ABSTRACT

In this work, we examine the correlation between the returns on oil prices and the stock market index returns of different nations, with a particular emphasis on the pre-, during, and post-Covid-19 pandemic eras. In order to account for exchange rate effects, we take the oil price series from OPEC and Brent, which are then transformed into local currency. Copula models are then used to capture the overall dependence structure. According to our research, pre-Covid Pearson's rho and Kendall's tau dependence measures were comparatively minor; during the Covid era, they rose; and post-Covid, they dropped. The Covid-19 epidemic increased the impact of oil prices on stock markets, with France and India showing particularly uneven dependence. Stronger tail dependencies were seen for major oil-consuming nations like France and India. The degree of dependence varied. Though there were some outliers, most relationships showed symmetrical reliance, especially in times of extreme market conditions. Our findings highlight how disturbances to the world economy affect the relationship between oil prices and stock markets, providing important information to investors and decision-makers.

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CHAPTER 1

1. Introduction

1.1 Background and Context

As economies are growing, demand for energy is also increasing. These are fueled by supply and demand. Increasing economies will have a higher demand for energy which leads to crude oil demand. Gasoline and diesel fuels are the main petroleum products used in the global transportation industry. They're even used in many places to make power and cook. Crude oil is the raw material used to make petroleum products, which account for over one-third of global energy use.

Oil continues to dominate headlines due to its undeniable grip on the world's economic engine. Its significance stems from its historical prevalence as fuel for most economies (Nandha & Faff, 2008). Furthermore, as developing nations like China and India surge forward, their oil consumption rises in tandem with their growth. Even established economies, despite fervent efforts to find alternatives, haven't curbed their oil dependence. This unwavering reliance ensures oil's continued influence on the global economic landscape, with major oil producers wielding considerable power in terms of output and pricing. Consequently, a comprehensive understanding of oil prices and the strategies behind them remains crucial.

The undeniable link between Oil prices & Economic health have been well-established. However, the sure nature of this connection can vary significantly depending on a country's unique oil profile – namely, its level of production and consumption. For instance, a rise in oil prices might translate to a positive GDP swing for a major producer like Saudi Arabia, while conversely impacting a net consumer like France. This research aims to bridge this knowledge gap by exploring how this relationship changes across diverse economies. By incorporating a wide range of countries – from major oil producers and consumers to those with a mix of both and also to the world's largest importers– this study will provide light on the magnitude and direction from the fluctuations in the oil-economy relationship.

1.2 Importance of studying their importance

The majority of the association between costs of Oil and equity indices has been analyzed Considering the likelihood of normalcy, which implies symmetric dependence type relationship conveniently represented by Linear Correlation. However, this approach often overlooks potential non-linear and asymmetric relationships. Despite a number of research ([3];[22];[40];[8];[42]) Despite having looked at these asymmetric links, much remains unknown about the general structure of reliance between Costs of Oil & Global equity indexes. Instead of concentrating on a particular kind of relationship, our work uses the copula method to investigate the general reliance between various series. Multivariate analysis, the copula approach has two main advantages: it allows for the independent modeling of marginal distributions & their dependence structures, which isolates each variable's unique impacts; also, it gives a thorough representation of the interdependencies between variables. With a wide variety of copulas available, this method can accommodate diverse dependence structures, including fat-tailed distributions, asymmetry, and tail dependence.

1.3 Objectives of the Study

We assess the connection between Costs of Oil and Global equity indices in this research, taking into account the fact that different indices provide varied weights to the stocks of oil and gas companies. This distinction is crucial because the connection between equity indices & returns on oil prices could be significantly impacted with comovements of crude costs series and crude and gas stocks. Here we used two Oil price series: Brent & OPEC, with OPEC data specifically employed for sensitivity analysis. To see for the impact of forex rates on prices of oil & indices of the equity market, each & every price of oil series is converted to local economic currencies. For instance The prices Brent oil is converted to Indian rupees, or INR, the country's indigenous currency. We explore the overarching obsession structure without assuming anything about the series distribution. In order to do this, we model the pattern of dependence over the whole distribution using copula functions. Furthermore, our assessments encompass major oil-producing and -consuming countries as well as developed and emerging states. In order to ascertain whether these series' dependencies have changed significantly over time, we lastly look at the relationship dynamics between them.

1.4 Structure of the Report

This is how the remaining part of the article is structured. In Part 2, a succinct overview of the body of literature is presented. The data and technique are explained in Part 3. Part 4 presents the primary findings of the study, while Part 5 reports the conclusions and their consequences.

CHAPTER 2

2. Literature review

Previous research has indicated a connection between the nation's economic expansion and the price of oil. It has demonstrated that the majority of countries' economies are negatively correlated with changes in oil prices. Although this study's data and methodologies vary, they ultimately lead to the same conclusion—that the state ofeconomy is significantly reliant on crude oil.

Numerous studies have examined the relationship between prices of oils & the economies, mostly because actual data indicates that oil prices affect specific industries and, in turn, the whole economy. Numerous recent studies have examined how different industry sectors are affected by changes in oil prices. For example, Faff and Brailsford (1999) discovered a negative association for industries like paper and packaging, financials, and transportation, but a positive correlation for industries like oil, gas, and diversified resources.

Further research has focused on individual stocks, often corroborating the findings of Faff and Brailsford (1999) regarding the implications for different industries (Cong et al., 2008). The potential influence of Price of OIL Turmoil on equity markets has also been examined, driven by the understanding that The cost structures of firms are directly impacted by oil as a primary input. Increased costs, all else being equal, lead to reduced profits, lowering overall stock prices and a negative effect on projected earnings ([2];[8];[45]). These theories are supported by empirical research for the Republic of Greece (Papapetrou, 2001) & the United Kingdom[12], which demonstrate that fluctuations in crude prices have a marginally negative effect on stock returns unrelated to gas or oil. However, by boosting stock returns, increased oil prices can help oil-producing companies.

