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Correlation Dynamics and Investment Strategies; Application of the DCC-GARCH t-copula Model

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Abstract

This paper investigates dynamic volatility spillovers and their implications for investment strategies, focusing on selected Arab countries' stock market indices (Egypt, Iraq, Jordan, Kuwait, Oman, Qatar, and Saudi Arabia) and the global oil price index, spanning from the beginning of 2010 to mid-2024. Utilizing models like the Dynamic Conditional Correlation (DCC), the study captures the time-varying interdependencies between oil prices and stock markets in both oil-exporting and oil-importing countries. The findings reveal significant volatility spillovers from oil price fluctuations, with stronger effects observed during periods of geopolitical tension and financial crises. For oil-exporting countries, such as Saudi Arabia, Kuwait, and Qatar, oil price shocks strongly influence stock market performance due to their central role in economic growth. The study highlights the importance of understanding these dynamic interdependencies to optimize portfolio allocation and risk management strategies in highly volatile and interconnected markets.

Kewords: Dynamic volatility, investment strategies, spillovers, Oil, Stock Market

Introduction

Dynamic volatility spillovers and investment strategies are critical concepts in financial economics, particularly in the context of globalized markets where the interconnectedness between different asset classes and regions is increasingly prominent. Volatility spillovers refer to the transmission of shocks from one market or asset to another, which can lead to increased uncertainty and fluctuations across interconnected financial systems (Diebold & Yilmaz, 2012). This phenomenon is especially relevant in markets that are heavily influenced by external factors, such as the stock markets of Arab countries and global oil prices. The oil market, as a key driver of economic performance in many Arab countries, exerts a substantial influence on regional stock market dynamics (Arouri, Jouini, & Nguyen, 2012).

Research on dynamic volatility spillovers has shown that oil prices significantly impact the stock market indices of oil-exporting and importing countries (Zhu, Su, & You, 2017). For instance, countries like Saudi Arabia, Kuwait, and Qatar, which are major oil exporters, tend to experience strong correlations between their stock market performance and oil price fluctuations. These correlations are primarily due to the central role of oil revenues in their economies (Al-Maadid, Caporale, Spagnolo, & Spagnolo, 2020). Conversely, for oil-importing countries such as Egypt and Jordan, changes in oil prices may lead to increased inflationary pressures and impact overall economic stability, thereby influencing their stock market returns (Antonakakis, Chatziantoniou, & Filis, 2013).

The study of dynamic volatility spillovers is crucial for developing effective investment strategies. For investors, understanding how volatility is transmitted between markets can inform portfolio allocation decisions, risk management, and hedging strategies (Nguyen & Walther, 2020). Traditional investment strategies often rely on the assumption that returns are independently distributed; however, the presence of volatility spillovers challenges this assumption and necessitates more sophisticated approaches (Engle, 2002). Time-Varying Parameter Vector Autoregressive (TVP-VAR) models, for example, have been employed to capture the dynamic nature of these relationships and provide a more accurate understanding of market interdependencies (Zhu et al., 2022).

The interaction between oil prices and the stock market indices of Arab countries is particularly complex due to the dual role of oil as both a commodity and a macroeconomic indicator. Oil price shocks can have asymmetric effects on different markets, depending on whether a country is an oil exporter or importer, the structure of its economy, and its exposure to external shocks (Wen, 2020). This complexity makes it essential to analyze dynamic volatility spillovers and their implications for investment strategies in these markets.

The ongoing geopolitical tensions, global economic shifts, and evolving energy market dynamics further underscore the importance of understanding these spillovers. Recent studies have highlighted that periods of financial crises or geopolitical uncertainties tend to amplify volatility spillovers, making it even more critical for investors and policymakers to adapt their strategies accordingly (Gong & Xu, 2022; Bentzen, 2023). Thus, this paper argues that a comprehensive understanding of dynamic volatility spillovers between Arab countries' stock markets and the oil price index is essential for formulating robust investment strategies that can withstand periods of high uncertainty and market turbulence**.**

1- Theoretical Basis of Dynamic Volatility Spillovers and Investment Strategies

The concept of dynamic volatility spillovers stems from the notion that financial markets are interconnected, and shocks or volatility in one market can be transmitted to others, affecting their stability and performance. This phenomenon is grounded in several key theories in finance and economics, including the Efficient Market Hypothesis (EMH), the Arbitrage Pricing Theory (APT), and the theory of volatility transmission.

