**DYNAMIC RISK SPILLOVERS FROM OIL TO STOCK MARKETS AMONG THE EMERGING ECONOMIES:**

*EVIDENCE FROM A*

*GARCH COPULA QUANTILE REGRESSION-BASED CoVar MODEL*

In Partial Fulfillment of the FINANCIAL RISK ANALYSIS AND MANAGEMENT - FIN F414 Course.

SUBMITTED TO **MR. ASHWINI KUMAR MISHRA**



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Highlights:

* Estimation of returns spillover among emerging economies using GARCH Copula Quantile Regression-based CoVar model analysis.
* Focus on the impact of oil market fluctuations on stock markets for examination of economic events, geopolitical conflicts, and energy market volatility.
* Significant findings on the influence of COVID-19 pandemic and housing crisis of 2008.
* Insights into complexities of investment strategies and implications for effective supervisory policies.

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### ABSTRACT

This research investigates risk spillovers from relationships between Brent Crude oil, WTI, and stock markets in six emerging nations (Brazil, China, India, Indonesia, South Korea, and Mexico) using daily MSCI indices data from January 2001 to December 2022. Employing graphical and statistical analyses, the study reveals notable correlations between oil and stock market trends during major global events. The research uses ARMA-GARCH models to estimate marginal distributions, identifying the ARMA(1,1)- EGARCH(1,1). The study then explores nonlinear relationships through copula functions, revealing the asymmetric nature of risk spillovers.

The empirical results of risk spillover analysis from Brent Crude oil to six emerging economies indicate that the Indian and Indonesian stock markets experience the highest downside and upside risk impacts, respectively. However, in contrast, the Mexican stock market displayed the least risk spillovers, showcasing a non-symmetric pattern that aligned with flight-to-quality dynamics. Additionally, our findings highlight temporal heterogeneity in dynamic risk spillover effects.

Our findings have crucial implications for international investors and supervisory authorities seeking to optimize investment strategies and develop effective policy responses in light of evolving risk spillover dynamics.

*Keywords:*

Risk Spillover, Stock Market Volatility, Emerging Economies, CoVar, Geopolitical Events, Oil Market

***JEL classifications:***

***C58***

***G14***

***G15***

***Q43***

### 1. INTRODUCTION

Any nation's economic stability highly depends on the country's energy supply in modern society. Since the outbreak of the COVID-19 epidemic in 2020, there has been a period of global economic decline. Low demands have caused multiple production-line shutdowns, causing a significant decline in energy demand and prices. The Russia-Ukraine conflict, on the other hand, has led to a sharp rise in energy prices (Gong et al., 2023). Despite the increased usage of renewable energy, 83.1% of energy consumption in 2020 was derived from fossil fuels, according to BP's 2021 report(British Petroleum, 2022), and petroleum continues to account for the most significant portion of the energy consumption structure.

The phrase "spillover of shocks" has increased, especially after the 2008 financial crisis. Therefore, it is crucial to understand the concept of "spillover". Our report interchangeably uses spillover, co-movement, contagion, and co-integration(Khan et al., 2023). *Contagion* is defined by the World Bank as a substantial increase in cross-market linkages after a disruption to a single country (or group of countries), as measured by the extent to which asset prices or financial flows move together across markets relative to this co-movement in times of relative calm. When a crisis strikes one country, investors are compelled to withdraw funds from other countries due to liquidity constraints (Richard N. Cooper, n.d.).

The shocks of changes in oil prices can affect stock prices through several economic channels. First, a rise in crude prices causes inflation and a decrease in economic consumption, which results in increased unemployment and a damped outlook for economic expansion. The resultant recession can hurt the stock market (Rasche & Tatom, 1977).

Secondly, an increase in the price of commodities caused by a rise in oil prices reduces the profits of companies highly dependent on oil and energy, resulting in a decline in their stock prices. This path is known as the inflation effect. In addition, because a portion of the effect of the oil price increase is being passed to consumers, the cost of living for consumers rises, as does the demand for money. If there is no change in the money supply, the short-term interest rate will rise, increasing the company's financing costs and the discount rate for future earnings, resulting in a decline in the stock price, called the real balance effect (Bernanke et al., 1997).

Third, the rise of oil prices impacts economic activity and stock prices by shifting purchasing power from oil-importing countries to oil-exporting countries. This effect is called "income transfers and aggregate demand". The increase in oil prices results in a fall in oil-importing nations' stock prices while increasing oil-exporting countries' stock prices (Abbott, 2007).

The fourth channel, the uncertainty effect, is caused by the increased volatility of oil prices, which can impact actual economic activity and stock prices(Bernanke, 1983).

Although GARCH copula quantile regression-based CoVaR models are a sophisticated framework for understanding spillover effects, emerging economies still need research. Many studies have focused on only developed economies and select developing countries(Tian et al., 2022) (Jones & Kaul, 1996). Hence, a significant gap exists in understanding how these models perform in emerging markets.

Most existing studies have assumed a linear relationship in their models. This ignores the non-linear dynamics of commodity markets. Investigating the non-linear relationships through copula modelling can provide a more accurate representation of cross-market spillover effects (B. & Paul, 2021).

Our primary benchmark, Brent Crude Oil, is named after the North Sea Brent oil field. It represents a category of crude oil that is "light sweet" due to its low density and sulfur content. This makes it ideal for refining into valuable products like gasoline. Brent Crude is critical in setting global oil prices, traded on the Intercontinental Exchange (ICE), and referenced in approximately two-thirds of internationally traded crude oil. Its prices are closely monitored, significantly impacting the global economy and influencing energy costs for consumers and businesses. It is subject to volatility caused due to common factors such as geopolitical events and supply and demand dynamics (Barbaglia et al., 2020). Our research contributes to the preset literature in the following ways: First, we have used the oil-stock price relationship in a novel CoVaR model based on the recently developed GARCH CQR model by Tian and Ji (2022). We have used this analysis to find the positive tail dependence between the oil and stock markets at varying risk levels. Seven distinct copulas are modelled to evaluate the non-linear relationships in both the downside and upside-tail dependence, with the marginal distributions being established using the GARCH family of models. The GARCH CQR model has substantially enhanced our understanding of the spillovers from the energy and stock markets. Based on our results, we have also provided suggestions for policy-makers and international investors (Tian et al., 2022)

Secondly, unlike previous studies, we have used an expanded dataset from January 1, 2001, to December 29, 2022, with 5745 daily observations. Using this data, we aim to capture the effects of COVID-19 from 2020-2021 and, after that, the ongoing Russia-Ukraine War.

Finally, we have analysed six emerging economic nations that have not been explored before(China, India, Brazil, South Korea, Mexico, and Indonesia). Countries experiencing rapid economic growth and development are mostly called emerging economies. They have transitioned from agrarian to industrialised economies, are currently opening up to foreign investment, and may undergo rampant political and regulatory changes to attract capital and promote stability. Emerging economies can be separated from other nations due to their standard features like investment in infrastructure, urbanisation, and the rise of the middle class. While they offer growth opportunities, they also carry the risk of political instability and currency volatility (Basher & Sadorsky, 2006).

### 2. METHODOLOGY

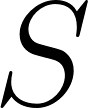
A GARCH CQR model is used for accurately capturing the upside-tail dependence. Consequently, the downside and upside CoVaR and risk spillovers can be calculated by the GARCH CQR-based DCoVaR and UCoVaR model, respectively.

#### *2.1 CoVaR model*

We apply the risk measure ΔCoVaR to estimate downside and upside risk spillovers from crude oil market to stock market. Firstly, we review the risk measure VaR. For a stock market ⅈ, the downside and upside at a confidence level are defined as:

The given confidence level implies that the probability of the maximum possible loss greater than the VaR is less than or equal to . It is obvious that for a portfolio manager with a long position (a short position), the risk measure VaR is related to downside risk (upside risk).

According to the VaR measure, the CoVaR measure (Adrian and Brunnermeier, 2016) is defined as follows. Given confidence level (1 -  ), the downside and upside for the stock market , conditional on the downside and upside , for the returns of the oil market ⅈ at the confidence level satisfy

Here, and are the returns of oil markets ⅈ and stock market , respectively. Therefore, the risk spillover effect of one oil market  on the stock market  at confidence level can be defined as follows,

where and are the VaR of the stock market S conditional on the oil market  being in a distress state and a benchmark state, respectively.

Similarly, the upside risk spillover effect can be calculated by the following equation:

The estimation of the downside risk spillover by the GARCH CQR-based DCoVaR model has been proposed by Tian and Ji (2022). In the following subsections, we will derive the GARCH CQR-based UCoVaR model.

#### *2.2 Marginal distribution model*

In this subsection, we introduce the ARMA-GARCH model, the most widely used approach to describe the properties of serial correlations, volatility clustering and conditional heteroskedasticity of financial returns. In general, the ARMA(p,q)-GARCH(m,s) model is constructed as follows:

Where and are nonnegative integers and and are the

autoregressive and moving average parameters, respectively. is the conditional variance that has dynamics as given by the GARCH model:

where is a sequence of i.i.d. random variables with mean 0 and variance 1 and with

and

To allow for asymmetric effects between positive and negative asset returns, the EGARCH model (Nelson, 1991) is proposed as follows:

where again is a sequence of i.i.d. random variables with mean 0 and variance 1, and

It is obvious that

,

where is the expected value of absolute standardized innovation . Thus, the parameter captures the sign effect and the magnitude effect, which denotes the asymmetry of the volatility for positive and negative returns which is commonly attributed to the leverage effect of equity returns.

The standardized residuals generally exhibit the characteristics of both kurtosis and skewness, which follow a standardized skew Student’s distribution (SSST) (Tsay, 2012). Let be the SSST distribution, and its PDF (probability density function) is

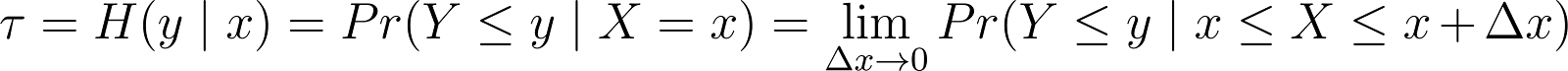
where is the PDF of the standardized Student’s distribution (SST):

where is the gamma function and is the degree of freedom. is equal to the ratio of probability masses above and below the mode of the distribution; hence, is the skewness parameter, , and .

#### *2.3 CQR model*

Let the cumulative distribution functions (CDFs) be and , respectively. They can be connected by the copula function , ) with parameter and we can get the joint distribution function , (Sklar, 1959). The bivariate one-parameter copula families given in Joe (1997) include B1 (Normal copula), B2 (Plackett copula), B3 (Frank copula), B4 (Clayton copula), B5 (Joe copula), B6 (Gumbel copula), B7 (Galambos copula), B8 (Hüsler-Reiss copula), B9 (Raftery copula), B10 (Morgenstern copula), B11 and B12. However, B1, , B3 and B10 cannot capture the property of asymmetric tail dependence, moreover the function of B9, B11 and B12 are complicated and non-differentiable. Among the other five copulas, the Clayton copula can describe downside tail dependence structure, and the Joe copula, Gumbel copula, Galambos copula and Hüsler-Reiss copula can capture upside tail dependence structure. Therefore, these five copulas and their 180-degree rotated forms (Joe,1997; Nelsen, 2006) are selected in this study to capture the nonlinearity and asymmetry of the tail dependence structure, which are shown in Table 1.

Based on the definition of conditional CDF H(yx)



where is conditional copula. The conditional copula functions of the copula families shown in Table 1 are presented in Table 2. Fixing the conditional probability of given at quantile ; we can get

by solving for . Eq. (7) presents the copula quantile curve for .