Some research suggests that overall indices of the stock market are not significantly tied to oil price shocks, despite the fact that changes in costs of oil have an impact on the returns of individual stocks. On another side, several studies (Sadorsky, 1999; Miller and Ratti, 2009; Papapetrou, 2001;) contend that changes in the costs of oil play a major role in the explanation of overall equity returns. Additionally, studies of asymmetric or nonlinear relationships between prices of oil and equity markets and the economy show that these interactions are nonlinear, with increases in costs of oil having a greater negative(-ve) impact on the financial markets and the U.S. economy than do drops.

The majority of oil prices have been expressed in US dollars. But OPEC is now considering using other currencies for the pricing of crude oil as a result of the US dollar's depreciation vs other currencies ([1];[23];[50];[54]). The devaluation of the US dollar in the late 1970s & early 1980s gave rise to this problem, which has since returned as the dollar's value and dominance in the world economy continue to decline. The arguments that prices of oil movements are partially influenced by currency movements, suggesting that changes in forex rates cause changes in costs of oil, highlight the significance of choosing the right currency for crude oil pricing ([48];[49];[52]). Because large fluctuations in exchange rates could mask the real relationship between these variables, this is an important factor to take into account in research looking at the relationship between costs of oil and equity indices. Moreover, a plethora of research has demonstrated that exchange rate variations impact stock markets across different nations [10];[16];[24];[32]). Forex rates must therefore be taken into consideration in these types of studies since they are common elements influencing both oil costs and indices of the equity market. In spite of this, not many research have examined the relationship between costs of oil and equity indices while accounting for exchange rates.

Studies employing copula techniques have looked at the relationship between the costs of crude oil & equity market indexes. In their 2014 investigation of this interdependence[51], focused on the dependent structure surrounding the introduction of the Euro, a momentous financial event. They conducted a comparison between pre- and post-Euro times. In contrast, our study checks the interdependence of crude oil costs and equity market indices for the pre covid period, during and pos covid period. While there is another study that examines the COVID period, it primarily focuses on the African market using a wavelength approach (Hung & Vo, "Multi-Scale Features of Interdependence Between Oil Prices and Stock Prices for the African Market, 2022"). Our work here uses copula methodologies and covers the earth's major economies, carrying the greatest oil importer and exporter as well as developing and developed nations. Our ability to analyze the global interconnectedness between oil costs and equity market indexes is enhanced by this expanded breadth.

In this study, we suggest analyzing the broad dependence structure between costs of oil and equity indices using copula functions. Copula functions make it possible to estimate dependence using the whole dependence structure as opposed to only univariate measures and to model univariate marginal distributions in a flexible manner (Chollete et al., 2005). This method will assist in identifying the type of relationship: nonlinear, linear, asymmetric, or symmetric.

3. Introduction to Copula

A copula is a multivariate CDF for which each variable's marginal distribution of probability is uniform on the interval [0,1] in prob theory & stats. To specify the relation among random variables, copulas are utilized.
In quantitative finance, copulas are utilized for portfolio optimization and risk management.

3.1 Mathematical Definition

A random vector $(X_1, X_2, \ldots\ldots, X_d)$ is considered. Assume that its marginals are continuous functions, that is, that the marginal CDFs $F_i(x) = Pr[X_i \leq x]Fi(x)$ are continuous. After each component is subjected to a probability integral transformation, the random vector.

$(U_1, U_2, \ldots., U_d) = F_1(X_1), F_2(X_2), \ldots., F_d(X_d))$. Possesses uniformly distributed marginals on the interval [0,1].

The Copula of $(X_1, X_2, \ldots\ldots, X_d)$ is stated as the joint cumulative distribution function of

$(U_1, U_2, \ldots., U_d)$: $C(u_1, u_2, \ldots, u_d) = \Pr[U_1 \leq u_1, U_2 \leq u_2, \ldots\ldots, U_d \leq u_d]$.

Therefore the Copula C contains all the knowledge about the dependence relationship structure for the components of $(X_1, X_2, \ldots\ldots, X_d)$ whereas the marginal cumulative distribution functions F_i contain all the knowledge on the marginal distribution of X_i.

3.2 Definition

If C is a joint CDF of d-dimensional random vector on the unit cube $[0,1]^d$ with uniform marginals, then C: $[0,1]^d$ > [0,1] is a d-dimensional copula in probabilistic terms.

Copula specifically models the dependence structure between variables. This means they can capture the way in which variables co-move or relate to each other without being influenced by the individual marginal distributions of those variables.

3.3 Sklar's theorem

Imagine you have a bunch of random variables, $(X_1, X_2, \ldots\ldots, X_d)$, and you want to understand how they're connected. Sklar's theorem provides a powerful way to do this by breaking down their joint distribution into two key components:

Marginal Distributions (F_i): These describe the individual behavior of each variable X_i. They tell you the probability of X_i falling below a certain value ($X_i \leq$ x).

Copula (C): This captures the dependence type relationship structure between the variables. It describes how likely it is for them to move together independent of their individual distributions.

The Mathematical Formulation:

A unique copula C exists such that:

$H: (x_1, x_2, \ldots, x_d) = C(F_i(x_i), F_2(x_2), \ldots., F_d(x_d))$ for every continuous joint cumulative distribution function (CDF) of the random vector $(x_1, x_2, \ldots, x_d)$, denoted by H$(x_1, x_2, \ldots, x_d)$.

In this case, $F_i(x_i)$ stands for the marginal CDF of X_i as determined at x_i. To put it another way, the copula, which represents the "glue" that keeps all the variables together, and the individual distributions of the variables can be used to define the combined distribution of all the variables.

3.4 Stationary Conditions

Copulas function best in situations when the time series is continuous and stationary. Therefore, determining the series' auto-correlation, trend, and seasonality is a crucial pre-processing step. They could provide an erroneous copula dependence structure and an absent reliance between sets of variables when time is auto-correlated.

3.5 Types of Copulas

1. *Elliptical Copula*

Captures linear dependence where random variables tend to move together in a proportional way.

