gold prices and S&P500. We further confirmed the findings by a test of asymmetry which further stresses on the slight difference between the upper and lower joint tails. The last empirical chapter focuses on the use of ES-VaR model proposed by Patton, Ziegel and Chen (2018). Since, the use of Expected Shortfall along with VaR is less significantly used in researches, this model stresses to measure the worst outcomes at bad times. This chapter adds to Patton, Ziegel and Chen (2018) which suggests that implementation of the third Basel Accord in coming years, will stress the risk managers and the regulators to focus on expected shortfall (ES) as a measure of risk, which complements and to a partial extent substituting emphasis on Value-at-Risk (VaR). From recent results of (Fissler and Ziegel, 2016); Patton, Ziegel and Chen (2018) has proposed this new dynamic model for ES and VaR. By applying the model on gold prices and S&P500 we can see the expected shortfalls and worst-case scenario quite significantly. It can be seen from the results that gold prices seemed to be a good choice in a portfolio for financial investors to minimise the risk of their investment from other stocks during all times. Overall, the thesis contributes to knowledge that volatility alone is not sufficient in assessing risk and interdependence is good to measure the dependency of one variable over the other while investing in commodity or stock or both. Lastly, the use of ES-VaR further enables the financial regulators and investors to measure risk in worst case scenario and worst outcomes forecasts to mitigate their losses.

6.2 Findings of the Thesis

The Thesis is based on the main three questions proposed in chapter 1. The findings suggest answers to these questions as follow:

Question 1 (Chapter 2): What are the different kinds of volatility measures? How volatility is effective in measuring risk? What is the volatility of S&P500 and Gold Price Index? Why volatility alone is not a good indicator of risk?

The finding for the chapter 2 proposes a VaR model technique, by using parametric and non-Parametric techniques which include VaR calculations, Expected shortfall, Historical VaR ARCH GARCH, GJR GARCH and constant copula model, for estimating VaR for Gold Prices index and S&P500 Index. Empirical results demonstrated that the methodologies have certainly measured volatility (ARCH GARCH, GJR GARCH) in estimating the existence of risk. In terms of measuring accurate volatility, ARCH and GARCH models have demonstrated a good standing of univariate methods for measuring the sudden ups and downs in the returns of gold prices and S&p500.

The factors of risk are the turmoil periods in which the shifts in the market are unpredictable. On the other hand, the volatility of assets is unpredictable and the VaR techniques have suggested that risk in certain quantity will mitigate losses. The theoretical aspects of parametric and non-parametric VaR techniques are good for understanding but practical implementation and use.

Question 2 (Chapter 3): Does the prices of S&P500 depends on the changes in the prices of Gold price? What is the correlation between the two indexes? Will sudden rises during different time intervals will affect either of the indexes? How independent are both indexes? Which market is safer choice for investing in for a profitable gain using the Time Varying copula?

In fact, our result of chapter 3 showed that there was extreme reliance on a tail with proof of an asymmetrical effect in lower and upper quantiles. Such proof of predictability has not been previously reported, from the option-implied volatility of S&P500 to that of gold price index in particular amounts and regimes of cross volatility and provides a nice extension to some earlier researches. The relationship between stock and commodity market suggests to be neutral and mainly depends on the condition of the external factors like the shifts in economy and financial recessions etc. Financial market participants frequently manage many financial assets at the same time in the financial world. In practise, this is accomplished by diversifying across multiple stock markets or asset classes. Asymmetric Conditional Dependence aims to measure the correlation between competing stock markets to more clearly understand recent trends. In this empirical chapter We run an asymmetrical conditional dependence analysis between the stock market and commodity index in S&P500and Gold prices. We use the time-varying copular. Patton (2006) theorized that the time-varying copula model should consider both the past and historical parameters to explain the current parameters. Once the time-varying copular parameters have been applied, the correlational coefficient can be measured. In the case of comparing the stock market in USA to that of commodity market we observe a decrease in correlation leading up to the 2008 financial crisis. This correlation can be seen as S&P500 was more open to "foreign investors" where Gold prices had fewer stock devoted toward "foreign capital." The research further signifies the importance of tail dependence. Tail dependence is a prime factor in measuring the shift of financial benefits. In the ongoing process of calculating the asymmetric dependence, it is crucial to find the upper and lower

Question 3 (Chapter 4): How does ES-VaR relate to investors' risk management? What is the effectiveness of value-at-risk (VaR) and Expected Shortfall (ES) in measuring the uncertainty involved in Gold prices and S&P500?

The findings of chapter 3 suggest that among the suite of tried copula-based models, the hybrid copula in this consider is found to be a prevalent in capturing the tail conditions compared to the other multivariate copula models examined. There are numerous complex variables influencing the investment of Gold and consequent investors like counting cost variances, government approach and portfolio management extremes. Portfolio enhancement is distinguished as a potential risk adjustment and choice back instrument that might help makers to decrease ominous money related impacts due to the variability volatility of the stocks, as associated with political varieties. There has been constrained investigate performed on the viability of this procedure. This chapter findings proposes a modern measurable approach to explore whether the financial turmoil of investing portfolios over stock markets might possibly decrease monetary dangers for master spread within the stock markets. A suite of well-known and measurably vigorous instruments connected within the budgetary division based on the well-established factual speculations, comprised of the Value-at-Risk (VaR) and the joint copula models were utilized to assess the adequacy risk involved in investing on stocks and commodities. VaR and copula measures is used to benchmark the misfortunes (i.e., the drawback chance), whereas the copula work is utilized to show the joint conveyance among negligible returns (i.e., benefit in each stock). The VaR improvements show that portfolio expansion can be a doable agrarian hazard administration approach for Gold Stock portfolio supervisors in accomplishing their advanced anticipated returns whereas controlling the dangers (i.e., sudden financial turmoil and political risks). Advance, in this think about, the copula-based VaR demonstrate is seen to superior mimic extraordinary misfortunes compared to the ordinary multivariate-normal models, which think little of the least chance levels at a given target of anticipated return. The findings suggest that copula measurement shows effective and practical results and that the investment organizations should use this for mitigating risks.

The display consider gives inventive arrangements to Copula GAS VaR approach chance administration with progressed factual models utilizing stock markets as a case consider locale, too with broader suggestions to other districts were investing the stocks may be optimized through copula-statistical models.

For illustration, the fluctuation metric may be a symmetrical degree that does take into thought the course of the co-movement. Limiting the fluctuation drawback, the risk in a way appearing the same as the high volatility risk of the portfolio return dissemination. Usually, an issue since a resource that encounters superior than the expected return is regarded to be an unsafe situation relative to resource that's suffering from a lower than anticipated return. To address this issue, change local risk-based measures such as the Value-at-Risk (VaR) have been presented in this chapter and the results show the superiority of hybrid Copula technique along with GAS. The results show practical results and good findings. The ES-VaR approach along with copula makes the findings quite clear and this technique is most superior.

6.3 Contribution to Knowledge and Implications

The risk of a commodity or stock refers to the chance of financial loss due to the joint movement of systematic economic variables such as interest, exchange rates and commodity prices. Quantifying risk is significant to financial regulators, policy makers and investors in assessing solvency and to risk managers in allocating scarce capital. Furthermore, risk is often centrally faced by financial institutions. Value-at-risk (VaR) is a valuable risk measure broadly used by financial institutions all over the world. VaR is admired among researchers, practitioners, regulators and risk managers of financial institutions. VaR has been widely used for to measure risk exposure in developed markets like of the US, Europe and Asia.

Regarding the policy implications, we are using our research as useful tools for commodity and stock diversification, as well as for tail or catastrophic event coverage, in particular to support investors and risk managers. Basically, our empirical studies can be used by computational finance practitioners, financial regulators and investors in the formation of tail and quantile trade strategies. Consequently, they are able to take into account the implicit heterogeneity of insecurity between Gold Price Index S&P500 Index and avoid potential losses arising from an unfairly widespread assumption that Gold price Index and S&P500 stock markets have homogenous market types.

First empirical chapter hypothesis recommends that the investment enhancement procedure might help investors in decreasing the impacts of the variabilities confronted in regard to the volatility of the stock related with financial variabilities and the changes in other sorts of components (Bradshaw et al., 2004; Mishra et al., 2004). This implies that investing frameworks and strategies are diversified over space to decrease the effect of systemic dangers. Volatility isn't necessarily a bad thing; it can occasionally create entry possibilities for investors to profit from. Investors who feel markets will perform well in the long run might benefit from lower market volatility by purchasing extra stocks in companies they like at cheaper prices. When a stock or commodity increases rapidly, the procedure is the same. Investors might take advantage of this by selling their holdings and investing the cash in other sectors with better potential. Investing when markets are volatile, and values are lower having the potential to provide investors with excellent long-term profits. The first empirical chapter is beneficial for the investors, policy makers and financial regulators to determine the volatile during the time period 1992 to 2020. But since, it is critical to consider the same in the long run. Long-term investors are less worried with volatility than short-term investors. Therefore, the chapter emphasises on the three factors which are challenging for the investors, financial regulators and the policy makers to access. The first is the unstable time period in the market - It's nearly hard to anticipate when a market will reach its top or bottom. Attempting to 'time the market' exposes investors to the risk of purchasing high and selling low. During volatile times, improper timing can increase losses, which is why investors would be better off sticking the course than than attempting to time things incorrectly. The second is the significant impact of the best days - Stock markets tend to correct after three bearish waves, according to history. This means that exiting investors may lose out on the greatest recovery days and most appealing buying chances, which can have a big impact on long-term profits. If policy makers, investors and the financial regulators take a long-term view, staying involved when markets are tumultuous usually pays off. The last factors are successful businesses require time- When economic conditions slow or market volatility rises, quality companies with good fundamentals tend to do better. Investors may be better off weathering the storm because these companies often emerge stronger, even if it takes time for the stock price to reflect this. Similarly, the stock values of rising companies or the prices of the commodity performing well can get ahead of themselves and rise at an unsustainable rate. As prices vary, investors can take advantage of cheap opportunities to invest in a rising company or commodity in this case it is the S&p500 and gold process and then wait for long-term growth. The chapter focuses on the most important thing to remember is that market volatility is natural, and it should not be used to determine whether or not to abandon your investment. Understanding volatility and its causes can help investors take advantage of the investing possibilities it creates, resulting in higher long-term returns.

Second empirical chapter focuses on accessing the time varying copula. In times of crisis, stock and commodity markets are often more volatile for financial instruments than when financial markets are considered stable. As a result, investors may lose more money than they intended. Even though basic volatility models like ARCH, GARCH and risk model like basic VaR do not capture market dynamics, it is essential that financial institutions deliver reliable financial market information. This information is fed into the models by risk managers. When models are unable to completely reflect market shifts, it might lead to risk underestimating. Several simulations using VaR models have been conducted to several crises in recent decades in order to estimate the VaR. The models produced varying findings, some of which were more accurate than others, due in part to the various financial instruments used and in part to the various time factors. This thesis adds information to this discussion as other financial instruments have been studied. To narrow the problem even more, the time varying copula has been investigated to see which correlation better during the financial time period utilised for the research. This will further help the investors to further access the relationship between the stock and the commodity.

The final empirical chapter used the ES-VaR model. The largest loss that may be avoided with a certain probability within a specific time horizon is known as Value-at-Risk (VaR). VaR has grown in relevance as a primary risk indicator. Its popularity stems from the fact that it is very intuitive, and its numerical values are easier to grasp than other risk metrics. Another reason is because regulators have approved it in the Basel II and Basel III agreements. Although conceptually easy, calculating the VaR can be difficult. Because this risk measure concentrates on infrequent events, there are only a few historical observations on which to calibrate models. Parametric distributions, on the other hand, appear to function well for most of the distribution but not so well for the tails. Along with VaR ES which is the expected shortfalls has been utilised. This further gave the results of the worst-case scenarios. This chapter further adds to the contribution to knowledge by providing sufficient knowledge to the investors, policy makers and the financial regulators to access and utilise the models to measure risk in different time intervals to get the best for their investments or even to take good decisions.

6.4 References

Aas, K., 2016. Pair-Copula Constructions for Financial Applications: A Review. *Econometrics*, 4(4), p.43.

Aas, K., Czado, C., Frigessi, A. and Bakken, H., 2009. Pair-copula constructions of multiple dependence. *Insurance: Mathematics and Economics*, 44(2), pp.182-198.

Aatola, P., Ollikainen, M. and Toppinen, A., 2013. Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. Energy Economics, 36, pp.380-395.

Abad, P. and Benito, S., 2013. A detailed comparison of value at risk estimates. *Mathematics and Computers in Simulation*, 94, pp.258-276.

Abbas, F. and Awan, H., 2017. What Determines Health Status of Population in Pakistan? *Social Indicators Research*, 139(1), pp.1-23.

Acerbi, C. and Tasche, D., 2002. Expected Shortfall: A Natural Coherent Alternative to Value at Risk. *Economic Notes*, 31(2), pp.379-388.

Acharya, V. and Carpenter, J., 2002. Corporate Bond Valuation and Hedging with Stochastic Interest Rates and Endogenous Bankruptcy. *Review of Financial Studies*, 15(5), pp.1355-1383.

Adrian, T. and Brunnermeier, M., 2016. CoVaR. *American Economic Review*, 106(7), pp.1705-1741.

Adrian, T., Etula, E. and Muir, T., 2014. Financial Intermediaries and the Cross-Section of Asset Returns. The Journal of Finance, 69(6), pp.2557-2596.

Aepli, M., Füss, R., Henriksen, T. and Paraschiv, F., 2017. Modelling the multivariate dynamic dependence structure of commodity futures portfolios. *Journal of Commodity Markets*, 6, pp.66-87.

Aggarwal, R., Inclan, C. and Leal, R., 1999. Volatility in Emerging Stock Markets. *The Journal of Financial and Quantitative Analysis*, 34(1), p.33.

Akbar, M., Iqbal, F. and Noor, F., 2019. Bayesian analysis of dynamic linkages among gold price, stock prices, exchange rate and interest rate in Pakistan. *Resources Policy*, 62, pp.154-164.

Akbar, M., S. Ali and M.F. Khan. (2012). The relationship of stock prices and macroeconomic variables revisited: Evidence from Karachi Stock Exchange. African Journal of Business Management, 6(4), 1315-1322.

Akgül, I. and Sayyan, H., 2008. Modelling and forecasting long memory in exchange rate volatility vs. stable and integrated GARCH models. *Applied Financial Economics*, 18(6), pp.463-483.