Considering and , Eq. (7) can be rewritten as

Therefore, we can get the CQR function for at quantile as follows

*Table 1: Copula models.*

| Copula models | | | Copula function | Parameter | | |
| --- | --- | --- | --- | --- | --- | --- |
| Clayton | |  | | | |  | | |
| Rotated Clayton | |  | | | |  | | |
| Joe | |  | | | |  | | |
| Rotated Joe |  | | | |  | | |
| Gumbel |  | | | |  | | |
| Rotated Gumbel |  | | | |  | | |
| Galambos |  | | | |  | | |
| Rotated Galambos |  | | | |  | | |
| Hüsler-Reiss |  | | | |  | | |
| Rotated Hüsler- Reiss |  | | | |  | | |

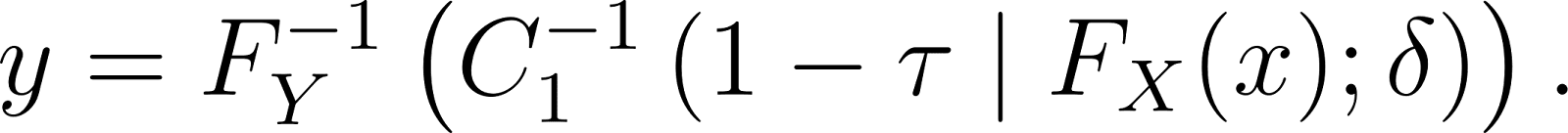
*Note: is the CDF of standard normal distribution, where is the quantile function.*

Similarly, based on the definition of upside CoVaR, for the conditional quantile of given , we have

or .

Solving for yields the CQR curve for as the following equation:

Therefore, the CQR function for at quantile is



*Table 2: Conditional distributions of copula models.*

| Copula models | Conditional distribution functions |
| --- | --- |
| Clayton |  |
| Rotated Clayton |  |
| Joe |  |
| Rotated Joe |  |
| Gumbel |  |
| Rotated Gumbel |  |
| Galambos |  |
| Rotated |  |
| Galambos |  |
|  |  |
| Hüsler-Reiss |  |
| Rotated Hüsler- |  |
| Reiss |  |

Among all the above-mentioned copulas presented in Tables 1 and 2, Clayton copula, rotated copulas of Joe, Gumbel, Galambos and HüslerReiss can describe downside tail dependence and upside tail independence. In contrast, the rotated Clayton copula, Joe copula, Gumbel copula, Galambos copula and Hüsler-Reiss copula can capture upside tail dependence and downside tail independence. Thus, the corresponding CQR function could properly describe the lower or upper tail dependence between random variables or . To illustrate this desirable property, we generate 2000 random values of for different copula with different parameters , and the marginal distributions of and follow the SSST distribution with different parameters. We plot the CQR curves for ten copula families in Appendix A displaying different tail dependence behaviour.

#### *2.4 GARCH CQR-based UCoVaR model*

and denote the CDFs of and , returns of oil market and stock market , respectively. Thus, according to the definition of upside CoVaR and Eq. (10), we have

or

where and denote the CDFs of and , the standardized residuals of and and are the conditional mean and standard deviation of the returns of oil market and stock market , estimated by Eqs. (3), (4) or (5).

According to Eqs. (11) and (12), Eq. (14) is equivalent to

Therefore, the upside CoVaR can be estimated by

or

where is the quantile function of . Following Tian and Ji (2022), we can estimate the parameter in Eq. (17) by interior point algorithm for nonlinear quantile regression model (Koenker and Park, 1996) at the quantile:

based on , where is the conditional quantile of given is the zooming parameter and is the panning parameter.

Therefore, given confidence levels and , the upside CoVaR of the stock market conditional on the upside value at risk of the oil market being can be obtained as follows:

Eq. (19) is the GARCH CQR-based UCoVaR model. Meanwhile, the following equation is the GARCH CQR-based DCoVaR model (Tian and Ji, 2022):

In particular, the upside and downside CoVaRs of the stock market conditional on oil market being in its benchmark state can also be calculated by Eqs. (19) and (20), respectively. Therefore, the downward and upward risk spillover effects are determined by

and

It is worth noting that when applying Eq. (19) to calculate the upside risk spillover effect, the copula function should be selected from rotated Clayton copula, Gumbel copula, Joe copula, Hüsler-Reiss copula and Galambos copula, which can describe the lower tail independence and upper tail dependence between financial returns. Meanwhile, regarding the downside risk spillovers, the copula function in Eq. (20) is the optimal one of Clayton copula, rotated copulas of Gumbel, Joe, HüslerReiss and Galambos, which can capture the upper tail independence and lower tail dependence. In addition, the GARCH CQR model has the following two advantages over other similar approaches, first, it can describe the nonlinearity of the downside and upside tail dependence structure between the oil and the stock market returns at different risk levels; second, it can accurately capture the properties of serial correlation and volatility clustering of the financial asset returns.

### 3. DATA

Examining risk spillovers from the Brent Crude oil market and WTI oil market to six nations' stock markets - Brazil, China, India, Indonesia, South Korea and Mexico: we selected daily data of MSCI indices. These were chosen as a representation for the stock market indices–from January 1st, 2001 through December 31st, 2022 (a total of 5739 observations). In addition to this dataset acquisition—Bloomberg terminal provided us with Brent Crude oil prices' collection.

We initially graphed the basic daily closing prices of the index against each country's daily oil market closure. This step illuminated long-term trends in MSCI price indices and Brent Crude oil prices over our analyzed period; moreover, it became evident that significant fluctuations among all eight price indices are relatively similar. Figure 2 typically illustrates a drastic downward trend of the eleven price indices following severe risk events such as: the European debt crisis, global financial crisis, COVID-19 pandemic and Russia-Ukraine conflict; this implies a notable correlation between these events and substantial market downturns.

We then graphed each index's log returns alongside those of the Brent Crude oil market. A similar volatility clustering occurs about this specific period, yet responses to the shocks differ across diverse financial markets (see Figure 3).

Each country's oil and index returns exhibit a nonlinear relationship in the scatter plots, specifically within their upper and lower tails; this implies the necessity of employing a nonlinear model to scrutinize risk spillover effects from the oil market onto stock markets.

Finally, we employed descriptive statistics for a numerical analysis of the trend. The table incorporates: mean, maxima and minima; median; skewness; standard deviation - also known as volatility - and kurtosis.

Saudi Arabia's and Kuwait's data was found to be of a much lesser time period, thus both were excluded from this study after severe discussions. WTI data was giving errors while plotting the final CoVaR graphs, hence it was omitted at the last minute. WTI is produced in the US, hence it may not have that much impact in countries as it is not that widespread as compared to Brent Crude.

### 4. RESULTS & DISCUSSION

#### *4.1 Estimates of the marginal distribution*

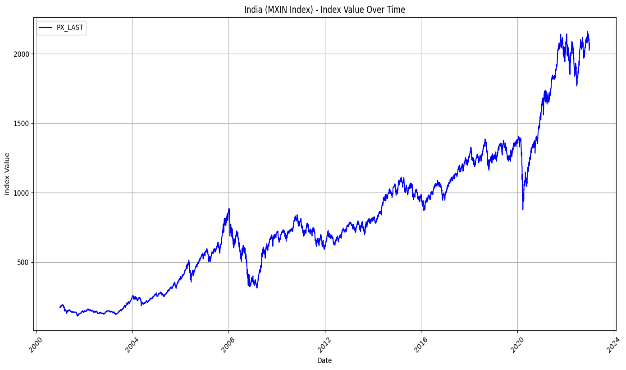
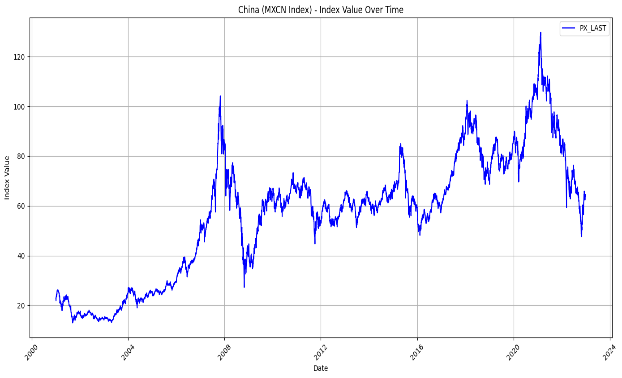
As indicated in section 3, to capture the distribution properties of heavy tails, skewness, autocorrelation and volatility clustering, marginal distribution for Oil and stock market returns are built on the ARMA-GARCH family models with the standard normal distribution, SST and SSST distribution, respectively.Table 5 presents the estimated parameters, the Ljung-Box and ARCH tests for model adequacy.

Ljung-Box test applied to the standardize residuals (and the square of the standardized residuals) of the ARMA(1,1)-EGARCH(1,1) model with SSST innovation does not reject the null hypothesis of autocorrelations at lag 20 at the 5% significance level.

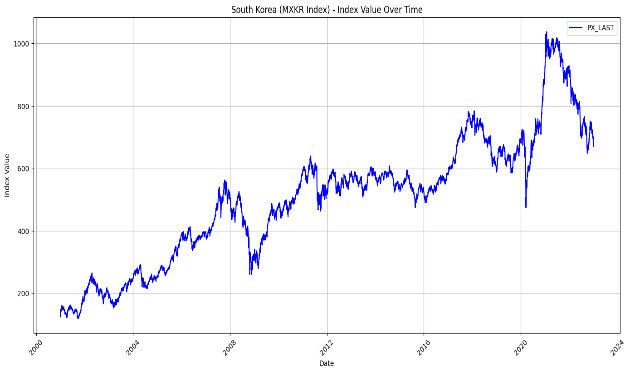
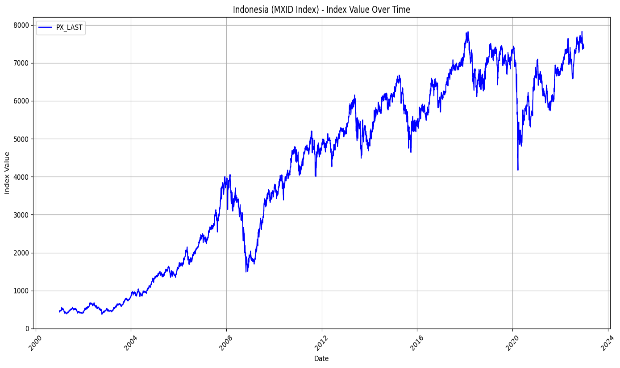
The Engle's LM test suggests the absence of ARCH effects in all the return series at the 5% significance level.The estimates of parameters and the standard deviations show that the ARMA(1,1)-EGARCH(1,1) model is adequate. Furthermore, the parameter estimates of the SSST distribution confirm that the standardized residuals do not follow the normal distribution, which is consistent with the negative values for skewness and high values for the kurtosis statistic reported in Table 3.

Fig. 1 presents the long-term trends of the MSCI price indices and the Brent oil price over the period analyzed. Note that the huge fluctuations of eleven price indices are quite similar. Specifically, the extreme risk events, such as the global financial crisis, the European debt crisis and the COVID-19 pandemic, usually resulted in an extreme downward trend of the eleven price indices.