A. Gaussian Copula

Description: A distribution across the unit hypercube is the Gaussian Copula. A multivariate normal distribution serves as the foundation for this copula. In order to model selectivity in the context of continuous but non-normal distributions, Lee (1983) introduced the copula function shown above. Even in cases where the marginal distributions are not normal, it is assumed that the combined distribution of the variables adheres to a multivariate normal distribution.

Properties-

Symmetry: Gaussian Copula Captures symmetrical dependence

1. Symmetry: Gaussian Copula Captures symmetrical dependence

2. No Tail Dependence: Not suitable for modeling extreme co-movements (tail dependence).

Application: Used for its simplicity and analytical convenience in finance and risk management.

The normal copula takes the form

$$\begin{aligned} C(u_1, u_2; \theta) &= \Phi_G\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta\right), \\ &= \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \\ &\quad \times \left\{ \frac{-(s^2 - 2\theta st + t^2}{2(1-\theta^2)} \right\} dsdt \end{aligned}$$

where ΦG(u1,u2) is the standard bivariate normal distribution with correlation parameter θ limited to the interval (−1, 1) and Φ is the standard normal distribution's CDF. [Zimmer, D. M. & Trivedi, P. K. (2007)].

B. t-Copula

Description: The t-copula is based on the multivariate t-distribution and has heavier tails compared to the Gaussian copula, making it more suitable for financial data where extreme events are common.

Properties:

Tail Dependence: Captures tail dependence, modeling extreme co-movements better. Flexibility: Suitable for data with heavy tails.

Application: Widely used in finance to model joint extreme risks.

$$C^t(u_1, u_2; \theta_1, \theta_2) = \int_{-\infty}^{t_{\theta_1}^{-1}(u_1)} \int_{-\infty}^{t_{\theta_2}^{-1}(u_2)} \frac{1}{2\pi(1-\theta_2^2)^{1/2}} \times \left\{1 + \frac{(s^2 - 2\theta_2 st + t^2}{\nu(1-\theta_2^2)}\right\}^{-(\theta_1+2)/2} dsdt,$$

where the inverse of the CDF of the typical univariate t-distribution with θ1 degrees of freedom is represented by the notation t −1 □1 (u1). (θ1,θ2) are the two dependence parameters. The tails' heaviness is controlled by the parameter θ1 [Trivedi, P. K., & Zimmer, D. M. (2007)].

2. Archimedean Copula

Offer more flexibility for modeling non-linear dependence, where the strength of dependence changes across the range of variables.
Defined through a generator function, with various copulas derived from it.

A. Clayton Copula

Description: This type of copula is useful for modeling relationships in the lower tails of the distribution. It belongs to the Archimedean family of copulas.

Properties:

Lower Tail Dependence: Efficient in situations when exceptionally low values in one variable are linked to exceptionally low values in another.

Asymmetry: Captures asymmetrical dependence.

Application: Used in risk management and insurance, where lower tail dependence is significant.

$C(u_{1,}, u_2, \theta) = (u_1{}^{-\theta} + u_2{}^{-\theta} - 1)^{-1/\theta}$

limiting the dependency parameter θ to the interval (0,∞). The marginals become independent as θ gets closer to zero [Trivedi, P. K., & Zimmer, D. M. (2007)].

B. Gumbel Copula

Description: this type of copula is suitable for modeling the upper tail's dependence and is part of the Archimedean family.

Properties:

Upper Tail Dependence: Models scenarios where extreme high values in one variable are linked to extreme high values in another.

Asymmetry: Captures asymmetrical dependence.

Application: Useful in environmental studies and finance where upper tail events (extreme highs) are of interest.

$C(u_{1,}, u_2; \theta) = \exp(-(\underline{x}_1{}^{\theta} + \underline{x}_2{}^{\theta})^{1/\theta}))$

where ˜uj = −loguj . Only the interval [1,∞] is allowed for the dependent parameter. According to Trivedi, P. K., and Zimmer, D. M. (2007), this copula does'nt reach the Fr´echet lower bound for any value of θ, although values of 1 and ∞ correspond to independence and the Fr´echet upper bound.

C. Frank Copula

Description: This type of copula is a symmetric copula from the Archimedean family, capable of modeling both positive and negative dependencies.

Properties:

Symmetry: Does not exhibit tail dependence.

Flexibility: Can handle both positive and negative dependencies equally.

Application: General-purpose copula, applicable in various fields where symmetry in dependence is assumed.

$$C(u_{1,}, u_2;\ \theta) = -\theta^{-1} log \left\{1 + \frac{(e^{-\theta u1}-1)(e^{-\theta u2}-1)}{e^{-\theta}-1}\right\}$$

You can give the reliance parameter any real value between $-\infty$ and ∞. The Frechet upper bound, independence, and lower bound are represented by values of $-\infty$, 0, and ∞, respectively [Trivedi, P. K., & Zimmer, D. M. (2007)].

3. Other Copulas

A. Plackett Copula

Description: The Plackett copula is a symmetric copula that is particularly useful for modeling moderate dependence structures. It is derived from a bivariate distribution with a specific form of joint survival function.

Properties:

Symmetry: Models symmetric dependence.

Moderate Dependence: Suitable for data with moderate dependence.

Application: Used in various fields, including finance and hydrology, where moderate dependence between variables is observed.

Overview of the summary of the copulas we discussed above.

Gaussian Copula	For symmetric dependence with no tail dependence.
t-Copula	For data with heavy tails and tail dependence.
Clayton Copula	For lower tail dependence.
Gumbel Copula	For upper tail dependence.
Frank Copula	For symmetric, general-purpose modeling
Plackett Copula	For moderate, symmetric dependence

Figure 1. Types of Copulas and Their Dependence Characteristics

Therefore, here in statistical modeling understanding the dependence type relationship structure between random variables is crucial especially when analyzing the financial data where relationships can be complex and nonlinear. Conventional methods such as linear correlation often assume normality & symmetry which is not sufficient and adequately capture the true dependence structure. This is when copula models come into play providing a robust framework for analyzing the interaction between variables without the limitation of traditional approaches.