According to the Efficient Market Hypothesis proposed by Fama (1970), asset prices fully reflect all available information, and any new information is quickly incorporated into prices, resulting in volatility. However, when markets are interconnected, volatility in one market may spill over to others, causing them to adjust their prices accordingly. This spillover effect suggests that markets are not completely independent, contradicting the assumption of fully efficient markets in the short term (Lo, 2004). The EMH implies that such interdependencies could be influenced by common factors like global economic news, geopolitical events, and changes in commodity prices, including oil.

The Arbitrage Pricing Theory (APT), developed by Ross (1976), provides a multi-factor framework that explains asset returns based on various systematic risk factors. APT suggests that stock prices are influenced by multiple macroeconomic factors, such as inflation rates, interest rates, and commodity prices like oil, which serve as critical risk factors for many economies, particularly in oil-exporting regions. Since oil is a major export and a significant source of revenue for many Arab countries, changes in oil prices can directly impact their stock markets through economic channels such as changes in national income, government spending, and inflation (Chen, Roll, & Ross, 1986).

The theory of volatility transmission further explains the mechanisms through which shocks in one market, such as fluctuations in oil prices, can affect another market. Engle and Kroner (1995) highlighted that volatility spillovers occur due to various channels, such as trade linkages, investment flows, and shared investor behavior. For instance, in oil-exporting countries like Saudi Arabia, Kuwait, and Qatar, oil price volatility can have significant effects on stock market performance due to the direct impact on government revenues, foreign exchange reserves, and overall economic growth (Taghizadeh-Hesary, Yoshino, & Shimizu, 2018). Conversely, for oil-importing countries such as Egypt and Jordan, volatility in oil prices can lead to inflationary pressures and increased production costs, which may negatively affect stock market returns (Antonakakis, Chatziantoniou, & Filis, 2013).

Dynamic Conditional Correlation (DCC) models developed by Engle (2002) and subsequent extensions by other scholars provide the empirical basis for analyzing how correlations between markets change over time. These models allow researchers to capture the time-varying nature of correlations between stock markets and oil prices, reflecting how spillovers evolve in response to different market conditions (Engle, 2002). For example, during periods of heightened geopolitical tension or economic uncertainty, the correlations between oil prices and stock markets tend to increase, as observed in various empirical studies (Nguyen & Walther, 2020; Gong & Xu, 2022).

The use of Time-Varying Parameter Vector Autoregressive (TVP-VAR) models also supports the study of dynamic volatility spillovers. These models allow for the coefficients governing the relationships between variables to change over time, providing a flexible framework for capturing the dynamic nature of these relationships. TVP-VAR models have been applied to analyze the complex interdependencies between oil prices and stock markets in both developed and emerging markets (Zhu, Fang, & Wang, 2022). This approach is particularly useful for capturing the asymmetries in how markets react to positive and negative shocks, reflecting the non-linear nature of volatility spillovers (Kanas, 1998).

Moreover, portfolio theory developed by Markowitz (1952) provides a framework for understanding how volatility spillovers influence investment strategies. According to portfolio theory, investors seek to maximize returns for a given level of risk by diversifying their investments across different assets. However, when there are strong volatility spillovers between assets, the benefits of diversification may be reduced, as the risk of the portfolio may increase due to correlated movements (Longin & Solnik, 2001). Understanding dynamic volatility spillovers, therefore, becomes crucial for portfolio management, especially in markets with high exposure to oil price fluctuations.

Behavioral finance theories also provide insights into dynamic volatility spillovers. Behavioral biases, such as herding behavior, overreaction, and panic selling, can amplify volatility spillovers during times of market stress (Shiller, 2003). When investors react to changes in oil prices or geopolitical events, their collective behavior can lead to contagion effects, where negative sentiment in one market spills over to others, intensifying overall market volatility (Bikhchandani & Sharma, 2000).

In summary, the theoretical basis for studying dynamic volatility spillovers and their impact on investment strategies in the context of Arab stock markets and oil prices is grounded in a combination of classical finance theories, empirical models, and behavioral finance insights. This comprehensive framework helps explain the mechanisms of volatility transmission and provides the tools necessary for assessing risk, optimizing portfolios, and making informed investment decisions in interconnected and volatile markets.

2- Review of Empirical Studies

Kang et al (2015) employ a time-varying parameter model to examine the impact of different types of oil market shocks (supply, demand, and risk shocks) on stock returns in G7 countries. Their findings suggest that demand shocks have the most persistent effects, while risk shocks tend to have short-lived impacts.

