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Analyzing the Impact of Oil Shocks on Arab Countries' Stock Markets Using Quantile Vector Autoregression

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Abstract: - This study aims to explore how stock markets in selected Arab countries—specifically Saudi Arabia, Egypt, Qatar, Iran, and Oman—react to oil shocks. Utilizing bivariate Quantile Vector Autoregression (QVAR) and time-series data on oil prices and stock market indices from early 2011 to the end of 2023, the research reveals that QVAR offers a more nuanced assessment of the potential responses to shocks across various quantiles compared to traditional VAR models. The findings indicate that oil shocks negatively impact stock markets at lower quantiles, while at higher quantiles, these shocks produce positive effects. This heterogeneity suggests that the impact of oil shocks is neither uniform nor predictable, but rather varies depending on the distribution of total stock market index data. Furthermore, 3D visualizations of impulse response functions highlight that oil shocks create complex and varied influences on stock market indices across the studied nations, with effects dissipating after 20 periods[2].

Keywords: Oil Shocks, Stock Market, Quantile Vector Autoregression

I. INTRODUCTION

The increasing trend of economic globalization has intensified challenges for the sustainable development of financial markets. As economic globalization progresses, the interconnectedness of financial markets—particularly regarding capital flows and information exchange—has deepened, leading to heightened cross-market effects. When a financial disruption occurs, risks often propagate across various markets, resulting in significant asset price fluctuations. A strong correlation between financial markets increases the likelihood of risk transfer; consequently, price volatility in one market can induce similar fluctuations in others. Such interconnected dynamics may disrupt markets and undermine the sustainable advancement of financial systems (Xu et al., 2020; Forbes & Rigobon, 2002).

Typically, stock markets serve as key indicators of economic and financial activities within a country or region. Stock prices are subject to substantial volatility, influenced by diverse uncertainties, including economic downturns and financial crises, thereby posing considerable risks for investors (Baker et al., 2018). Moreover, the explosion of online trading and the advent of big data have accelerated the dissemination of information across financial and commodity markets. Major crises, such as the global financial crisis, political upheavals, and military conflicts, significantly affect investor confidence and asset allocation, resulting in risk spillover between interconnected markets (Zhang & Ma, 2019; Mällsten et al., 2020). Such dynamics highlight the importance of understanding the interdependencies among markets to address sustainability challenges effectively.

Oil, recognized as the primary energy source, plays a pivotal role in determining the global economic landscape. Often termed "economic oil," it serves as a crucial raw material across various industries (Jiang et al., 2022). Fluctuations in crude oil prices significantly impact worldwide economic development, as oil is integral to numerous sectors and directly influences the pricing of consumer goods. In recent years, the crude oil market has increasingly undergone financialization, with the growing use of derivatives such as futures contracts, options, and swaps. This dynamic, coupled with the strong connection between crude oil and industrial production, has made the interplay between oil prices and stock markets a central focus in economic research (Li & Wei, 2018).

In Arab countries, oil represents a vital source of revenue, establishing a complex relationship with their stock markets. Variations in crude oil prices can directly influence the economic performance of these nations, as such fluctuations are often correlated with movements in local financial markets. Research indicates that changes in oil prices can substantially impact stock indices in oil-exporting countries, primarily due to their effects on

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government revenues and economic policies (Khan et al., 2018). Furthermore, fluctuations in oil prices can affect investments, job creation, and other economic factors, ultimately influencing stock market demand (Sadorsky, 2012). Understanding this relationship is crucial for policymakers and investors in Arab countries to navigate the economic implications of oil price dynamics effectively.

This paper is structured as follows: the second section reviews the theoretical foundations and discusses relevant empirical studies. The third section presents the applied model, while the fourth section details the results of the model estimation. Finally, the conclusion is provided in the fifth section.

Theoretical Foundations

Since the foundational work of Koenker and Bassett (1978), Quantile Regression models have gained prominence across various academic disciplines, including finance, labor economics, and macroeconomics, due to their flexibility in exploring the relationships between economic variables. Initially, advancements in both theory and practice were primarily concentrated on cross-sectional data. However, the application of quantile regression has since expanded to encompass time-series and panel data analyses. The literature on this topic is extensive and cannot be easily summarized; a comprehensive overview of crucial aspects of quantile regression can be found in Koenker (2005) and further explored by White et al. (2015).

Quantile regression models are valuable tools for enhancing our understanding of financial spillovers and the sensitivity of different markets to international shocks. These models are particularly effective for analyzing financial time series due to their semiparametric nature, which requires minimal distributional assumptions within the Data Generation Process (DGP). This flexibility allows for a nuanced analysis of various market scenarios. For instance, lower quantiles may correspond to bearish market conditions, while higher quantiles are linked to bullish markets. Consequently, extreme quantiles are expected to be associated with significant financial phenomena, such as bubbles, contagion effects, or periods of financial turmoil (Chuliá et al., 2017; Ang et al., 2006).

