Major Research Project

On

ENERGY PORTFOLIO RISK MANAGEMENT USING VAR MODEL

Submitted By

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CERTIFICATE

This is to certify that **Mr.Prabhakar Mallik** , Roll No. 2K20/DMBA/158 has submitted the project report titled "**Energy portfolio risk management using VAR model**" in partial fulfilment of the requirements for the award of the degree of Master of Business Administration (MBA) from Delhi School of Management, Delhi Technological University, New Delhi during the academic year 2021-22**.**

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DECLARATION

I, hereby declare that I have worked on a project titled “Energy Portfolio risk management using VAR model”, in partial fulfilment of the requirement for the Master of Business Administration Program and the report submitted is a record of original dissertation work done by me, under the guidance of Mr. Dhiraj Kumar Pal, Assistant Professor, Delhi School of Management, DTU.

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EXECUTIVE SUMMARY

In most circumstances, the degree of risk associated with a specific investment is directly proportionate to the potential future returns. It is difficult for investors, shareholders, and financial managers to assess the overall loss of their asset portfolio in the present environment since standard deviation is inadequate to depict the real total loss. The notion of Value at Risk (VaR) is discussed in this study since it has been demonstrated to be an excellent risk measuring tool in quantifying the complete loss of investment in precise currency that would be borne by the investors over a period of time. A portfolio's greatest probable loss in value over a specific time for a particular confidence interval under normal market conditions is defined as the volatility of a portfolio's value over a set period.

This paper compares the COVID-19 crisis to the worldwide financial crisis of 2008 from the standpoint of a retail investor, utilizing a VAR model analysis. In addition, study demonstrates which method of VAR is better to find risk associated with portfolio for the retail investors. The study will anticipate the Value at Risk using a variety of parametric and nonparametric models, as well as explain why business risk assessment and management are critical for financial institutions and retail investors.

The three methodologies of Delta Normal, Historical Simulation, and Monte Carlo Simulation are used to measure the VAR for a hypothetical portfolio of stocks, respectively. Finally, the research demonstrates that, when compared to the other two techniques, the Monte Carlo Simulation methodology is the most relevant and adaptable in determining Value at Risk (VAR).

According to research, sophisticated VAR type models for predicting future variation are critical for effective energy portfolio risk management. Despite this, there has been a failure to offer a clear picture of the amount of money at risk on behalf of the shareholders or any other stakeholder immediately affected by price changes in specific or multiple energy commodities. As a consequence, risk managers must go a step further and discover the most reliable and accurate technique for precisely monitoring and accurately calculating the overall portfolio value-at-risk (VAR), which, by essence, provides a good evaluation of the whole real amount at risk. Using a strategy that takes into consideration the specific features of the energy product transaction is the most effective approach to decrease risk and correctly predict future prospective losses.

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1. Introduction

1.1 Background

Portfolio Management

It is the method of gauging and managing a portfolio of assets that are set to achieve the financial objectives and risk aversion of the investors. It is up to individuals to decide whether they will construct and administer their personal portfolios or whether they will seek the assistance of a professional licensed portfolio manager to do so on their behalf. Throughout every circumstance, the aim of the investor is to increase the predicted rate of return the investments while maintaining a risk cluster level. Portfolio management is the competence to analyze the advantages and disadvantages, as well as the possibilities and dangers, of a number of investment alternatives. In all of the possibilities, there are trade-offs, including debt vs equity, local versus international, and growth vs. stability, among other considerations. It’s nature can be classified into passive or active in nature.

A long-term strategy called passive management is one that is established and then set about. It might include purchasing one or more exchange-traded funds that follow a certain index. This is referred to as indexing or index investing in the financial industry. Portfolio theory may be used by those who design indexed portfolios to assist them get the best asset mix possible.

Key Elements of Portfolio Management

Asset Allocation

The long-term combination of commodities is the most important factor in efficient portfolio management. Generally speaking, this includes stocks, bonds, and "cash," such as certificates of deposit (CDs).Investment choices include real estate, commodities, and derivatives, among others, which are also known as "alternative investments."

When it comes to asset allocation, it is important to remember that various kinds of assets do not move in lockstep, and that some are more volatile than others. A diverse portfolio of assets offers balance while also protecting against risk. The portfolios of investors with a more assertive character include a higher proportion of more volatile assets, such as growth companies.Bonds and blue-chip stocks are preferred investments for investors with a conservative character since they are more stable than other types of investments.

Diversification

The only thing you can be sure of in investing is that it is impossible to predict winners and losers. This is the best way to get a good look at a whole group of assets. Diversification spreads the risk and return of individual assets across the asset category or across forms of investment because it is hard to forecast which section of an investment industry or sector will surpass another, diversification encapsulates the profits of all sectors over time while minimizing volatility at any one time. Diversification is done through making an investment in a wide range of assets, industries, and geographic locations.

Portfolio Variance = $w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2Cov_{1,2}$

where:
w_1 = the portfolio weight of the first asset
w_2 = the portfolio weight of the second asset
σ_1= the standard deviation of the first assetσ_2 = the standard deviation of the second asset
$Cov_{1,2}$ = the covariance of the two assets, which can thus be expressed as $p_{(1,2)}\sigma_1\sigma_2$, where $p_{(1,2)}$ is the correlation coefficient between the two assets

Rebalancing

Rebalancing is done on a regular basis, usually once a year, to return a portfolio to its original target allocation. When market movements cause the asset mix to get out of balance, adjustment is done to put it back into balance. Rebalancing is selling expensive assets and investing the profits in relatively inexpensive, out-of-favour assets. The annual rebalancing technique allows the investor to profit from gains and expand the opportunity for growth in high-potential sectors while preserving the portfolio's risk/return profile.

Things to Consider

Numerous factors and investment characteristics are considered while creating the optimum portfolio. The risk and return characteristics of the particular assets under consideration are the most critical of these factors. Correlations between individual assets, as well as future cash flows, are significant contributors to portfolio risk. Developing a strategy for a client requires knowledge of the investor's risk profile. While historical averages over extended periods might help you make risk decisions, it's difficult to forecast (and impossible to know) if the historical averages will work in your favor given your individual circumstances and objectives and desires.

Even if you invest in a large, diversified portfolio of companies like the S&P 500 for a long time, there's no assurance that you'll get a rate of return that matches the strong historical average .

Both strategies, on the other hand, often raise your investment's expenditures, lowering prospective earnings. Hedging often includes speculative, high-risk activities such as derivatives trading or investing in discounted stocks.

At the end of the day, all transactions include some degree of risk.You can increase your chances of meeting your financial objectives by managing risks and using risk mitigation measures.

Managing risk in the financial industry is the process of recognizing, assessing, and accepting or minimizing ambiguity in investment decisions. It is described as the method by which an investor or portfolio manager looks at the likelihood of risks in an investments, such as perverse incentives, and tries to quantify it before taking the appropriate action (or inaction) depending on the fund's investment goals and tolerance for risk.

Volatility are inseparable concepts in finance. Investing in US T-bills or evolving stocks or real estate comes with some amount of risk, which may vary from near zero to quite high in high-inflationary conditions. Both the absolute and relative amounts of risk may be quantified. Investors may have a better understanding of the benefits, drawbacks, and costs of different investment methods by being well-versed in risk.

A variation from an anticipated result is a standard definition of investment risk.It is possible to express this difference in terms of a reference point, such as a market benchmark, or in terms of absolute values. While variance may be beneficial or negative, most investing experts believe it indicates some level of the desired result for your assets.

As a result, in order to maximize earnings, one must be willing to accept greater risk. Additionally, it is a generally held view that increasing risk is associated with increased volatility. While investment professionals are always on the lookout for — and occasionally discovering — solutions to reduce fluctuation, there is no complete consensus on how to do so.

The range of sensitivity permitted by an investor's financial goals, or, in the case of a financial expert, their risk aversion, determines how much volatility an investor should tolerate. Standard deviation is a commonly used relative risk indicator since it is a quantitative measure of spread around a central tendency.

Consider the average return on capital and afterwards the average standard deviation throughout that time period. Normal distributions predict that the anticipated return on investment will be one point difference from the average 67 percent of time and two standard deviations the rest of the time from the average 95 percent of the time (the classic bell-shaped curve).This assists investors in estimating risk. They invest only if they feel they can withstand the financial and emotional dangers.