4. Applications of Copula in Financial Modeling

1. Portfolio Risk Management: The Copula helps in understanding how the assets co-move when the market is stressed. They are used to model the combined distribution of assets. By this we can compute VAR and CVAR for a portfolio. Therefore, to have a precise risk assessment we can use t-copula for example during market downturns for modeling heavy-tailed dependence structure between stock returns.
2. Credit Risk Modeling: Through default of different entities we can use copula to know the dependence structure between them which is crucial for understanding the likelihood of joint defaults. Application of copula is Credit Default Swaps(CDS): They help in setting the pricing for CDS by modeling the joint default probabilities of the underlying entities. The

Gaussian copula model, for instance, can be used to provide data on the correlation between defaults in the CDS market.

3. Option Pricing: For multi-asset options like Basket options copula are used to know the dependence between them. Therefore, Copulas provide more accurate pricing of basket options. Application will be the Exotic options where copulas are used to price the exotic options where the payoff depends on multiple underlying assets. For example, We can use gumbel copula to model the upper tail dependent on a basket of tech stocks, affecting the pricing of basket options of these stocks.

4. Market Risk Analysis: Copulas are used to analyze market risk by modeling the dependence type relationship structure between a variety of financial markets or assets. Application would be the Hedge Fund Risk Management where Copulas help in understanding the comovement of stock returns between hedge funds and traditional assets. Help in managing systematic risk. To help with global risk management, a frank copula, for instance, can be used to simulate the symmetric dependence structure between the equities markets of various nations.

CHAPTER 3

5. Methodology

5.1 Data

The study's data sources included daily oil prices, industry cost indices, currency rates, and their market values from both developed and developing nations between January 1, 2015, and March 31, 2024. We take into account two oil prices: the FOB daily price of Brent crude oil, which serves as a benchmarks for Asia, the Middle Eastern Countries, Europe-France and North America-USA, latter is used for cross-checking results- specifically examining the India region, in the event that our findings significantly differ when the benchmark is excluded. Dollars per barrel are used to indicate both oil price series. Saudi Arabia, France, the United States, and India are the nations we examined in our investigation. A variety of sources are used to retrieve data.

Using the Python yfinance package, the study's data were downloaded from the Yahoo Finance website. In particular, we obtained daily stock market index data for the following: the CAC 40 (France) [^FCHI], Nifty50 (India) [^NSEI], S&P 500 (USA) [^GSPC], and TASI (Saudi Arabia) [TASI.SR] for the period spanning January 1, 2015, to March 31, 2024. We can examine the connections between these stock market indexes and oil price returns over a long time horizon, capturing different economic cycles and important world events like the Covid-19 pandemic, thanks to this extensive dataset..

For crude oil from the Atlantic basin, BRENT crude oil is the primary international price standard. 2/3rd of the world's globally traded crude oil supply is priced using it. It and West Texas Intermediate (WTI) are the two primary benchmark prices used globally for oil purchases [https://en.wikipedia.org/wiki/Brent_Crude]. The

‘OPEC’ oil cost price of a specific basket of crude oils that are produced by OPEC member countries. This basket known as the OPEC Reference Basket (ORB) is an average price of various crude oils from different OPEC countries. It serves as a benchmark to track the price of oil from the member nations. The OPEC Reference Basket is composed of crude oils from the following countries:
1.Algeria(SaharanBlend),2.Angola(Girassol),3.Congo(Djeno),4.Ecuador(Oriente), 5.EquatorialGuinea(Zafiro),6.Gabon(RabiLight),7.Iran(IranHeavy),8.Iraq(BasraLight),9.Kuwait(KuwaitExport),10.Libya(EsSider),11.Nigeria(BonnyLight),12.SaudiArabia(ArabLight),13.UnitedArabEmirates(Murban), 14.Venezuela(Merey).
The ORB price is an important indicator for the global oil market as it reflects the production cost and market conditions for oil from these key exporting countries. Brent crude oil price data were downloaded from the FRED database, and OPEC oil price data were obtained from the OPEC Annual Statistical Bulletin.

The financial markets and economies of the world have been greatly impacted by the outbreak of the coronavirus pandemic, or Covid-19. The full sample of data is truncated into Before Covid, During-covid19 & After-Covid periods. The Before-Covid period starts on January 1, 2015 till February 29, 2020. The during covid19 period spans from March 1, 2020 till February 28, 2022. The after-Covid period begins from 1st march, 2022 & extends upto the sample period on 31st March, 2024. Both crude costs are converted into local forex rates for each nation. Additional analysis is performed using the modified data's logarithmic difference, or log returns. In the next part, the return data is filtered to make copula parameter estimation easier.

5.2 Copula Functions and Estimation approach

In this work, we examine the broad dependence structure between oil costs & the equity market using the copula approach. We use the assumption that an autoregressive (AR) process governs the evolution of the conditional means of the series, in accordance with Patton (2006a). An GARCH-gjr model, first presented by Glosten et al. (1992), is assumed to govern the evolution of the conditional variance. Franses and Dijk (1996) demonstrate that by taking into account the non symmetric returns of financial gains, the GARCH-GJR model will overshadow the old simple GARCH model. A review of summary statistics for several variables (refer to Table 1) indicates that most of the series that are shown have a slight propensity toward returns that are negatively skewed. Furthermore, compared to the pre-COVID era, the majority of series exhibit less skewness in the post-COVID era. It is clear that there are relatively significant excess kurtosis values, particularly during the COVID period. Therefore, there is compelling evidence of a deviation from the norm.The Jarque-Bera statistics validate the return series' non-normality. Therefore, it’s more acceptable to employ GARCH-gjr rather than the normal simple GARCH since negative skewness was found in a large number of the study's series.