In the existing literature, Tsai (2012) identifies a negative relationship between exchange rates and stock price indices at both the upper and lower quantiles of the distribution. Notably, the study finds no significant relationship between these variables in the quantiles near the median. Lee and Li (2012) investigate the nonlinear diversification effects on firm performance based on the quantile distribution, showcasing how performance varies significantly across different quantile levels. Ciner et al. (2013) utilize quantile regression to explore whether correlations between various asset classes in the US and UK differ during periods of pronounced price volatility. Gebka and Wohar (2013) analyze strong nonlinear causality in the extreme quantiles of volume and stock return series for Pacific countries, employing quantile regression techniques. Their results reveal a non-statistically significant relationship between volume and return in the central portion of the distribution. Lastly, Rubia and Sanchis-Marco (2013) assess the predictability of various stock portfolios in extreme quantiles, incorporating variables related to market liquidity and trading conditions to understand their impact.

Review of Empirical Studies

Nguyen and Bhatti (2012) try to understand the relationship between China and Vietnam markets using nonparametric (chi and K-plots) and parametric (Copula) methods. Their findings indicate there is a left tail dependency between international oil prices and Vietnam's stock market, implying that the stock market of Vietnam decreases when there is a decline in the international oil price. They also found no tail dependency in the relationship between oil price changes and the Chinese stock market.

Pan (2014) examined the structure of tail dependency between energy market return and the stock market in BRIC countries (Brazil, Russia, India, and China) from 12 January 2000 to 28 December 2012. They used the regime-switching dynamic symmetrized Joe-Clayton (SJC) copula model and found that the tail dependency has been considerably increased during the financial crisis of 2008/12. Moreover, the lower tail dependency for all the paired returns is almost greater than the upper dependency and varies during the financial crisis. Finally, it was found that tail dependency is strongest for Russia and weakest for China.

Chuliá et al. (2015) used multivariate quantile models to measure the response of six main Latin American (LA) stock markets to a shock in the US stock index. They compared the regional response with the responses of seven developed markets. In general, they record weaker tail dependences between the US and LA compared to the dependence between the US and mature markets. Their results offer possible diversification strategies that can be used through investing in LA after a large shock to the US market. Also, they documented asymmetrical responses to the shocks depending on the conditional quantile in which they are measured.

Liu et al. (2017) examined the mean and volatility spillover effects between international crude oil markets and stock markets based on the historical data of stock markets in China and the US and international crude oil prices from January 2003-December 2016 by using the Vector Auto Regression-Generalized Auto Regressive Conditional Heteroskedasticity (VAR-GARCH). Their results show that, first, there are two-way mean spillover effects between the stock markets of the US and the international crude oil market, while there are only one-way volatility effects from the international crude oil market to the US stock market. second, there are only one-way spillover effects from the international crude oil market to the Chinese stock market, and there is no evidence of volatility spillover effects between the Chinese stock market and the international crude oil market.

Trabelsi (2017) uses a DCC-GARCH approach and CoVaR delta measurement to assess the oil price shock spillover among total stock indexes and a part of KSA, UEA, and Russia over the period between 2007 and 2016. The results have shown that the response of stock indicators to oil price shocks is considerably positive, with the intensity that is different between considered countries and various sectors. Also, there is evidence that tail spillover effects depend on the origin of oil price shocks. More precisely, it seems that Russia's stock is more exposed to the aggregate demand-side oil shock like what occurred over the GFC period. KSA stock indicators and DFM indicators are more exposed to recent supply fields, such as oil shocks that have occurred since mid-2014.

Peng et al. (2018) investigate the extreme risk spillover of international crude oil to the stock returns for 529 firms listed on the A-share market of the Shanghai Stock Exchange. They applied a kernel-based nonparametric method to test quantile-on-quantile Granger causality from crude oil to firm returns. In terms of analysis at the firm level, findings are described as follows. First, the empirical results offer strong evidence to show asymmetry in the relationship between extreme movements from crude oil to firm returns, which means the positive risk spillover is more severe than the negative risk spillover. This phenomenon reveals the strong driving force of economic cycles. Second, risk transfer from oil price shocks to the firm return depends on the firm's industry features. Third, they confirm that the refined oil pricing reforms of China had intensifying effects on the negative spillovers from oil prices to firms on 27 March 2013.