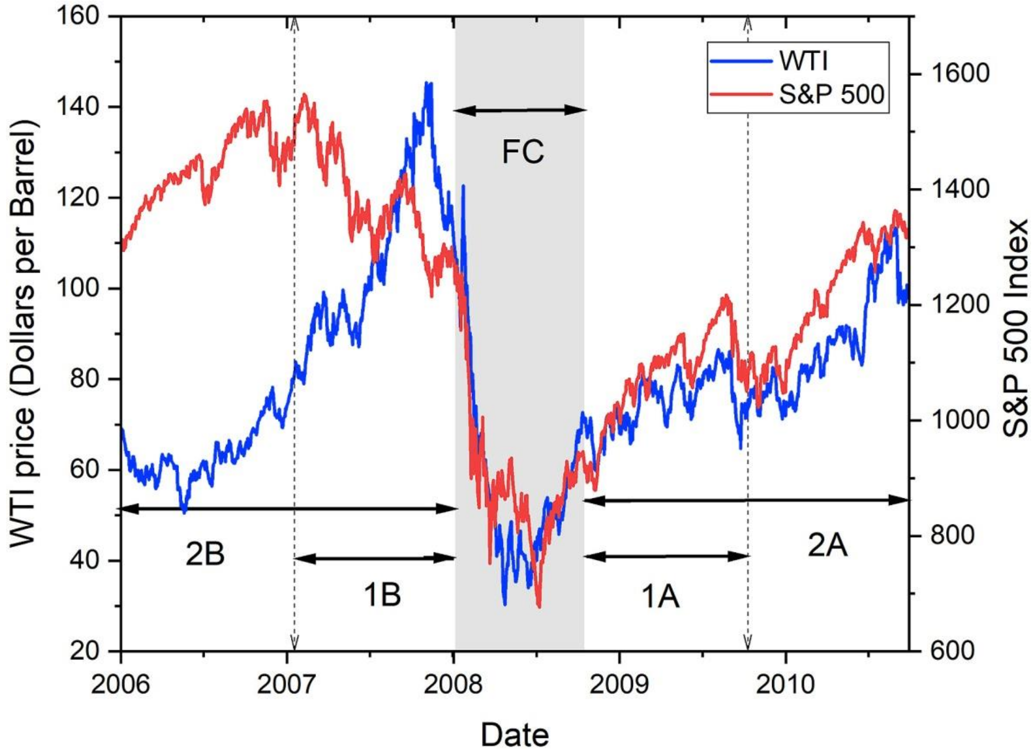
Market factors and under-lying pricing variables can cause the worth of oil and gas companies trades to fluctuate over time. A price prediction is used to assess a company's risk in managing its energy supply and forward contracts for energy trading.

Value-at-Risk has become an indispensable instrument. Value-at-risk can be used in the oil market to calculate the maximum oil price variations associated with a probability level. When it comes to developing risk management strategies, this quantification is crucial. Risk management is the assessment and management of risk in a company, portfolio of financial, commodities, and other assets. Portfolio risk of a firm is calculated using the risk exposure from variations in any of the factors that influence current agreements, as well as the company predictions from demand, supply, and pricing. The company can maximize the usage of both physical and financial assets by calculating projected return on assets using VAR . As suggested by Parsons (1998), a risk management approach that reports both portfolio and operational risk lets corporations to avoid large losses due to price variations or shifting energy consumption patterns, decrease volatility in earnings whereas maximizing return on investment, and comply with regulations that limit risk exposure.

Debt risks for Oil and Gas companies

At the time of the COVID-19 ,outbreak several oil-exporting countries were significantly in debt, having increased borrowing in reaction to falling commodity prices since 2014. The shifting structure of these nations' debt portfolios, away from traditional subsidized sources of funding, multilateral and bilateral partners, and private creditors, is strongly linked to the dangers of increased debt that these countries confront.

Figure1. WTI price (left axis) and S&P 500 Index (right axis) for the period 2/3/2006 - 31/12/2010.

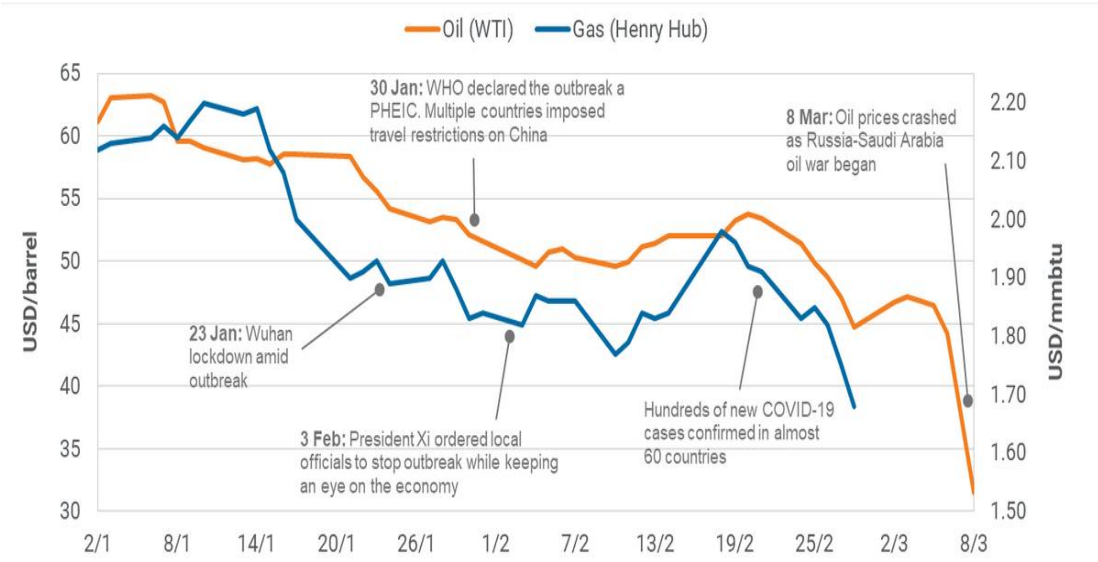


Source- Bloomberg

Oil companies have been able to borrow huge sums owing to investors' increasing readiness to lend against oil deposits and income at a time when debt levels have risen more generally due to lose financial policy. Companies in the oil industry have borrowed from banks and bond markets since 2008.The issuance of debt instruments by oil and gas corporations has greatly surpassed the issuance of debt instruments by other industries.

The total amount of bonds issued by oil and gas corporations climbed by 15% every year, from $455 billion in 2006 to $1.4 trillion in 2014.Banks have also lent a lot of money to the energy sector. In 2014, syndicated loans to the oil and gas industry totalled $1.6 trillion, up 13% from 2006's $600 billion.

Figure2. WTI Index (left axis) and Henry hub Index (right axis) during Covid breakdown.

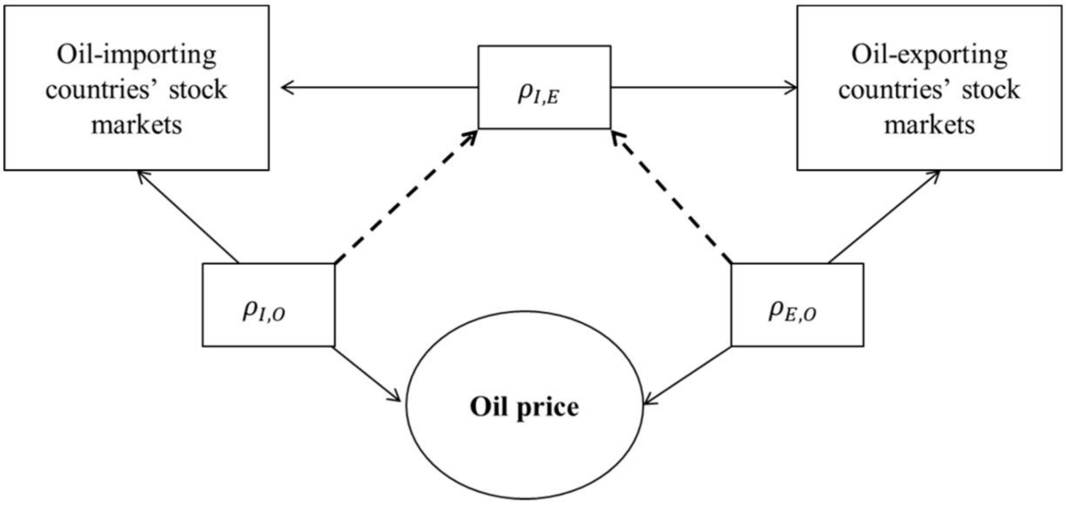


Source- Bloomberg

Although consumption of oil was already poor before to this, the COVID-19 pandemic will have a substantial influence on the already excess supply oil sector in 2020 Q1 and Q2.There will be a low oil price as long as the OPEC+ production cuts continue unless a huge boost is announced. It seems unlikely that prices would increase as rapidly as they did during the global economic downturn of 2008, notwithstanding the recent recovery..As a result of technological developments, falling renewable energy costs, an increased focus on decarbonisation, as well as waning investor interest, the fossil fuel industry is on the decline.

Concerns have been raised regarding the volatility that is largely swing by the epidemic and its subsequent spillovers to the rest of the financial markets, since the oil market has developed a causal influence on other capital sector, which are in turn intertwined with one another.(Bouri et al., 2020) looked studied the prediction potential of previous uncertainty for oil return volatility in relation to several infectious illnesses (such as COVID-19, SARS, MERS, Ebola, H1N1, H5N1). However, (Bouri et al., 2020) employed an approach based on the most current newspaper-based index created by (Bouri et al., 2020). (Baker et al., 2020).