Aktham M. 2003. Causal Relations among Stock Prices and Macroeconomic Variables in the Small, Open Economy of Jordan. Economics & Administration 17: 3-12.

Alexander, C. (2009) Market risk analysis, value at risk models. John Wiley & Sons.

Al-Raimony, A. and El-Nader, H., 2012. The Sources of Stock Market Volatility in Jordan. *International Journal of Economics and Finance*, 4(11).

Alqaralleh, H. and Canepa, A., 2022. The role of precious metals in portfolio diversification during the Covid19 pandemic: A wavelet-based quantile approach. Resources Policy, 75, p.102532.

Al-Yahyaee, K., Mensi, W. and Yoon, S., 2018. Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters*, 27, pp.228-234.

Alabed, M. and Al-Khouri, R., 2008. The pattern of intraday liquidity in emerging markets: The case of the Amman Stock Exchange. *Journal of Derivatives & Hedge Funds*, 14(3-4), pp.265-284.

Alameer, Z., Elaziz, M., Ewees, A., Ye, H. and Jianhua, Z., 2019. Forecasting gold price fluctuations using improved multilayer perceptron neural network and whale optimization algorithm. *Resources Policy*, 61, pp.250-260.

Alareeni, B.A. and Hamdan, A. (2020), "ESG impact on performance of US S&P 500-listed firms", Corporate Governance, The International Journal of Business in Society. Vol. 20 No. 7, pp. 1409-1428.

Allen, D., Singh, A. and Powell, R., 2013. EVT and tail-risk modelling: Evidence from market indices and volatility series. *The North American Journal of Economics and Finance*, 26, pp.355-369.

Alcock, J. and Satchell, S., 2018. Assymetric Dependence in Finance. Somerset: John Wiley & Sons, Incorporated.

Aloui, R., Gupta, R. and Miller, S., 2016. Uncertainty and crude oil returns. *Energy Economics*, 55, pp.92-100.

Aloui, R., Hammoudeh, S. and Nguyen, D., 2013. A Time Varying copula approach to oil and stock market dependence: The case of transition economies. *Energy Economics*, 39, pp.208-221.

Amadeo. K. (2022) The S&P 500 and How It Works. Available at: https://www.the-balance.com/what-is-the-sandp-500-3305888.

Amaresh, M., Anandasayanan, S. and Ramesh, S., 2020. Macro-Economic Variables and Stock Market Performance: Empirical Evidence from Colombo Stock Exchange. *Vidyodaya Journal of Humanities and Social Sciences*, 05(02), pp.106-118.

Andersen, T., 2001. The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1), pp.43-76.

Andersen, T., Bollerslev, T. and Diebold, F., 2007. Roughing It Up: Including Jump Components in the Measurement, Modeling, and Forecasting of Return Volatility. *Review of Economics and Statistics*, 89(4), pp.701-720.

Andersen, T., Bollerslev, T., Christoffersen, P. and Diebold, F., 2005. Volatility Forecasting. *SSRN Electronic Journal*.

Andersson, M., Krylova, E. and Vähämaa, S., 2008. Why does the correlation between stock and bond returns vary over time? *Applied Financial Economics*, 18(2), pp.139-151.

Ang, A., Boivin, J., Dong, S. and Loo-Kung, R., 2011. Monetary Policy Shifts and the Term Structure. *The Review of Economic Studies*, 78(2), pp.429-457.

Angelidis, T., Benos, A. and Degiannakis, S., 2004. The use of GARCH models in VaR estimation. *Statistical Methodology*, 1(1-2), pp.105-128.

Arouri, M., Jouini, J., Nguyen, D.K., 2011. Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. J. Int. Money Finance 30, 1387–1405.

Arouri, M., Jouini, J. and Nguyen, D., 2012. On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. Energy Economics, 34(2), pp.611-617.

Artzner, P., Delbaen, F., Eber, J. and Heath, D., 1999. Coherent Measures of Risk. *Mathematical Finance*, 9(3), pp.203-228.

Aussenegg, W., Resch, F. and Winkler, G., 2011. Pitfalls and remedies in testing the calibration quality of rating systems. *Journal of Banking & Finance*, 35(3), pp.698-708.

Babazadeh, H. and Esfahanipour, A., 2019. A novel multi period mean-VaR portfolio optimization model considering practical constraints and transaction cost. *Journal of Computational and Applied Mathematics*, 361, pp.313-342.

Badshah, I., 2017. Volatility Spillover from the Fear Index to Developed and Emerging Markets. *Emerging Markets Finance and Trade*, 54(1), pp.27-40.

Baele, L., Bekaert, G. and Inghelbrecht, K., 2010. The Determinants of Stock and Bond Return Comovements. *Review of Financial Studies*, 23(6), pp.2374-2428.

Balcilar, M., Bouri, E., Gupta, R. and Roubaud, D., 2017. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, 64, pp.74-81.

Balcilar, M., Ozdemir, Z.A. and Ozdemir, H., 2021. Dynamic return and volatility spillovers among S&P 500, crude oil, and gold. International Journal of Finance & Economics, 26(1), pp.153-170.

Balcilar, M., Ozdemir, Z.A., and Ozdemir, H., 2019. Dynamic return and volatility spillovers among S&P 500, crude oil, and gold. International Journal of Finance & Economics, [e-journal] 26(1), pp.153-170. https://doi.org/10.1002/ijfe.1782

Balcılar, M., Demirer, R., Hammoudeh, S. and Nguyen, D., 2016. Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. *Energy Economics*, 54, pp.159-172.

Balcombe, K. and Fraser, I., 2017. Do bubbles have an explosive signature in markov switching models? *Economic Modelling*, 66, pp.81-100.

Bali, T., 2003. An Extreme Value Approach to Estimating Volatility and Value at Risk*. *The Journal of Business*, 76(1), pp.83-108.

Barber, A., 2015. Bitcoin and The Philosophy of Money: Evaluating the Commodity Status of Digital Currencies. *Spectra*, 4(2).

Bariviera, A., 2017. The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, 161, pp.1-4.

Barone-Adesi, G., Engle, R. and Mancini, L., 2008. A GARCH Option Pricing Model with Filtered Historical Simulation. Review of Financial Studies, 21(3), pp.1223-1258.

Barrdear, J. and Kumhof, M., 2016. The Macroeconomics of Central Bank Issued Digital Currencies. *SSRN Electronic Journal*.

Barriopedro, D., Fischer, E., Luterbacher, J., Trigo, R. and Garcia-Herrera, R., 2011. The Hot Summer of 2010: Redrawing the Temperature Record Map of Europe. *Science*, 332(6026), pp.220-224.

Bartram, S., Taylor, S. and Wang, Y., 2007. The Euro and European financial market dependence. *Journal of Banking & Finance*, 31(5), pp.1461-1481.

Basel Committee on Banking Supervision, 2010, Basel III: A Global Regulatory Frame- work for More Resiliant Banks and Banking Systems, Bank for International Settlements. http://www.bis.org/publ/bcbs189.pdf

Basher, S., Nechi, S. and Zhu, H., 2014. Dependence patterns across Gulf Arab stock markets: A copula approach. *Journal of Multinational Financial Management*, 25-26, pp.30-50.

Baur, D. and Lucey, B., 2009. Is Gold a Hedge or a Safe Haven? an Analysis of Stocks, Bonds and Gold. *SSRN Electronic Journal*.

Baur, D. and Lucey, B., 2010. Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review*, 45(2), pp.217-229.

Baur, D. and McDermott, T., 2010. Is gold a safe haven? International evidence. *Journal of Banking & Finance*, 34(8), pp.1886-1898.

Baur, D. and McDermott, T., 2016. Why is gold a safe haven? *Journal of Behavioral and Experimental Finance*, 10, pp.63-71.

Bedford, T. and Cooke, R., 2002. Vines--a new graphical model for dependent random variables. *The Annals of Statistics*, 30(4), pp.1031-1068.

Bekaert, G., Harvey, C. and Lundblad, C., 2003. Equity Market Liberalization in Emerging Markets. *Review*, 85(4).

Bel, G. and Joseph, S., 2015. Emission abatement: Untangling the impacts of the EU ETS and the economic crisis. *Energy Economics*, 49, pp.531-539.

Beneki, C., Koulis, A., Kyriazis, N. and Papadamou, S., 2019. Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Research in International Business and Finance*, 48, pp.219-227.

Bennett, B., Stulz, R.M. and Wang, Z., 2020. Does joining the S&P 500 index hurt firms? (No. w27593). National Bureau of Economic Research

Benninga, S. and Wiener, Z., 1999. An investigation of cheapest-to-deliver on Treasury bond futures contracts. *The Journal of Computational Finance*, 2(3), pp.39-55.

Benninga, S. and Wiener, Z. (1998) Value-at-risk (VaR). matrix, 32, p.s33

Berkowitz, J., Christoffersen, P. and Pelletier, D., 2007. Evaluating Value-at-Risk Models with Desk-Level Data. *SSRN Electronic Journal*.

Bessa, R., Miranda, V., Botterud, A., Zhou, Z. and Wang, J., 2012. Time-adaptive quantile-copula for wind power probabilistic forecasting. *Renewable Energy*, 40(1), pp.29-39.

Bhatia, V., Das, D., Tiwari, A., Shahbaz, M. and Hasim, H., 2018. Do precious metal spot prices influence each other? Evidence from a nonparametric causality-in-quantiles approach. *Resources Policy*, 55, pp.244-252.

Birz, G. and Lott, J., 2011. The effect of macroeconomic news on stock returns: new evidence from newspaper coverage. *Journal of Banking & Finance*, 35(11), pp.2791-2800.

Blasques, F., Koopman, S. and Lucas, A., 2014. Stationarity and ergodicity of univariate generalized autoregressive score processes. *Electronic Journal of Statistics*, 8(1), pp.1088-1112.

Blau, B., 2018. Price dynamics and speculative trading in Bitcoin. *Research in International Business and Finance*, 43, pp.15-21.

Bloom, N., 2009. The Impact of Uncertainty Shocks. *Econometrica*, 77(3), pp.623-685.

Boako, G. and Alagidede, P., 2016. Global commodities and African stocks: A 'market of one?'. *International Review of Financial Analysis*, 44, pp.226-237.

Boako, G. and Alagidede, P., 2017. Currency price risk and stock market returns in Africa: Dependence and downside spillover effects with stochastic copulas. *Journal of Multinational Financial Management*, 41, pp.92-114.

Boako, G. and Alagidede, P., 2018. African stock markets in the midst of the global financial crisis: Recoupling or decoupling. *Research in International Business and Finance*, 46, pp.166-180.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), pp.307-327.

Bollerslev, T., 2006. Leverage and Volatility Feedback Effects in High-Frequency Data. *Journal of Financial Econometrics*, 4(3), pp.353-384.

Boubaker, H. and Sghaier, N., 2013. Portfolio optimization in the presence of dependent financial returns with long memory: A copula-based approach. *Journal of Banking & Finance*, 37(2), pp.361-377.

Boubaker, H. and Sghaier, N., 2016. Markov-Switching Time-Varying Copula Modelling of Dependence Structure between Oil and GCC Stock Markets. Open Journal of Statistics, 06(04), pp.565-589.

Bouoiyour, J., Selmi, R. and Tiwari, A., 2015. Is Bitcoin Business Income or Speculative Foolery? New Ideas Through an Improved Frequency Domain Analysis. *Annals of Financial Economics*, 10(01), p.1550002.

Bouri, E., Gupta, R., Lau, C., Roubaud, D. and Wang, S., 2018. Bitcoin and global financial stress: A copula-based approach to dependence and causality in the quantiles. The Quarterly Review of Economics and Finance, 69, pp.297-307.

Bouri, E., Jain, A., Biswal, P. and Roubaud, D., 2017. Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. *Resources Policy*, 52, pp.201-206.

Bouri, E., Lien, D., Roubaud, D. and Shahzad, S., 2018. Directional predictability of implied volatility: From crude oil to developed and emerging stock markets. *Finance Research Letters*, 27, pp.65-79.

Bouri, E., Roubaud, D., Jammazi, R. and Assaf, A., 2017. Uncovering frequency domain causality between gold and the stock markets of China and India: Evidence from implied volatility indices. *Finance Research Letters*, 23, pp.23-30.

Bouyé, E. and Salmon, M., 2009. Dynamic copula quantile regressions and tail area dynamic dependence in Forex markets. *The European Journal of Finance*, 15(7-8), pp.721-750.

Bouyé, E., Durrleman, V., Nikeghbali, A., Riboulet, G. and Roncalli, T., 2001. Copulas: An Open Field for Risk Management. *SSRN Electronic Journal*.

Boyarchenko, N., Fuster, A. and Lucca, D., 2019. Understanding Mortgage Spreads. *The Review of Financial Studies*, 32(10), pp.3799-3850.

Boyle, M., (2021). What Drives the Price of Gold? Investopedia. Available at:

<https://www.investopedia.com/financial-edge/0311/what-drives-the-price-of-gold.aspx>

Bradshaw, B., Dolan, H. and Smit, B., 2004. Farm-Level Adaptation to Climatic Variability and Change: Crop Diversification in the Canadian Prairies. *Climatic Change*, 67(1), pp.119-141.

Brandtner, M., 2013. Conditional Value-at-Risk, spectral risk measures and (non-)diversification in portfolio selection problems – A comparison with mean–variance analysis. *Journal of Banking & Finance*, 37(12), pp.5526-5537.

Brechmann, E. and Czado, C., 2014. COPAR-multivariate time series modelling using the copula autoregressive model. Applied Stochastic Models in Business and Industry, 31(4), pp.495-514.

Brooks, C., 2014. The effects of corporate social performance on the cost of corporate debt and credit ratings. [online] Centaur.reading.ac.uk. Available at: <http://centaur.reading.ac.uk/35763/1/The%20Effects%20of%20Corporate%20Social%20Performance%20on%20the%20Cost%20of%20Corporate%20Debt%20and%20Credit%20Ratings%20Oikonomou%20et%20al.pdf>

Burney, S.M. Aqil and Bin Ajaz, Osama. (2020). Copulas: A Historical Literature Review and Major developments Abstract.

Butler, K. and Okada, K., 2009. The relative contribution of conditional mean and volatility in bivariate returns to international stock market indices. *Applied Financial Economics*, 19(1), pp.1-15.