Shahzad et al. (2018) examined the risk spillovers and descending-ascending dependence structures between five Islamic stock markets (the Islamic Market World index, Islamic indices of the USA, UK, Japan, and the Islamic Financial sector index), which are highly important for the religion-oriented investors. The ascending and descending VaRs, CoVaRs, and delta CoVaRs with spillover effects evaluation are among the methods used in this study. The results confirm the time-varying lower tail dependence between Oil and Islamic stock markets. Moreover, they presented supportive evidence of descending and ascending asymmetric spillovers from oil to Islamic stock markets and vice versa. Ultimately, these asymmetric risk spillovers have considerably increased following the world financial crisis.

Wen et al. (2019) examined the risk spillover effect between oil and stock markets using a multivariate quantile model (VAR for VaR approach) and impulse response functions. They studied the risk spillover in different quantiles using daily data over the period from January 4, 2000, to August 31, 2018. Their results showed that asymmetry in the spillover effect is significant at upside quantiles but is not significant at downside quantiles. According to the analysis of subsamples, they found that risk spillover became stronger after the financial crisis of 2008, while the spillover effects were very weak before the crisis. The international evidence shows that asymmetric risk spillover can also be found in the other six major stock indicators of the G7 group.

Tiwari et al. (2020) examined systematic risk and dependence between oil and the stock market of G7 economies between January 2003 and November 2017. They used several time-constant, time-varying, and time-varying Markov-copula models to examine the dependence. They used the delta conditional value-at-risk (ΔcoVaR) and marginal expected shortfall (MES) to illustrate the risk spillover effects and provide evidence of systematic risk. Based on the copula analysis, they found the difference in dependence structure between price variations of oil tail and stock market return of G7 for the studied countries. For France, Germany, and Japan, the dependence is through Markov-switching time-varying. While it is time-varying for the US and Canada, is constant for the UK and around zero for Italy. Their empirical evidence on the systematic risk indicates that oil price dynamics significantly contribute to G7 stock market return during volatile times compared to tranquil times. In particular, the stock market of Canada seems more sensitive and vulnerable to the negative external shocks caused by the crude oil market rather than other markets. Moreover, analysis results show that the crude oil market can be a good diversifier for investors in Japan and France, and investors in the rest of the G7 countries must act more carefully.

Uddin et al. (2020) studied the characteristics of risk spillover under the extreme scenarios between the US stock market and precious metals (gold, silver, platinum) and oil, by using the copula approach for tail dependence and CoVaR spillover measures. The results imply asymmetric tail dependence of the US stock market with silver and platinum, which is through the profound market recession. Gold and oil symmetrically move with the US stock market under normal and extreme market scenarios. Silver and Platinum have the most effect on the US stock market in a downside trend, while oil posits it in the upside trend. The US stock market strongly influences oil and silver through both market downturns and upturns. Gold weakly spillovers to the US stock market, indicating that investors can use gold as a portfolio diversifier.

Hanif et al. (2021) investigated the nonlinear dependence dynamics and downside and upside risk spillovers between oil prices and world food prices, which are recorded by a world food price index and its subsets of dairy, cereals, vegetable oil, and sugar. They illustrated their empirical results using static and dynamic bivariate copula methods, VaR and CoVaR. Their empirical findings indicate that oil price and aggregate food price, as measured by the world food price index, independently move during upturns and downturns. However, lower and upper tail dependence is seen between oil prices, and cereals, vegetable oil, and sugar prices. They also identified upside and downside asymmetric risk spillovers from separate food commodities to oil and from oil to food commodities. Oil prices have the highest effect on the sugar and vegetable oil prices (downside and upside), while oil prices are under the effect of vegetable oil prices and sugar prices within downside and upside trends, respectively.

Chavleishvili and Manganelli (2024) estimated a QVAR model for industrial production growth and financial crisis index based on the Euro Region data. Their results showed that extreme financial shocks leave an asymmetric effect on the real variable distribution, so that when a financial shock is imposed on the system then a strong, stable, and asymmetric effect is left on the industrial production distribution that removal of shock effect takes around two years.

II. METHOD

The model used in this study is adopted from the study conducted by Chavleishvili and Manganelli (2024), which is introduced in summary herein. For a time-series vector $\{Y_t\} \equiv \{[Y_{1t}, \ldots, Y_{nt}]'\}$ with Ωt as recursive information set in time t, we say that $\{Y_t\}$ follows a QVAR(1) process if the recursive θi quantile of Y_{it} can be written as:

$$\boldsymbol{Q\theta_1(Y_{1t}|\Omega_{1t}) = w_1(\theta_1) + a_{11}(\theta_1)Y_{1,t-1} + a_{12}(\theta_1)Y_{2,t-1} + \cdots + a_{1n}(\theta_1)Y_{n,t-1}}$$