Figure 3: Transactions of Oil prices between oil exporting and importing markets.

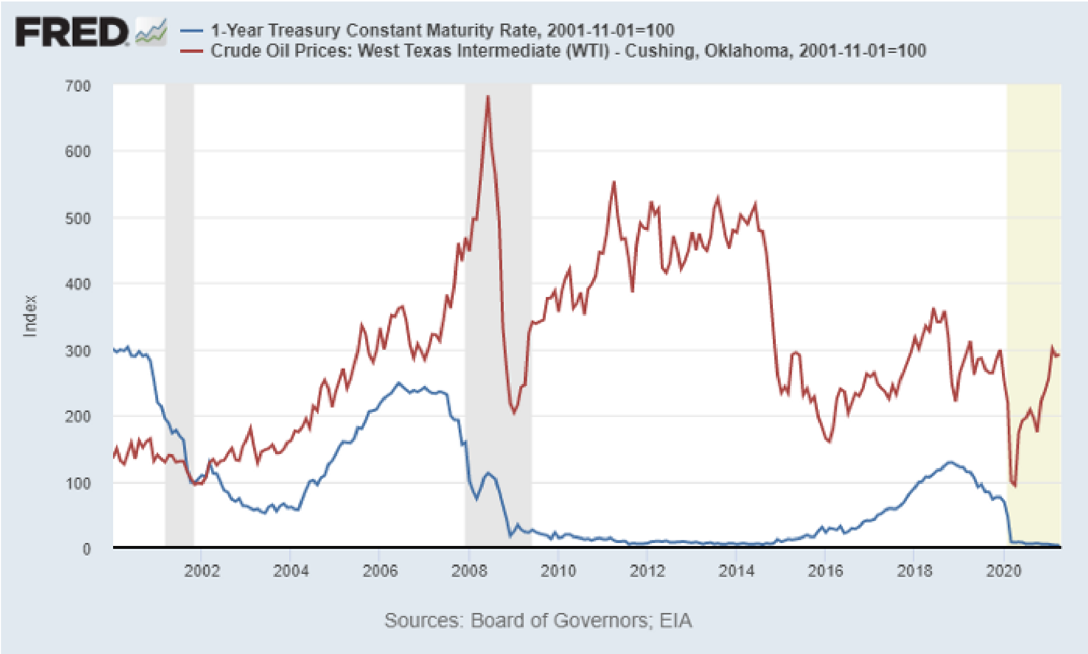


Source- OPEC report

This paper's main contribution is to provide readers with a quantified comparative viewpoint on the volatility in the oil market, which is largely generated by worldwide catastrophic occurrences. Because the COVID-19 situation is still unfolding, our inquiry aids policymakers and investors in building the groundwork for a well-informed and planned reaction if the oil market continues to be volatile.

Association between stock and oil

The correlation between stock and oil returns swings between high and low values, indicating that the link between shares and oil is inherently volatile. To put it another way, the prices of stocks and oil often move in the same direction, but sometimes they move in different ways. However, the association is often positive ,stocks and oil move in the same direction. Stocks and oil may have a positive association since both are reacting to fundamental movements in global demand. Over shorter time horizons, a spike in oil prices reduces predicted growth and raises inflationary expectations.. Below figure shows movement of price of crude oil and treasury maturity rate.

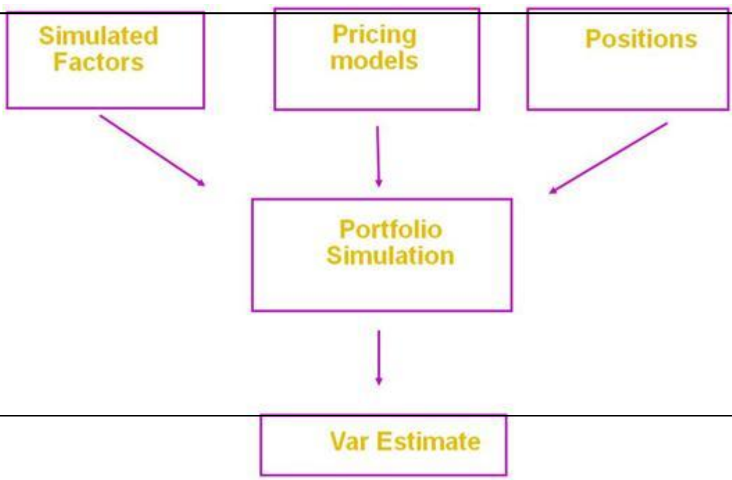


The whole market and sector stock price performances over times of high and low real oil prices are consistent with the notion that rises in oil prices have a negative effect on stock prices by impacting the outlook for corporate profitability. In this regard, investors' fears that rising oil prices would have a particularly large dampening impact on profits in this sector, which is the most closely associated to the economic cycle, possibly explain the cyclical goods sector's relative shortfalls.

Value-at-Risk (VAR)

The word VAR did not enter the financial vernacular until the early 1990s, although VAR measurements have a far longer history. These may be traced back to capital requirements for early twentieth-century security businesses in the United States.

Figure: 4 Factors influencing VAR



Source - O'Reilly

VAR is a method used to anticipate the possible losses that a firm, portfolio, or strategy may experience over a certain time period.Investment and commercial banks use this figure to assess the risk of loss in their business portfolios.Risk managers use this tool to measure and manage their own risk exposure.

$$\text{Value at Risk} = v_m \frac{v_i}{v_{i-1}}$$

$$l_p = l_1 + l_2 + l_3 + \cdots + l_n$$

$$\sigma_p^2 = \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \cdots + \sigma_n^2 + \rho_{1,2,3,\ldots n}\sigma_1\sigma_2\sigma_3 \ldots\ldots \sigma_n$$

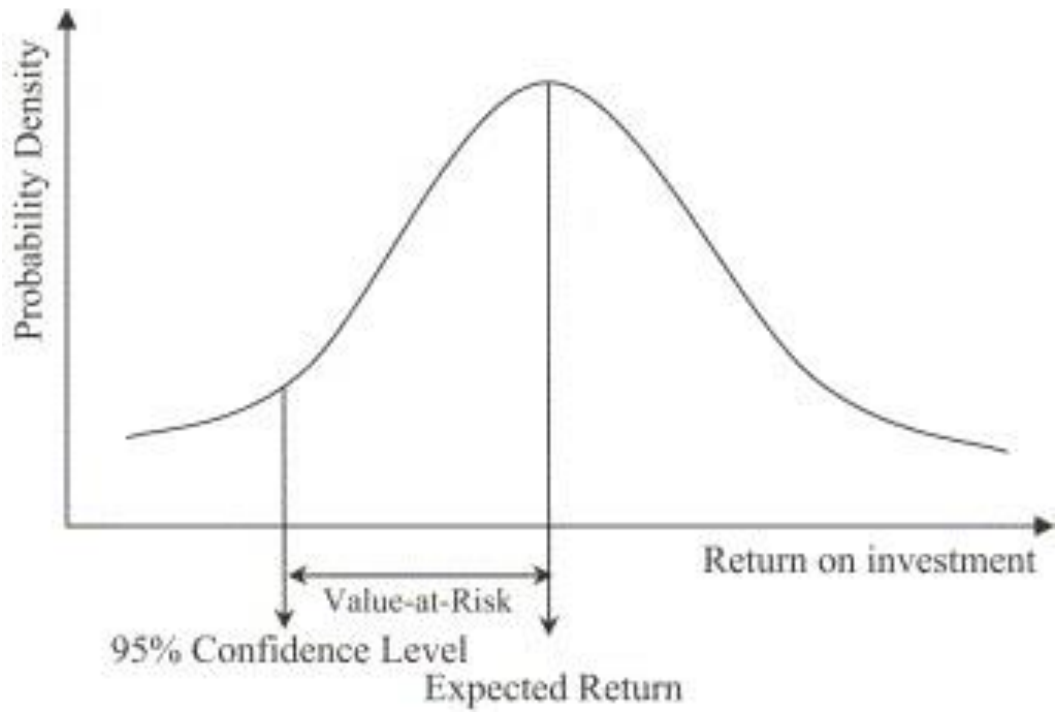
Where:

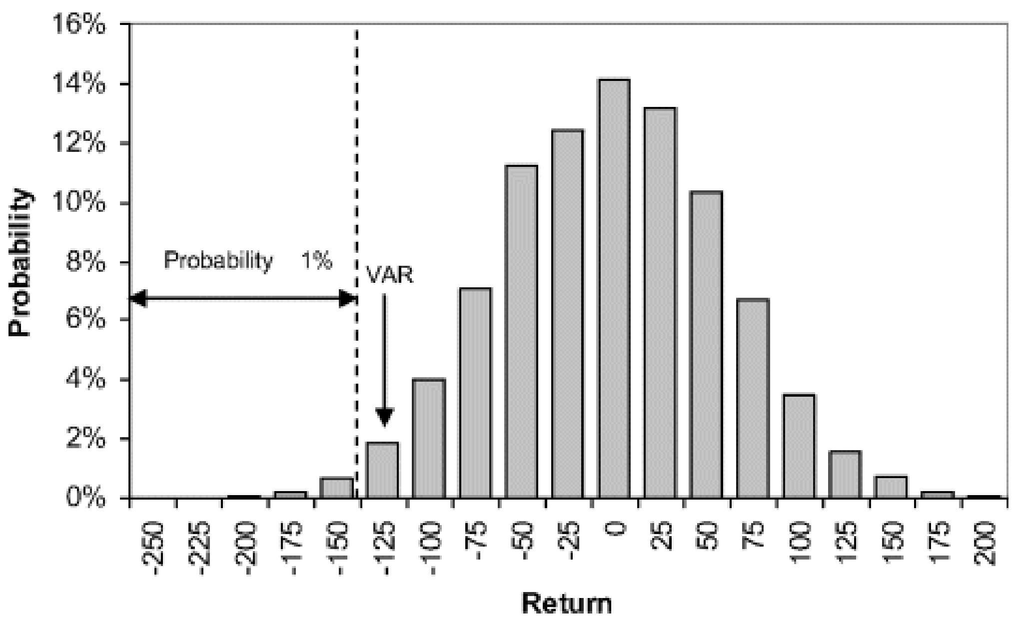
σ_p^2 = Standard Deviation of the loss on portfolio

σ_1^2 = loss form instrument 1

$\rho_{1,2,3,\ldots n}$ = Correlation between losses 1 to n

Illustation1: VAR risk orientation. These figures show risk and return mapping.





1.2 Problem Statement

The purpose of this paper is to discuss the significance of oil price risk in controlling price risk in the energy markets. Using the Value at Risk Model, this research seeks to evaluate the portfolio's underlying volatility. The VaR model assesses the loss that investors would face in real exchange terms over a particular time period for a given confidence level.Similarly, the risk density of the energy sector during the financial crisis and the Covid-induced economy will be compared in this research.

Energy markets risk management

Recently, there has been a flurry of activity around the use of VaR for risk disclosure and reporting. In the aftermath of numerous well-publicized derivatives snafus, such as the Barrings Bank disaster, various regulatory organizations have advised or enforced the reporting of VaR estimates by businesses that retain substantial derivatives positions. Valuation at Risk calculations give a clear gauge of the company's potential negative risk.SEC rules for disclosing quantitative and qualitative risks associated with market sensitive assets (i.e., derivatives holdings) of reporting enterprises were established in January 1997 by the Securities and Exchange Commission

VaR was one of three quantitative risk reporting methodologies approved by the Securities and Exchange Commission for use in SEC filings (Linsmeier and Pearson 1997).Similarly, futures exchanges employ VaR to determine the likelihood of clearing members defaulting (Fuhrman).VaR is considered by many to be a more intuitive measure of risk and easier to understand by top-level managers and outside investors who may or may not be well-versed in statistical methodologies due to its emphasis on downside risk.

Non parametric methodologies

The standard historical modelling method is by far the quickest and easiest way for estimating VaR, since it utilizes previous projected data for the current portfolio combination.This method generates a hypothetical return distribution from which future

probable returns may be anticipated. The VaR value is calculated in this situation by ascending the asset or portfolio returns for the time period under consideration. The observation that satisfies the criteria of having a percent of the observations fall inside and above (1-a percent) provides the VaR value for the previously chosen confidence .

Semi-parametric methodologies

ARMA forecasting approach

One may argue that the most significant advancement in the original notion of historical simulation in the context of decision making applied to energy commodities.

This is accomplished via the use of an ARMA model, which serves as the foundation for the return distribution. While the earlier simulation method employed prior returns' distributions, or GARCH frameworks that assumed a normal distribution, this new method uses the distribution of current returns.

$$y_t = c + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + ..\theta_q \epsilon_{t-q}$$

1.3 Objective of the study

Followings are the objective of this study:

- To estimate the probability of the loss, with a confidence interval by defining the probability distributions of individual risks appetite of investors.
- Using VAR model analysis, Comparison of COVID-19 crisis with the global financial crisis of 2008 in perspective of retail investor investment in energy sector.
- To study which method of VAR is most suitable to find risk associated with portfolio for the retail investors.

1.4 Scope of Study

The purpose of this research is to detect, assess, and forecast market risk for oil and gas companies amid 2008 global financial crisis and Covid induced crises. The study will anticipate the Value at Risk using a variety of parametric and nonparametric models, as well as explain why business risk assessment and management are critical for investors.

2. Literature Review

The enormous expansion of financial markets and the provision of financial products and services throughout the 1970s and 1980s reflected economic growth.As a consequence of these modifications, persons operating in the financial markets now face an urgent need for risk management and risk quantification tools.It was a big hit with regulators because it enabled banks to examine and report their risk exposure on a daily or weekly basis.

The VaR was developed as the official assessment of risk exposure for financial institutions as a result of this agreement.Basel II also urged financial institutions to calculate their minimum capital requirements for overall market risk using their own VaR estimates.The bankruptcy of the British bank Barings in the same year — which came as a shock to the global banking industry, causing major turbulence in financial markets and a rise in investor fear — prompted this development.

Complex returns and price patterns, non-normality and outliers, significant mean deviation, and high and unpredictable volatility and correlations are all characteristics of the energy industry when it comes to risk management.Due to these features, additional risk management tools and procedures outside of typical financial market approaches have become necessary.In this regard, the VaR technique has become the most often used example in the economics field.

Due to its simple structure, the VaR idea may be an extremely useful tool for banks, firms, and investors to monitor the entire market risk exposure of their portfolios and assets.It gives critical information for investors' current accepted level of risk, allowing them to either lower their exposure to speculative-high risk assets or become more conservative if their existing position allows.

According to Jorion (2001), VaR reflects the worst-case scenario for a time horizon and a predefined confidence level under normal market circumstances.According to Hendrick (1996), Saunders and Allen (2002), and Holton (2003), VaR can indicate a financial asset's or portfolio's market price risk exposure in the case of a statistically poor day. Thereby, if a company reports a 1% one-day VaR of a million euros, it means that 99 percent of the time, given its current active portfolio mix and standard operating conditions, the corporation will take a loss of a million euro or less in a mono day, while a 1% chance of losing more than a million euro in a single day exists.

$$VaR = a * \sigma * V0\sqrt{\Delta t}$$

The VaR for a portfolio of assets, assumes that the returns are normally distributed, can be estimated as follows:

$$VaR = a * \sqrt{X' \sum X}$$

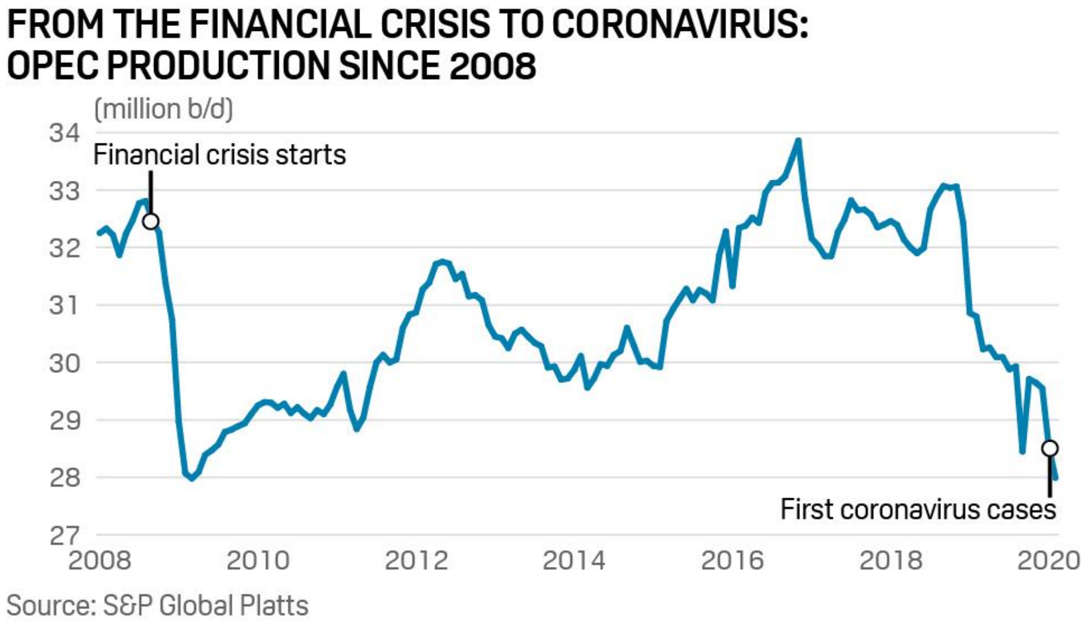
This fundamental technique for calculating VaR correlates to the 'delta-normal' approach, which is popular among risk management analysts due to its simplicity, since it needs little computing work while offering a rapid and preliminary estimate of the firm's risk exposure.