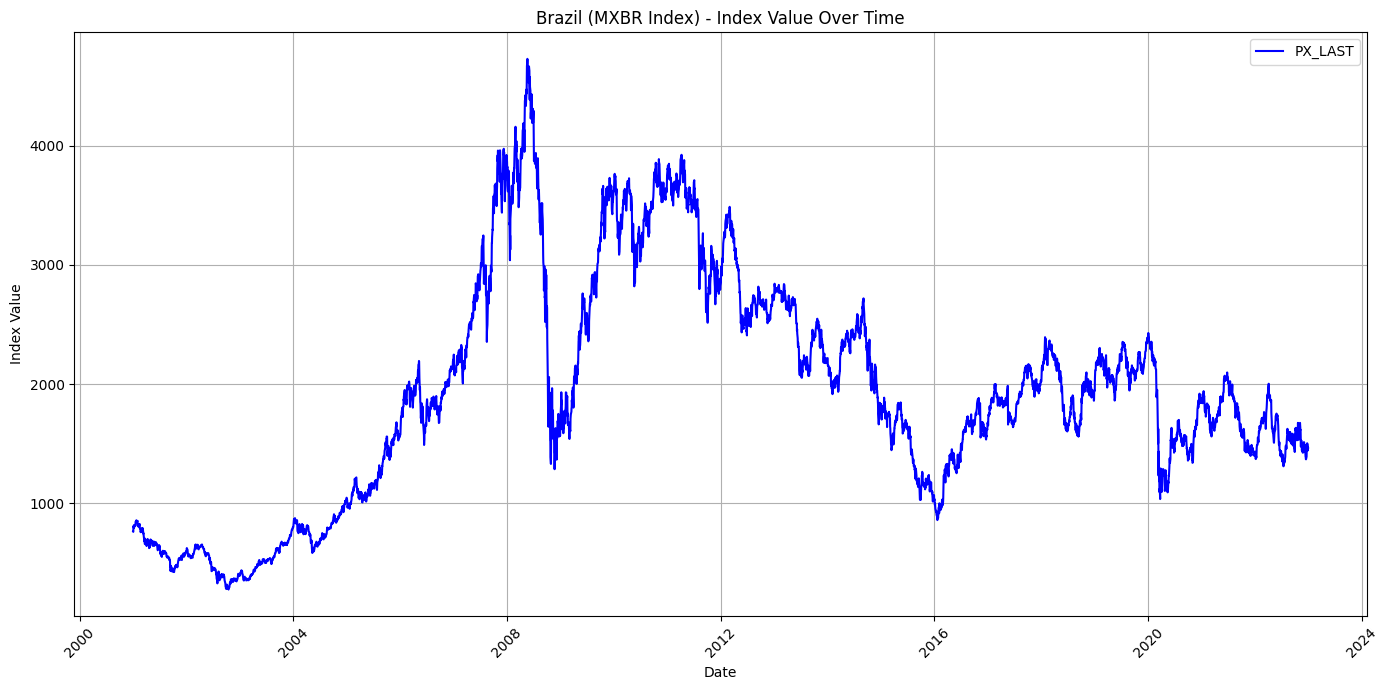
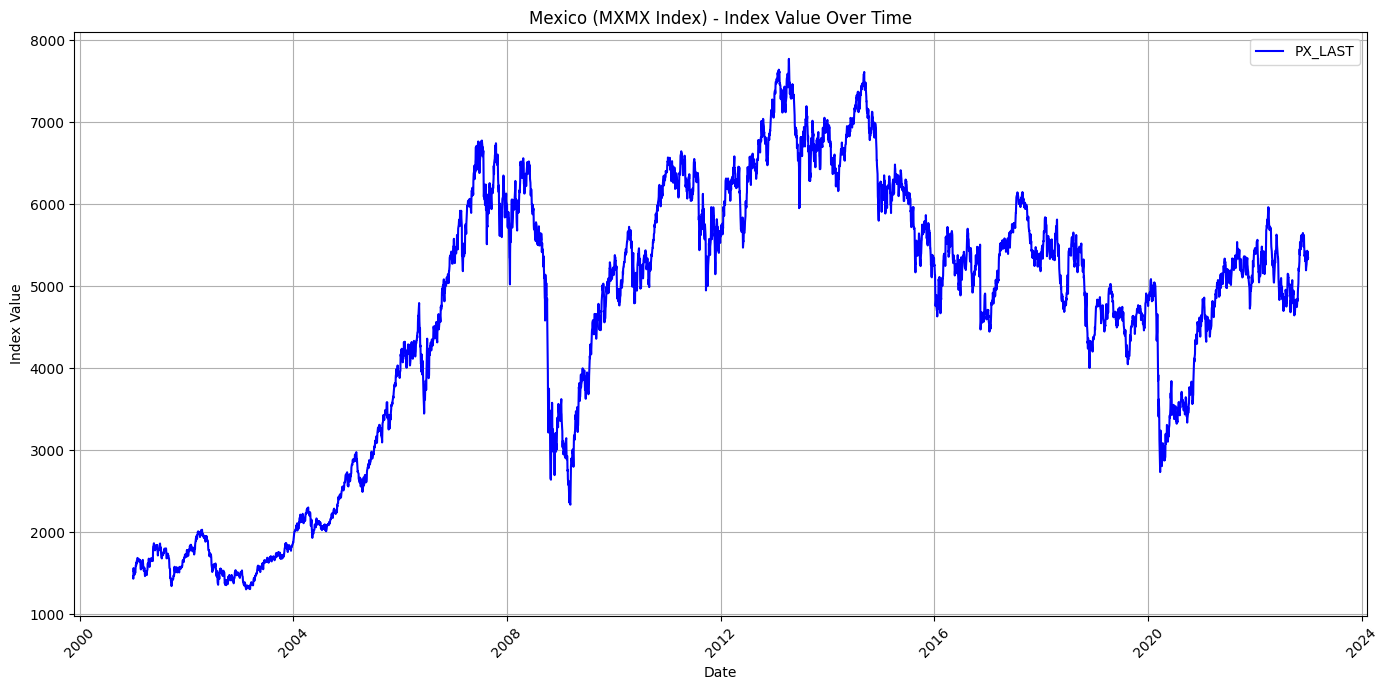
China India



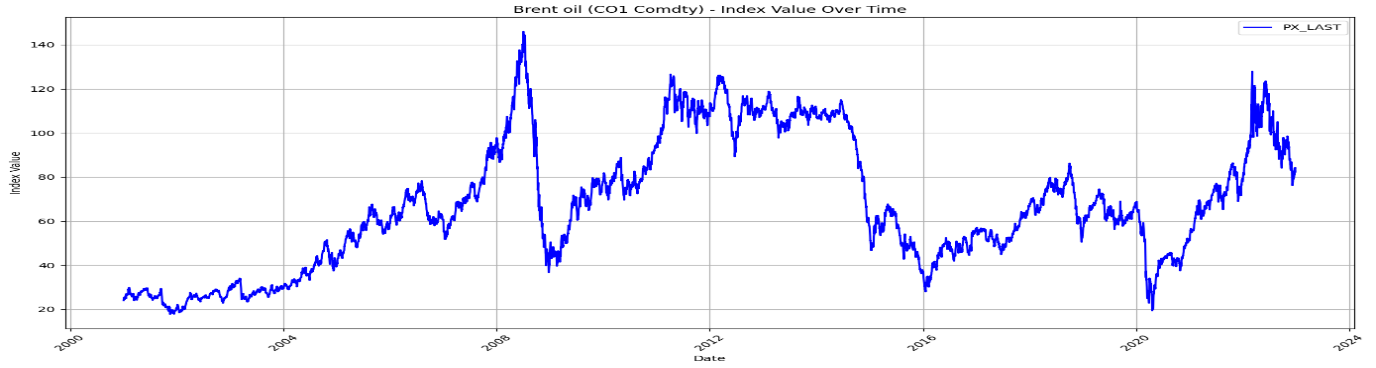
Indonesia                                                       South Korea