Byström, H., 2005. Extreme value theory and extremely large electricity price changes. *International Review of Economics & Finance*, 14(1), pp.41-55.

Cai, W. and Wang, S., 2018. The Time Varying Effects of Monetary Policy on House Prices in China: An Application of TVP-VAR Model with Stochastic Volatility. *International Journal of Business and Management*, 13(4), p.149.

Cai, Z. and Wang, X., 2008. Nonparametric estimation of conditional VaR and expected shortfall. *Journal of Econometrics*, 147(1), pp.120-130.

Campbell, J., Lo, A., MacKinlay, A. and Whitelaw, R., 1998. THE ECONOMETRICS OF FINANCIAL MARKETS. *Macroeconomic Dynamics*, 2(4), pp.559-562.

Capie, F., Mills, T. and Wood, G., 2005. Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions and Money*, 15(4), pp.343-352.

Cappiello, L., Engle, R. and Sheppard, K., 2006. Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics*, 4(4), pp.537-572.

Carlozo, L., (2018). US news. Available at: <https://money.usnews.com/investing/investing-101/articles/2018-10-02/why-investors-love-the-s-p-500>

Celis, E., 2017. Causal relationship of stock performance and macroeconomic variables: Empirical evidences from Brazil, Russia, India and China (BRIC). *Archives of Business Research*, 5(3).

Cenedese, G., Sarno, L. and Tsiakas, I., 2014. Foreign exchange risk and the predictability of carry trade returns. *Journal of Banking & Finance*, 42, pp.302-313.

CFA Institute (2022) Measuring and Managing Market risk. Available at: https://www.cfainstitute.org/en/membership/professional-development/refresher-readings/measuring-managing-market-risk

Chan, W., Le, M. and Wu, Y., 2019. Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *The Quarterly Review of Economics and Finance*, 71, pp.107-113.

Chang, C., McAleer, M. and Tansuchat, R., 2010. Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. *Energy Economics*, 32(6), pp.1445-1455.

Chang, K., 2012. The Time Varying and asymmetric dependence between crude oil spot and futures markets: Evidence from the Mixture copula-based ARJI–GARCH model. *Economic Modelling*, 29(6), pp.2298-2309.

Charles, A. and Darné, O., 2019. Volatility estimation for Bitcoin: Replication and robustness. *International Economics*, 157, pp.23-32.

Charpentier, A. and Segers, J., 2007. Lower tail dependence for Archimedean copulas: Characterizations and pitfalls. *Insurance: Mathematics and Economics*, 40(3), pp.525-532.

Charpentier, A. and Segers, J., 2009. Tails of multivariate Archimedean copulas. *Journal of Multivariate Analysis*, 100(7), pp.1521-1537.

Chen, J., 2021. Defensive stock. Investopedia. Available at: https://www.investopedia.com/terms/d/defensivestock.asp

Chen, S., 2005. Nonparametric Inference of Value-at-Risk for Dependent Financial Returns. *Journal of Financial Econometrics*, 3(2), pp.227-255.

Chen, S., 2007. Nonparametric Estimation of Expected Shortfall. *Journal of Financial Econometrics*, 6(1), pp.87-107.

Chen, X. and Fan, Y., 2006. Estimation of copula-based semiparametric time series models. *Journal of Econometrics*, 130(2), pp.307-335.

Cheng, A.W.W., Chow, N.S.C., Chui, D.K.H. and Wong, W.K., 2019. The three musketeers' relationships between Hong Kong, Shanghai and Shenzhen before and after Shanghai–Hong Kong stock connect. Sustainability, 11(14), p.3845.

Cheng, L., 2008. Deconstructing the shì … de construction. *The Linguistic Review*, 25(3-4).

Chernozhukov, V. and Umantsev, L., 2001. Conditional value-at-risk: Aspects of modeling and estimation. *Empirical Economics*, 26(1), pp.271-292.

Cherubini, U. and Luciano, E., 2002. Bivariate option pricing with copulas. *Applied Mathematical Finance*, 9(2), pp.69-85.

Cheung, K. C. 2006. Reducing risk by merging counter-monotonic risks. IEE journal.

Choi, S., 2010. Estimating Exchange Rate Exposure of Trade-intensive Firms: Application to Korean Oil-refiners and Petrochemicals. *Global Economic Review*, 39(3), pp.327-348.

Choudhry, T., 2016. Time Varying risk premium yield spread effect in term structure and global financial crisis: Evidence from Europe. *International Review of Financial Analysis*, 48, pp.303-311.

Chowdhary, H., Escobar, L. and Singh, V., 2011. Identification of suitable copulas for bivariate frequency analysis of flood peak and flood volume data. *Hydrology Research*, 42(2-3), pp.193-216.

Christiana, A., Setiana, E. and Mamduch, M., 2016. The Empirical Relationship between Stock Return and Trading Volume based on Stock Market Cycles. *Indonesian Capital Market Review*, 8(1).

Christiano, L. and Fitzgerald, T., 2003. The Band Pass Filter*. *International Economic Review*, 44(2), pp.435-465.

Christoffersen, P., Errunza, V., Jacobs, K. and Langlois, H., 2012. Is the Potential for International Diversification Disappearing? A Dynamic Copula Approach. *Review of Financial Studies*, 25(12), pp.3711-3751.

Christoffersen, P., Jacobs, K., Jin, X. and Langlois, H., 2017. Dynamic Dependence and Diversification in Corporate Credit*. *Review of Finance*, 22(2), pp.521-560.

Christoffersen, P., Jacobs, K., Ornthanalai, C. and Wang, Y., 2008. Option valuation with long-run and short-run volatility components☆. *Journal of Financial Economics*, 90(3), pp.272-297.

Chu, J., Chan, S., Nadarajah, S. and Osterrieder, J., 2017. GARCH Modelling of Cryptocurrencies. *Journal of Risk and Financial Management*, 10(4), p.17.

Ciaian, P., Rajcaniova, M. and Kancs, d., 2016. The digital agenda of virtual currencies: Can BitCoin become a global currency? *Information Systems and e-Business Management*, 14(4), pp.883-919.

Ciaian, P., Rajcaniova, M. and Kancs, d., 2018. Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, 52, pp.173-195.

Connolly, R., Stivers, C. and Sun, L., 2007. Commonality in the time-variation of stock–stock and stock–bond return comovements. *Journal of Financial Markets*, 10(2), pp.192-218.

Corbet, S., Lucey, B. and Yarovaya, L., 2017. Datestamping the Bitcoin and Ethereum Bubbles. *SSRN Electronic Journal*.

Corbet, S., Lucey, B. and Yarovaya, L., 2018. Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, 26, pp.81-88.

Corbet, S., Dowling, M. and Cummins, M., 2015. Analyst recommendations and volatility in a rising, falling, and crisis equity market. Finance Research Letters, 15, pp.187-194.

Corporate Finance Institute, 2022. *2008-2009 Global Financial Crisis.* Available at: https://corporatefinanceinstitute.com/resources/knowledge/finance/2008-2009-global-financial-crisis/

Coumou, D. and Rahmstorf, S., 2012. A decade of weather extremes. *Nature Climate Change*, 2(7), pp.491-496.

COVITZ, D. and DOWNING, C., 2007. Liquidity or Credit Risk? The Determinants of Very Short-Term Corporate Yield Spreads. *The Journal of Finance*, 62(5), pp.2303-2328.

Creal, D., Koopman, S. and Lucas, A., 2012. Generalized Autoregressive Score Models with Applications. *Journal of Applied Econometrics*, 28(5), pp.777-795.

Cumming, D., Helge Haß, L. and Schweizer, D., 2012. Strategic Asset Allocation and the Role of Alternative Investments. *European Financial Management*, 20(3), pp.521-547.

Cuthbertson, K., 2004. Introductory econometrics for finance, Chris Brooks, Cambridge University Press, Cambridge, 2002. *International Journal of Finance & Economics*, 9(1), pp.82-83.

Daks. M. (2021) The S&P 500 is seen as a gauge of the stock market itself – Here´s how this widely watched stock index works.

Danielsson and De Vries, 2000. Value-at-Risk and Extreme Returns. *Annales d'Économie et de Statistique*, (60), p.239.

Danielsson, J., de Vries, C. and Jorgensen, B., 1998. The Value of Value at Risk: Statistical, Financial, and Regulatory Considerations. *SSRN Electronic Journal*.

Daníelsson, J., Jorgensen, B., Samorodnitsky, G., Sarma, M. and de Vries, C., 2013. Fat tails, VaR and subadditivity. *Journal of Econometrics*, 172(2), pp.283-291.

Darbha, G. 2001. Value-at-Risk for Fixed Income portfolios. Munich journal of Germany of Statistics.

Darrat, A., Rahman, S. and Zhong, M., 2003. Intraday trading volume and return volatility of the DJIA stocks: A note. *Journal of Banking & Finance*, 27(10), pp.2035-2043.

DAY, T., 1984. Real Stock Returns and Inflation. *The Journal of Finance*, 39(2), pp.493-502.

De Gómezgil, M. and de Gomezgil, M., 1967. American Journal of Sociology. Vol. 72, núm. 3, noviembre 1966. *Revista Mexicana de Sociología*, 29(1), p.155.

De Lira Salvatierra, I. and Patton, A., 2015. Dynamic copula models and high frequency data. *Journal of Empirical Finance*, 30, pp.120-135.

De Michele, C., Salvadori, G., Vezzoli, R. and Pecora, S., 2013. Multivariate assessment of droughts: Frequency analysis and dynamic return period. *Water Resources Research*, 49(10), pp.6985-6994.

de Oliveira, F., Maia, S., de Jesus, D. and Besarria, C., 2018. Which information matters to market risk spreading in Brazil? Volatility transmission modelling using MGARCH-BEKK, DCC, t-Copulas. *The North American Journal of Economics and Finance*, 45, pp.83-100.

Degiannakis, S., Floros, C. & Livada, A., 2012. Evaluating value-at-risk models before and after the financial crisis of 2008: International evidence. *Managerial Finance,* 9 March, 38(4), pp. 436-452.

Delatte, A. and Lopez, C., 2013. Commodity and equity markets: Some stylized facts from a copula approach. *Journal of Banking & Finance*, 37(12), pp.5346-5356.

Demarta, S. and McNeil, A., 2007. The t Copula and Related Copulas. *International Statistical Review*, 73(1), pp.111-129.

Demir, E., Gozgor, G., Lau, C. and Vigne, S., 2018. Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*, 26, pp.145-149.

Deo, R., Hurvich, C. and Lu, Y., 2006. Forecasting realized volatility using a long-memory stochastic volatility model: estimation, prediction and seasonal adjustment. *Journal of Econometrics*, 131(1-2), pp.29-58.

Devia SS, V., 2019. Analysis of Crude Oil Price and Exchange Rate Volatility on Macroeconomic Variables (Case Study of Indonesia as Emerging Economic Country). *International Journal of Business and Administrative Studies*, 5(5).

Diebold, F. and Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), pp.57-66.

Diebold, F.X. and R.S. Mariano, 1995. Comparing predictive accuracy, Journal of Business & Economic Statistics,13(3), 253ñ263.

Ding, Z., Granger, C. and Engle, R., 1993. A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1(1), pp.83-106.

Dobrić, J. and Schmid, F., 2005. Nonparametric estimation of the lower tail dependence λLin bivariate copulas. *Journal of Applied Statistics*, 32(4), pp.387-407.

Doukhan, P., Fermanian, J. and Lang, G., 2008. An empirical central limit theorem with applications to copulas under weak dependence. *Statistical Inference for Stochastic Processes*, 12(1), pp.65-87.

Dowd, K., 1998. Beyond Value at Risk: The New Science of Risk Management. Working Paper No. 99-07-05.

Du, Z. and Escanciano, J., 2015. Backtesting Expected Shortfall: Accounting for Tail Risk. *SSRN Electronic Journal*.

Duffie, D. and Pan, J., 1997. An Overview of Value at Risk. *The Journal of Derivatives*, 4(3), pp.7-49.

Dutta, A., 2018. A note on the implied volatility spillovers between gold and silver markets. *Resources Policy*, 55, pp.192-195.

Dutta, A., Bouri, E. and Noor, M., 2021. Climate bond, stock, gold, and oil markets: Dynamic correlations and hedging analyses during the COVID-19 outbreak. Resources Policy, 74, p.102265.

Dutta, D. and Bhattacharya, B., 2002. A Bootstrapped Historical Simulation Value at Risk Approach to S & P CNX Nifty. Igidr.ac.in. Available at: <http://www.igidr.ac.in/conf/money/mfc-13/mfc_10/Debashis%20Dutta_submission_27.pdf>

Duignan, Brian. "Financial crisis of 2007–08". Encyclopaedia Britannica, 7 Oct. 2019, https://www.britannica.com/event/financial-crisis-of-2007-2008.

Echaust, K. (2021) Asymmetric tail dependence between stock market returns and implied volatility, The Journal of Economic Asymmetries. 23. DOI: 10.1016/j. jeca2020. e.00190

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R. and Baronchelli, A., 2017. Evolutionary dynamics of the cryptocurrency market. *Royal Society Open Science*, 4(11), p.170623.

Elton, E., Gruber, M., Agrawal, D. and Mann, C., 2002. Factors Affecting the Valuation of Corporate Bonds. *SSRN Electronic Journal*.

Embrechts, P. and Schmidli, H., 1994. Modelling of extremal events in insurance and finance. *ZOR Zeitschrift for Operations Research Mathematical Methods of Operations Research*, 39(1), pp.1-34.

Engle, R. 2001. Financial econometrics} A new discipline with new methods. Vol. 7 No. 4 1998 Mathematica in Education and Research.

Engle, R. and Bollerslev, T., 1986. Modelling the persistence of conditional variances. *Econometric Reviews*, 5(1), pp.1-50.

Engle, R. and Granger, C., 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 55(2), p.251.

Engle, R. and Manganelli, S., 2004. CAViaR. *Journal of Business & Economic Statistics*, 22(4), pp.367-381.

Engle, R. and Russell, J., 1998. Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data. *Econometrica*, 66(5), p.1127.

Engle, R. and White, H., 2021. *Cointegration, Causality, and Forecasting*. Oxford University Press.

Engle, R., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), p.987.

Engle, R., 2004. Robert F Engle: Understanding volatility as a process. *Quantitative Finance*, 4(2), pp.C19-C20.

Engle, R.F. and S. Manganelli, 2004a, CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles, Journal of Business & Economic Statistics, 22, 367-381.