Energy Companies on Capital Markets

The spread between stock costs and loan costs shows risk allocation in each sector, which is distinct from the other. Access to capital markets and investment risks fluctuate among capital markets and sectors, as seen by differences in the WACC scores. When two or more segments or industries are compared using the WACC approach, the results are more similar. Younger markets with shorter histories, on the other hand, are characterized by a higher average cost of capital. The WACC idea is also commonly used in the identification of energy cost technologies.

According to Zhu, the rate of return in the energy sector was explored via the examination of macroeconomic variables such as inflation, money creation, exchange rate, industrial output and bond returns, as well as export and import, foreign reserve and unemployment rate. Korajczyk and Levy (2011) put fresh light on the notion that macroeconomic variables are equally important in determining the structure of the capital market. They stated that market circumstances are important for unconstrained enterprises when deciding whether or not to issue new shares to their shareholders. Then there's the matter of favourable macroeconomic circumstances.

Figure 5: OPEC countries oil production during crisis. This figure shows fluctuations in oil productions and precisely shows the downfall of oil production during covid out break and financial crisis.



The main reason behind the down fall of oil production during financial crisis and covid induced economy was collapse in the demand of crude oil. Oil price went negative ,which signals there was no place to store the production of crude oil since demand went down but production was not halted. When it comes to the energy industry, there is variability in WACC among locations and technologies based on variables such as political stability and the economic cycle. In the energy industry, the WACC level is influenced by the enterprises' varied levels of exposure to policy. As a result, OPEC countries cut down 9.7 million /barrels a day production (10% of global oil output).

3. Research Methodology

In this paper, we will calculate VaR using three different methods namely Historical Simulation Approach, Monte Carlo Simulation Method and Variance–Covariance methods.

3.1 Historical Simulation

Historical Simulation is a non-parametric approach that does not require parameter approximation and does not rely on a certain statistical distribution. It is the simplest method for calculating VaR. This strategy presupposes that the historical return distribution accurately predicts future returns. It is also the major flaw of this method since historical correlations tend to disintegrate during moments of high volatility and market turmoil. Historical value at risk (VaR) is a technique of determining VaR that is also known as historical simulation or the historical method.

Each day, we calculate the percentage change in price for the energy index, which sets our daily gain or loss probability distribution. The daily rate of return for the index may be expressed as historical

VAR returns formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where Rt is the (arithmetic) return over the time interval [t-1, t], and Pt is the price at time t. (the closing price for daily data).It's worth noting that the logarithmic return is occasionally employed.

It is a non-parametric technique since historical VaR is computed directly from data without estimating or assuming any other parameters.

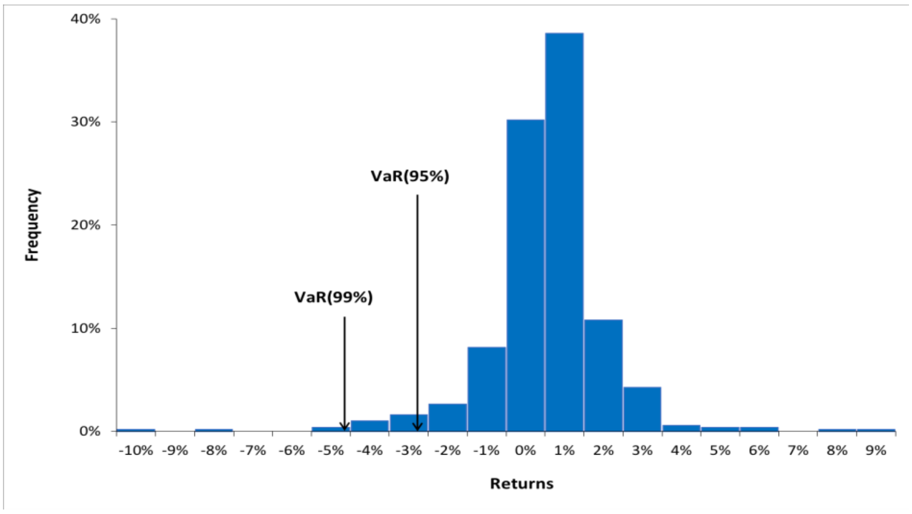
Let’s say, we have a 99 percent chance of not suffering a loss greater than our VaR estimate (for the 99 percent confidence level).Similarly, at a 95% confidence level, VaR corresponds to the top 5% of the worst returns.

$$\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n}(R_t - E(R))^2$$

Where R_t is the rate of return at time t and E(R) is the mean of the return distribution, i.e.

$$E(R) = \frac{1}{n}\sum_{t=1}^{n} R_t$$

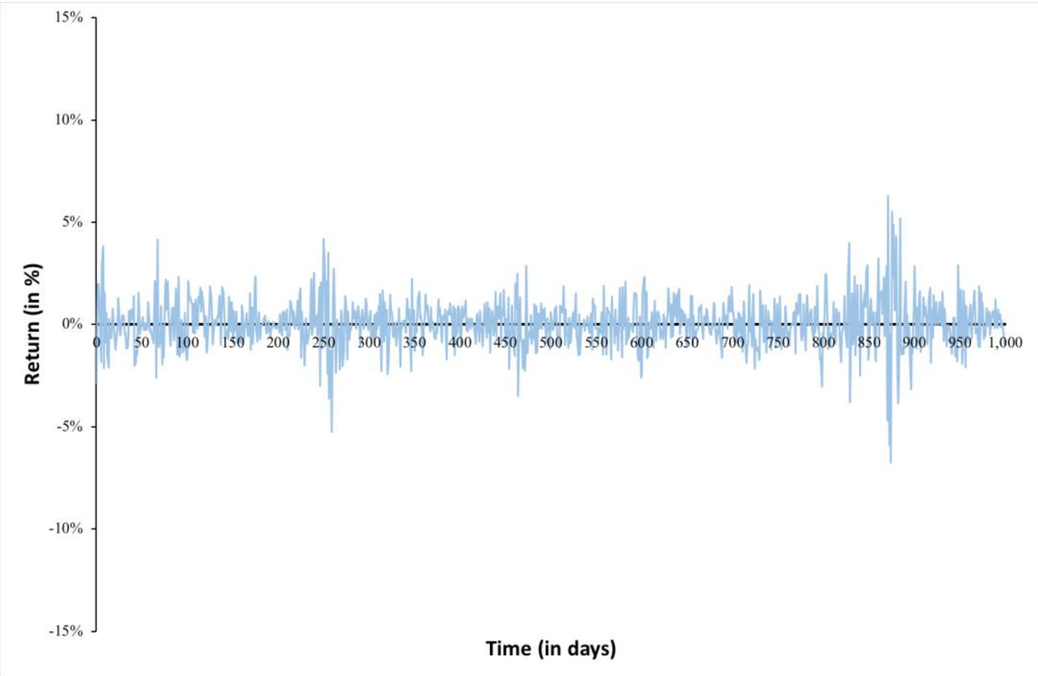
Illustration 3: Historical returns of stock



3.2 Monte Carlo Simulation

Monte Carlo Simulation is a semi-parametric approach. A random variable is utilized in Monte Carlo Simulation rather than historical data to generate a huge number of hypothetical stock price changes.After multiple reruns on the same data set, it is then utilized to forecast hypothetical returns with a much higher degree of accuracy. This simulation generates models of possible outcomes by substituting a range of values (a probability distribution) for any element having inherent uncertainty.A new set of random values is generated using probability functions, and the results are iterated several times.There may be as many as a million computations required to run the Monte Carlo simulation before it is finished due to its complexity.

Illustration 4: Monte Carlo simulation returns



3.3 Variance-covariance technique

This technique exert the risk factors & clusters of covariance as well as the portfolio values sensitivities to these risk factors to approximate the vvalue at risk. This approach yields the conclusion, which is the portfolio & value at risk, with no knowledge about market situations. All through computation, the variance-covariance technique uses linear approximations of the risk components itself, often overlooking the drift. The confidence level indicates how confident a risk management may be while computing the VaR.. The confidence level is a percentage indicating how often the VaR falls within the confidence interval. With a 95 percent confidence level, a risk manager an be 95 percent certain that the VaR will fall inside the confidence interval.

Population mean is known

$$var(x) = \frac{\sum_i^n (x_i - \mu)^2}{N}$$

Population mean is unknown

$$var(x) = \frac{\sum_i^n (x_i - \overline{x})^2}{N - 1}$$

3.4 Normality test

A normality test: The test is carried out in Excel using the Pivot table to see if the sample data was chosen from a regularly distributed population (within some tolerance). This test is necessary since the data will be fitted into a normal distribution for Monte Carlo and CV simulations. The empirical distribution of portfolio returns (the histogram) is bell-shaped and mimics the normal distribution.