Mexico Brazil

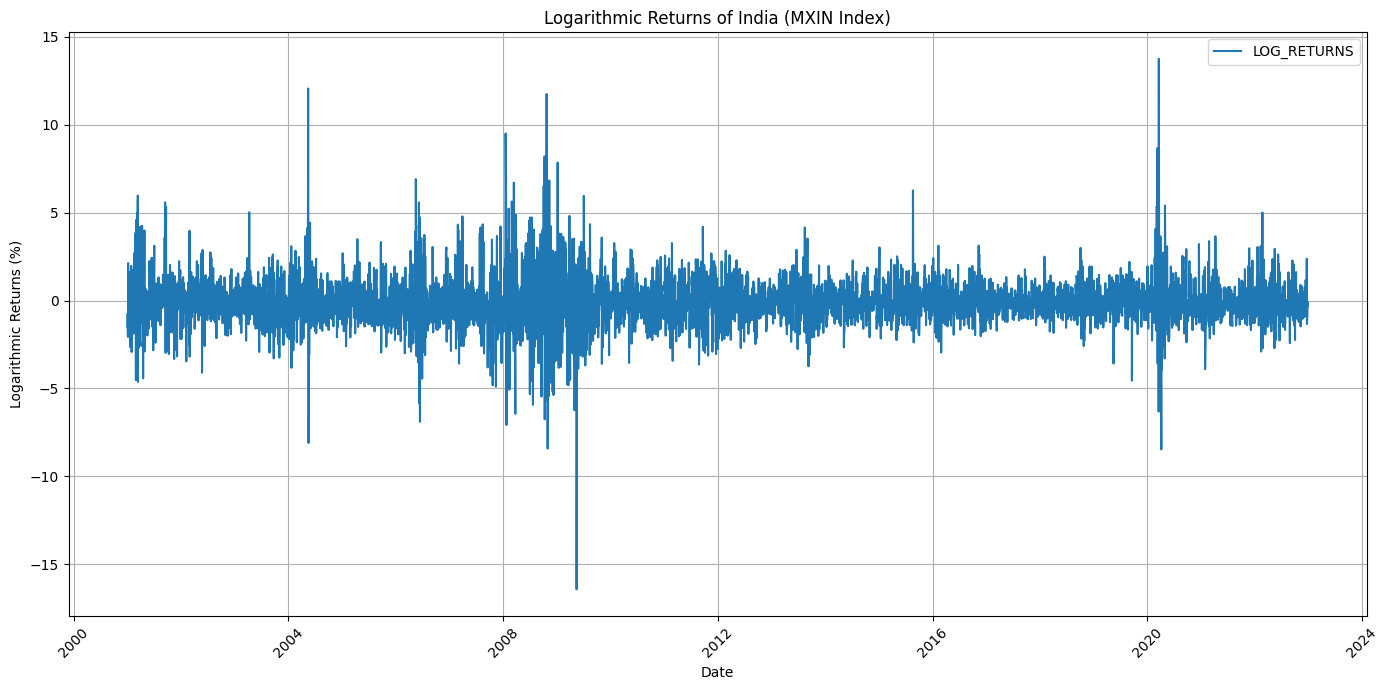


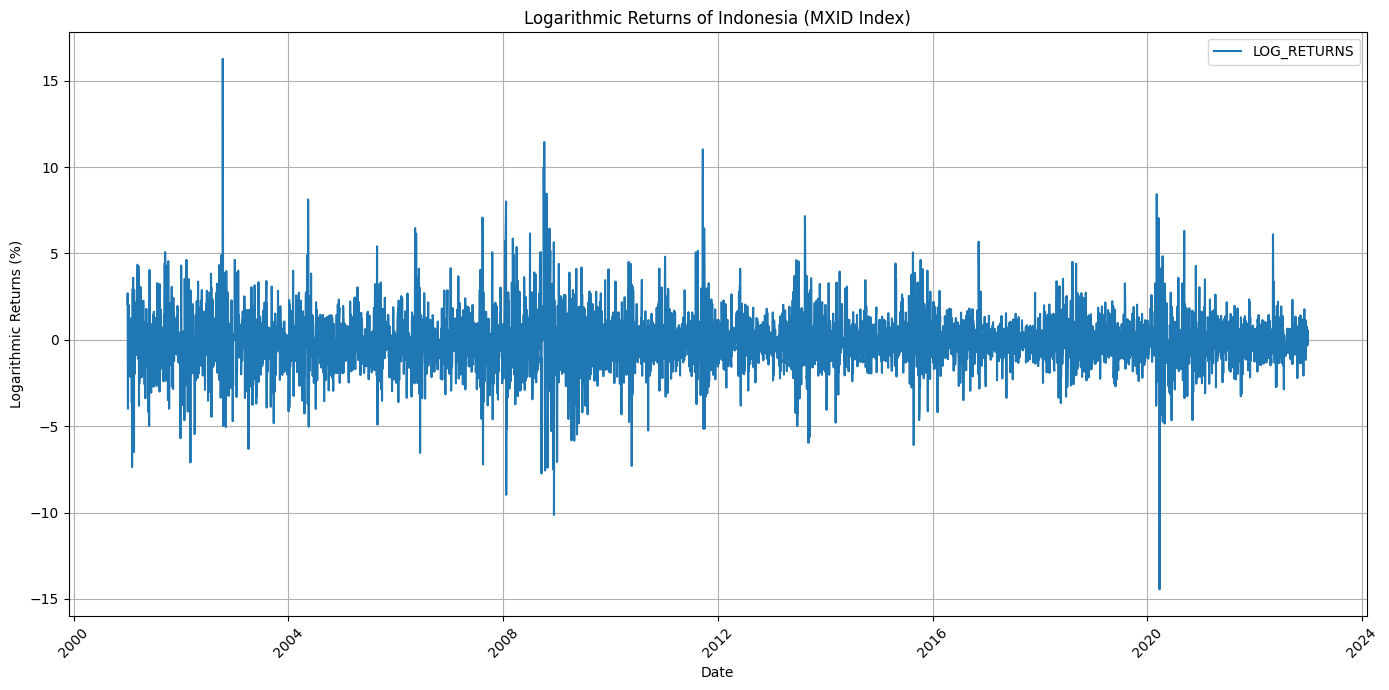
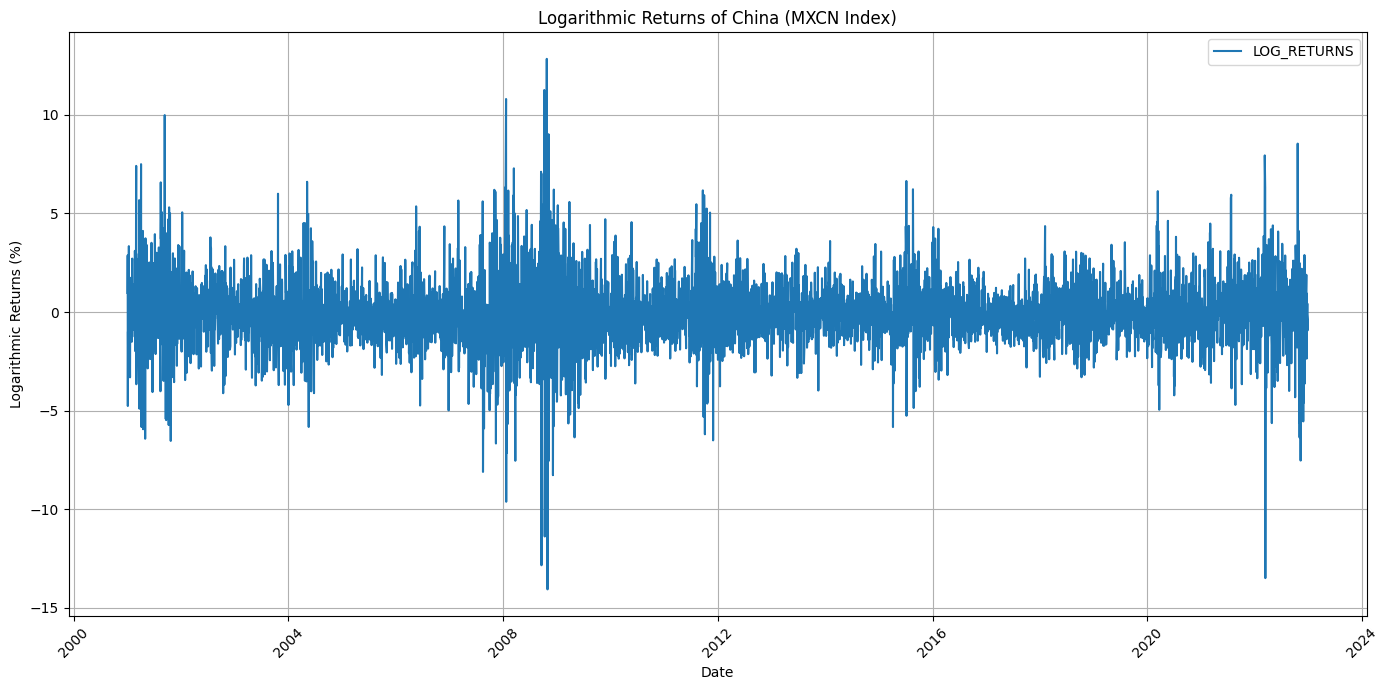
Brent Oil

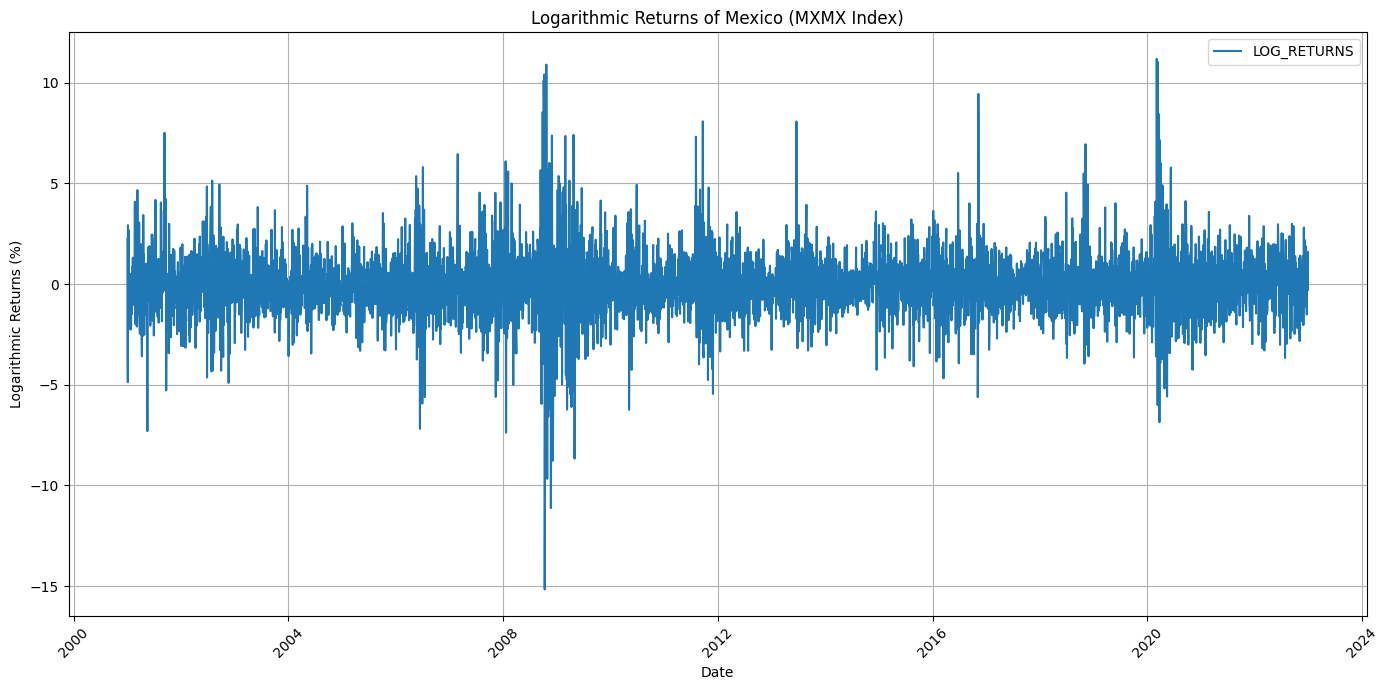


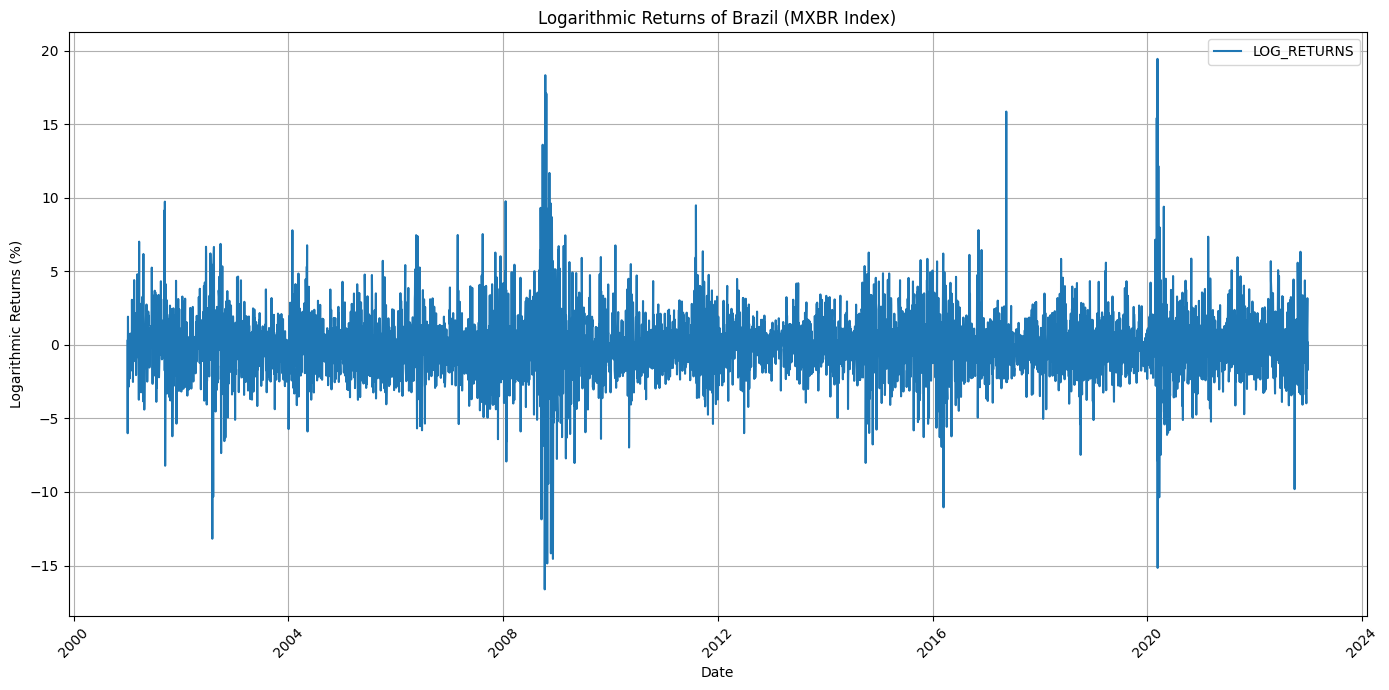
*Fig. 1. MSCI indices of different oil markets*

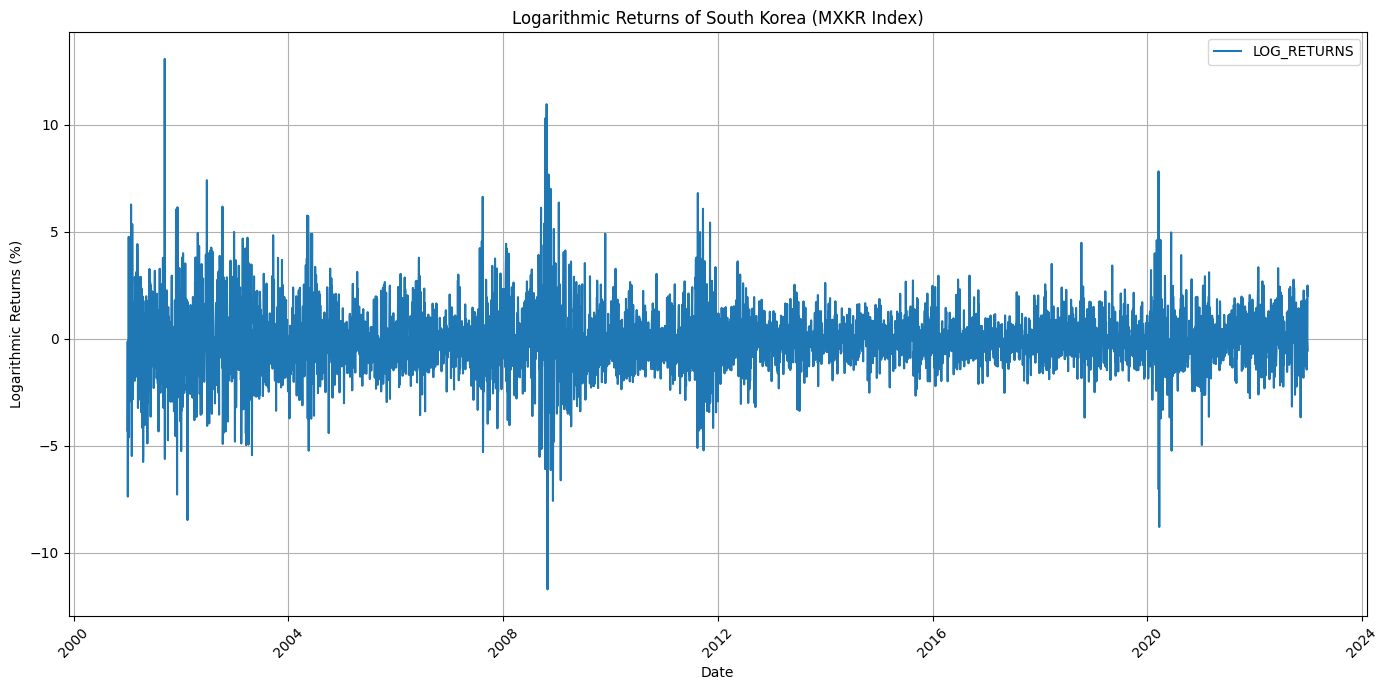
Fig. 2 plots the returns of these price indices which are given as rt = 100 × (lnPt − ln Pt− 1). Obviously, there is also a similar volatility clustering along with the occurrence of the global financial crisis, the European debt crisis and the COVID-19 pandemic. However, the reactions of different financial markets to extreme shocks have been heterogeneous over time. These characteristics provide an opportunity to explore risk spillovers from the oil market to the stock markets.