Evans, C., 2015. Bitcoin in Islamic Banking and Finance. *Journal of Islamic Banking and Finance*, 3(1).

Eyüboğlu, S. and Eyüboğlu, K., 2019. Borsa İstanbul sektör endekslerinin karşılıklı bağımlılıklarının test edilmesi. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, (53), pp.246-260.

Fama, E. F., 1965. The Behaviour of Stock-Market Prices. Chicago: http://stevereads.com/papers_to_read/the_behavior_of_stock_market_prices.pdf.

Fama, E., 1965. The Behavior of Stock-Market Prices. *The Journal of Business*, 38(1), p.34.

Fan, J., Qi, L. and Xiu, D., 2014. Quasi-Maximum Likelihood Estimation of GARCH Models with Heavy-Tailed Likelihoods. *Journal of Business & Economic Statistics*, 32(2), pp.178-191.

Fan, Y., Zhang, Y., Tsai, H. and Wei, Y., 2008. Estimating 'Value at Risk' of crude oil price and its spillover effect using the GED-GARCH approach. *Energy Economics*, 30(6), pp.3156-3171.

Fang, Y., Liu, L. and Liu, J., 2014. A dynamic double asymmetric copula generalized autoregressive conditional heteroskedasticity model: application to China's and US stock market. *Journal of Applied Statistics*, 42(2), pp.327-346.

Fasanya, I. and Akinbowale, S., 2019. Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. Energy, 169, pp.186-205.

Favre, A., El Adlouni, S., Perreault, L., Thiémonge, N. and Bobée, B., 2004. Multivariate hydrological frequency analysis using copulas. *Water Resources Research*, 40(1).

Fei, F., Fuertes, A. and Kalotychou, E., 2012. Credit Rating Migration Risk and Business Cycles. *Journal of Business Finance & Accounting*, 39(1-2), pp.229-263.

Ferris, S., Guo, W. and Su, T., 2003. Predicting Implied Volatility in the Commodity Futures Options Markets. *International Journal of Banking and Finance*.

Finance Management (2022) Market risk. Available at: https://efinancemanagement.com/investment-decisions/market-risk

Fischer, M., 2006. Zivot Eric and Jiahui Wang, Modelling Financial Time Series with S-PLUS. *Allgemeines Statistisches Archiv*, 90(4), pp.631-632.

Fissler, T. and Ziegel, J., 2021. Correction notes: Higher order elicitability and Osband's principle. *Annals of Statistics*, 49(1), pp.614-614.

Fissler, T., and J. F. Ziegel, 2016, Higher order elicitability and Osbandís principle, Annals of Statistics, 44(4), 1680-1707.

Fissler, T., Ziegel, J. F. & Gneiting, T., 2015. Expected Shortfall is jointly elicitable with Value at Risk - Implications for backtesting. Risk, 12 July.pp. 58-61.

Flynn, E., 2007. The Security Council's Counter-Terrorism Committee and Human Rights. *Human Rights Law Review*, 7(2), pp.371-384.

Forbes, K. and Rigobon, R., 2002. No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance*, 57(5), pp.2223-2261.

Frahm, G., Junker, M. and Schmidt, R., 2005. Estimating the tail-dependence coefficient: Properties and pitfalls. *Insurance: Mathematics and Economics*, 37(1), pp.80-100.

Francis, T., 2011. Stock returns and inflation: An autoregressive distributed lag (ARDL) econometric investigation on Ghana. *African Journal of Business Management*, 5(26).

Francq, C. and Zakoïan, J., 2013. Inference in nonstationary asymmetric GARCH models. *The Annals of Statistics*, 41(4), pp.1970-1998.

Francq, C. and Zakoïan, J., 2015. Risk-parameter estimation in volatility models. *Journal of Econometrics*, 184(1), pp.158-173.

Frino, A., Prodromou, T., Wang, G., Westerholm, P. and Zheng, H., 2017. An empirical analysis of algorithmic trading around earnings announcements. *Pacific-Basin Finance Journal*, 45, pp.34-51.

Fu, F., 2010. On the Robustness of the Positive Relation between Expected Idiosyncratic Volatility and Expected Return. *SSRN Electronic Journal*.

Gallagher. T. (2020) What´s Driving Gold Prices So High, and What Might the Future Hold? Available at: https://www.forbes.com/sites/forbesfinancecouncil/2020/09/22/whats-driving-gold-prices-so-high-and-what-might-the-future-hold/?sh=33b0a9013b9c

Garcia, R. and Tsafack, G., 2011. Dependence structure and extreme comovements in international equity and bond markets. *Journal of Banking & Finance*, 35(8), pp.1954-1970.

Gay, G. and Hull, J., 1990. Options, Futures, and Other Derivative Securities. *The Journal of Finance*, 45(1), p.312.

Gençay, R. and Selçuk, F., 2004. Extreme value theory and Value-at-Risk: Relative performance in emerging markets. *International Journal of Forecasting*, 20(2), pp.287-303.

Genest, C. and Rémillard, B., 2008. Validity of the parametric bootstrap for goodness-of-fit testing in semiparametric models. *Annales de l'Institut Henri Poincaré, Probabilités et Statistiques*, 44(6), pp.1096-1127.

Genest, C., Rémillard, B. and Beaudoin, D., 2009. Goodness-of-fit tests for copulas: A review and a power study. *Insurance: Mathematics and Economics*, 44(2), pp.199-213.

Giannopoulos, K. and Tunaru, R., 2005. Coherent risk measures under filtered historical simulation. *Journal of Banking & Finance*, 29(4), pp.979-996.

Gibson, M. and Pritsker, M., 2001. Improving Grid-Based Methods for Estimating Value at Risk of Fixed-Income Portfolios. *SSRN Electronic Journal*.

Giglio, S., Kelly, B. and Pruitt, S., 2016. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 119(3), pp.457-471.

Gilchrist, S. and Zakrajšek, E., 2012. Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, 102(4), pp.1692-1720.

Gilli, M. and këllezi, E., 2006. An Application of Extreme Value Theory for Measuring Financial Risk. *Computational Economics*, 27(2-3), pp.207-228.

Gilmore, C., McManus, G., Sharma, R. and Tezel, A., 2009. The Dynamics of Gold Prices, Gold Mining Stock Prices and Stock Market Prices Comovements. *Research in Applied Economics*, 1(1).

Glasserman, P., Heidelberger, P. and Shahabuddin, P., 2002. Portfolio Value-at-Risk with Heavy-Tailed Risk Factors. *Mathematical Finance*, 12(3), pp.239-269.

Glosten, L., Jagannathan, R. and Runkle, D., 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, 48(5), pp.1779-1801.

Gneiting, T., 2011, Making and Evaluating Point Forecasts, Journal of the American Statistical Association, 106(494), 746-762.

Gobler, E., 2022. Diversifying Your Portfolio Reduces Your Risk in Investing. Here's Why That's So Important. Available at: https://time.com/nextadvisor/investing/why-diversifying-portfolio-is-important.

Gokbulut, R. and Pekkaya, M., 2014. Estimating and Forecasting Volatility of Financial Markets Using Asymmetric GARCH Models: An Application on Turkish Financial Markets. *International Journal of Economics and Finance*, 6(4).

Gokcan, S., 2000. Forecasting volatility of emerging stock markets: linear versus non-linear GARCH models. *Journal of Forecasting*, 19(6), pp.499-504.

Gokmenoglu, K. and Fazlollahi, N., (2015). The Interactions among Gold, Oil, and Stock Market: Evidence from S&P500. Procedia Economics and Finance, 25, pp.478-488.

Gómez, Y., Oviedo, L., Correal, L., Romero, J. and Velasco, S., 2018. Problemática de empresas mineras en Soacha. *Documentos de trabajo Areandina*, (1).

Goodwin, B. and Hungerford, A., 2014. Copula-Based Models of Systemic Risk in U.S. Agriculture: Implications for Crop Insurance and Reinsurance Contracts. *American Journal of Agricultural Economics*, 97(3), pp.879-896.

Goudarzi, H. and Ramanarayanan, C., 2011. Modeling Asymmetric Volatility in the Indian Stock Market. *International Journal of Business and Management*, 6(3).

Gräler, B., 2014. Modelling skewed spatial random fields through the spatial vine copula. *Spatial Statistics*, 10, pp.87-102.

Grigoryeva, L., Ortega, J. and Peresetsky, A., 2015. Volatility Forecasting Using Global Stochastic Financial Trends Extracted from Non-Synchronous Data. *SSRN Electronic Journal*.

Grossmass, L. and Poon, S., 2015. Estimating dynamic copula dependence using intraday data. *Studies in Nonlinear Dynamics & Econometrics*, 19(4).

Guermat, C. and Harris, R., 2002. Forecasting value at risk allowing for time variation in the variance and kurtosis of portfolio returns. *International Journal of Forecasting*, 18(3), pp.409-419.

Guesmi, K., Saadi, S., Abid, I. and Ftiti, Z., 2019. Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, 63, pp.431-437.

Guidolin, M. and Liu, H., 2016. Ambiguity Aversion and Under diversification. *Journal of Financial and Quantitative Analysis*, 51(4), pp.1297-1323.

Guidolin, M. and Tam, Y., 2013. A yield spread perspective on the great financial crisis: Break-point test evidence. *International Review of Financial Analysis*, 26, pp.18-39.

Gürgün, G. and Ünalmış, İ., 2014. Is gold a safe haven against equity market investment in emerging and developing countries? Finance Research Letters, 11(4), pp.341-348.

Gwanoya, T., 2007. Quantitative Risk Management: Concepts, Techniques, Tools. By Alexander J. McNeil, Rüdiger Frey & Paul Embrechts (Princeton University Press, 2005). *Annals of Actuarial Science*, 2(1), pp.187-189.

Haferkorn, M., Siering, M. and Zimmermann, K., 2019. Strategic Competitive Advantages through Enterprise Systems: The Case of Exchange Systems. *SSRN Electronic Journal*.

Hafner, C. and Manner, H., 2010. Dynamic stochastic copula models: estimation, inference and applications. *Journal of Applied Econometrics*, 27(2), pp.269-295.

Hamilton J.D.A., 1994. The time series analysis. New Jersey, Princeton University Press.

Hammoudeh, S., Mensi, W., Reboredo, J. and Nguyen, D., 2014. Dynamic dependence of the global Islamic equity index with global conventional equity market indices and risk factors. *Pacific-Basin Finance Journal*, 30, pp.189-206.

Hammoudeh, S., Yuan, Y., McAleer, M. and Thompson, M., 2010. Precious metals–exchange rate volatility transmissions and hedging strategies. *International Review of Economics & Finance*, 19(4), pp.633-647.

Hansen, P. and Lunde, A., 2005. A forecast comparison of volatility models: does anything beat a GARCH (1,1)? *Journal of Applied Econometrics*, 20(7), pp.873-889.

Hao, Z. and Singh, V., 2016. Review of dependence modeling in hydrology and water resources. *Progress in Physical Geography: Earth and Environment*, 40(4), pp.549-578.

Harvey, A.C., 2013, Dynamic Models for Volatility and Heavy Tails, Econometric Society Monograph 52, Cambridge University Press, Cambridge.

He, K., Liu, Y., Yu, L. and Lai, K., 2016. Multiscale dependence analysis and portfolio risk modeling for precious metal markets. *Resources Policy*, 50, pp.224-233.

He, Y., and Hamori, S., 2019. Conditional dependence between oil prices and exchange rates in BRICS countries: An application of the Copula-GARCH model. Journal of Risk and Financial Management, [e-journal] 12(2), pp. 99.

He, Z., O'Connor, F. and Thijssen, J., 2018. Is gold a Sometime Safe Haven or an Always Hedge for equity investors? A Markov-Switching CAPM approach for US and UK stock indices. International Review of Financial Analysis, 60, pp.30-37.

Hendricks, D., 1996. Evaluation of Value-at-Risk Models Using Historical Data. *SSRN Electronic Journal*.

Herold, N., Ekström, M., Kala, J., Goldie, J. and Evans, J., 2018. Australian climate extremes in the 21st century according to a regional climate model ensemble: Implications for health and agriculture. *Weather and Climate Extremes*, 20, pp.54-68.

Hilal, S., Poon, S. and Tawn, J., 2014. Portfolio risk assessment using multivariate extreme value methods. *Extremes*, 17(4), pp.531-556.

Holton, G. A., 2002. History of Value at Risk 1922-1998. *IEEE journal* .

Holton, G. A., July 25, 2002. History of Value at Risk 1922-1998. IEEE journal.

Hsieh, D., 1989. Modelling Heteroscedasticity in Daily Foreign-Exchange Rates. *Journal of Business & Economic Statistics*, 7(3), p.307.

Hsu, C., Tseng, C. and Wang, Y., 2008. Dynamic hedging with futures: A copula-based GARCH model. *Journal of Futures Markets*, 28(11), pp.1095-1116.

Hu, J., 2010. Dependence structures in Chinese and US financial markets: a Time Varying conditional copula approach. *Applied Financial Economics*, 20(7), pp.561-583.

Hu, L., 2006. Dependence patterns across financial markets: a mixed copula approach. *Applied Financial Economics*, 16(10), pp.717-729.

Hua, L., 2017. On a bivariate copula with both upper and lower full-range tail dependence. *Insurance: Mathematics and Economics*, 73, pp.94-104.

Huang, J., Lee, K., Liang, H. and Lin, W., 2009. Estimating value at risk of portfolio by conditional copula-GARCH method. *Insurance: Mathematics and Economics*, 45(3), pp.315-324.

Hui, E. and Chan, K., 2013. Contagion Across Real Estate and Equity Markets During European Sovereign Debt Crisis. *International Journal of Strategic Property Management*, 17(3), pp.305-316.

Huisman, R., Koedijk, K. and Campbell, R., 1999. Asset Allocation in a Value-at-Risk Framework. *SSRN Electronic Journal*.

Hull, J. (2006). Options, Futures, and Other Derivatives, 6thEdition. Upper Saddle River: Pearson Prentice Hall, 435,442.

Hull, J.; White, A.1998. Incorporating volatility updating into the historical simulation method for value-at-risk, Journal of Risk 1(1): 1–19.

Hung, N. T., 2022. Asymmetric connectedness among S&P 500, crude oil, gold and bitcoin. Managerial Finance, [e-journal] 48(4), pp.587-610. https://doi.org/10.1108/mf-08-2021-0355

Hussain, S. and Li, S., 2018. The dynamic dependence between stock markets in the greater China economic area: a study based on extreme values and copulas. *Financial Markets and Portfolio Management*, 32(2), pp.207-233.