	Country	Mean	Max	Min	SD	Skew	Ex.Kurt.	J-B
Pre_Covid_Period								
	India	0.000204	0.051825	-0.060973	0.008223	-0.298200	4.493214	1210.423206
	USA	0.000273	0.048440	-0.045168	0.008535	-0.666175	4.280081	1109.369989
	France	0.000167	0.040604	-0.083844	0.010648	-0.626526	4.929200	1431.315523
	Saudi	-0.000076	0.071208	-0.131626	0.010665	-1.432742	20.627104	25316.560629
	Brent	-0.000058	0.110701	-0.080825	0.022529	0.300206	1.924361	222.824048
	OPEC	-0.000023	0.107978	-0.088521	0.018599	0.423871	3.276350	634.217383
During_Covid_Period								
	India	0.000673	0.084003	-0.139038	0.014463	-1.973024	20.902819	11519.873908
	USA	0.000675	0.089683	-0.127652	0.016261	-1.038208	15.256267	5087.023678
	France	0.000432	0.080561	-0.130983	0.015967	-1.335683	13.135807	3848.266950
	Saudi	0.000885	0.068315	-0.086846	0.010448	-2.420880	23.583555	14683.876754
	Brent	0.001333	0.412023	-0.643699	0.053128	-2.884307	54.177365	62585.112611
	OPEC	0.001261	0.228699	-0.331150	0.040470	-1.499374	22.232850	10799.809486
Post_Covid_Period								
	India	0.000466	0.028482	-0.026891	0.022578	-0.124241	1.789256	86.338293
	USA	0.000373	0.053953	-0.044199	0.011586	-0.179857	1.861547	79.983237
	France	0.000467	0.068828	-0.050929	0.010753	0.205383	4.455117	444.539610
	Saudi	-0.000032	0.025900	-0.045437	0.008087	-0.700654	3.478303	370.891874
	Brent	-0.000482	0.081564	-0.133124	0.025074	-0.498366	2.127598	120.523292
	OPEC	-0.000349	0.111785	-0.091622	0.020682	-0.099259	2.931196	192.766075

Table 1. Summary statistics for daily log returns on market indices (in local currency), Brent oil price (in dollars), and OPEC oil price (in dollars). Note: J–B is the Jarque–Bera test for normality.

This study employs a two-step approach to estimate the marginal distributions of Oil costs and equity indices from a GARCH-GJR model. The first step involves obtaining filtered standardized residuals. The empirical distribution is then utilized to estimate the marginal distributions using these residuals. Whole Kernell Smoothing, as proposed by Cherubini et al. (2004), is a common method for this purpose, recent research (Embrechts et al., 1997; Mikosch, 2003; McNeil et al., 2005) suggests limitations for capturing the extreme tails of the distribution. We use Extreme Value Theory (EVT) on the residuals in each tail to address this. With an upper and lower threshold of 10%, this method concentrates on the data points that lie inside them. This makes it possible to estimate the tails more precisely, especially for distributions with heavy tails. The probability integral transform is then applied to convert the estimated distribution into a uniform distribution. This final step facilitates the subsequent estimation of copula functions. This approach offers a more accurate representation of the marginal distributions, particularly by capturing the behavior of the tails, which is crucial for financial data analysis.

The second stage here in the canonical maximum approximation(CML) focuses on estimating the parameters of the copula. For this to estimate, we have used the marginal distribution obtained from the first stage. Copulas are then found via Maximum likelihood Estimation (MLE) method

$$\hat{\theta}_2 = \operatorname{argmax}_{\theta_2} \sum_{t=1}^{T} \ln c\left(\hat{F}_1(X_{1t}), \hat{F}_2(X_{2t}); \theta_2\right)$$

here $\underline{\theta_2}$ is the copula estimator, c() is a copula density and ^F1 (X1t), ^F1 (X2t) is the marginal distribution predicted by Cherubini et al. (2004). The alternative strategy, which estimates the parameters of the MD & copulas simultaneously, is generally more difficult and computationally less appealing than the CML computation method utilized in this work.

This study have 9 different parametric copula functions, namely: Student's t, Clayton, Rotated Clayton, Frank, Plackett, Gumbel, Rotated Gumbel, and Gaussian (Normal), from various copula families and classes. The best copula from each bivariate model is chosen using two metrics (selection criteria) and the log-likelihood functions.

AIC => $-2 \times LLF + 2 \times Params$

BIC => $-2 \times (-2 \times LLF + log(T)) \times Params$

LLF here is loglikelihood function, number of variables is the parameters(Params) and quantity of observations is T (2430 and 2346 for the before- and after-Euro eras, respectively). Except for the Student t and SJC, which have two multivariables, every copula function has a single parameter. In the event that there is a discrepancy between the three criteria, the model will be chosen using the BIC.

5.3 Dependence Measures

Copula functions illustrate the dependence structure and are helpful markers of possible co-movement between series, as we have previously explained (Patton, 2006b). Additionally, copulas are associated with a number of association notions including concordance, reliance on tail, positive(+ve) quadrant dependency, linear correlation & other related measures, including the index of tail dependency, Kendal's tau, and Pearson's rho (Cherubini et al., 2004; Hu, 2006). These metrics of relationships are used in this study: the index of tail dependence, Kendall's tau, & Pearson's rho.

Pearson's correlation

The long-used Pearson's correlation coefficient indicates the linear dependence between the relevant variables. It is a natural scalar measure of dependency in elliptical distributions and is easy to use (Embrechts et al., 2003). It provides only a partial dependence measure in non-elliptical distributions, though. Furthermore, the linear correlation coefficient can be impacted by non-normality, non-linearity, unequal variances, and outliers (Carmona, 2004). Therefore, linear correlation is only reliable and appropriate in some situations.