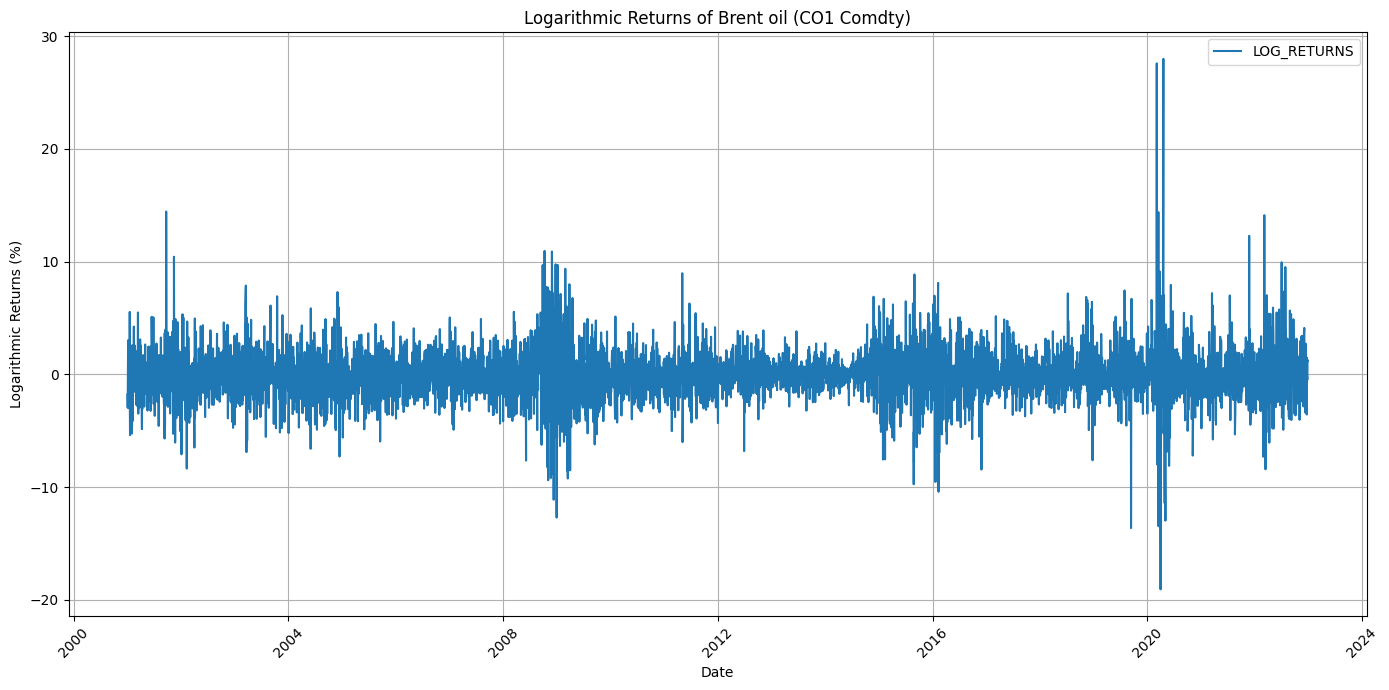








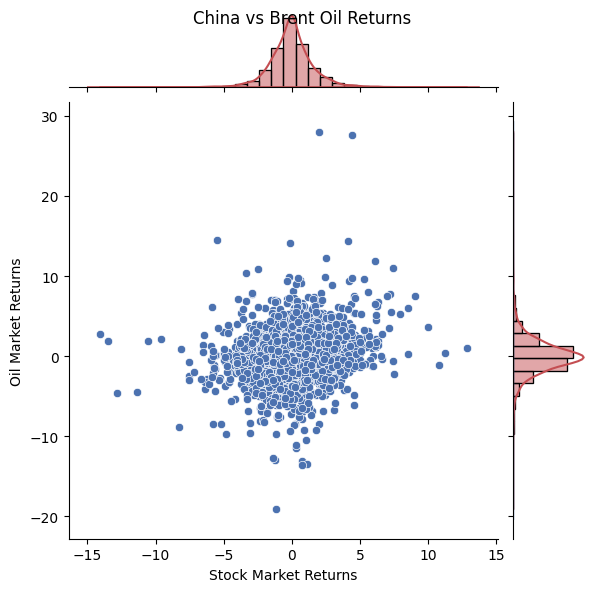
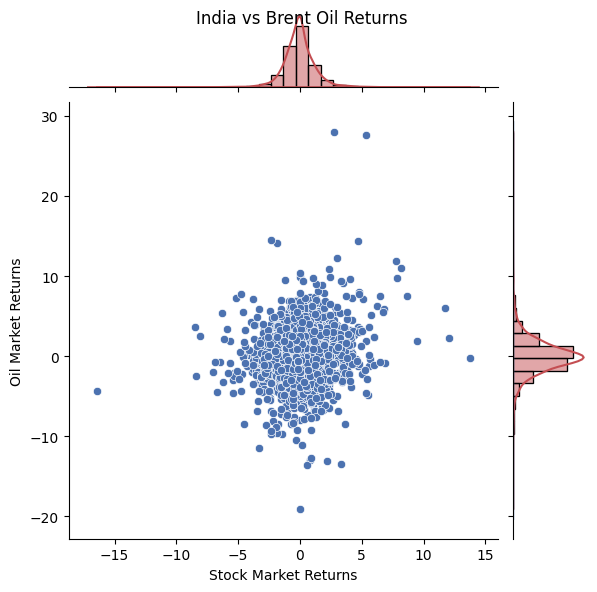


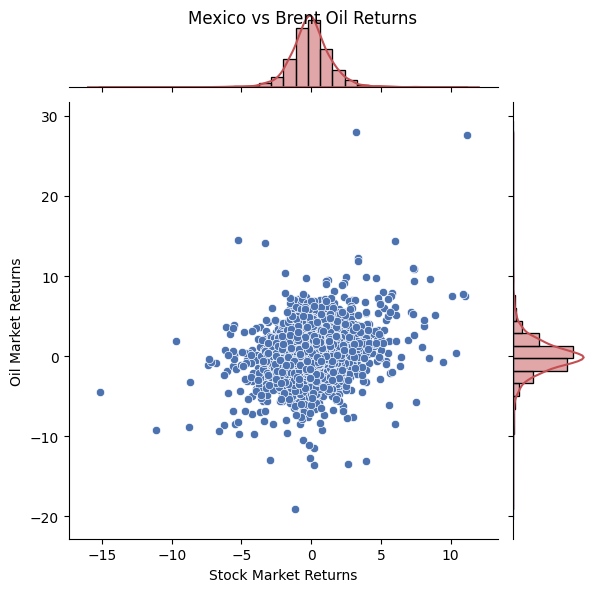
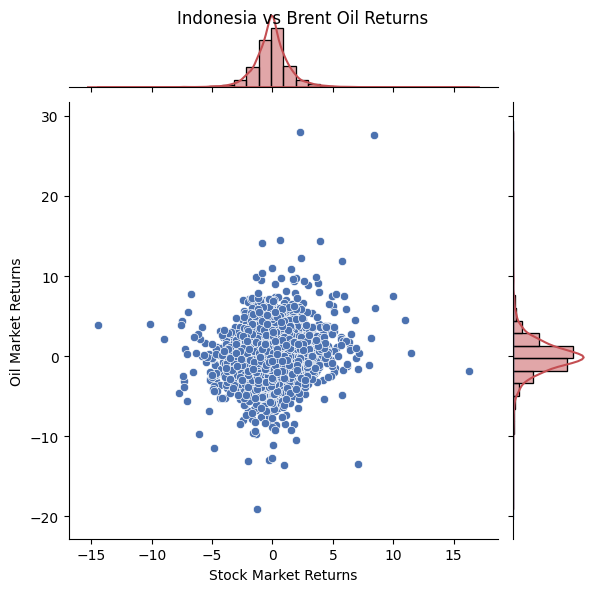


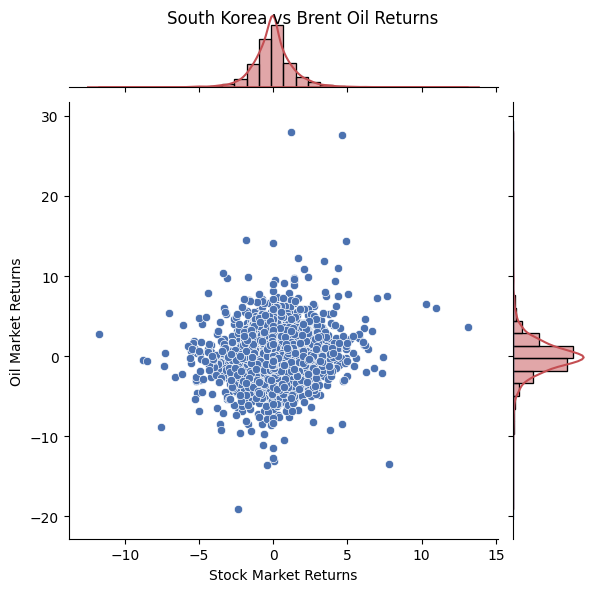
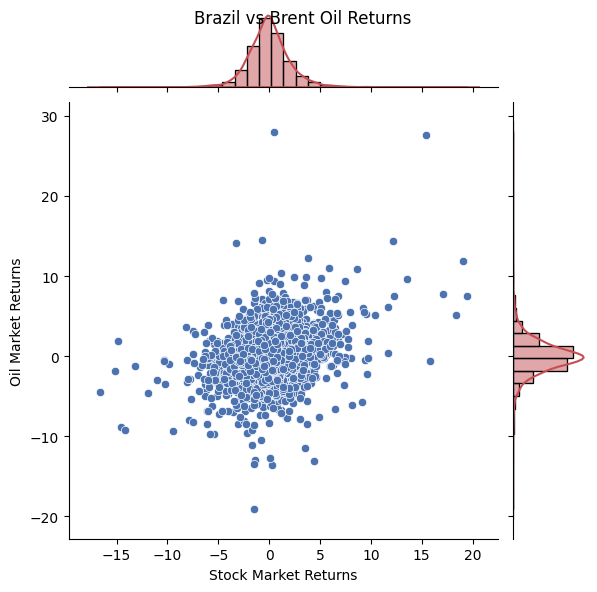
*Fig. 2. Returns of different financial markets*

Table 3 reports the descriptive statistics of these financial market returns. The means and medians of returns are close to zero, and high standard deviations of the returns imply large dispersion in volatility. All financial returns have negative skewness values and high values for the kurtosis statistic, consistent with the properties of sharp peaks, fat tails and being skewed for the return distributions. At the same time, the normality of stock returns is rejected by Jarque-Bera statistics. Furthermore, the results of Ljung-Box test reject the null hypothesis of autocorrelations at lag 20 at the 5% significance level; and Engle's Lagrange multiplier (LM) test reveals strong evidence of ARCH effects in all the financial return series at the 5% significance level.

Finally, the correlation coefficients between returns of Brent crude oil market and stock markets are positive and significantly different from zero, which is in line with the scatter plots presented in Fig. 3. Same with WTI crude oil in Fig 4. The scatter plots showing a nonlinear relationship in the upper and lower tails indicates that we should use the nonlinear model to study the risk spillover effect from oil market to stock markets.