Antonakakis et al (2017) examines the impact of oil price shocks on stock market volatility in the Eurozone using a GARCH model. The results show that oil price shocks have a significant impact on stock market volatility, with different intensities across countries. The study finds that oil-exporting countries experience higher volatility spillovers compared to oil-importing countries, indicating that the oil market plays a crucial role in shaping stock market behavior.

Su et al (2018) uses wavelet coherence techniques to analyze the relationship between oil prices and stock markets in major emerging economies (China, India, Brazil, Russia, and South Africa). The results indicate significant time-varying co-movements, especially during periods of economic or financial crises.

Cheng et al (2019) utilizes the TVP-VAR model to explore volatility spillovers between oil prices and major Asian stock markets, including Japan, China, and South Korea. The results reveal significant time-varying spillovers, with stronger effects observed during periods of global financial instability.

Baumeister & Hamilton (2019) revisits the role of oil supply and demand shocks in influencing stock markets by using structural vector autoregressions (SVAR) with incomplete identification. The authors argue that oil supply shocks have a more significant impact on stock markets than previously thought, particularly during periods of geopolitical instability.

Wen (2020) examines the asymmetric effects of oil price shocks on stock market returns in oil-importing and oil-exporting countries using a two-stage GARCH model. It finds that positive oil price shocks have a more pronounced effect on oil-exporting countries, while negative shocks tend to impact oil-importing countries more significantly.

Nguyen & Walther (2020) employ a wavelet-based multiscale approach to analyze risk spillovers between oil prices and stock markets in emerging economies. Their findings suggest that spillovers are more pronounced at higher frequencies, indicating that short-term shocks in the oil market can have immediate effects on stock market volatility.

Umaret al (2021) analyzes volatility spillovers between oil prices and various commodities (gold, silver, and agricultural products) during the COVID-19 pandemic using a quantile coherence approach. The results show that the pandemic significantly increased volatility spillovers, particularly during periods of extreme market movements.

Zhu et al (2022) uses a multivariate GARCH model to investigate the time-varying interdependencies between oil prices and agricultural commodity markets, including wheat, corn, and soybeans. The results reveal strong dynamic correlations between oil prices and agricultural markets, particularly during periods of geopolitical tension or financial instability.

Gong & Xu (2022) applies a quantile regression approach to assess the asymmetric spillovers between energy markets (crude oil) and agricultural commodities (corn, wheat, and soybeans). The results show that spillover effects are more significant during periods of market downturns and that negative oil price shocks have a greater impact on agricultural markets.

3- Method

The Dynamic Conditional Correlation (DCC) model is a statistical approach developed by Robert Engle in 2002 to estimate time-varying correlations between multiple financial assets. The DCC model extends the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework to allow for dynamic, time-varying correlations, which is particularly useful for understanding how the relationships between asset returns change over time.

The DCC model captures the time-varying nature of correlations between different assets. Unlike static correlation models that assume constant correlations over time, the DCC model allows for the correlation structure to evolve, reflecting changes in market conditions, such as periods of high or low volatility, financial crises, or geopolitical events.

1. Two-Step Estimation Procedure: The DCC model estimation is typically performed in two steps:

    Step 1: Estimating Volatilities: In the first step, univariate GARCH models are used to estimate the conditional variances of each asset return series. The GARCH model is specified as follows:

$$r_{i,t} = \mu_i + \epsilon_{i,t}, \quad \epsilon_{i,t} = \sigma_{i,t} z_{i,t},$$

where $r_{i,t}$ is the return of asset i at time t, μ_i is the mean return, $\epsilon_{i,t}$ is the error term, $\sigma_{i,t}$ is the conditional variance, and $z_{i,t} \sim N(0,1)$ is a standard normal shock. The conditional variance $\sigma_{i,t}^2$ is modeled as:

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 \epsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2,$$

where α_0,α_1 and β_1 are parameters to be estimated. This step captures the individual volatilities of each asset.

    Step 2: Estimating Dynamic Correlations: In the second step, the standardized residuals from the first step, $z_{i,t} = \frac{\epsilon_{i,t}}{\sigma_{i,t}}$, are used to estimate the time-varying correlations. The dynamic correlation matrix R_t is computed as:

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

where Q_t is the time-varying covariance matrix of the standardized residuals, given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} z_{t-1}' + \beta Q_{t-1}.$$

Here, Q^{-} is the unconditional covariance matrix of the standardized residuals, and α and β are parameters controlling the impact of past shocks and past correlations on the current correlation.