Kendall's tau

Based on the sample's order statistics, Kendall's tau is a nonparametric concordance measure that is frequently employed for non-oval distributions (Embrechts et al., 2003). Strong rank correlations are produced by minimizing the distortions that have an impact on the linear correlation coefficient. Dissemblace in probabilities of discordance & concordance is measured by Kendall's tau. The following is the definition of Kendall's tau using the ordered stats of X & Y:

$$\tau = Pr((X_! - X_2)(Y_1 - Y_2) > 0) - Pr((X_1 - X_2)(Y_1 - Y_2) < 0$$

Comparable to the correlation coefficient which is linear, its values range from ϵ $[1, -1]$. Additionally, it can be expressed using copula functions as follows:

$$\tau = 4 \int_0^1 \int_0^1 C(u,v) dC(u,v) - 1$$

Copula parameter values can be estimated using kendall's tau or maximum likelihood function. The tau coefficient of Kendall's tau estimator is a helpful model adequacy measurement for copula models. If the relationship parameter is unaffected by the calculation method used, the copulas are properly defined.

Tail Dependence

Finally, tail dependency is also used in this study as a dependence measure. According to Marshal and Zeevi (2002), tail dependency is a characteristic of a copula that is accustomed to condense the possibility of ultimate joint motions among a group of attributes. Diverse copula groups differ greatly in their tail reliance (Rodriguez, 2007). The tail dependence for the copulas taken into consideration in this work is summarized in Figure 3. Zero tail dependencies characterize Gaussian, Frank, and Plackett copulas, which don't reveal anything about extreme co-movements or tail relationship structure. The only symmetric tail reliance that the student's t copula captures (e.g., λL = λU) is more understanding than independence, but it doesn't account for potential asymmetries in the tails. Conversely, asymmetric reliance is revealed by the Clayton, Rotated Clayton, Gumbel, Rotated Gumbel, and SJC copulas. To be more precise, tail dependencies that target one or both tails differently can yield enough data to establish if oil cost series and equity indices are more dependent during a fall than a boom.

Copula	Upper tail (λ_U)	Lower tail (λ_L)
Gaussian	0	0
Clayton	0	$2^{-\frac{1}{\theta}}$
Rotated Clayton	$2^{-\frac{1}{\theta}}$	0
Frank	0	0
Plackett	0	0
Gumbel	$2-2^{\frac{1}{\theta}}$	0
Rotated Gumbel	0	$2-2^{\frac{1}{\theta}}$
Student's t	$2 \times \left(1-t_{v+1}\left(\frac{\sqrt{v+1}\sqrt{\rho-1}}{\sqrt{\rho+1}}\right)\right)$	$2 \times \left(1-t_{v+1}\left(\frac{\sqrt{v+1}\sqrt{\rho-1}}{\sqrt{\rho+1}}\right)\right)$

Figure 2. Tail Dependence for different copulas.

Note: θ denotes copula parameter for each copula model. For the Symmetrized Joe-Clayton (SJC) copula, the upper and lower tail dependences are SJC parameters estimated.

Source: Sukcharoen, K., Zohrabyan, T., Leatham, D., & Wu, X. (2014). Interdependence of oil prices and stock market indices: A copula approach. Department of Agricultural Economics, Texas A&M University.

CHAPTER 4

6. Results

The results for study are presented in this part. We talk about the relationship results between equity index returns and Brent type of oil cost returns. The outcomes for Brent in India are also contrasted with the prices of Opec oil. There is also discussion of the Covid and how it affects the dependence structure.

6.1 Results of degree and structure of dependence

The tables below summarize the findings of the mutual influence measure between stock market indices & the gains on the price of Brent petroleum (as well as OPEC) fuel . The measures of reliance are very minor prior to the Covid pandemic, somewhat larger during the pandemic, and smaller once more following the pandemic.

The tables below summarize the findings of the relationship measures between equity indices & the returns on the price of Brent (as well as OPEC) oil. The measures of reliance are very minor prior to the Covid pandemic, somewhat larger during the pandemic, and smaller once more following the pandemic.

For the Brent oil price returns, the largest Pearson's rho during the pre-Covid period is observed between France and Brent (0.233726), while the smallest is for India (0.082748). During the Covid period, the highest Pearson's rho is for the USA (0.247476) and the smallest for Saudi Arabia (0.053172). Post-Covid, the highest Pearson's rho is again for France (0.108793) and the smallest for India (0.068995).

For the OPEC oil price returns, the Pearson's rho values are generally lower compared to the Brent oil price returns. The pre-Covid Pearson's rho for India is quite low (0.007272). During the Covid period, it increases for India (0.112355) and post-Covid it slightly decreases (0.059948).

Kendall's tau values display comparable patterns of reliance to Pearson's rho. In terms of Brent, the countries with the greatest Kendall's tau during the pre-Covid era are France (0.157827) and India (0.055871). The USA has the highest Kendall's tau during COVID-19 (0.168524), while Saudi Arabia has the lowest (0.034765). Following the COVID-19 pandemic, India has the lowest Kendall's tau (0.042033) and France the highest (0.072889).

For OPEC oil price returns, Kendall's tau is generally lower. Pre-Covid Kendall's tau for India is very low (0.004219). During Covid it increases for India (0.070120) and post-Covid it slightly decreases (0.040229).

		Pearson's rho	Kendal's tau
		Brent	Brent
Pre_Covid_Period	Country		
	India	0.082748	0.055871
	USA	0.200662	0.135434
	France	0.233726	0.157827
	Saudi	0.166216	0.110773
During_Covid_Period			
	India	0.151301	0.111097
	USA	0.247476	0.168524
	France	0.220290	0.151205
	Saudi	0.053172	0.034765
Post_Covid_Period			
	India	0.068995	0.042033
	USA	0.080924	0.052990
	France	0.108793	0.072889
	Saudi	0.127969	0.084681

Table 2. Correlations between each stock market index and oil price returns (Brent).

		Pearson's rho	Kendal's tau
		OPEC	OPEC
Pre_Covid_Period	Country		
	India	0.007272	0.004219
During_Covid_Period			
	India	0.112355	0.070120
Post_Covid_Period			
	India	0.059948	0.040229

Table 3. Correlations between india stock market index and oil price returns (OPEC).