*Fig. 3. Scatter plots of returns between the oil market and the stock markets.*

*Table 3: Descriptive statistics of MSCI index returns of stock markets and oil market*

*.*

|  | mean | max | min | median | std | skewness | kurtosis | q05 | q95 | jarque\_bera | brent\_corr | ljung\_box | arch |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| India | -0.043 | 13.74 | -16.421 | -0.037 | 1.371 | 0.406 | 14.593 | -1.958 | 2.022 | (32292.832438699297, 0.0) | 0.155 | (102.53870667357401, 0.0) | (684.4374237140067, 0.0) |
| China | -0.018 | 12.838 | -14.059 | 0 | 1.686 | 0.033 | 9.491 | -2.486 | 2.676 | (10073.625219250529, 0.0) | 0.158 | (80.25228858689364, 0.0) | (1118.5683839252147, 0.0) |
| Brazil | -0.011 | 19.434 | -16.619 | -0.059 | 2.217 | 0.468 | 11.344 | -3.131 | 3.45 | (16854.551858621748, 0.0) | 0.305 | (68.44552102932323, 0.0) | (1470.3725793569363, 0.0) |
| South Korea | -0.029 | 13.091 | -11.722 | 0 | 1.424 | 0.279 | 9.455 | -2.118 | 2.283 | (10036.979160916595, 0.0) | 0.133 | (31.230140651633583, 0.052) | (813.6557424618001, 0.0) |
| Mexico | -0.023 | 11.183 | -15.159 | -0.051 | 1.586 | 0.282 | 9.778 | -2.341 | 2.391 | (11060.192585220986, 0.0) | 0.273 | (96.37611084851379, 0.0) | (1341.1080276692132, 0.0) |
| Indonesia | -0.049 | 16.261 | -14.444 | 0 | 1.565 | 0.304 | 10.775 | -2.354 | 2.393 | (14542.371776422493, 0.0) | 0.121 | (74.05872809103774, 0.0) | (468.8834420147517, 0.0) |
| Brent oil | -0.022 | 27.976 | -19.077 | -0.07 | 2.305 | 0.633 | 14.534 | -3.421 | 3.585 | (32190.194970732507, 0.0) | 1 | (42.97754086819164, 0.002) | (564.7412183573323,  0.0) |

#### *4.2. Estimates and selections of the copulas*

In this subsection, we will select the optimal copula functions for the oil market paired with each stock market based on the standardized residuals (εit, εst), by employing the inference function for margins (IFM) method (Nelsen, 2006). According to the LLF values presented in

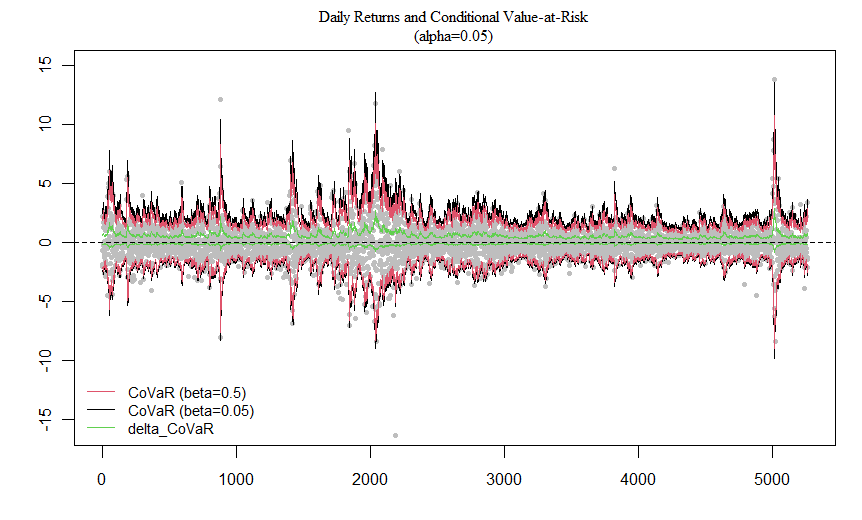
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#### *4.3 Dynamic risk spillovers from oil to ten stock markets*

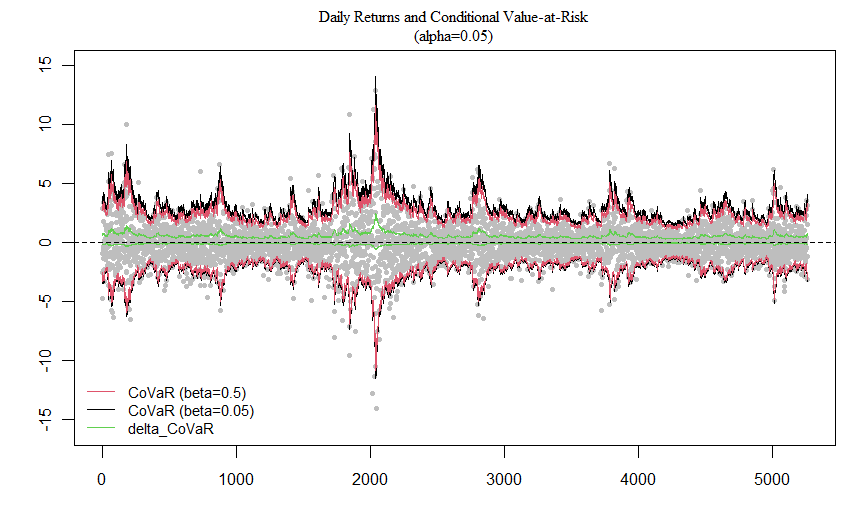
Fig. 4 and 5 presents the dynamics of CoVaR and ΔCoVaR for the six stock markets during the period under analysis at the 0.95 confidence level. First, the dynamic CoVaR and ΔCoVaR for each stock market are comparatively different, indicating that the impact of extreme risk in the oil market on stock markets' extreme risk tends to vary by country.

While the CoVaR and ΔCoVaR also have the similar shape, showing regional characteristics. For example, the risk spillovers to the American, Brazilian, Canadian, and Mexican stock markets follow the same trend. Moreover, the abrupt changes of the CoVaR and ΔCoVaR clearly reflect the impacts of some important risk events, such as the global financial crisis in 2008, the European debt crisis in 2010 and the COVID-19 crisis in 2020. For example, the CoVaR and ΔCoVaR for the Indian stock market were extremely large during the global financial crisis and the COVID-19 crisis. Specifically, due to the Russia-Ukraine conflict in 2014, the Russian stock market was severely affected by the volatile oil market. Therefore, the sharp down and up movements in the stock markets are not only from the macroeconomic environment but also the external geopolitical shocks which affect the oil price. Finally, this graphical evidence also suggests that the downside risk spillovers are shown to be noticeably greater than upside risk spillovers, which is consistent with the results and the spikes in the graphs.

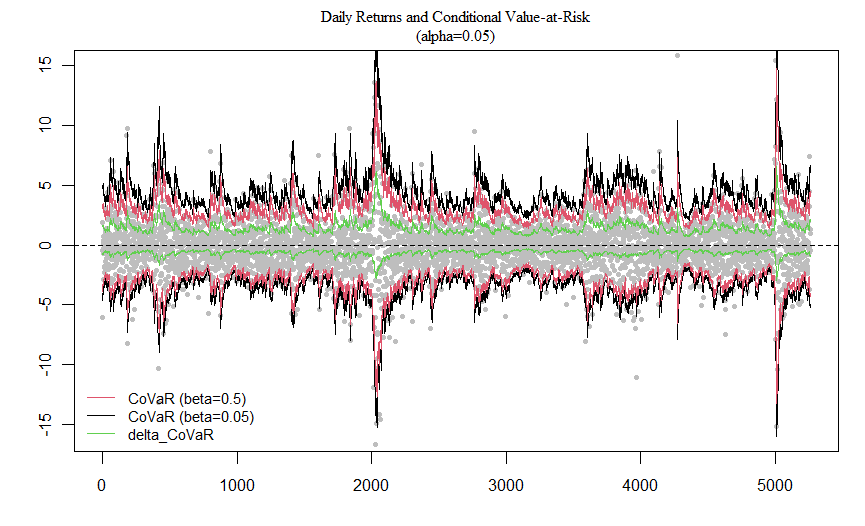
India



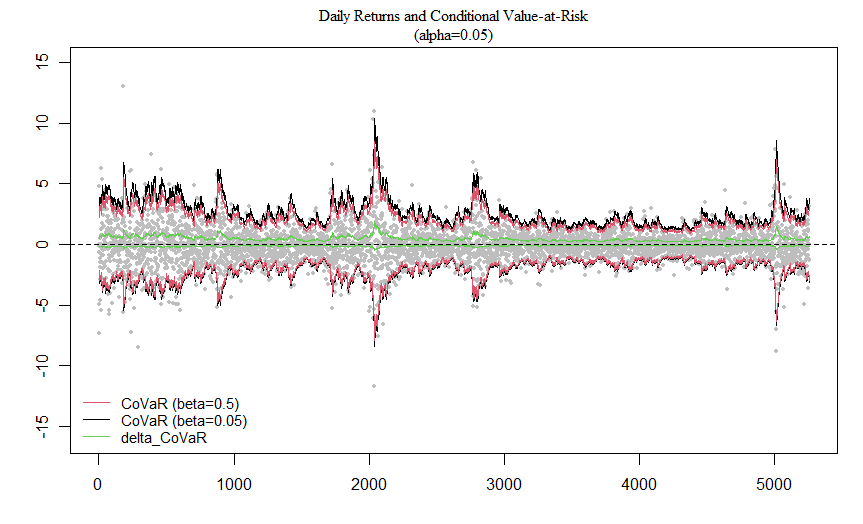
China



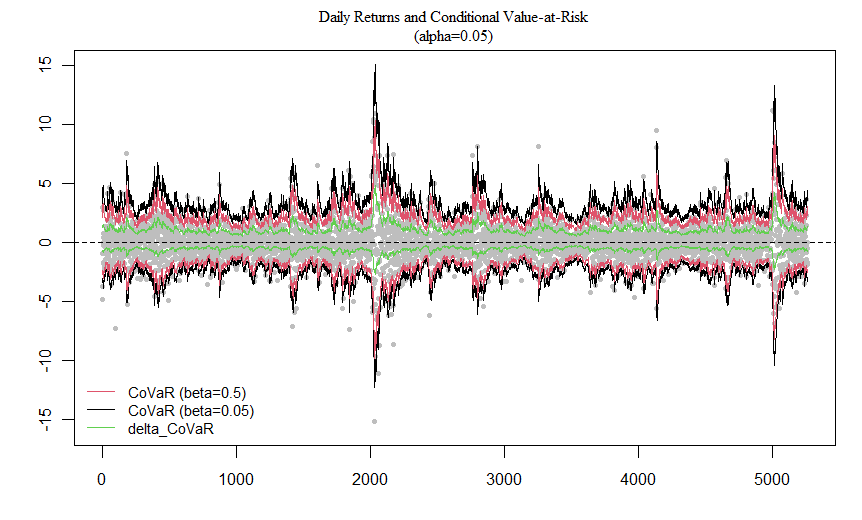
Brazil



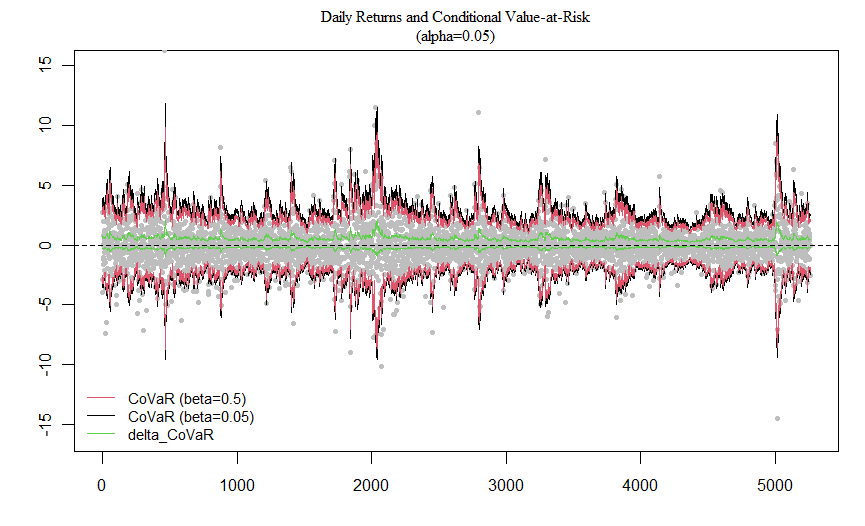
South Korea



Mexico



Indonesia



*Fig. 4. Dynamics CoVaR and risk spillovers.(Brent)*

*Notes: In each subfigure, the gray points are the stock market returns for ten countries. The red-black lines stand for the CoVaRs of the benchmark state and the distressed state, respectively.*

|  | Brent\_CoVaR\_Lower | Brent\_CoVaR\_Upper |
| --- | --- | --- |
| India | -1.676 | 1.774 |
| China | -2.091 | 1.828 |
| Brazil | -2.327 | 2.3 |
| South Korea | -2.194 | 2.19 |
| Mexico | -2.284 | 2.223 |
| Indonesia | -2.197 | 1.718 |

*Table 5: CoVaR Upper Lower values Brent vs Countries*

Fig 5 shows the code output values for WTI and Brent oil with other countries. The upper and lower values show the deviation due to the risk spillover.