4- Results of Model Estimation

The following table examines the average dynamic correlation estimated between the stock market index of the countries under review and the oil price index using the DCC-

GARCH t copula model. This model has been used to analyze temporal correlation and dynamic changes in correlation between these indicators.

Table 1: Average dynamic correlation

Country/Oil	Mean	Std Error
Egypt/Brent	0.03	0.04
Iraq/Brent	0.03	0.04
Jordan/Brent	0.00	0.01
Kuwait/Brent	0.04	0.02
Oman/Brent	0.01	0.02
Qatar/Brent	0.06	0.02
Saudi Arabia/Brent	0.08	0.03

The table presents the dynamic conditional correlations (DCC) between selected Arab countries' stock market indices and Brent crude oil prices, highlighting how closely the stock markets in each country move in relation to oil prices over time. The mean DCC values indicate the average strength and direction of the correlation, while the standard errors provide a measure of variability or uncertainty in these correlations.

- **Saudi Arabia/Brent**: Exhibits the highest mean correlation (0.08), suggesting a relatively strong positive relationship between Saudi Arabia's stock market and Brent oil prices. The moderate standard error (0.03) indicates some variability in this correlation.
- **Qatar/Brent**: Shows a notable mean correlation (0.06) with a lower standard error (0.02), indicating a moderately strong and more consistent positive relationship between Qatar's stock market and oil prices.
- **Kuwait/Brent**: Has a mean correlation of 0.04 with a standard error of 0.02, suggesting a moderate positive relationship, with some variability in the correlation over time.
- **Egypt/Brent and Iraq/Brent**: Both countries exhibit a mean correlation of 0.03 with a standard error of 0.04, indicating a weak positive relationship with Brent oil prices, coupled with relatively high variability in their correlations.

- **Oman/Brent**: Shows a lower mean correlation (0.01) with a standard error of 0.02, suggesting a minimal and more stable relationship between Oman's stock market and oil prices.
- **Jordan/Brent**: Has the lowest mean correlation (0.00) with a standard error of 0.01, indicating no significant correlation between Jordan's stock market and oil prices, with very low variability.

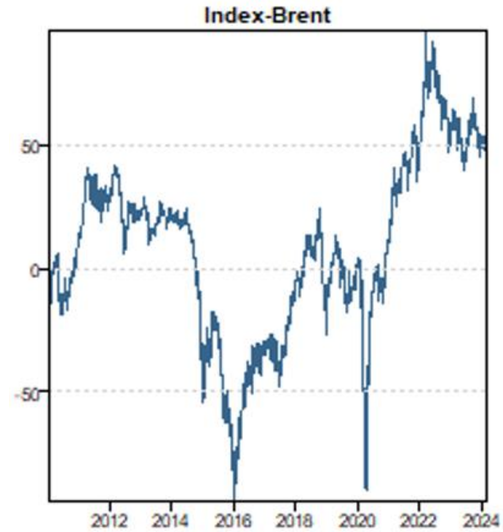
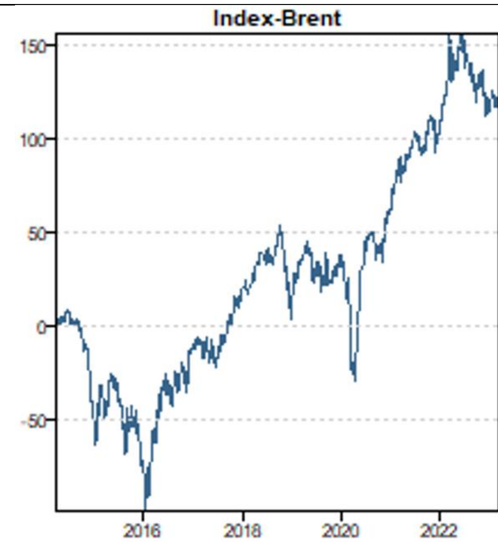
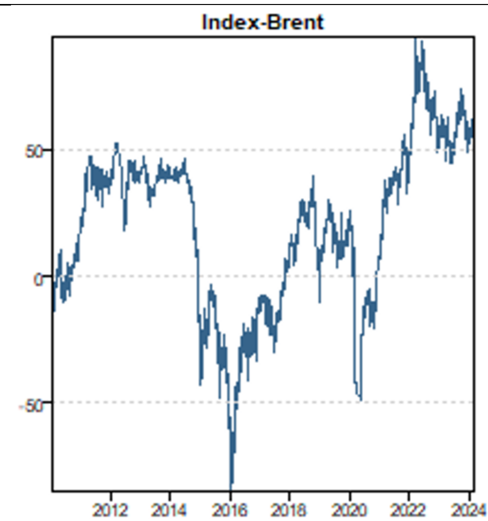
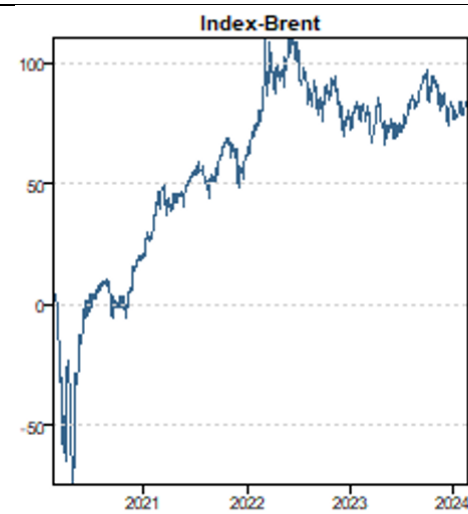
Overall, the data suggests that Saudi Arabia and Qatar have stronger and more consistent positive correlations with oil prices, reflecting their economies' greater dependence on oil. In contrast, countries like Jordan, Oman, Egypt, and Iraq show weaker and more variable correlations, indicating less sensitivity of their stock markets to oil price fluctuations.