Interpretations

Pre-Covid Period

The costs of Brent crude oil and the Indian equity index exhibited a weakly positive connection, suggesting that differences in oil costs had just a little impact on the equity market. There was a moderately good link between the costs of Brent crude oil and the US equity index. Since the USA is an oil exporter and importer, fluctuations in supply and demand have a beneficial effect on their economy, which suggests that the stock market is positively impacted by changes in oil prices. Out of all the nations included in our study, France demonstrated the most positive connection during the pre-COVID era. This implies a closer connection between the French equity indices and growing oil costs. Saudi Arabia, a major oil exporter, showed a marginally positive correlation.

During-Covid Period

India stock market & Brent crude oil showed a stronger positive association. The heightened volatility and economic downturns likely increased the striking power of the oil costs on the equity market. Throughout the covid period the USA kept showing a strong positive correlation. Because of the country's dual status as an importer and exporter, the impact of oil prices was increasingly large. France too continued to have a very significant positive correlation just like before covid pandemic. This suggests that the French market was still greatly influenced by the ups and downs in oil prices. One important piece of information from our research is that, if you will notice, During covid period Saudi Arabia's correlation with Brent crude oil declined. This might be because of the significant interruptions in the world's oil demand. Supply and demand was greatly affected when covid arrived. This had an impact on oil's profit and in turn decreased the predictability of stock market.

After-Covid Period

Post covid period is the period where everything is coming to the way it was before covid. People were showing confidence in the stock market. There was increased consumption of crude oil. India's correlation with Brent crude oil declined, demonstrating a return to market normalcy and a decrease in the impact of oil cost on the equity market. It's a Same story for the USA but not as strong as it was during covid period. Interesting to see that France's economy continued to show a heightened positive correlation with Brent crude oil. Now if we look into Saudi Arabia, Their correlation was once more positive in post-covid period as it was before covid indicating a return to more stable oil market conditions and the oil cost rebound for the equitymarket. As a result, all three of the countries—aside from France—saw a return to economic normalcy.

6.2 Copula Section Results

Potential asymmetries in the link between costs of oil and indices of the equity indices will be revealed through an analysis of tail results that are based on the calculated copula parameters. Nevertheless, it remains to be explored if asymmetric copula models provide a more accurate description of the relationship than symmetric models. As previously indicated, we rank the copula model using the LLF, AIC, and BIC approaches.

Models having the maximum LLF also tend to have the least AIC & BIC values. This suggests that the model which best fits the data according to the LLF are also chosen when considering the model simplicity.

To explain this we will take an example of the post-covid period for indian $tock market index (nifty50) & Brent Oil Price data.

	LLF	AIC	BIC
normal	0.7415102	0.5169795	4.970605
t	1.2487589	1.5024821	10.409732
clayton	-1.4573731	4.9147462	9.368371
rot_clayton	0.7068244	0.5863511	5.039976
frank	1.6409196	-1.2818392	3.171786
plackett	1.8741885	-1.7483771	2.705248
gumbel	1.1680871	-0.3361743	4.117451
rot_gumbel	0.4308745	1.1382510	5.591876
sjc	0.7622822	0.4754355	4.929061

Figure 3. LLF, AIC and BIC values for Indian stock market indices and oil prices

As you can see, Plackett Copula, which effectively characterizes our data, has the lowest AIC and BIC values and the greatest LLF values. Plackett is the selected copula as a result. This will be done for every nation, and the copula will be selected using this standard.

The outcomes of the information criteria, such as AIC and BIC, generally agree with the LLF results. This criterion indicates that Plackett copula was the best copula during the pre-COVID era, with the exception of Saudi Arabia, which had frank copula. In the during-covid period many bivariate random variables connections are best explained by frank, rotation clayton and gumbel copulas. But the Plackett copula found to be the most common copula for most of the countries except for India which is being best captured by the Gumbel copula. In the post-covid period, we can see different copulas for different countries. No same copulas have been observed for the post-covid period. Plackett for India, Gaussian for USA, Gumbel for France and Frank for Saudi Arabia.

The study in table 4 shows the dependence structure among three different time periods. The considerable values in the Gumbel copula which show more co-movement during extreme events indicate that the Covid-19 pandemic period is marked by heightened dependence in some nations. Some of these dependencies still exist after the pandemic, but in new forms. The lack of a distinct dependency structure pattern according to the country's levels of development suggests that both developed and developing countries are affected similarly. This study explains how economic interdependencies can change as a result of external shocks such as a worldwide epidemic and how these changes may last long after the current crisis has passed.

Now if we look at table 5 OPEC Oil Price and indian $tock market index we can see that for all the periods, frank copula defines the data accurately. This is an elliptical copula.

6.3 Tail dependency results

The tail dependencies for the pre-, during-, and post-COVID periods' equity market index return data, as well as the cost of Brent oil (as well as the price of oil produced by OPEC), are shown in Table 4-5.

The tail dependencies are nil in the pre-Covid era and are explained by the Plackett copula, suggesting that the costs of oil and equity indices are almost independently related. following the series' appropriate filtering. Table 5's OPEC exhibits tail dependence of zero, which can be explained by the frank copula. This further demonstrates the independence of the oil cost and equity market index.

In During-covid period, Tail dependencies are zero for most of the countries and are explained by Plackett copula except for India exhibits an upper tail dependence characterized by the Gumbel copula with a value of 0.14476. This indicates an increased co-movement in extreme events, similar to how certain dependencies were observed during extreme market conditions. Every country exhibits symmetrical tail dependence except for India which shows asymmetrical dependencies, very similar to the result seen for the India OPEC scenario.

			Plackett	Gumbel	Gaussian	Frank
Pre_Covid_Period						
	Country					
	India	Lower	0			
		Upper	0			
	USA	Lower	0			
		Upper	0			
	France	Lower	0			
		Upper	0			
	Saudi	Lower				0
		Upper				0
During_Covid_Period						
	India	Lower		0		
		Upper		0.14476		
	USA	Lower	0			
		Upper	0			
	France	Upper	0			
		Lower	0			
	Saudi	Lower				0
		Upper				0
Post_Covid_Period						
	India	Lower	0			
		Upper	0			
	USA	Lower			0	
		Upper			0	
	France	Upper		0.09256		
		Lower		0		
	Saudi	Lower				0
		Upper				0

Table 4. Tail dependence of chosen copula models (Brent).