#### *4.4 Results and Inference A*

The results of the significance test indicate the rejection of the null hypothesis at the 1% significance level.

Therefore, the oil market significantly contributes to the stock markets of all the six countries.

The mean absolute value of downside risk is the greatest for India followed by Indonesia at second. The largest downside risk spillover from oil market to the Indian stock market indicates that portfolio managers with long positions could suffer the largest risk over the bearish oil market. This is in continuum with the fact that India and oil are an important relationship. The Mexican stock market is least affected by the bearish oil market, but is  very volatile with respect to its downside effect.

Downside

| COUNTRIES | MEAN | STD DEV | RANK |
| --- | --- | --- | --- |
| India | -1.55348 | 0.09880 | 1 |
| China | -1.42972 | 0.08924 | 4 |
| Brazil | -1.36715 | 0.24856 | 5 |
| South Korea | -1.43353 | 0.07169 | 3 |
| Mexico | -0.95904 | 0.43837 | 6 |
| Indonesia | -1.44179 | 0.12145 | 2 |

*Table 6:Downside risk spillover using absolute means to rank*

The mean absolute value of upside of upside risk is the greatest for China, closely followed by South Korea. The largest upside risk spillover from the oil market to the Chinese stock market indicates that portfolio managers with short positions could suffer the largest risk over the bullish oil market.

Furthermore, oil has the smallest risk spillover effects on the Mexican and Brazilian stock markets for developed and emerging countries, respectively. This indicates that investing in both stock markets is the least risky when oil prices rise or fall sharply.

Oil price displays the largest downside and upside risk spillovers on the Indian and Chinese stock markets for emerging economies. These results imply that the downside and upside risk spillovers are country-specific, and it is necessary for the global investors to utilize this information.

Upside

| COUNTRIES | MEAN | STD DEV | RANK |
| --- | --- | --- | --- |
| India | 1.13630 | 0.37435 | 3 |
| China | 1.42644 | 0.25356 | 1 |
| Brazil | 0.74811 | 0.61404 | 4 |
| South Korea | 1.38498 | 0.25935 | 2 |
| Mexico | 0.69614 | 0.66527 | 5 |
| Indonesia | 1.38335 | 0.25723 | 2 |

*Table 7 :Upside risk spillover using absolute means to rank*

Observing the mean absolute values, it is found that the downside risk spillovers are comparatively more than the upside risk spillovers, which is indicative of the fact that oil is an important commodity for the emerging markets.

From the graphs, we can clearly see spikes at 2 different times, one between 2008-2009 period and the other between 2019-2021.

These spikes are from the 2008 Housing crisis ( Economic Depression) and the COVID-19 pandemic. The Russia-Ukraine conflict started in 2014, and turned into a war after 2022. We have considered the period just before 2023, hence the complete effect of it could not be covered.

China, obviously, showed no significant fluctuations during the COVID-19 period. India showed fluctuations due to slightest of turmoils in the oil commodity market. This is because India is heavily dependent on Oil.

Test done using the specifications:

Argument | Value

--------------------------------|--------------------------------

formula | y ~ GumbelModel(x, Δ, μ, σ, τ)

data | Dat

start (Δ) | 1.1257506

start (μ) | -0.1261274

start (σ) | 1.0103893

τ (tau) | [1] 0.05

trace | TRUE

control maxiter | 100

control k | 2

control InitialStepSize | 1

control big | 1e+20

control eps | 1e-07

control beta | 0.97

### 5. CONCLUSION

#### *5.1 Brent Oil vs the Countries*

Estimating the downside and upside risk spillovers from the oil market to the stock markets and accordingly identifying the riskiest stock markets are essential for international capital holders and supervisory authorities. To accurately evaluate the downside risk spillovers, Tian and Ji (2022) propose the GARCH CQR model that can describe the nonlinearity of the downside tail dependence structure between financial variables. As is known, measuring the upside risk and its spillovers is also critical especially for global investors with short positions of the stock markets.

In the empirical study, based on the MSCI daily data from January 2001 to December 2022, we assess the risk contribution of Brent crude oil and WTI crude oil to stock markets in six important countries, using the GARCH CQR-based DCoVaR and UCoVaR models. The empirical results reveal that oil displays the largest downside and upside risk spillovers on the Indian and Indonesian stock markets, and the Chinese and Indonesian stock markets for emerging market countries, respectively.

And the Mexican stock market displays the smallest downside and upside risk spillovers for the countries. We also find that the downside and upside risk spillovers show the asymmetric feature, with upside risk spillovers less than downside risk spillovers, which is consistent with the phenomenon of flight-to-quality. Moreover, the dynamic risk spillover effects show heterogeneity over time and are comparatively different for each country.

#### 

#### *5.2 From Graph*

Finally, based on these findings, we provide important implications for international capital holders and supervisory authorities optimizing the investment portfolios and formulating supervision policy.

Oil has been one of the most important commodities across the globe. Its need is of utmost importance to emerging economies. But, the fluctuation in its price has a heavy impact on growing nations and even some of the developed nations. We saw the risk spillover due to this volatility reach the stock indices of the countries affecting firms and companies across different countries.

Political conflicts often are a cause of the commodity disruption. The recent spikes in India, Brazil, Mexico, South Korea and Indonesia are a consequence of the Covid-19 pandemic and the Russia-Ukraine conflict.

A much bigger spike can be seen towards the 2008-2010 period caused by the infamous Economic crisis of 2008.

So, estimating the downside and upside risk spillovers from the oil market to the stock markets and accordingly identifying the riskiest stock markets are essential for international capital holders and supervisory authorities.

The dynamic risk spillover effects show heterogeneity over time and are comparatively different for each country.

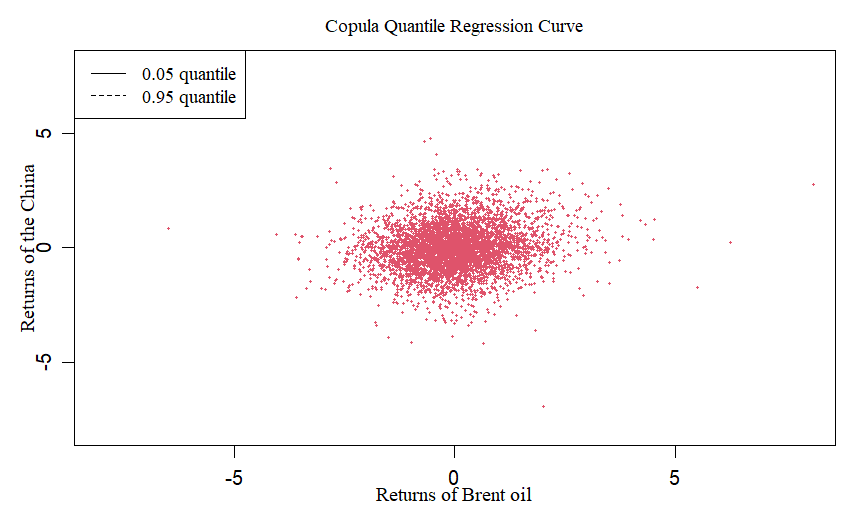
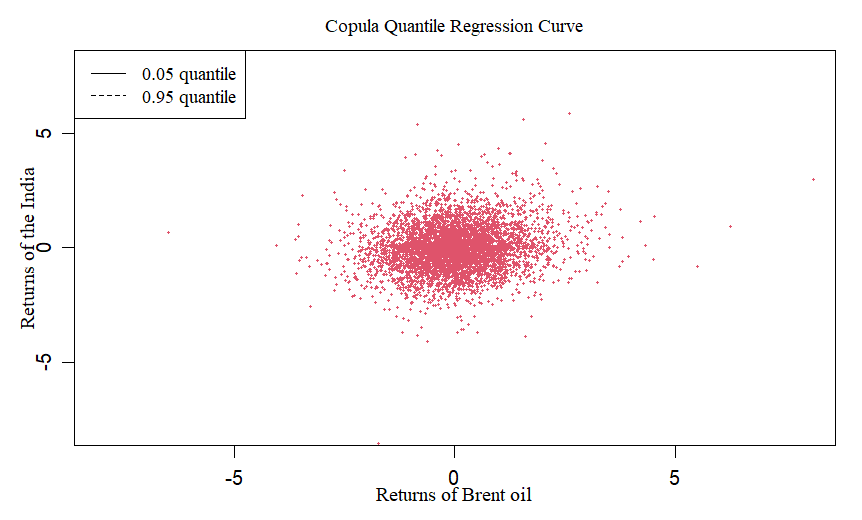
Finally, based on these findings, we provide important implications for international capital holders and supervisory authorities optimizing the investment portfolios and formulating supervision policy.

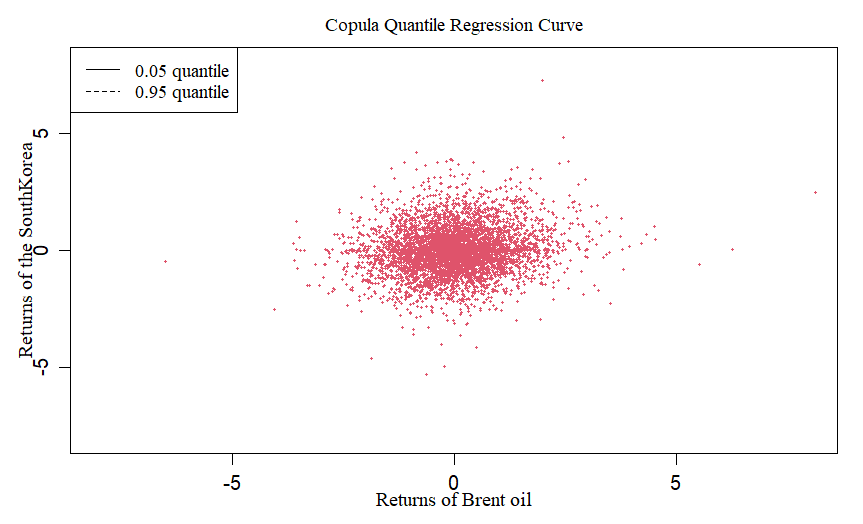
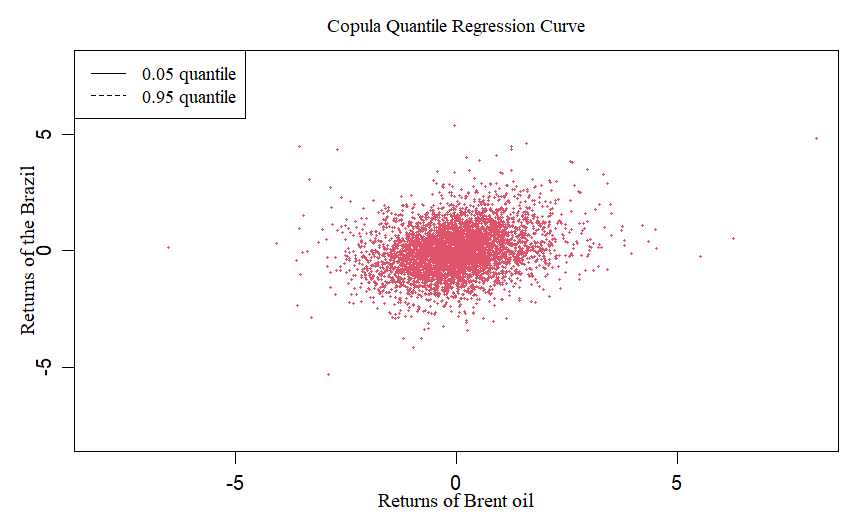
*5.3 Policy Recommendations*