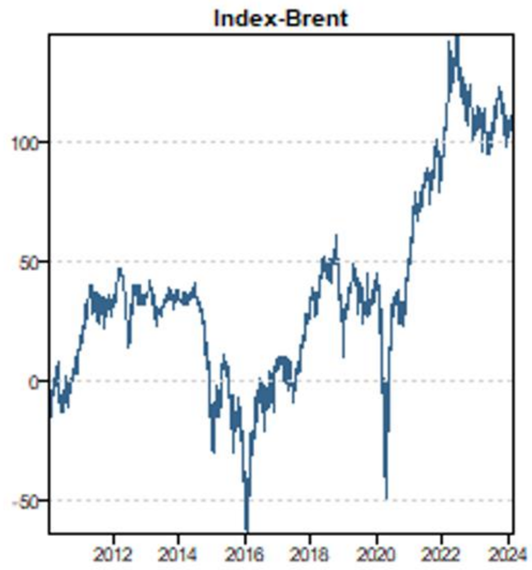
5-1- Dynamic conditional correlation coefficients

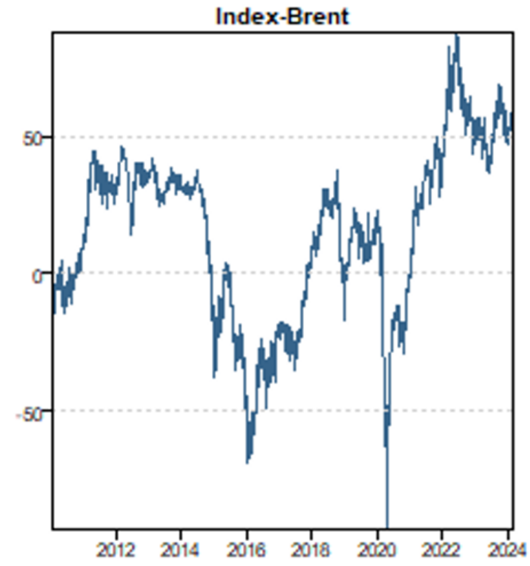
The dynamic conditional correlation coefficients obtained by the DCC-GARCH t Copula model indicate the dynamic and temporal correlations between different assets. The model dynamically calculates correlations between assets over time, such that correlations can change according to changes in market conditions. This model analyzes volatility and dynamic conditional correlations between assets. The DCC-GARCH model is able to examine changes in correlations over time, which is very useful for analyzing assets that have time-varying dependence. Copula t is used to model non-linear and probabilistic dependencies between assets, especially when the data distribution is not normal and has longer left and right tails. This feature makes this model able to identify and model unusual correlations and market shocks.