Ibragimov, R. and Walden, J., 2010. Value at risk and efficiency under dependence and heavy-tailedness: models with common shocks. *Annals of Finance*, 7(3), pp.285-318.

Iqbal Khan, K., Mudassar Ghafoor, M., Sheeraz, M. and Mahmood, S., 2018. Pay or not to Pay Dividends: Company Policy and Investor Expectations. *Lahore Journal of Business*, 7(1), pp.137-157.

Ismail, S., Koe, W., Halim Mahphoth, M., Abu Karim, R., Yusof, N. and Ismail, S., 2020. Saving Behavior Determinants in Malaysia: An Empirical Investigation. *KnE Social Sciences*.

Jaffar, Y., Dewandaru, G. and Masih, M., 2018. Exploring Portfolio Diversification Opportunities Through Venture Capital Financing: Evidence from MGARCH-DCC, Markov Switching, and Wavelet Approaches. *Emerging Markets Finance and Trade*, 54(6), pp.1320-1336.

Janga Reddy, M. and Ganguli, P., 2011. Application of copulas for derivation of drought severity-duration-frequency curves. *Hydrological Processes*, 26(11), pp.1672-1685.

Jenkinson, T., 2009. Testing Neo-Classical Theories of Labour Demand: An Application of Cointegration Techniques. *Oxford Bulletin of Economics and Statistics*, 48(3), pp.241-251.

Jewellery Quarter Bullion Ltd. (2022) Is gold a commodity or a currency? Available at:

https://www.bullionbypost.co.uk/index/gold/is-gold-a-commodity-or-a-currency/

Ji, Q., Bouri, E. and Roubaud, D., 2018. Dynamic network of implied volatility transmission among US equities, strategic commodities, and BRICS equities. International Review of Financial Analysis, 57, pp.1-12.

Ji, Q., Bouri, E., Gupta, R. and Roubaud, D., 2018. Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance*, 70, pp.203-213.

Ji, Q., Bouri, E., Roubaud, D. and Shahzad, S.J.H., 2018. Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. Energy Economics, 75, pp.14-27.

Ji, Q., Xia, T., Liu, F. and Xu, J., 2019. The information spillover between carbon price and power sector returns: Evidence from the major European electricity companies. *Journal of Cleaner Production*, 208, pp.1178-1187.

Ji, Q., Zhang, D. and Geng, J., 2018. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production*, 198, pp.972-978.

Jiang, H., Saart, P. and Xia, Y., 2016. Asymmetric conditional correlations in stock returns. The Annals of Applied Statistics, 10(2).

Jiang, Y., Lao, J., Mo, B. and Nie, H., 2018. Dynamic linkages among global oil market, agricultural raw material markets and metal markets: an application of wavelet and copula approaches. Physica A: Statistical Mechanics and its Applications, 508, pp.265-279.

Jiao, L., Liao, Y. and Zhou, Q., 2018. Predicting carbon market risk using information from macroeconomic fundamentals. *Energy Economics*, 73, pp.212-227.

Johannes, M., Polson, N. and Stroud, J., 2009. Optimal Filtering of Jump Diffusions: Extracting Latent States from Asset Prices. *Review of Financial Studies*, 22(7), pp.2759-2799.

Johansen, S. and Juselius, K., 2009. Maximum Likelihood Estimation and Inference on Cointegration - with Applications to the Demand for Money. *Oxford Bulletin of Economics and Statistics*, 52(2), pp.169-210.

Johansen, S., 1988. Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3), pp.231-254.

Johansen, S., 1991. Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica*, 59(6), p.1551.

Jondeau, E. and Rockinger, M., 2006. The Copula-GARCH model of conditional dependencies: An international stock market application. *Journal of International Money and Finance*, 25(5), pp.827-853.

Jorion, P., 1996. Risk2: Measuring the Risk in Value at Risk. *Financial Analysts Journal*, 52(6), pp.47-56.

Jouanin, Jean-Frédéric and Riboulet, Gaël and Roncalli, Thierry, Financial Applications of Copula Functions. Risk Measures for the 21st Century, Par Giorgio Szego, ed., John Wiley & Sons, 2004, Available at SSRN: https://ssrn.com/abstract=1032588

Junttila, J., Pesonen, J. and Raatikainen, J., (2018). Commodity market-based hedging against stock market risk in times of financial crisis: The case of crude oil and gold. Journal of International Financial Markets, Institutions and Money, 56, pp.255-280.

Jurado, K., Ludvigson, S. and Ng, S., 2015. Measuring Uncertainty. *American Economic Review*, 105(3), pp.1177-1216.

Kalaiselvan, A., M, K. and., S., 2016. Effect of backpack of 10% of the body weight on Cervical and shoulder posture. *International Journal of Pharma and Bio Sciences*, 7(4).

Kallsen, J. and Tankov, P., 2006. Characterization of dependence of multidimensional Lévy processes using Lévy copulas. *Journal of Multivariate Analysis*, 97(7), pp.1551-1572.

Kang, S.H., McIver, R. and Yoon, S.M., 2017. Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. Energy Economics, 62, pp.19-32.

Kang, W., Lee, Y., Song, J. and Gencturk, B., 2012. Further development of matrix-based system reliability method and applications to structural systems. *Structure and Infrastructure Engineering*, 8(5), pp.441-457.

Kanioura, A., & Turner, P. (2003). The error correction model as a test for cointegration.

Kato, K., 2012. Weighted Nadaraya-Watson Estimation of Conditional Expected Shortfall. *Journal of Financial Econometrics*, 10(2), pp.265-291.

Katsiampa, P., 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, pp.3-6.

Kaufmann, T. and Winters, R., 1989. The price of gold. *Resources Policy*, 15(4), pp.309-313.

Kayalar, D., Küçüközmen, C. and Selcuk-Kestel, A., (2017). The impact of crude oil prices on financial market indicators: copula approach. Energy Economics, 61, pp.162-173.

Kenourgios, D., Naifar, N. and Dimitriou, D., 2016. Islamic financial markets and global crises: Contagion or decoupling? *Economic Modelling*, 57, pp.36-46.

Kenourgios, D., Samitas, A. and Paltalidis, N., 2011. Financial crises and stock market contagion in a multivariate Time Varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money*, 21(1), pp.92-106.

Kenton, W., (2021). What Is a Copula in Probability? [online] Investopedia. Available at: <https://www.investopedia.com/terms/c/copula.asp>.

Kenton, W., 2022. Value at Risk (VaR). Available at: https://www.investopedia.com/terms/v/var.asp

Khalfaoui, R., Jabeur, S.B. and Dogan, B., 2022. The spillover effects and connectedness among green commodities, Bitcoins, and US stock markets: Evidence from the quantile VAR network. Journal of environmental management, 306, p.114493.

Kieu, T., Luu, P., Shon, B. and Yoon, N., 2021. Analysis of S&P 500 stocks: Long-term vs short-term investment.

Kilian, L. (2013). Structural vector autoregressions. In Handbook of research methods and applications in empirical macroeconomics. Edward Elgar Publishing.

Kim, H. and Koo, W., 2010. Factors affecting the carbon allowance market in the US. *Energy Policy*, 38(4), pp.1879-1884.

Kitamura, Y., 1998. Likelihood-Based Inference in Cointegrated Vector Autoregressive Models. *Econometric Theory*, 14(4), pp.517-524.

Kitamura, Y., 2010. Testing for intraday interdependence and volatility spillover among the euro, the pound and the Swiss franc markets. *Research in International Business and Finance*, 24(2), pp.158-171.

Koenker, R. and Bassett, G., 1978. Regression Quantiles. *Econometrica*, 46(1), p.33.

Koenker, R. and Park, B., 1996. An interior point algorithm for nonlinear quantile regression. *Journal of Econometrics*, 71(1-2), pp.265-283.

Koirala, K., Mishra, A., D'Antoni, J. and Mehlhorn, J., 2015. Energy prices and agricultural commodity prices: Testing correlation using copulas method. *Energy*, 81, pp.430-436.

Kojadinovic, I. and Yan, J., 2010. Modeling Multivariate Distributions with Continuous Margins Using the copula R Package. *Journal of Statistical Software*, 34(9).

Kole, E., Koedijk, K. and Verbeek, M., 2007. Selecting copulas for risk management. *Journal of Banking & Finance*, 31(8), pp.2405-2423.

Komunjer, I., 2005. Quasi-maximum likelihood estimation for conditional quantiles. *Journal of Econometrics*, 128(1), pp.137-164.

Koopman, S., Lucas, A. and Scharth, M., 2016. Predicting Time Varying Parameters with Parameter-Driven and Observation-Driven Models. *Review of Economics and Statistics*, 98(1), pp.97-110.

Koskinen, L., 2012. Copula Theory and Its Applications edited by Piotr Jaworski, Fabrizio Durante, Wolfgang Härdle and Tomasz Rychlik. *International Statistical Review*, 80(2), pp.328-328.

Koutsoyiannis, A., 1983. A short-run pricing model for a speculative asset, tested with data from the gold bullion market. *Applied Economics*, 15(5), pp.563-581.

Kovalova, K. and Misiura, I., 2019. Modeling and Forecasting Ukraine's Population by Time Series Using the Matlab Econometrics Toolbox. *Business Inform*, 5(496), pp.98-105.

Kresta, A. and Tichy, T., 2012. Some Results on Foreign Equity Portfolio Risk Backtesting via Lévy Ordinary Copula Model. *Journal of Competitiveness*, 4(2), pp.85-96.

Kristoufek, L., 2015. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLOS ONE*, 10(4), p.e0123923.

Krupskii, P. and Genton, M., 2017. Factor copula models for data with spatio-temporal dependence. *Spatial Statistics*, 22, pp.180-195.

Kuck, K., 2021. Gold and the S&P500: An analysis of the return and volatility relationship. Available at SSRN 3930548.

Kumar, S., Tiwari, A., Raheem, I. and Ji, Q., 2019. Dependence risk analysis in energy, agricultural and precious metals commodities: a pair vine copula approach. *Applied Economics*, 52(28), pp.3055-3072.

Kupiec, P., 1995. Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives*, 3(2), pp.73-84.

Kwon, C. and Shin, T., 1999. Cointegration and causality between macroeconomic variables and stock market returns. *Global Finance Journal*, 10(1), pp.71-81.

Kyriazis, 2019. A Survey on Efficiency and Profitable Trading Opportunities in Cryptocurrency Markets. *Journal of Risk and Financial Management*, 12(2), p.67.

Lahmiri, S. and Bekiros, S., 2018. Chaos, randomness and multi-fractality in Bitcoin market. *Chaos, Solitons & Fractals*, 106, pp.28-34.

Lahmiri, S. and Bekiros, S., 2018. Time Varying self-similarity in alternative investments. *Chaos, Solitons & Fractals*, 111, pp.1-5.

Lan, Y., Hu, Z. and Johnson, J., 2007. Improving Accuracy and Precision of Value-at-Risk Forecasts. *SSRN Electronic Journal*.

Larsen, R., Leatham, D. and Sukcharoen, K., 2015. Geographical diversification in wheat farming: a copula-based CVaR framework. *Agricultural Finance Review*, 75(3), pp.368-384.

Larsen, R., W. Mjelde, J., Klinefelter, D. and Wolfley, J., 2013. The use of copulas in explaining crop yield dependence structures for use in geographic diversification. *Agricultural Finance Review*, 73(3), pp.469-492.

Lau, M., Vigne, S., Wang, S. and Yarovaya, L., 2017. Return spillovers between white precious metal ETFs: The role of oil, gold, and global equity. *International Review of Financial Analysis*, 52, pp.316-332.

Lebo, M. J., & Kraft, P. W. (2017). The general error correction model in practice. Research & Politics, 4(2), 2053168017713059.

Ledford, A. and Tawn, J., 1998. Concomitant tail behaviour for extremes. *Advances in Applied Probability*, 30(01), pp.197-215.

Lee, D., Kim, K., Baek, J., Oh, S., Jang, S. and Park, E., 2020. Association of habitual alcohol use on risk-taking behaviors while using a car: The Korean National Health and Nutrition Examination Survey 2009–2013. *Accident Analysis & Prevention*, 144, p.105651.

Lee, Eun-Joo & Klumpe, Noah & Vlk, Jonathan & Lee, Seung-Hwan. (2017). Modelling Conditional Dependence of Stock Returns Using a Copula-based GARCH Model. International Journal of Statistics and Probability. 6. 32. 10.5539/ijsp. v6n2p32.

Lesk, C., Rowhani, P. and Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), pp.84-87.

Lettau, M. and Ludvigson, S., 2001. Consumption, Aggregate Wealth, and Expected Stock Returns. *The Journal of Finance*, 56(3), pp.815-849.

Li, S., 2011. China's huge investment on water facilities: an effective adaptation to climate change, natural disasters, and food security. *Natural Hazards*, 61(3), pp.1473-1475.

Li, X. and Wei, Y., 2018. The dependence and risk spillover between crude oil market and China stock market: New evidence from a variational mode decomposition-based copula method. *Energy Economics*, 74, pp.565-581.

Liao, Z., & Phillips, P. C. (2015). Automated estimation of vector error correction models. Econometric Theory, 31(3), 581-646.

Linsley, P. and Shrives, P., 2000. Risk management and reporting risk in the UK. *The Journal of Risk*, 3(1), pp.115-129.

Linton, O. and Xiao, Z., 2013. Estimation of and Inference about the Expected Shortfall for Time Series with Infinite Variance. *Econometric Theory*, 29(4), pp.771-807.

Linton, O., 1996. Estimation, Inference and Specification AnalysisH. White, Cambridge University Press, 1994. *Econometric Theory*, 12(3), pp.581-583.

Liu, B., Ji, Q. and Fan, Y., 2017. Dynamic return-volatility dependence and risk measure of CoVaR in the oil market: A Time Varying mixed copula model. *Energy Economics*, 68, pp.53-65.

LONGSTAFF, F., MITHAL, S. and NEIS, E., 2005. Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *The Journal of Finance*, 60(5), pp.2213-2253.

Loriano Mancini, F. T., 2010. Robust Value at Risk Prediction. Vol. 7 No. 4 1998 Mathematica in Education and Research.

Loudon, G., Watt, W. and Yadav, P., 2000. An empirical analysis of alternative parametric ARCH models. *Journal of Applied Econometrics*, 15(2), pp.117-136.