Tail dependencies for Saudi Arabia, the United States, and India are nil in the post-COVID era. This demonstrates how the price of oil and stock market indexes are unrelated. Therefore, no significant dependency recorded suggesting a return to pre-covid stability except for France which has upper tail dependence 0.09256 which is very close to zero.

This has a continued co-movement during extreme events, though close to a lesser extent.

For the OPEC India relationship, a Frank copula was observed and a symmetrical relationship.

			Frank
Pre_Covid_Period	Country		
	India	Lower	0
		Upper	0
During_Covid_Period			
	India	Lower	0
		Upper	0
Post_Covid_Period			
	India	Lower	0
		Upper	0

Table 5. Tail dependence of chosen copula models of India for all periods (OPEC).

Our results suggest that the observed correlation between the global stock market indexes and the price of oil is either nonexistent or extremely weak. The outcome is in line with some earlier research that suggested there was no correlation between the cost of oil and equity benchmark markets. There isn't much proof of an non symmetric relationship amongst the cost of crude and the little fossil fuel-yielding nations (such as the United States and India) in the pre-covid era, which suggests that in the event of a crash rather than a boom, there will probably be more dependence. This is also true in the post-covid and during-covid periods.

Nevertheless, the converse is seen for France during the post covid period and India during the covid period, suggesting that an increase in oil costs has a marginally greater impact on both equity market indexes than a fall in oil prices.

Regardless of the case taken into consideration, all of the bivariate correlations have tail dependence measures that are generally fairly minimal. Furthermore, a weak asymmetry in the relationship between the costs of oil & some equity indices returns has been identified.

CHAPTER 5

7. Conclusions and Future Work

7.1 Conclusions

An increasing number of articles are being written to explain the effects of rising oil costs and demand on the earth's economy, given the growing significance of oil for the advancement of global economic affairs. Still, relatively few research the correlation between oil costs and equity indices. Moreover there are not many studies for the recent extreme events like covid. There is one research, but it takes a very different approach from ours and only looks at the African continent. Understanding the co-movement of the oil cost and equity market during extreme events like COVID-19 is still lacking. Furthermore, there isn't much research done on the inclusion of different nations with varying degrees of economic growth. The non symmetric relationship for oil cost series and equity indices is also poorly fathomed. In a practice to gain a depth of understanding of the correlation between oil costs and equity market indices, this study aims to tackle all these concerns. We specifically investigate if there is a correlation between the movement of equity market indices and costs of oil? Is there any imbalance in the partnership? When there are extreme events, does the dependence (if any) increase? Does the reliance alter before, during, or after the COVID-19 pandemic? Does it matter which oil price series is chosen? Do nations that produce and use oil, as well as those that are developed and emerging, exhibit a particular pattern of dependence?

In order to model bivariate connections with more flexibility, we employ copula functions. They also make estimating the overall dependent structure easier. In order to account for exchange rate effects, the oil price data are additionally translated into the native currencies of the particular nations that were selected.

Furthermore, a majority of the interactions exhibit symmetry. This suggests that regardless of the status of the economy, the dependency (connection) between the costs of oil and equity market indices will be comparable. For large oil importing and consuming countries such as France and India, the tail dependencies are relatively significant. Some have, nevertheless, reported minor asymmetric patterns. The French and Indian stock market indices and oil prices have a right-tail association, meaning that there is a greater likelihood of an upper tail dependence than a lower tail dependence. This suggests that the two series are more likely to rise together than to fall together.Stated differently, there is a minor strengthening of the correlation between the return on oil costs and the equity market index returns during periods of market upswing and rising oil costs. Ciner (2001) discovered dual nonlinearity amongst the returns of the oil costs and the stock index, which may help to explain this conclusion. Put differently, oil prices are influenced by stock market returns as well. Maybe this explains why, during periods of market expansion, the movements of the oil costs and equity market index returns tend to coincide more.

Moreover, there appears to be a pattern whereby industrialized and emerging nations have distinct relationship parameters. Large exporting countries like the USA and Saudi Arabia have symmetrical relationships in all the pre,during and post covid periods, whereas countries which are importing oil showed weak dependencies

We find that depending on which oil cost series is selected, there is a reasonable variation in the tail dependences and copula parameter estimations. The two oil cost series may produce somewhat different outcomes for two reasons. The kind and quality of oil is the primary factor. The weighted average of the eleven oil blends is known as OPEC type oil series, and Brent petroleum oil is a low-sulfur, low-density oil. The second reason is that, unlike Brent type oil series, which is set by the market, the price of OPEC oil is set by the organization itself, which modifies production to keep it between upper and lower bounds. It is plausible to see after examining that Brent type crude petroleum price series are a better match for these types assessments given that the price of OPEC type oil is not discussed and set by market itself and the price of oil output from Europe, Africa & the middle easters is primarily priced with respect to the price of Brent petroleum oil.

Given that this analysis provides substantial verifiable evidence of a correlation between the equity market and crude petroleum costs returns, investors stand to gain the most from it. Given the factual results about the patterns of reliance in developed and developing countries, global investors would also gain. Results will give investors more possibilities to assess the interdependence between the two series when they are presented for a variety of probable scenarios.

Furthermore, the outcomes offer significant insights into the diversification and potential benefits.

7.2 Future Work

The findings demonstrate how shaky and unstable the connection is between oil costs and equity markets. The covid period's increased state of depending on the people shows how susceptible the world's markets are to outside shocks. This research provides knowledge by offering a detailed examination of both developed & under developing nation's reactions to such dramatic events on the oil stock market.

More and More investigations should be there in examining these correlations via more detailed and focused data concentrating the influence of additional disastrous factors like geopolitical incidents or climate policy. More advanced investigation into the function of exchange rate effects and other macroeconomic variables is necessary to have a deeper comprehension of the relationship between the stock and oil markets.

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