Figure 1: The dynamic conditional correlation coefficients obtained by the DCC-GARCH t Copula model

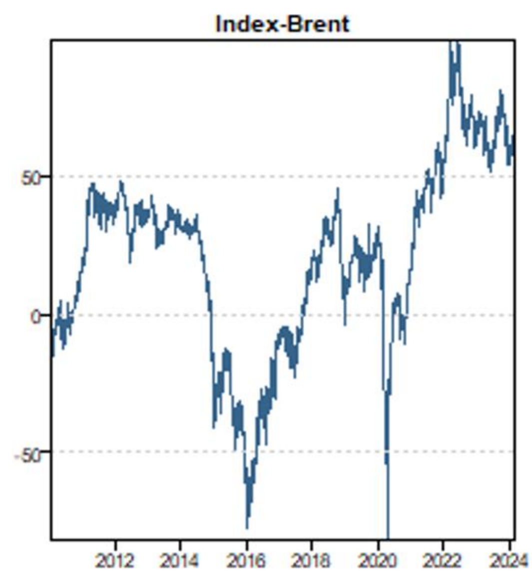
Egypt	Iraq

	
Jordan	Kuwait
	
Oman	Qatar





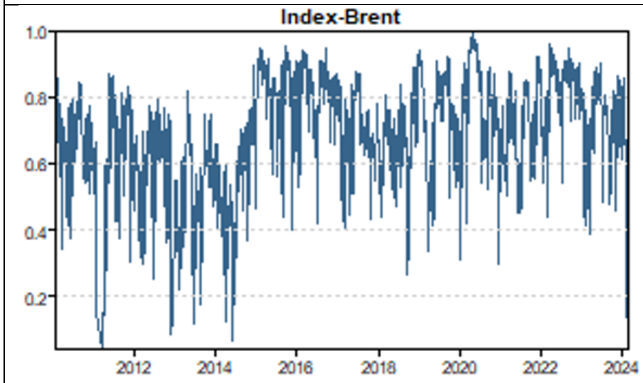
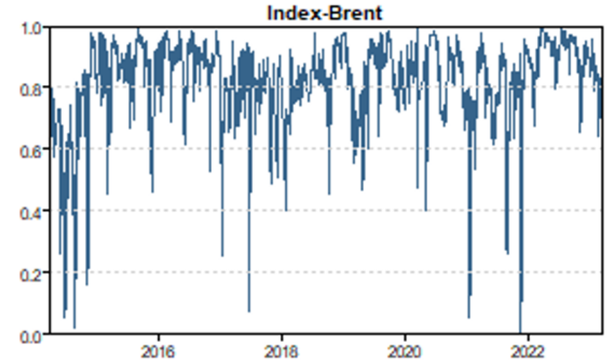
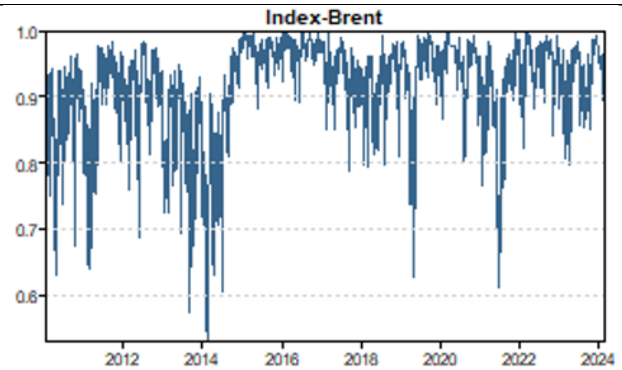
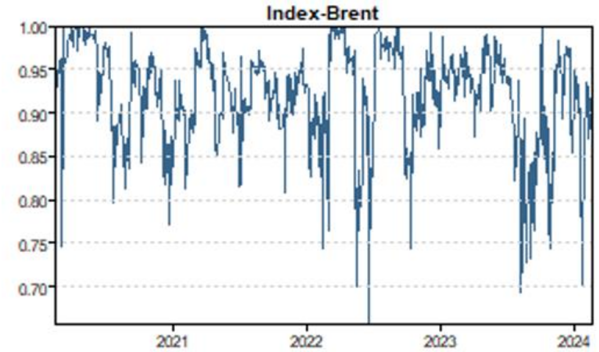
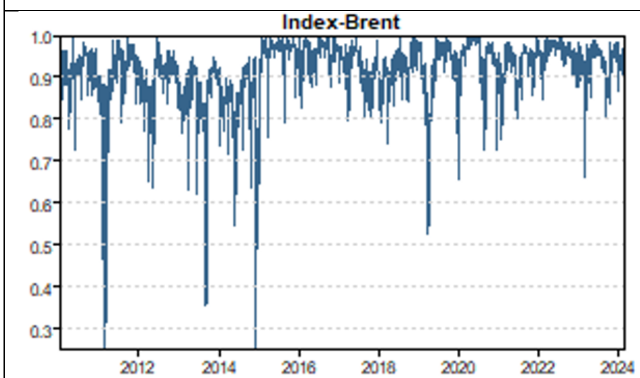
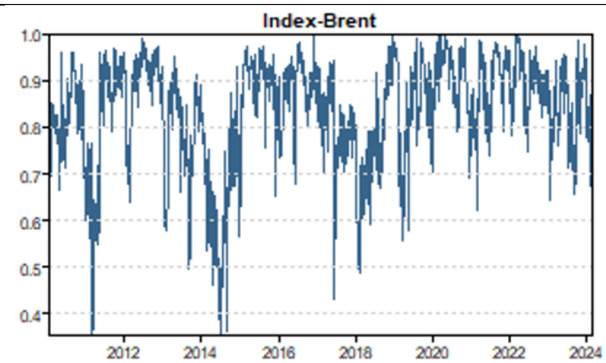
Saudi Arabia