Low, J., Chin, Y., Mushiroda, T., Kubo, M., Govindasamy, G., Pua, K., Yap, Y., Yap, L., Subramaniam, S., Ong, C., Tan, T., Khoo, A. and Ng, C., 2016. A Genome Wide Study of Copy Number Variation Associated with Nasopharyngeal Carcinoma in Malaysian Chinese Identifies CNVs at 11q14.3 and 6p21.3 as Candidate Loci. *PLOS ONE*, 11(1), p.e0145774.

Low, J., Chin, Y., Mushiroda, T., Kubo, M., Govindasamy, G., Pua, K., Yap, Y., Yap, L., Subramaniam, S., Ong, C., Tan, T., Khoo, A. and Ng, C., 2016. A Genome Wide Study of Copy Number Variation Associated with Nasopharyngeal Carcinoma in Malaysian Chinese Identifies CNVs at 11q14.3 and 6p21.3 as Candidate Loci. *PLOS ONE*, 11(1), p.e0145774.

Lu, X., Lai, K. and Liang, L., 2011. Portfolio value-at-risk estimation in energy futures markets with Time Varying copula-GARCH model. *Annals of Operations Research*, 219(1), pp.333-357.

Lucey, B. and Li, S., 2014. What precious metals act as safe havens, and when? Some US evidence. *Applied Economics Letters*, 22(1), pp.35-45.

Lucey, B. and Tully, E., 2006. The evolving relationship between gold and silver 1978–2002: evidence from a dynamic cointegration analysis: a note. *Applied Financial Economics Letters*, 2(1), pp.47-53.

Lütkepohl, H. (2013). Vector autoregressive models. In Handbook of research methods and applications in empirical macroeconomics. Edward Elgar Publishing.

Lutz, B., Pigorsch, U. and Rotfuss, W., 2013. Nonlinearity in Cap-and-Trade Systems: The EUA Price and its Fundamentals. *SSRN Electronic Journal*.

Ma, R., Deng, C., Cai, H. and Zhai, P., (2019). Does Shanghai-Hong Kong stock connect drive market comovement between Shanghai and Hong Kong: new evidence. The North American Journal of Economics and Finance, 50, p.100980.

Macroption, 2022. Value At Risk (VAR) Limitations and Disadvantages. Available at: https://www.macroption.com/value-at-risk-var-limitations-disadvantages/.

Maghyereh, A. and Al-Zoubi, H., 2006. Value-at-risk under extreme values: the relative performance in MENA emerging stock markets. *International Journal of Managerial Finance*, 2(2), pp.154-172.

Maghyereh, A. and Al-Zoubi, H., 2006. Value-at-risk under extreme values: the relative performance in MENA emerging stock markets. *International Journal of Managerial Finance*, 2(2), pp.154-172.

Maghyereh, A., Awartani, B. and Bouri, E., 2016. The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. *Energy Economics*, 57, pp.78-93.

Mancini, L. and Trojani, F., 2010. Robust Value at Risk Prediction. *SSRN Electronic Journal*.

Mandelbrot, B., 1963. The Variation of Certain Speculative Prices. *The Journal of Business*, 36(4), p.394.

Marcucci, J., 2005. Forecasting Stock Market Volatility with Regime-Switching GARCH Models. *Studies in Nonlinear Dynamics & Econometrics*, 9(4).

Marcus, E., 1956. Regularization of Business Investment. A conference of the Universities-National Bureau Committee for Economic Research. (Publication of the National Bureau of Economic Research.) Princeton: Princeton University Press, 1954. Pp. xxvi, 513. $8.00. - Business Concentration and Price Policy. A conference of the Universities-National Bureau Committee for Economic Research. (Publication of the National Bureau of Economic Research.) Princeton: Princeton University Press, 1955. Pp. x, 514. $9.00. *The Journal of Economic History*, 16(1), pp.67-69.

Markowitz, H., 1952. Portfolio Selection*. *The Journal of Finance*, 7(1), pp.77-91.

Marohn, F., 2005. Tail Index Estimation in Models of Generalized Order Statistics. *Communications in Statistics - Theory and Methods*, 34(5), pp.1057-1064.

Masarotto, G. and Varin, C., 2012. Gaussian copula marginal regression. *Electronic Journal of Statistics*, 6(0), pp.1517-1549.

Matlab, 2014. Mathworks. *Auto Tech Review*, 3(4), pp.8-9.

Mazur, M., Dang, M. and Vega, M., 2021. COVID-19 and the march 2020 stock market crash. Evidence from S& P1500. Finance Research Letters, 38, p.101690.

McAleer, M., 2005. Automated Inference and Learning in Modelling Financial Volatility. *Econometric Theory*, 21(01).

McKay, D.R. and Peters, D.A., 2017. The Midas touch: Gold and its role in the global economy. Plastic Surgery, [e-journal] 25(1), pp.61-63.

McNeil, A. and Frey, R., 2000. Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of Empirical Finance*, 7(3-4), pp.271-300.

Menger, K., Schweizer, B. and Sklar, A., 1959. On probabilistic metrics and numerical metrics with probability. I. *Czechoslovak Mathematical Journal*, 09(3), pp.459-466.

Mensi, W., Hammoudeh, S., Reboredo, J. and Nguyen, D., 2015. Are Sharia stocks, gold and U.S. Treasury hedges and/or safe havens for the oil-based GCC markets? *Emerging Markets Review*, 24, pp.101-121.

Mensi, W., Hammoudeh, S., Shahzad, S. and Shahbaz, M., 2017. Modelling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance*, 75, pp.258-279.

Mentel, G., 2013. Parametric or Non-Parametric Estimation of Value-At-Risk. *International Journal of Business and Management*, 8(11).

Miron, D., and Tudor, C., 2010. Asymmetric Conditional Volatility Models: Empirical Estimation and Comparison of Forecasting Accuracy. Romanian Journal of Economic Forecasting, [e-journal] 13(3).

Mishra, A., 2010. Australia's equity home bias and real exchange rate volatility. *Review of Quantitative Finance and Accounting*, 37(2), pp.223-244.

Mishra, A., 2019. Crude oil, stock market, and foreign exchange return volatility and spillover: a GARCH DCC analysis of Indian and Japanese financial market. *International Journal of Business Innovation and Research*, 20(1), p.25.

Mishra, A., El-Osta, H. and Sandretto, C., 2004. Factors affecting farm enterprise diversification. *Agricultural Finance Review*, 64(2), pp.151-166.

Moore, T. and Wang, P., 2014. Dynamic linkage between real exchange rates and stock prices: Evidence from developed and emerging Asian markets. International Review of Economics & Finance, 29, pp.1-11.

Moore, W. and Stephen, J., 2016. Should cryptocurrencies be included in the portfolio of international reserves held by central banks? *Cogent Economics & Finance*, 4(1), p.1147119.

Morgan, W., Cotter, J. and Dowd, K., 2011. Extreme Measures of Agricultural Financial Risk. *Journal of Agricultural Economics*, 63(1), pp.65-82.

Muhammad Akbar, 2012. The relationship of stock prices and macroeconomic variables revisited: Evidence from Karachi stock exchange. *African Journal of Business Management*, 6(4).

Muhammad, S., Hussain, A., Ali, A. and Jalil, M., 2009. Impact of Macroeconomics Variables on Stock Prices: Empirical Evidence in Case of KSE. *SSRN Electronic Journal*.

Muhammad, S., Hussain, A., Ali, A. and Jalil, M., 2009. Impact of Macroeconomics Variables on Stock Prices: Empirical Evidence in Case of KSE. *SSRN Electronic Journal*.

Mulvey, J. and Erkan, H., 2006. Applying CVaR for decentralized risk management of financial companies. *Journal of Banking & Finance*, 30(2), pp.627-644.

Musa, Y., Adamu, I. and Sani Dauran, N., 2020. Forecasting of the Nigeria Stock Returns Volatility Using GARCH Models with Structural Breaks. *Asian Research Journal of Mathematics*, pp.39-50.

Nadarajah, S. and Chu, J., 2017. On the inefficiency of Bitcoin. *Economics Letters*, 150, pp.6-9.

Nadarajah, S., Zhang, B. and Chan, S., 2013. Estimation methods for expected shortfall. *Quantitative Finance*, 14(2), pp.271-291.

Najaf, R., Najaf, K. and Yousaf, S., 2016. Gold And Oil Prices Versus Stock Exchange: A case Study of Pakistan. International Journal of Research -GRANTHAALAYAH, 4(2), pp.129-138.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Nelson, D., 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2), p.347.

Nguyen-Huy, T., Deo, R., An-Vo, D., Mushtaq, S. and Khan, S., 2017. Copula-statistical precipitation forecasting model in Australia’s agro-ecological zones. *Agricultural Water Management*, 191, pp.153-172.

Nguyen-Huy, T., Deo, R., Mushtaq, S., An-Vo, D. and Khan, S., 2018. Modelling the joint influence of multiple synoptic-scale, climate mode indices on Australian wheat yield using a vine copula-based approach. *European Journal of Agronomy*, 98, pp.65-81.

Nguyen, C., Bhatti, M., Komorníková, M. and Komorník, J., 2016. Gold price and stock markets nexus under mixed-copulas. *Economic Modelling*, 58, pp.283-292.

Nieto, M. and Ruiz, E., 2016. Frontiers in VaR forecasting and backtesting. International Journal of Forecasting, 32(2), pp.475-501.

Nikmanesh, L., Mohd Nor, A., Sarmidi, T. and Janor, H., 2014. Causal Relationship between the Volatility of Stock Market and Selected Macroeconomic Variables: Case of Malaysia. *Jurnal Ekonomi Malaysia*, 48(1), pp.143-154.

Nishat, M. and Shaheen, R., 2004. Macroeconomic Factors and Pakistani Equity Market". *The Pakistan Development Review*, 43(4II), pp.619-637.

Nobel Media., 2003. The Prize in Economic Sciences 2003 -Press Release.

Nolde, N. and Ziegel, J., 2017. Elicitability and backtesting: Perspectives for banking regulation. *The Annals of Applied Statistics*, 11(4), pp.1833-1874.

NorthstarRisk (2022) Expected Shortfall available at: https://www.northstarrisk.com/expected-shortfall.

Oh, D. and Patton, A., 2017. Time Varying Systemic Risk: Evidence from a Dynamic Copula Model of CDS Spreads. *Journal of Business & Economic Statistics*, 36(2), pp.181-195.

Oikonomou, I., Brooks, C. and Pavelin, S., 2014. The Effects of Corporate Social Performance on the Cost of Corporate Debt and Credit Ratings. Financial Review, 49(1), pp.49-75.

Okhrin, O., Odening, M. and Xu, W., 2012. Systemic Weather Risk and Crop Insurance: The Case of China. *Journal of Risk and Insurance*, 80(2), pp.351-372.

Okimoto, T., 2008. New Evidence of Asymmetric Dependence Structures in International Equity Markets. *Journal of Financial and Quantitative Analysis*, 43(3), pp.787-815.

Okimoto, T., 2008. New evidence of asymmetric dependence structures in international equity markets. Journal of Financial and Quantitative Analysis, [e-journal] 43(3), pp. 787-815.

Oliver Wyman INC (2021) Six steps to assess commodity risk exposure. Available at:

https://www.oliverwyman.com/our-expertise/insights/2012/feb/six-steps-to-assess-commodity-risk-exposure.html.

OLOWE, R., 2011. Inter-Bank Call Rate Volatility and the Global Financial Crisis: The Nigerian Case. *International Journal of Economics and Finance*, 3(1).

Oskooe, S., 2012. Oil price shocks and stock market in oil-exporting countries: evidence from Iran stock market. *OPEC Energy Review*, 36(4), pp.396-412.

ÖZDEN, Ü., 2020. Riske Maruz Değer (Rmd) Hesaplama Yöntemleri: İmkb Üzerine Uygulama. *Öneri Dergisi*, pp.279-285.

Papini, P., 2015. Bivariate copulas, norms and non-exchangeability. *Dependence Modeling*, 3(1).

Pasha, M., Ramzan, M. and Asif, M., 2019. Impact of Economic Value-Added Dynamics on Stock Prices Fact or Fallacy: New Evidence from Nested Panel Analysis. *Global Social Sciences Review*, IV(III), pp.96-105.

Pástor, Ľ. and Veronesi, P., 2013. Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), pp.520-545.

Patton, A. (2006a) 'Modelling Asymmetric Exchange Rate Dependence', International Economic Review, 47(2), 527-556.

Patton, A., 2001. Modelling Time Varying Exchange Rate Dependence using the Conditional Copula. *SSRN Electronic Journal*.

Patton, A., 2004. On the Out-of-Sample Importance of Skewness and Asymmetric Dependence for Asset Allocation. *Journal of Financial Econometrics*, 2(1), pp.130-168.

Patton, A., 2006b. Estimation of multivariate models for time series of possibly different lengths. *Journal of Applied Econometrics*, 21(2), pp.147-173.

Patton, A., 2012. A review of copula models for economic time series. *Journal of Multivariate Analysis*, 110, pp.4-18.

Patton, A., 2013. Copula Methods for Forecasting Multivariate Time Series. Handbook of Economic Forecasting, pp.899-960.

Patton, A., 2019. Comparing Possibly Misspecified Forecasts. *Journal of Business & Economic Statistics*, 38(4), pp.796-809.

Patton, A., Ziegel, J. and Chen, R., 2018. Dynamic semiparametric models for expected shortfall (and Value-at-Risk). Journal of Econometrics, 211(2), pp.388-413.

Patton, A.J. and K. Sheppard, 2009, Evaluating Volatility and Correlation Forecasts, in T.G. Andersen, R.A. Davis, J.-P. Kreiss and T. Mikosch (eds.) Handbook of Financial Time Series, Springer Verlag.

Patton, A.J., 2016, Comparing Possibly Mis specified Forecasts, working paper, Duke University.

Peihani, M., 2016. Basel Committee on Banking Supervision. *Brill Research Perspectives in International Banking and Securities Law*, 1(1), pp.1-87.

Peiró, A., 2016. Stock prices and macroeconomic factors: Some European evidence. *International Review of Economics & Finance*, 41, pp.287-294.

Pérignon, C. and Smith, D., 2010. The level and quality of Value-at-Risk disclosure by commercial banks. *Journal of Banking & Finance*, 34(2), pp.362-377.