4. Data Analysis

Stocks, bonds, commodities, cash, cash equivalents, and exchange-traded funds are all examples of financial assets that may be included in a portfolio.A portfolio's basis is typically made up of stocks, bonds, and cash.However, this doesn't have to be the case.A portfolio may include a variety of assets, such as real estate, fine art, and other forms of private investment.

You have the option of managing your own portfolio or hiring a financial advisor, money manager, or other financial specialist to do it for you. Managing distinct portfolio-level issues is a popular view of portfolio risk management. These are dangers that undermine the achievement of strategic objectives. The goal of portfolio risk management is to improve the chances of favourable events while reducing the chances of negative consequences on the project portfolio. This component of portfolio risk management happens mostly during the lifecycle phase 'Protect Portfolio Value.'

Young professionals, for example, can afford to choose a higher-risk retirement plan in order to expedite their retirement savings. Seniors, on the other hand, will switch to a low-risk investing plan in order to safeguard their savings.

4.1 Data Collection

The study is empirical in nature and is purely based on the secondary data collected. We used daily closing stock prices from November 2020 to November 2022.We extracted data using python scrapping using yahoo finance. In this study, four stocks from the energy sector that are listed on the Dow Jones were chosen for an investment portfolio.

Table 1: Name of Oil and Gas producing companies

No	Company Name	Symbol
1	**ConocoPhillips**	**COP**
2	**Devon**	**DVN**
3	**Chevron**	**CVX**
4	**Exxon Mobil**	**XOM**

First and foremost, historical data on daily stock closing prices for the 4 firms is gathered during a period from 2019 to April 2022 & 2008 series data. Apart from that, each stock and weighting in the portfolio must be defined. Here we assume of portfolio value to be $106700. Since the stocks in this portfolio are evenly weighted, each has a 1/25 weight.

4.2 Analysis and Discussion

Python Scrapping

#Extraction of data from Python Library

```
import numpy as np

import pandas as pd

import pandas_datareader as web

from scipy.stats import norm

#loop for computation

tickers=['XOM','COP','CVX','DVN']

my_data=pd.DataFrame()

for t in tickers:

    my_data[t]=wb.DataReader(t,data_source='yahoo',start='2019-1-1')['Adj Close'my_data.info()
```

0		XOM		832	non-null		float64
1		COP		832	non-null		float64
2		CVX		832	non-null		float6

								4
3		DVN		832	non-null			float6 4

my_data.tail()

Date	XOM	COP	CVX	DVN
2022-04-12	85.599998	100.000000	169.009995	62.259998
2022-04-13	86.809998	100.230003	171.669998	63.750000
2022-04-14	87.830002	101.370003	171.589996	62.560001
2022-04-18	88.550003	103.470001	173.889999	63.540001
2022-04-19	87.760002	101.559998	171.830002	63.000000

#Simulating returns and volatility

#Indexing

```
my_data.iloc[0]
```

Out[9]: XOM	60.208527
COP	59.991459
CVX	107.241875
DVN	22.642521
Name:	2019-12-31 00:00:00, dtype: float64

```
weights=np.array([0.25,0.25,0.25,0.25])
np.dot(returns,weights)
```

Out[22]:	array([	nan,	2.08789887e-02,	-1.03787880e-02,	3.07093956e-02,
		1.04277467e-02,	6.65915295e-03,	1.84764003e-02,	1.19312324e-02,
		-1.00117392e-02,	-7.92374686e-03,	5.41649716e-03,	-8.45894855e-03,
		1.45734901e-02,	1.86588911e-02,	-2.24782767e-02,	-5.66985080e-03,
		9.00983842e-03,	1.07476771e-02,	-1.87716051e-02,	2.84481951e-03,
		1.39995111e-02,	7.12266721e-03,	2.20113809e-02,	8.47879338e-03,
		-5.11397045e-03,	-3.41284702e-03,	-2.45941359e-02,	-9.65310577e-03,

		6.65589880e-03,	1.52487748e-02,	1.43419245e-02,	1.02927787e-02,
		2.07909211e-02,	-3.48882563e-03,	2.57587885e-02,	-9.22560923e-03,
		-1.33935652e-03,	-4.31585301e-03,	1.54223830e-04,	5.81014277e-03,
		-1.18943670e-02,	1.79560995e-02,	-1.96325381e-04,	-3.72880100e-03,
		-9.56487656e-03,	-9.04059905e-03,	-2.78158459e-02,	1.81287377e-02,
		8.33775322e-03,	1.70124439e-02,	-2.20402672e-04,	5.04688172e-03,
		1.03193439e-02,	-5.13843027e-03,	8.99450665e-03,	9.52207103e-03,
		-2.88847272e-02,	7.80264337e-03,	1.85769577e-02,	-9.30177901e-03,
		2.87231945e-03,	-5.39722217e-03,	1.01221255e-02,	-1.02067801e-02,
		-1.14020277e-02,	4.54087801e-03,	1.87998435e-02,	2.39771780e-03,
		-1.62248892e-02,	8.72525923e-03,	-3.17394776e-03,	9.46741642e-03,
		-1.18533989e-02,	2.52407347e-03,	1.14267687e-03,	1.79311684e-03,

Table2: Price of shares. This table shows the tail position (recent) share price of the company.

	XOM	COP	CVX	DVN
Date				
18/04/2022	88.55	103.47	173.89	63.54
19/04/2022	87.76	101.56	171.83	63.00
20/04/2022	87.96	102.67	172.53	64.61
21/04/2022	87.03	98.67	164.58	61.15
22/04/2022	85.13	96.01	160.95	58.07

Figure 6: Price of shares pre and post Covid Outbreak. This figure shows the changes in the price of stocks. Before 2020 the movement in the prices were as per industry standard. The upward movement in the prices are due to strong oil demand and resuming of global supply chain.

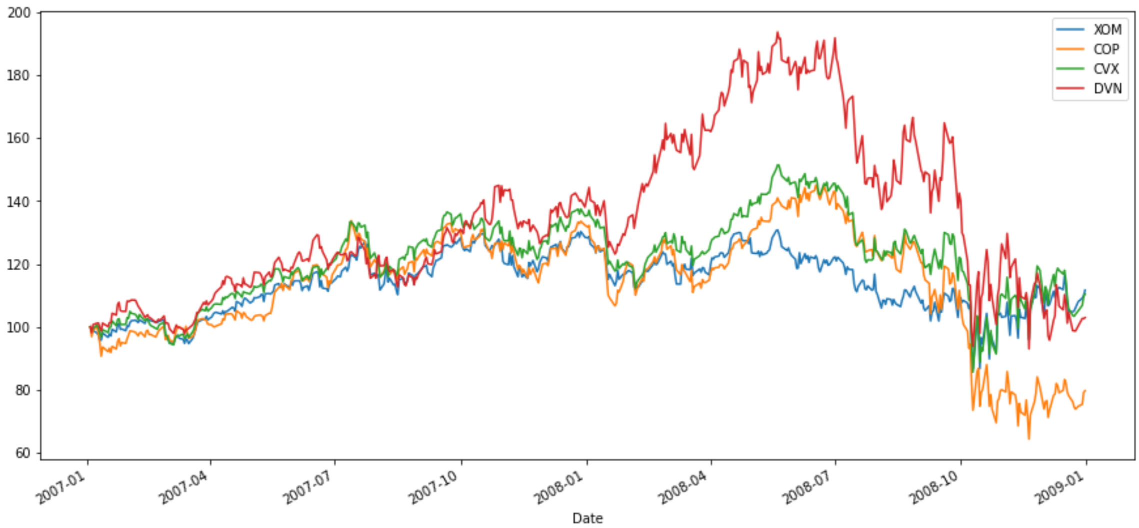
(Own Creation)

From the above table and figure, we can observe that there was a downfall of share price of oil and gas companies from march 2020 due to outbreak of covid. The prices went upto negative holdings per barrel. This was highly turbulence time for the energy sector, since entire world was going through lockdown and the demand of oil and gases were all time low. Later, as the world economy starts to resume its operations, we can see v shaped recovery for this sector. Currently, the demand for the energy sector is sky rocketing and supply side is not able to fill the gap between supply and demand. As a result, the price of oil and gases are all time high, which we can observe from the figure.

Table 3: Price of shares during financial crisis (2007-2009)

	XOM	COP	CVX	DVN
Date				
24/12/2008	46.256176	23.105223	41.102596	47.86789
26/12/2008	47.116829	23.389225	41.533573	48.64301
29/12/2008	47.623474	23.586584	42.242043	49.81329
30/12/2008	47.971382	24.765903	43.322437	49.76771
31/12/2008	48.728298	24.93438	43.670773	49.93489

Figure 7: Price of share Pre and post financial crisis.(own creation)



Oil and gas firms were hit hard during the 2008 financial crisis. The global economic disaster was triggered by the financial crisis, which began in mid-2007 and intensified severely in the second half of 2008.Financial difficulties caused by plummeting asset values have significantly hampered banks' ability and willingness to lend money, limiting investment, constricting consumption, and stalling economic activity. The energy industry, like all other economic sectors, is being impacted by the worsening business climate and financial limitations. A reduction in asset values and a change in investor behaviour throughout the economy are important aspects of the systemic transition phase to diminished demand. From the above table and diagram, we can assess how badly this segment was badly impacted and it was more severe than 2020 covid outbreak crisis in terms of risk clustering.