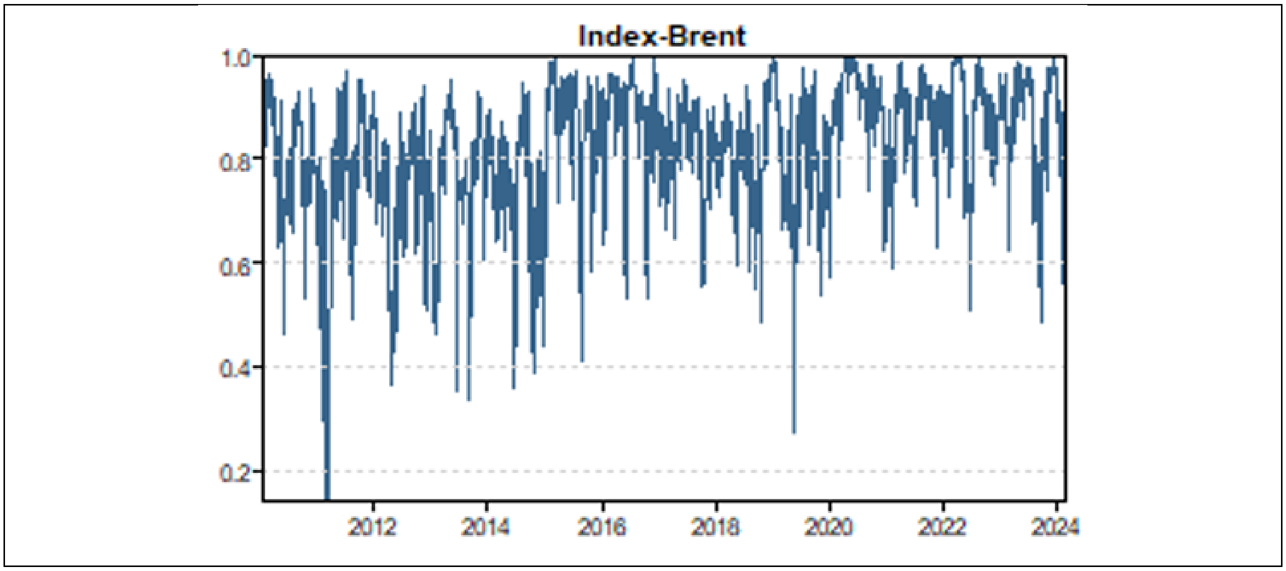


5-2- Optimal Hedging Ratios

In this section, the following charts display the optimal dynamic hedging ratios for various asset pairs. These ratios are used to determine the amount of risk coverage between two different assets. In other words, these ratios show how much of another asset is needed to reduce the risk of a long position in a particular asset.