Perugini, M. and Maioli, C., 2014. Bitcoin: Tra Moneta Virtuale E Commodity Finanziaria (Bitcoin: Between Digital Currency and Financial Commodity). *SSRN Electronic Journal*.

PHILLIPS, P. and PERRON, P., 1988. Testing for a unit root in time series regression. *Biometrika*, 75(2), pp.335-346.

Pierdzioch, C., Risse, M. and Rohloff, S., 2015. Cointegration of the prices of gold and silver: RALS-based evidence. *Finance Research Letters*, 15, pp.133-137.

Pieters, G. and Vivanco, S., 2016. Financial Regulations and Price Inconsistencies across Bitcoin Markets. *Federal Reserve Bank of Dallas, Globalization and Monetary Policy Institute Working Papers*, 2016(293).

Piotroski, J., 2002. The Impact of Management Forecasts on Short-term Stock Price Volatility. *SSRN Electronic Journal*.

Portmann, F., Siebert, S. and Döll, P., 2010. MIRCA2000-Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modelling. *Global Biogeochemical Cycles*, 24(1), p.n/a-n/a.

Pravin K. Trivedi and David M. Zimmer (2007), "Copula Modelling: An Introduction for Practitioners", Foundations and Trends® in Econometrics: Vol. 1: No. 1, pp 1-111. http://dx.doi.org/10.1561/0800000005

Pritsker, M., 2006. The hidden dangers of historical simulation. *Journal of Banking & Finance*, 30(2), pp.561-582.

Quiggin, J., 2011. What Have We Learned from the Global Financial Crisis? Australian Economic Review, 44(4), pp.355-365.

Rachel A.J. Pownall, K. G. 1999. Capturing downside risk in financial markets: Frbny Economic Policy Review / October.

Rafiq, A. and Hasan, S., 2016. Co-integration analysis between stock prices & exchange rates: Evidence from Pakistan. *International Journal of Accounting and Economics Studies*, 4(2), p.148.

Rahim, A. and Masih, M., 2016. Portfolio diversification benefits of Islamic investors with their major trading partners: Evidence from Malaysia based on MGARCH-DCC and wavelet approaches. *Economic Modelling*, 54, pp.425-438.

Rana Shahid Imdad Akash, 2011. Co-integration and causality analysis of dynamic linkage between economic forces and equity market: An empirical study of stock returns (KSE) and macroeconomic variables (money supply, inflation, interest rate, exchange rate, industrial production and reserves). *African Journal of Business Management*, 5(27).

Rao, A., 2018. Empirical Analysis of Joint Impact of Enterprise Risk Management and Corporate Governance on Firm Value. *International Review of Advances in Business, Management and Law*, 1(1), pp.34-50.

Raraga, F. and Muharam, H., 2013. VAR Analysis on Mutual Relationship between Stock Price Index and Exchange Rate and the Role of World Oil Price and World Gold Price. *SSRN Electronic Journal*.

Rashid, D. and Shabbir, A., 2021. Predicting Stock Returns Volatility: An Evaluation of Linear vs. Nonlinear Methods. International Research Journal of Finance and Economics. Available at: https://www.healthgrades.com/physician/dr-abdul-rashid-xd92r.

Rashid, Dr. Abdul & Ahmad, Shabbir. (2008). Predicting Stock Returns Volatility: An Evaluation of Linear vs. Nonlinear Methods. International Research Journal of Finance and Economics. 22.

Rasool, N. and Hussain, M., 2014. The Impact of Macroeconomic Variables on Stock Prices: An Empirical Analysis of Islamabad Stock Exchange. *Journal of Global Economy*, 10(2), pp.73-93.

Rayens, B. and Nelsen, R., 2000. An Introduction to Copulas. Techno metrics, 42(3), p.317.

Reboredo, J. and Ugolini, A., (2017). Quantile causality between gold commodity and gold stock prices. Resources Policy, 53, pp.56-63.

Reboredo, J. and Ugolini, A., 2015. Downside/upside price spillovers between precious metals: A vine copula approach. *The North American Journal of Economics and Finance*, 34, pp.84-102.

Reboredo, J., 2012. Modelling oil price and exchange rate co-movements. *Journal of Policy Modelling*, 34(3), pp.419-440.

Reboredo, J., 2013. Is gold a hedge or safe haven against oil price movements? *Resources Policy*, 38(2), pp.130-137.

Reboredo, J., 2014. Volatility spillovers between the oil market and the European Union carbon emission market. *Economic Modelling*, 36, pp.229-234.

Reboredo, J.C. and Ugolini, A., 2016. The impact of downward/upward oil price movements on metal prices. Resources Policy, 49, pp.129-141.

Regnier, E., 2007. Oil and energy price volatility. Energy Econ. 29, 405–427.

Richardson, M., Boudoukh, J. and Whitelaw, R., 1998. The Best of Both Worlds: A Hybrid Approach to Calculating Value at Risk. *SSRN Electronic Journal*.

Ringrose, T. and Joe, H., 1998. Multivariate Models and Dependence Concepts. *Biometrics*, 54(3), p.1201.

RiskMetrics (1996). RiskMetrics Technical Document.

Ritala, P., Huotari, P., Bocken, N., Albareda, L. and Puumalainen, K., (2018). Sustainable business model adoption among S&P 500 firms: A longitudinal content analysis study. Journal of Cleaner Production, 170, pp.216-226.

Rizas, K., Hamm, W., Kääb, S., Schmidt, G. and Bauer, A., 2016. Periodic Repolarisation Dynamics: A Natural Probe of the Ventricular Response to Sympathetic Activation. *Arrhythmia & Electrophysiology Review*, 5(1), p.31.

Roch, O. and Alegre, A., 2006. Testing the bivariate distribution of daily equity returns using copulas. An application to the Spanish stock market. *Computational Statistics & Data Analysis*, 51(2), pp.1312-1329.

Rockafellar, R. and Uryasev, S., 2002. Conditional value-at-risk for general loss distributions. *Journal of Banking & Finance*, 26(7), pp.1443-1471.

Rockafellar, R.T. and Uryasev, S. (2000) ‘Optimization of conditional value-at-risk’, Journal of risk, 2, pp.21-42.

Rohmawati, A.A. and Syuhada, K. (2015) ‘Value-at-risk and expected shortfall relationship’, International Journal of Applied Mathematics and Statistics, 53(5), pp.211-215.

Rokach, A. and Matalon, R., 2007. ‘Tails’ – A fairy tale on furry tails: A 15-year theatre experience for hospitalized children created by health professionals. *Paediatrics & Child Health*, 12(4), pp.301-304.

Ross, M., 2013. Basel Committee’s Fundamental Review of the Trading Book: A Commentary. *CFA Digest*, 43(3).

Roy, I. 2011. Estimation of Portfolio Value at Risk using Copula. India: http://rbi-docs.rbi.org.in/rdocs/Publications/PDFs/EVRC_270411.pdf.

Sa R, Soytas U. 2006. The Relationship between Stock Returns, Crude Oil Prices, Interest Rates, and Output: Evidence from a Developing Ecomomy. The Empirical Economics Letters.

Sadorsky, P., 2006. Modelling and forecasting petroleum futures volatility. Energy Econ.

28, 467–488.

Sakti, M. and Harun, M., 2015. Relationship between Islamic Stock Prices and Macroeconomic Variables: Evidence from Jakarta Stock Exchange Islamic Index. *Global Review of Islamic Economics and Business*, 1(1), p.071.

Salmon, F., 2012. The formula that killed Wall Street. *Significance*, 9(1), pp.16-20.

Samanta SK, Zadeh AHM, 2012. Co-Movement of Oil, Gold, the US Dollar, and Stocks. Modern Economy 3: 111-117.

Sandberg Patton, K. and Reschly, A., 2013. Using Curriculum-Based Measurement to Examine Summer Learning Loss. *Psychology in the Schools*, 50(7), pp.738-753.

Sari, R., Hammoudeh, S. and Soytas, U., 2010. Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, 32(2), pp.351-362.

Sari, Y., Prieto, A., Barton, S., Miller, B. and Rebec, G., 2010. Ceftriaxone-induced up-regulation of cortical and striatal GLT1 in the R6/2 model of Huntington's disease. *Journal of Biomedical Science*, 17(1), p.62.

Sarkar, S., Chatterjee, S. and Misra, S., 2018. Assessment of the Suitability of Fog Computing in the Context of Internet of Things. *IEEE Transactions on Cloud Computing*, 6(1), pp.46-59.

Schepsmeier, U., 2016. A goodness-of-fit test for regular vine copula models. *Econometric Reviews*, 38(1), pp.25-46.

Schweikert, K., 2018. Are gold and silver cointegrated? New evidence from quantile cointegrating regressions. *Journal of Banking & Finance*, 88, pp.44-51.

Seifert, J. and Uhrig-Homburg, M., 2006. Modelling Jumps in Electricity Prices: Theory and Empirical Evidence. *SSRN Electronic Journal*.

Selçuk, F., 2004. Free float and stochastic volatility: the experience of a small open economy. *Physica A: Statistical Mechanics and its Applications*, 342(3-4), pp.693-700.

Sensoy, A., 2013. Dynamic relationship between precious metals. Resources Policy, 38(4), pp.504-511.

Sensoy, A., 2019. The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies. *Finance Research Letters*, 28, pp.68-73.

Sethapramote, Y., Prukumpai, S. and Kanyamee, T., 2014. Evaluation of Value-at-Risk Estimation Using Long Memory Volatility Models: Evidence from Stock Exchange of Thailand. *SSRN Electronic Journal*.

Shahzad, S., Mensi, W., Hammoudeh, S., Rehman, M. and Al-Yahyaee, K., 2018. Extreme dependence and risk spillovers between oil and Islamic stock markets. *Emerging Markets Review*, 34, pp.42-63.

Shaked, M. and Joe, H., 1998. Multivariate Models and Dependence Concepts. *Journal of the American Statistical Association*, 93(443), p.1237.

Shakil, M.H., Mustapha, I.M., Tasnia, M., and Saiti, B., 2018. Is gold a hedge or a safe haven? An application of ARDL approach. Journal of Economics, Finance and Administrative Science, [e-journal] 23(44), pp.60-76. https://doi.org/10.1108/jefas-03-2017-0052

Sherman, E., 1983. A gold pricing model. *The Journal of Portfolio Management*, 9(3), pp.68-70.

Shen, H., Tang, Y., Xing, Y. and Ng, P., 2020. Examining the evidence of risk spillovers between Shanghai and London non-ferrous futures markets: a dynamic Copula-CoVaR approach. International Journal of Emerging Markets, 16(5), pp.929-945.

Shrydeh, N., Shahateet, M., Mohammad, S. and Sumadi, M., 2019. The hedging effectiveness of gold against US stocks in a post-financial crisis era. *Cogent Economics & Finance*, 7(1), p.1698268.

Silva Filho, O., Ziegelmann, F. and Dueker, M., 2012. Modelling dependence dynamics through copulas with regime switching. *Insurance: Mathematics and Economics*, 50(3), pp.346-356.

Singh, D., 2005. Basel Committee on Banking Supervision: Compliance and the compliance function in banks. *Journal of Banking Regulation*, 6(4), pp.298-300.

Singh, T., S. Mehta and M.S. Versha. (2011). Macroeconomic factors and stock returns: Evidence from Taiwan. Journal of Economics and International Finance, 2(4), 217-227.

Singhal, S., Choudhary, S. and Biswal, P., 2019. Return and volatility linkages among international crude oil price, gold price, exchange rate and stock markets: Evidence from Mexico. *Resources Policy*, 60, pp.255-261.

Sjaastad, L. and Scacciavillani, F., 1996. The price of gold and the exchange rate. *Journal of International Money and Finance*, 15(6), pp.879-897.

Sklar, A. (1959) Fonctions de Répartition à n Dimensions et Leurs Marges. Publications de l'Institut Statistique de l'Université de Paris, 8, 229-231.

Slim, S., Koubaa, Y. and BenSaïda, A., 2017. Value-at-Risk under Lévy GARCH models: Evidence from global stock markets. *Journal of International Financial Markets, Institutions and Money*, 46, pp.30-53.

Smithson, C. and Simkins, B., 2005. Does Risk Management Add Value? A Survey of the Evidence. *Journal of Applied Corporate Finance*, 17(3), pp.8-17.

So, M. and Yu, P., 2006. Empirical analysis of GARCH models in value at risk estimation. *Journal of International Financial Markets, Institutions and Money*, 16(2), pp.180-197.

Sohail, N., 2020. Short Run and Long Run Association of Macro-Economic Indicators with Stock Market: Evidence from Pakistan Stock Market. *Global Social Sciences Review*, V(I), pp.36-43.

Šoja, T., 2019. Gold in investment portfolio from perspective of European investor. The European Journal of Applied Economics, [e-journal] 16(1), pp.41-58.

https://doi.org/10.5937/ejae15-19652

Soumen, 2012. A Study on the Behaviour of Volatility in Saudi Arabia Stock Market Using Symmetric and Asymmetric GARCH Models. *Journal of Mathematics and Statistics*, 8(1), pp.98-106.

Soytas, U. and Sari, R., 2003. Energy consumption and GDP: causality relationship in G-7 countries and emerging markets. *Energy Economics*, 25(1), pp.33-37.

Stoimenov, P., 2009. Philippe Jorion, Value at Risk, 3rd Ed: The New Benchmark for Managing Financial Risk. *Statistical Papers*, 52(3), pp.737-738.

Studer, G. (1997) Maximum loss for measurement of market risk (Doctoral dissertation, ETH Zurich).

Su, E., 2016. Measuring and Testing Tail Dependence and Contagion Risk Between Major Stock Markets. *Computational Economics*, 50(2), pp.325-351.

Su, J. and Hua, L., 2017. A general approach to full-range tail dependence copulas. *Insurance: Mathematics and Economics*, 77, pp.49-64.

Su, Y., Chen, M. and Huang, H., 2010. An application of closed-form GARCH option-pricing model on FTSE 100 option and volatility. *Applied Financial Economics*, 20(11), pp.899-910.

Su, Y., Huang, H. and Lin, Y., 2011. GJR-GARCH model in value-at-risk of financial holdings. *Applied Financial Economics*, 21(24), pp.1819-1829.

Süss, S., 2006. Alexander McNeil, Rüdiger Frey, Paul Embrechts (2005): "Quantitative Risk Management", Princeton Series in Finance, $79.50.-. *Financial Markets and Portfolio Management*, 20(2), pp.239-240.