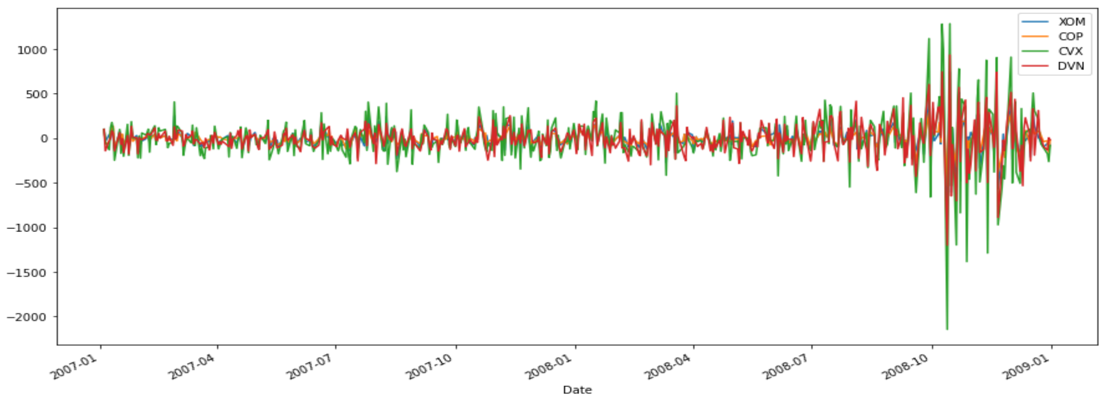
Table 4:

4.3 Descriptive statistics of daily oil returns.

Company	Mean	
	Annual Oil Returns% (2008)	Annual Oil Return% (2020)
XOM	0.13412	0.19989
COP	-0.00880	0.29407
CVX	0.13817	0.25949
DVN	0.14653	0.57785

Figure 8: (Own creation)

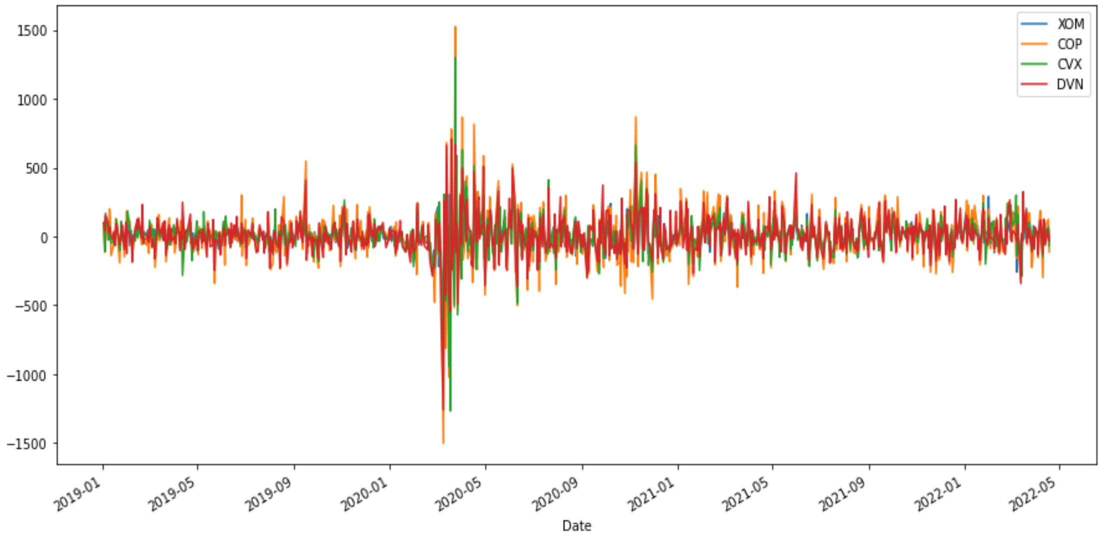
Portfolio return during Covid Crisis(Monetary value).This figure shows how risk impacts share Price and volatility in returns.



Portfolio return during Covid Crisis

	XOM	COP	CVX	DVN
Date				
28/04/2022	3.02%	4.82%	3.55%	3.13%
29/04/2022	-2.24%	-2.08%	-3.16%	-2.87%
02/05/2022	1.36%	0.42%	1.97%	0.31%
03/05/2022	2.06%	3.14%	1.72%	10.16%
04/05/2022	3.98%	4.98%	3.14%	5.38%

Figure 9 :(own creation) Portfolio return during Covid Crisis(Monetary value).This figure shows how risk impacts share price and volatility in returns.



#volatility cluster analysis

```
def Port_Var(start_date,end_date,stocks,exposure,CI,Days):
stock=pd.DataFrame()

stock=web.DataReader(stocks,start=start_date,end=end_date,data_source='yahoo
stock'_return'=stock.pct_change()

stock_vol=stock_return.std()CL=norm.ppf(CI/100)

stock_cov=np.array(stock_return.cov()

weights=np.array(exposure)/sum(exposure)
weight_mat=np.mat(weights)

port_var=(weight_mat*stock_cov)*weight_mat.T

Port_Var=np.sqrt(port_var)*CL*np.sqrt(Days)


print('The total exposure is USD ',sum(exposure))

print('{} day portfolio Var at {}% Confidence Interval'.format(Days,CI), 'isprint('{} day
portfolio Var at {}% Confidence Interval'.format(Days,CI).
```

Table: 5

Covid Outbreak HS VAR

CI	No of Days	Historical VAR%
90%	30	14.24
95%	30	16.49
99%	30	17.32

Financial Crisis HS VAR

CI	No of Days	Historical VAR%
90%	30	15.55
95%	30	18.05
99%	30	23.47

VAR during Financial crisis (Cov Var)

- **The total exposure is USD 106700**
- **30 day portfolio Var at 95% Confidence Interval is 22.60%.**
- **30 day portfolio Var at 95% Confidence Interval is USD 24121.86.**

- **30 day portfolio Var at 99% Confidence Interval is 31.974%**
- **30 day portfolio Var at 99% Confidence Interval is USD 34116.01**

VAR during Covid 19 Outbreak

- **The total exposure is USD 106700**
- **30 day portfolio Var at 95% Confidence Interval is 20.86%**
- **30 day portfolio Var at 95% Confidence Interval is USD 22260.65**

- **30 day portfolio Var at 99% Confidence Interval is 29.50%.**
- **30 day portfolio Var at 99% Confidence Interval is USD 31483.67.**

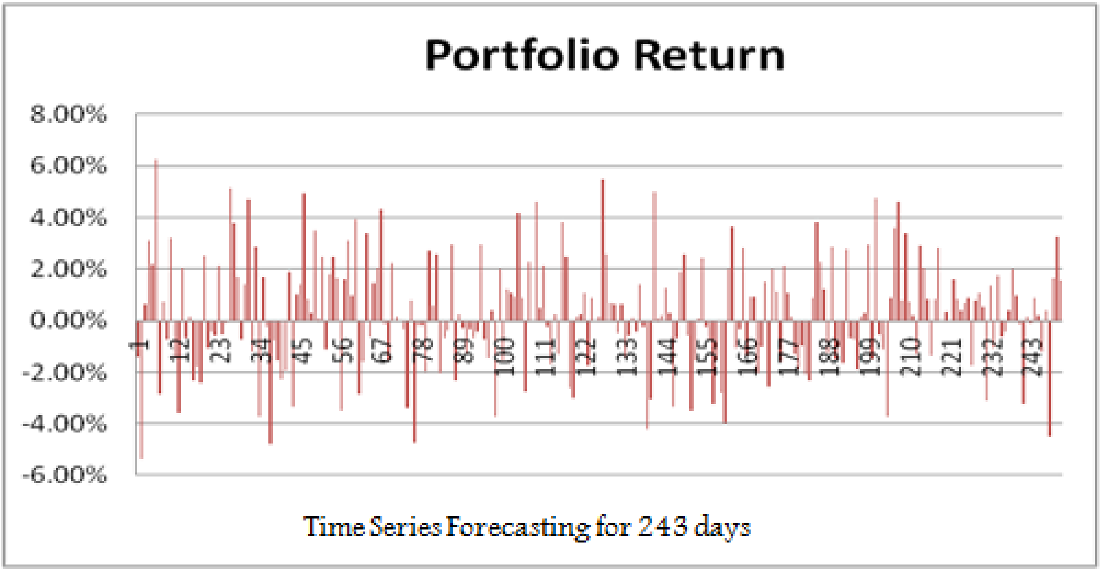
From the above table we can observe that if a fund manager invests during financial crisis above mentioned fund with 95% and 99% confidence interval, he has to bear risk around 22.60% and 31.974% respectively. However, if the same amount of fund is invested during Covid break, he has to bear risk around 20.86% and 29.50% respectively. It shows that if your investment amount is under retail investor category, oil and gas stocks were more risky during financial crisis compare to Covid induced crisis.