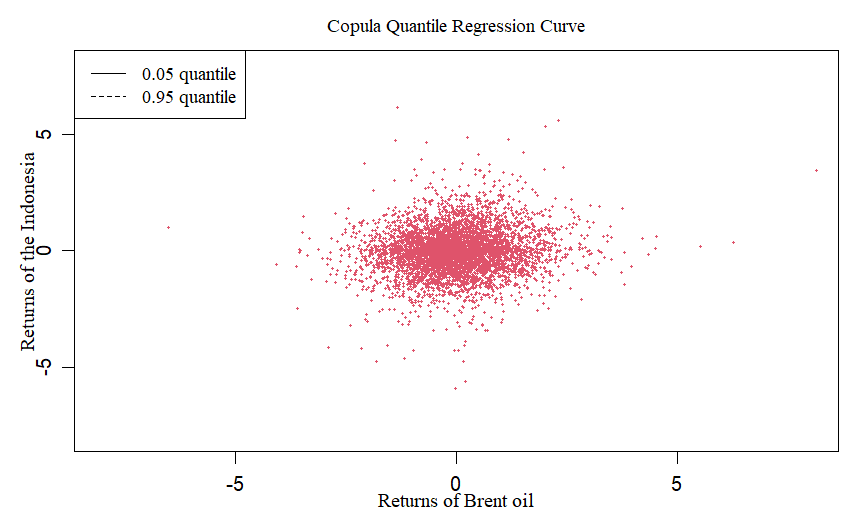
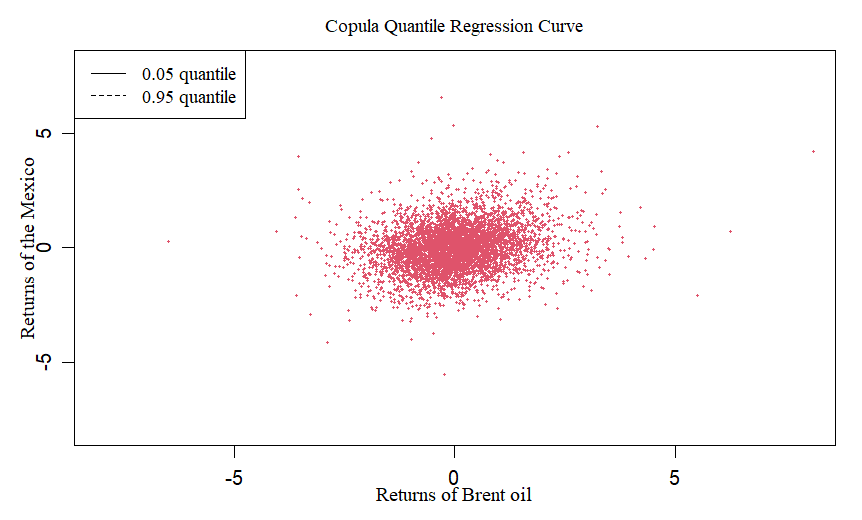
* **Focus of Supervision:** It is necessary for supervisory authorities to regulate the Indonesian, South Korean and Indian stock markets, rather than simply focusing on the supervision of stock markets with higher market capitalization, such as the US stock market.
* **Risk Management Strategy:** To mitigate asset losses from oil market risk spillovers, it’s crucial for fund managers and global investors to thoroughly assess risk contagion measurements and adjust their positions accordingly to optimize portfolio strategy. Greater downside risk spillovers from the oil market to the Indian and Indonesian stock markets suggest that portfolio managers with long positions in these markets could face larger risks during bearish oil market periods. To mitigate this, they should consider closing their long positions or allocating proper instruments to hedge the downside risk spillovers, especially during oil market crises.
* **Regulatory Measures:** Sharp changes in oil prices could trigger extreme risk in stock markets. Therefore, financial regulators should closely monitor and effectively contain the impacts of the oil market’s extreme risk. Identifying the ranking of risk spillovers to the stock markets based on dramatic decreases or increases in oil market returns can help regulatory authorities precisely locate the riskiest stock markets.

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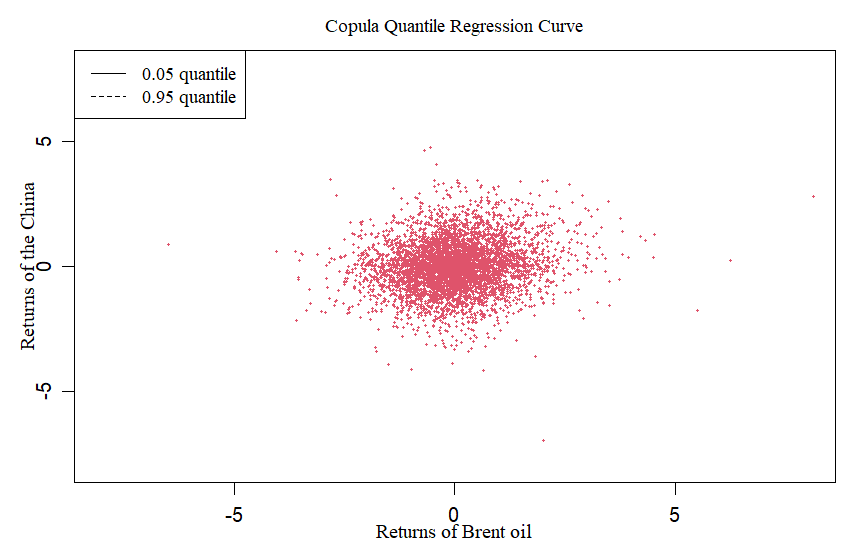
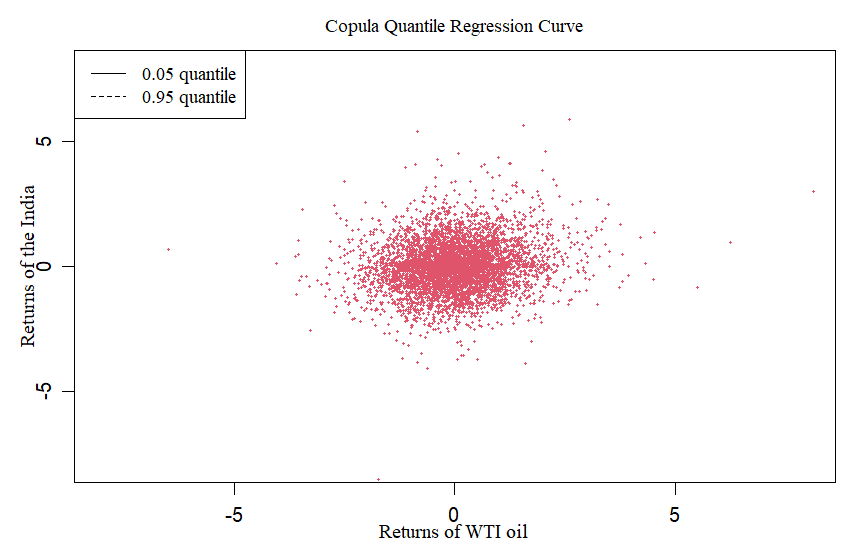
### APPENDIX

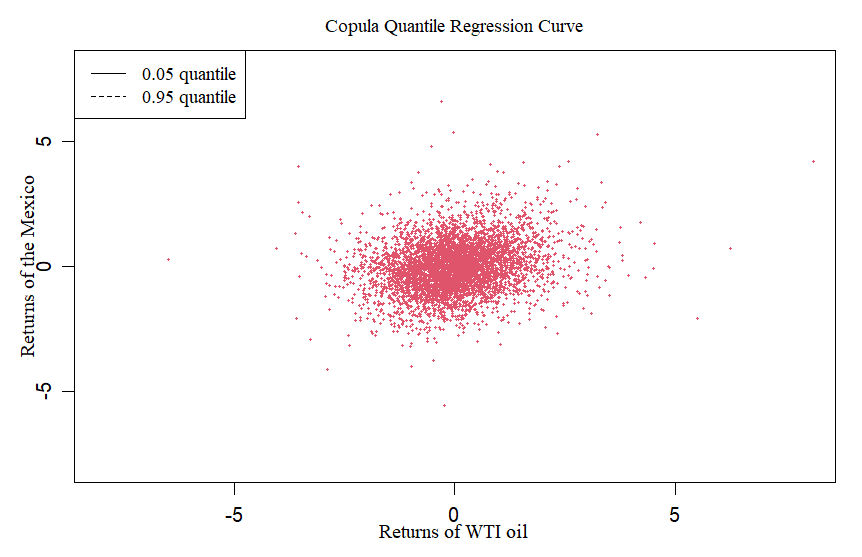
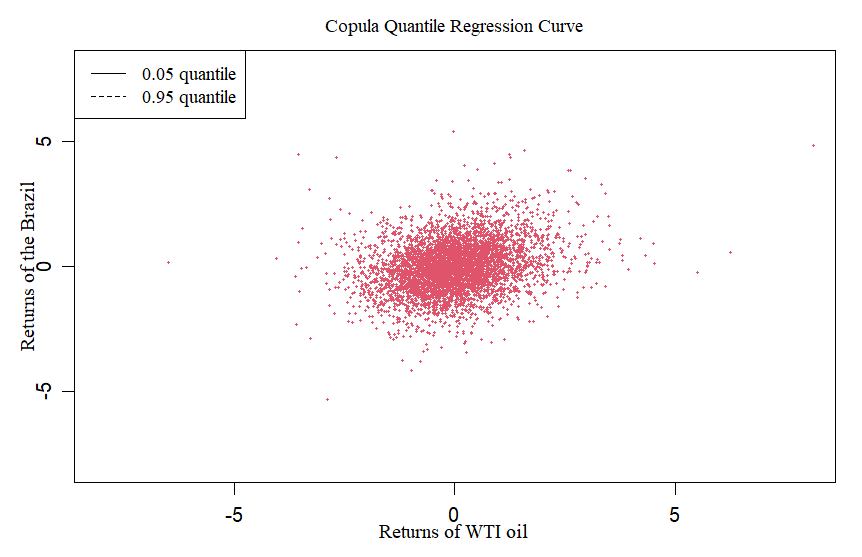


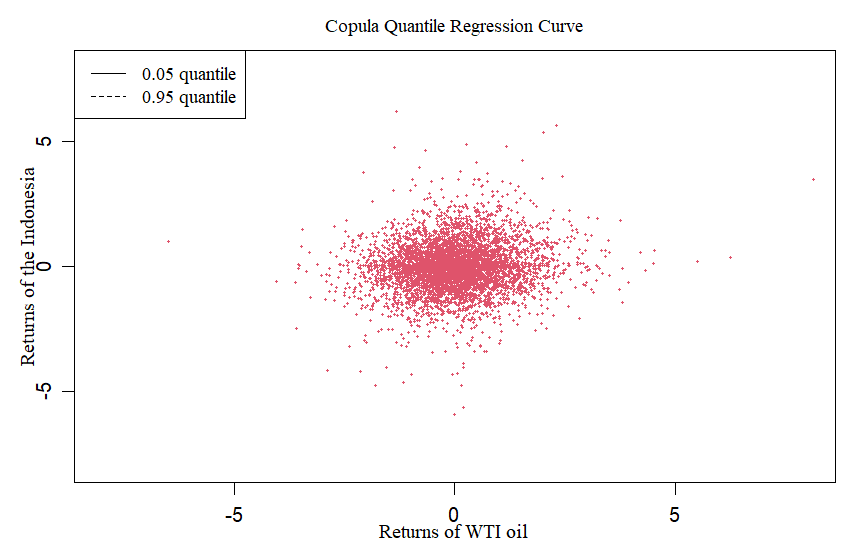




*Fig 5: Gumbel CQR Country-wise for Brent*







*Fig 6: Gumbel CQR Country-wise for WTI*

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