Figure 2: Optimal Dynamic Hedging Ratios for Various Asset pairs

<table>
<tr><td>Egypt</td><td>Iraq</td></tr>
<tr><td></td><td></td></tr>
<tr><td>Jordan</td><td>Kuwait</td></tr>
<tr><td></td><td></td></tr>
<tr><td>Oman</td><td>Qatar</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">Saudi Arabia</td></tr>
</table>



5-3- Optimal dynamic portfolio weights

The table presents the average optimal weights of a dynamic portfolio consisting of stock market indices from selected Arab countries paired with Brent crude oil. These weights represent the proportion of Brent oil that should be included in the optimal portfolio to achieve objectives like maximizing returns or minimizing risk. The analysis includes the mean weight, standard error, and the range between the 5th percentile low and high values for each country.

Table 2: Average Optimal Weights of a Dynamic Portfolio

Country/Oil	Mean	Std Error	5% Low	5% High
Egypt/Brent	0.69	0.16	0.41	0.90
Iraq/Brent	0.82	0.14	0.57	0.97
Jordan/Brent	0.82	0.14	0.57	0.97
Kuwait/Brent	0.92	0.06	0.81	0.99
Oman/Brent	0.91	0.08	0.79	0.99
Qatar/Brent	0.83	0.11	0.61	0.96
Saudi Arabia/Brent	0.82	0.12	0.57	0.97

- Egypt/Brent: The optimal weight for Brent oil in the portfolio is 0.69, suggesting that 69% of the portfolio should be allocated to Brent oil. The standard error of 0.16 indicates moderate variability, and the 5% confidence interval ranges from 41% to 90%, reflecting a relatively wide range of possible optimal weights.
- Iraq/Brent and Jordan/Brent: Both countries show an average optimal weight of 0.82 for Brent oil, implying that 82% of the portfolio should be allocated to Brent oil. The standard error for both is 0.14, indicating moderate variability, with a 5% confidence interval ranging from 57% to 97%, suggesting a consistent, high reliance on Brent oil in the portfolio.
- Kuwait/Brent: The highest mean weight of 0.92 indicates that 92% of the optimal portfolio should be allocated to Brent oil, suggesting a very strong dependence on oil. The standard error is low (0.06), and the 5% confidence interval ranges from 81% to 99%, reflecting relatively low variability and strong confidence in the high weight of Brent oil.
- Oman/Brent: With a mean weight of 0.91, Oman also shows a high optimal allocation to Brent oil (91%). The standard error is 0.08, and the 5% confidence interval ranges from 79% to 99%, indicating a high and relatively stable allocation to oil.
- Qatar/Brent: The mean weight is 0.83, suggesting that 83% of the portfolio should consist of Brent oil. The standard error is 0.11, and the 5% confidence interval ranges from 61% to 96%, showing moderate variability and a strong preference for Brent oil.
- Saudi Arabia/Brent: Similar to Iraq and Jordan, Saudi Arabia's mean weight for Brent oil is 0.82, with a standard error of 0.12, and a 5% confidence interval ranging from 57% to 97%. This indicates a consistent preference for a high allocation to Brent oil in the optimal portfolio.

5- **Conclusion**

The analysis of dynamic conditional correlations (DCC) and optimal portfolio weights between Arab countries' stock market indices and Brent crude oil prices, spanning from the beginning of 2010 to mid-2024, reveals varied degrees of sensitivity and dependence on oil prices across the region.

Saudi Arabia and Qatar display the strongest and most consistent positive correlations with Brent oil prices over this period, indicating a higher level of economic dependence on oil. This is reflected in their optimal portfolio weights, with significant allocations to Brent oil, underscoring their reliance on oil as a crucial component for maximizing returns or managing risks. Kuwait and Oman also demonstrate a strong dependence on oil, with high optimal weights and relatively low variability, highlighting their stable reliance on Brent oil.

In contrast, countries such as Jordan, Egypt, and Iraq show weaker correlations and more variability. Jordan exhibits negligible correlation with oil prices, while Egypt and Iraq show moderate correlations with higher variability. This variability suggests that their stock markets are less sensitive to oil price fluctuations, which is mirrored in their portfolio weights that, while still notable, reflect a more balanced approach to oil exposure.

Overall, the findings indicate a clear pattern where oil-dependent economies, such as Saudi Arabia, Qatar, Kuwait, and Oman, align their investment strategies heavily towards Brent oil, whereas countries with less direct dependence on oil exhibit weaker correlations and more variability in their portfolio allocations. This divergence highlights the varying impacts of oil price changes on stock markets across the Arab world and underscores the importance of tailored investment strategies that account for each country's unique economic and market dynamics throughout the research period from early 2010 to mid-2024.

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