Table contains numerous factors that may aid in determining the severity of the COVID-19 oil price issue. The mean returns from COVID-19 until now are all negative, but the data that follow are the most shocking Similarly, the staggering statistics of skewness (13.66) and kurtosis (215.85), which is nearly 23 times worse than the GFC and indicate a high degree of fat tail risk, implying that the COVID-19 situation is a low probability but high severity event, cannot be overlooked.

We can observe how VAR changes across different confidence interval and how it is different from the respective variance – covariance VAR very high confidence interval, at the very end of the left tail. There is substantial empirical evidence showing that asset prices exhibit fat tails. The lower the tail index, the more frequent are extreme events and therefore fat tails.

Below diagram is the projected return of our portfolio which is calculated using application of Monte Carlo simulation.

Figure 10: Forecasted return for 243 days .This figure shows portfolio return for upcoming 243 days using Monte Carlo simulation. (Own Creation).



This diagram depicts the maximum gain and loss investors could have if they follow iterative model of Monte Carlo simulation. The upward and downward red lines indicate returns investors can expect in coming future. These returns are risk adjusted returns under simulated risk density projection performed by application on Spyder. As these returns are projected returns, it may or may not be exactly similar to real returns but it could be best possible approximation. Investors can rely on this method and protect their investments from different form of fluctuations.

Day	Projected Returns
1	-1.12%
2	-5.70%
3	0.80%
4	3.20%
5	2%
6	6.12%
7	-2.52%

We can verify the iterated returns from 2022-4-22 to 2022-5-2 to see accuracy of our projected model.

Verification of iterated portfolio return

Table 6

7 days portfolio return (start=2022-4-22, end=2022-5-2)

	XOM	COP	CVX	DVN
Date				
28/04/2022	3.02%	4.82%	3.55%	3.13%
29/04/2022	-2.24%	-2.08%	-3.16%	-2.87%
02/05/2022	1.36%	0.42%	1.97%	0.31%
03/05/2022	2.06%	3.14%	1.72%	10.16%
04/05/2022	3.98%	4.98%	3.14%	5.38%

```
#syntax_code

iterated_return=returns.mean()*7

iterated_return

XOM   -0.005132
COP   -0.025296
CVX   -0.027966
DVN   -0.043672
dtype: float64


np.dot(iterated_return,weights)

-0.0255
pfolio_1=str(round(np.dot(iterated_return,weights),9)*100) + '%'
pfolio_1
'-2.551%' (real return)
```

We can observe that, our projected portfolio return for 7 days is closer to the real return of the portfolio for 7 days. Hence, we could state that our projected modelling is viable.

In monetary terms, we have invested as a retail investor and created hypothetical portfolio of 4 oil and gas companies. We have invested $ 106700 and our VAR in monetary terms will be portfolio times VAR. From observation, we can observe the monetary loss that we would expect to undertake at certain scenario as per volatility of the market.

We have also considered market risk regulation in Basel designed form. As small investors have small reserve funds against likely losses, so in most cases investors would calculate risk according to particulate technique, and then would reserve capital as a proportion of its likely loss, so that they can provide for this unlikely negative volatile market

```
#Portfolio _synatx_Formation

        stock_a_Monte_var = wx.StaticText(self, -1, str(stocks_3[0]) + " – 30 days _VaR (5%)",
(20, 20))   stock_b_ Monte_var = wx.StaticText(self, -1, str(stocks_3[1]) + " - 30 days _VaR
(5%)", (20, 20))

        stock_c_ Monte_var = wx.StaticText(self, -1, str(stocks_3[2]) + " - 30 days _VaR
(5%)", (20, 20))  stock_d_ Monte_var = wx.StaticText(self, -1, str(stocks_3[3]) + " - 30 days
_VaR (5%)", (20, 20))  stock_a_Monte = wx.StaticText(self, -1, str(round(Monte_return[0] *
100, 2)), (20, 20))  stock_b_Monte = wx.StaticText(self, -1, str(round(Monte_return[1] * 100,
2)), (20, 20)) stock_c_Monte = wx.StaticText(self, -1, str(round(Monte_return[2] * 100, 2)),
(20, 20))

        stock_d_Monte = wx.StaticText(self, -1, str(round(Monte_return[3] * 100, 2)), (20, 20))
```

Table 7: Monte Carlo simulated risk association since covid outbreak.

CI	VAR%	Absolute Loss
90%	3.1%	$26939.10
99%	4.6%	$45812.15
95%	3.4%	$33485.56

In VAR, Monte Carlo simulation, we simulated on 90% 95% and 99% confidence interval, which shows simulation at 95% could have maximum loss at 3.4% and for the 99% is 4.6% which is 36.8% higher than the interval of 95%. This shows the downside risk worst possible scenario. In monetary terms portfolio max downside risk should not excess $45812.15 at 99% interval. As a VAR technique, the Monte Carlo method is particularly appealing. In addition, this method, explores the extreme cases of risk association, which would be more beneficial model compare to HS and Covar model. It provides us maximum risk density that investor can suffer. When other approaches are difficult to apply, it might be employed and can easily handle a portfolio of nonlinear instruments and account for a wide range of factors influencing our portfolio. As a result, we can incorporate volatility, bounce, and so on, while also dealing with fat tails.

Summary table of VAR calculations:

CI	No of Days	Historical var %		Cov Var %	
		Covid outbreak	Financial crisis	Financial crisis	Covid outbreak
95%	30	16.49	18.05	22.6	20.86
99%	30	17.32	23.47	31.97	29.5

From the above table, we can observe how risk clusters were associated with energy portfolio during financial crisis and covid outbreak induced economy. With our calculation, we can say that the risk factors during financial crisis were high compare to covid outbreak. This calculation was conducted on hypothetical portfolio consisting of energy company stocks within different confidence interval.

5. Conclusion

The energy market is one of the biggest victims of the COVI-19 epidemic, among numerous financial markets. Due to the global lockdown implemented soon after the onset of COVID-19, almost all sectors that generate major demand for oil, such as transportation, tourism, and airlines, were brought to a standstill. Unfortunately, the collapse of the oil market and stakeholder panic has a pestilence effect, and it has the potential to aggravate the circumstance in other financial markets, as well as disrupt growth in the economy in oil-producing and exporting countries, which could have a ripple effect on their trade relations, and thus has the potential to turn into a full-fledged global financial crisis.

Although the existence of volatility clustering in oil prices is shown to be substantial in both crises, the scale of the Risk density impact in COVID-19 is significantly less than that of the Financial crisis. In COVID-19, we also discovered that the asymmetry parameter 1 is not only important, but also the highest.

This suggests that negative shocks in oil price returns may produce significant volatility in the following days, and since volatility is tenacious, once caused by negative shocks, it can last for many days in the oil market.

Similarly, the Monte Carlo approach is highly interesting in VaR methodology. It can easily manage a portfolio of nonlinear instruments and account for a broad variety of variables impacting our portfolio when other techniques are difficult to use. As a result, we can account for volatility, bounce, and other factors while simultaneously dealing with wide tails.

5.1 Recommendation

Among financial services firms, where assets are mostly marketable securities and capital is limited and rules emphasize short-term exposure to high risks, Value at Risk is a preferred approach of risk assessment.The VAR technique may be useful for project managers who need to examine risks accurately.To help you analyze and manage risk across several project areas, it is possible to use this tool.

You'll get better results if you use a variety of approaches in different parts of your task and then combine them into a single strategy.You'll be able to manage risk to a tee using this.

The value at risk strategy, on the other hand, may need a more advanced quantitative and analytical approach.

5.2 Limitation

This study has potential limitations. The study on the application of risk measurement methods and portfolio frameworks is limited in selecting the sample used, which only focuses on four energy stocks listed on NASDAQ. We did not include any stocks apart from the energy sector and companies outside the USA. The results obtained in this study may not be applicable to portfolios with a large no of stocks from different sectors and huge funds. Any investors with stalwart or cyclical stocks in their portfolio would have a different level of risk associations. In addition, this study precisely looks at the risk associated with portfolios under the timeframe of the financial crisis and the Covid outbreak. This study did not include daily market conditions and seasonal market swings where risk fluctuation is quite different than the recession time. This research is solely on the basis that stocks return follow the normal distribution, which may lead to an underestimation of the risk and capital allocation because in the reality the data series have elongated tails corresponding to extreme market movements and sentiment of the investors. It is possible that stock returns follow up trend and down trend where this study is not applicable and further approach should be used.

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