Syllignakis, M. and Kouretas, G., 2011. Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics & Finance*, 20(4), pp.717-732.

Symitsi, E. and Chalvatzis, K., 2018. Return, volatility and shock spillovers of Bitcoin with energy and technology companies. *Economics Letters*, 170, pp.127-130.

Syrichas, N., 2020. Stress-Testing Net Trading Income: The Case of European Banks. *SSRN Electronic Journal*.

Szakmary, A., Ors, E., Kyoung Kim, J. and Davidson, W., 2003. The predictive power of implied volatility: Evidence from 35 futures markets. *Journal of Banking & Finance*, 27(11), pp.2151-2175.

Tai, C., 2007. Market integration and contagion: Evidence from Asian emerging stock and foreign exchange markets. *Emerging Markets Review*, 8(4), pp.264-283.

Tai, C., 2010. Foreign exchange risk and risk exposure in the Japanese stock market. *Managerial Finance*, 36(6), pp.511-524.

Takaishi, T., 2018. Statistical properties and multifractality of Bitcoin. *Physica A: Statistical Mechanics and its Applications*, 506, pp.507-519.

Tamakoshi, G. and Hamori, S., 2013. An asymmetric dynamic conditional correlation analysis of linkages of European financial institutions during the Greek sovereign debt crisis. *The European Journal of Finance*, 19(10), pp.939-950.

Tauchen, G., 2001. Notes on financial econometrics. *Journal of Econometrics*, 100(1), pp.57-64.

Taylor, A., 1998. Argentina and the world capital market: saving, investment, and international capital mobility in the twentieth century. *Journal of Development Economics*, 57(1), pp.147-184.

Thai Hung, Ngo. (2020). Conditional dependence between oil prices and CEE stock markets: a copula-GARCH approach. Eastern European Countryside. 11. 62-86.

The Recession of the Early 1990s. (2015, June 24). Retrieved from https://study.com/academy/lesson/the-recession-of-the-early-1990s.html

The Pharmaceutical Journal, 2015. Parliament approves changes to regulations governing controlled drugs.

Thiele, S., 2019. Modeling the conditional distribution of financial returns with asymmetric tails. *Journal of Applied Econometrics*, 35(1), pp.46-60.

Tian, Y., Akimov, A., Roca, E. and Wong, V., 2011. Does the Carbon Market Help or Hurt the Stock Price of Electricity Companies? Further Evidence from the European Context. *SSRN Electronic Journal*.

Tiwari, A., Albulescu, C. and Yoon, S. (2017) A multifractal detrended fluctuation analysis of financial market efficiency: Comparison using Dow Jones sector ETF indices, Physica A: Statistical Mechanics and Its Applications, 483, pp. 182-192.

Torlais, D., 1959. Inventaire de la correspondance et des papiers de Réaumur conservés aux Archives de l'Académie des Sciences de Paris. *Revue d'histoire des sciences et de leurs applications*, 12(4), pp.315-326.

Tripathy, N., 2012. Long-run relationship between macroeconomic variables and stock market - evidence from India. *International Journal of Accounting and Finance*, 3(4), p.291.

Troster, V., Bouri, E. and Roubaud, D., 2019. A quantile regression analysis of flights-to-safety with implied volatilities. *Resources Policy*, 62, pp.482-495.

Troster, V., Tiwari, A., Shahbaz, M. and Macedo, D., 2019. Bitcoin returns and risk: A general GARCH and GAS analysis. *Finance Research Letters*, 30, pp.187-193.

Tschorsch, F. and Scheuermann, B., 2016. Bitcoin and Beyond: A Technical Survey on Decentralized Digital Currencies. *IEEE Communications Surveys & Tutorials*, 18(3), pp.2084-2123.

Tsitsiklis, J. and Van Roy, B., 2001. Regression methods for pricing complex American-style options. *IEEE Transactions on Neural Networks*, 12(4), pp.694-703.

Turner, N., 2004. Agronomic options for improving rainfall-use efficiency of crops in dryland farming systems. *Journal of Experimental Botany*, 55(407), pp.2413-2425.

Tursoy, T. and Faisal, F., 2018. The impact of gold and crude oil prices on stock market in Turkey: Empirical evidences from ARDL bounds test and combined cointegration. *Resources Policy*, 55, pp.49-54.

Tzang, S., Wang, C. and Yu, M., 2016. Systematic risk and volatility skew. *International Review of Economics & Finance*, 43, pp.72-87.

Ugurlu, E., Thalassinos, E. and Muratoglu, Y., 2014. Modeling Volatility in the Stock Markets using GARCH Models: European Emerging Economies and Turkey. *International Journal of Economics and Business Administration*, II (Issue 3), pp.72-87.

Ullah, A., Hussain, S., Khan, Z. and Rafiq, M., 2011. Shocks In Macroeconomic Variables and Stock Market Stability: Case Study of Kse-100 Index. *Business & Economic Review*, 3(2), pp.154-

Urquhart, A., 2016. The inefficiency of Bitcoin. *Economics Letters*, 148, pp.80-82.

Urquhart, A., Batten, J., Lucey, B., McGroarty, F. and Peat, M., 2015. Does Technical Analysis Beat the Market? Evidence from High Frequency Trading in Gold and Silver. *SSRN Electronic Journal*.

Uryasev, S. (2000) 'Conditional value-at-risk: Optimization algorithms and applications', In proceedings of the IEEE/IAFE/INFORMS 2000 conference on computational intelligence for financial engineering, pp. 49-57. IEEE.

Vedenov, D., 2008. 19th Annual Meeting of The North American Menopause Society September 24-27, 2008, Orlando, FL. *Menopause*, 15(6), pp.1197-1232.

Verbrugge, B. and Geenen, S., 2019. The gold commodity frontier: A fresh perspective on change and diversity in the global gold mining economy. The Extractive Industries and Society, 6(2), pp.413-423.

Vergni, L., Todisco, F. and Mannocchi, F., 2015. Erratum to: Analysis of agricultural drought characteristics through a two-dimensional copula. *Water Resources Management*, 29(11), pp.4203-4204.

Verma, R. and Ozuna, T., 2005. Are emerging equity markets responsive to cross-country macroeconomic movements? *Journal of International Financial Markets, Institutions and Money*, 15(1), pp.73-87.

Wang, C., 2021. Different GARCH models analysis of returns and volatility in Bitcoin. Data Science in Finance and Economics, 1(1), pp.37-59.

Wang, J., Zhang, Y., Feng, Y., Zheng, X., Jiao, L., Hong, S., Shen, J., Zhu, T., Ding, J. and Zhang, Q., 2016. Characterization and source apportionment of aerosol light extinction with a coupled model of CMB-IMPROVE in Hangzhou, Yangtze River Delta of China. *Atmospheric Research*, 178-179, pp.570-579.

Wang, K., 2013. Can Gold Effectively Hedge Risks of Exchange Rate? *Journal of Business Economics and Management*, 14(5), pp.833-851.

Wang, K., Chen, Y. and Huang, S., 2011. The dynamic dependence between the Chinese market and other international stock markets: A Time Varying copula approach. *International Review of Economics & Finance*, 20(4), pp.654-664.

Wang, Y. and Guo, Z., 2018. The dynamic spillover between carbon and energy markets: New evidence. *Energy*, 149, pp.24-33.

Wang, Y. and Wu, C., 2012. Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models? *Energy Economics*, 34(6), pp.2167-2181.

Wang, Y., Wu, J. and Lai, Y., 2013. A revisit to the dependence structure between the stock and foreign exchange markets: A dependence-switching copula approach. *Journal of Banking & Finance*, 37(5), pp.1706-1719.

Wasiuzzama, S. and Angabini, A., 2011. GARCH Models and the Financial Crisis-A Study of the Malaysian Stock Market. *The International Journal of Applied Economics and Finance*, 5(3), pp.226-236.

Wen, X., Wei, Y. and Huang, D., 2012. Measuring contagion between energy market and stock market during financial crisis: A copula approach. *Energy Economics*, 34(5), pp.1435-1446.

Wearden, G. and Batty, D., 2011. Stock markets plunge - Thursday 4 August 2011. [online] the Guardian. Available at: <https://www.theguardian.com/business/2011/aug/04/stock-markets-exchange-plunge-business>

William Schwert, G., 2002. Stock volatility in the new millennium: how wacky is Nasdaq? *Journal of Monetary Economics*, 49(1), pp.3-26.

Williams, W., 2022. Timeline of US Stock Market Crashes. Investopedia. Available at: <https://www.investopedia.com/timeline-of-stock-market-crashes-5217820>

Wong, W., Chang, M. and Tu, A., 2009. Are magnet effects caused by uninformed traders? Evidence from Taiwan Stock Exchange. *Pacific-Basin Finance Journal*, 17(1), pp.28-40.

World Gold Council, 2021. Gold: the most effective commodity investment, Available at:

<https://www.sprott.com/media/4272/wgc-gold-effective-commodity-2021.pdf>

Wiecki, T., 2018. An intuitive, visual guide to copulas. While My MCMC Gently Samples Atom. Available at: https://twiecki.io/blog/2018/05/03/copulas/

Wright, C., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. *SSRN Electronic Journal*.

Wu et al. (2017) Modelling Asymmetric Conditional Dependence between Shanghai and Hong Kong stock markets, Research in International Business and Finance, 0275-5319, pp. 1137-1149.

Wu, C., Chung, H. and Chang, Y., 2012. The economic value of co-movement between oil price and exchange rate using copula-based GARCH models. *Energy Economics*, 34(1), pp.270-282.

Wu, W., Lau, M.C.K. and Vigne, S.A., (2017). Modelling asymmetric conditional dependence between Shanghai and Hong Kong stock markets. Research in International Business and Finance, 42, pp.1137-1149.

Xu, K., 2014. Model-Free Inference for Tail Risk Measures. *Econometric Theory*, 32(1), pp.122-153.

Xu, Q., Jiang, C. and He, Y., 2015. An exponentially weighted quantile regression via SVM with application to estimating multiperiod VaR. *Statistical Methods & Applications*, 25(2), pp.285-320.

Xu, W., Filler, G., Odening, M. and Okhrin, O., 2010. On the systemic nature of weather risk. *Agricultural Finance Review*, 70(2), pp.267-284.

Yamai, Y. and Yoshiba, T. (2002) 'Comparative analyses of expected shortfall and value-at-risk under market stress1', In This volume contains papers presented and papers based on presentations at the Third Joint Central Bank Research Conference on Risk Measurement and Systemic Risk held at the BIS in March 2002. The views expressed in this volume are those of the authors and do not necessarily reflect the views of the BIS or the central banks represented at the conference. Authors retain the copyright for their individual papers, pp. 216.

Yang, J., Zhou, Y. and Wang, Z., 2009. The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance*, 33(4), pp.670-680.

Yang, L. and Hamori, S., 2013. Dependence structure among international stock markets: a GARCH–copula analysis. *Applied Financial Economics*, 23(23), pp.1805-1817.

Yang, L., 2019. Connectedness of economic policy uncertainty and oil price shocks in a time domain perspective. *Energy Economics*, 80, pp.219-233.

Yao, C. and Sun, B., 2018. The study on the tail dependence structure between the economic policy uncertainty and several financial markets. *The North American Journal of Economics and Finance*, 45, pp.245-265.

Yermack, D., 2013. Is Bitcoin a Real Currency? *SSRN Electronic Journal*.

Yildirim, I., 2015. Financial Risk Measurement for Turkish Insurance Companies Using VaR Models. *Journal of Financial Risk Management*, 04(03), pp.158-167.

Yilmazkuday, H., (2021). COVID-19 effects on the S&P 500 index. Applied Economics Letters, pp.1-7.

Yiu, M., Alex Ho, W. and Choi, D., 2010. Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil. *Applied Financial Economics*, 20(4), pp.345-354.

Young, J., 2021. Investing with cyclical stocks. Investopedia. Available at: https://www.investopedia.com/terms/c/cyclicalstock.asp.

Yu, L., Li, J., Tang, L. and Wang, S., 2015. Linear and nonlinear Granger causality investigation between carbon market and crude oil market: A multi-scale approach. *Energy Economics*, 51, pp.300-311.

Yu, W., Kwon, T. and Shin, C., 2013. Multicell Coordination via Joint Scheduling, Beamforming, and Power Spectrum Adaptation. *IEEE Transactions on Wireless Communications*, 12(7), pp.1-14.

Zakoian, J., 1994. Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18(5), pp.931-955.

Zhang, L. and Singh, V., 2014. Trivariate Flood Frequency Analysis Using Discharge Time Series with Possible Different Lengths: Cuyahoga River Case Study. *Journal of Hydrologic Engineering*, 19(10), p.05014012.

Zhang, W., Wang, P., Li, X. and Shen, D., 2018. Some stylized facts of the cryptocurrency market. *Applied Economics*, 50(55), pp.5950-5965.

Zhang, X. and Jiang, H., (2019). Application of Copula function in financial risk analysis. Computers & Electrical Engineering, 77, pp.376-388.

Zhang, Y. and Sun, Y., 2016. The dynamic volatility spillover between European carbon trading market and fossil energy market. *Journal of Cleaner Production*, 112, pp.2654-2663.

Zhang, Y., Gomes, A. T., Beer, M., Neumann, I., Nackenhorst, U., and Kim, C., 2019. Modelling asymmetric dependences among multivariate soil data for the geotechnical analysis – The asymmetric copula approach. Soils and Foundations, [e-journal] 59(6), pp. 1960-1979.

Zhao, H., 2010. Dynamic relationship between exchange rate and stock price: Evidence from China. *Research in International Business and Finance*, 24(2), pp.103-112.

Zhu, B., Wang, P., Chevallier, J. and Wei, Y., 2013. Carbon Price Analysis Using Empirical Mode Decomposition. *Computational Economics*, 45(2), pp.195-206.

Zhu, D. and Galbraith, J., 2010. A generalized asymmetric Student- distribution with application to financial econometrics. *Journal of Econometrics*, 157(2), pp.297-305.

Zhu, D. and Galbraith, J., 2011. Modelling and forecasting expected shortfall with the generalized asymmetric Student-t and asymmetric exponential power distributions. *Journal of Empirical Finance*, 18(4), pp.765-778.

Zhu, H., Peng, C. and You, W., 2016. Quantile behaviour of cointegration between silver and gold prices. *Finance Research Letters*, 19, pp.119-125.