$$\boldsymbol{Q(\theta_1)(Y_{1t}|\Omega_{1t}) = w_1(\theta_1) + a_{11}(\theta_1)Y_{1,t-1} + a_{12}(\theta_1)Y_{2,t-1} + \cdots + a_{1n}(\theta_1)Y_{n,t-1}}$$

$$\vdots$$

$$\boldsymbol{Q\theta_n(Y_{nt}|\Omega_{nt}) = w_n(\theta_n) + a_{0n1}(\theta_n)Y_{1t} + \cdots + a_{0n,n-1}(\theta_n)Y_{n-1,t} + a_{n1}(\theta_n)Y_{1,t-1} + a_{n2}(\theta_n)Y_{2,t-1} + \cdots + a_{nn}(\theta)Y_{n,t-1}}$$

For any $\theta_i \in (0,1), i \in \{1, \cdots, n\}$. When n=1, this model is converted to a quantile autoregressive process of Koenker and Xiao (2006). In matrix expression, we can write:

$$Q_\theta(Y_t|\Omega_t) = w(\theta) + A_0(\theta)Y_t + A_1(\theta)Y_{t-1} \tag{1}$$

$$n \times 1 \quad n \times 1 \quad n \quad n \quad n \quad n$$

where $\theta \in (0,1)^n$ and the matrix $A_0(\theta)$ is a lower triangular n×n coefficient matrix with zeros along the main diagonal. For a sequence of independent standard uniform random variable vectors with similar distribution of $\{U_t\}$, the QVAR above can be rewritten as follows:

$$\boldsymbol{Y_t = w_0(U_t) + A_0(U_t)Y_t + A_1(U_t)Y_{t-1}} \tag{2}$$

For a better understating of the link with the traditional VAR, the QVAR model can be interpreted as a VAR model with time-series dependence in its error structure:

$$\boldsymbol{Y_t = w_0 + A_0Y_t + A_tY_{t-1} + \varepsilon_t} \tag{3}$$

where $w_0 = E(w(U_t))$, $A_i = E\big(A_i(U_t)\big)$ for i = 0, 1 and

$$\varepsilon_t = w(U_t) - w_0 + (A_0(U_t) - A_0)Y_t + (A_1(U_t) - A_1)Y_{t-1}$$

If the process data generation of a standard VAR was done with i.i.d innovations, innovations were simplified to $\varepsilon \sum y_t^{t-1} t = w(U_t) - w_0$ which is indeed an i.i.d tail. Under this assumption, VAR and QVAR are determined through a similar dynamic[3].

III. MODEL ESTIMATE AND ANALYSIS OF RESULTS

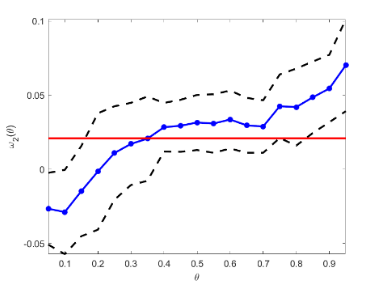
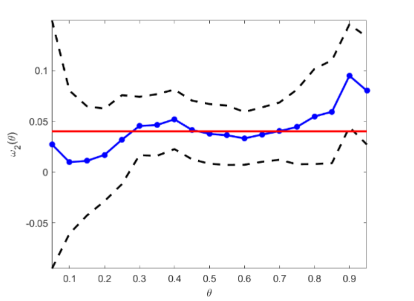
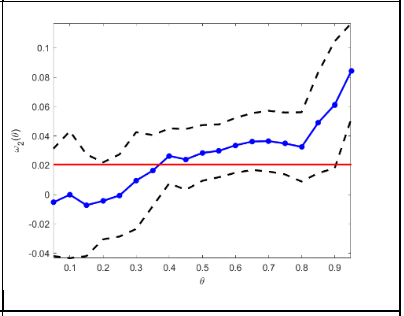
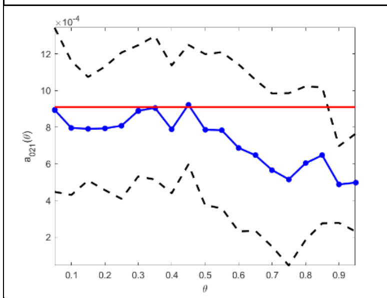
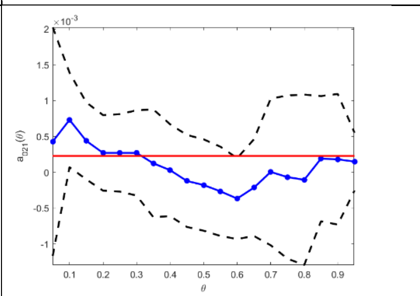
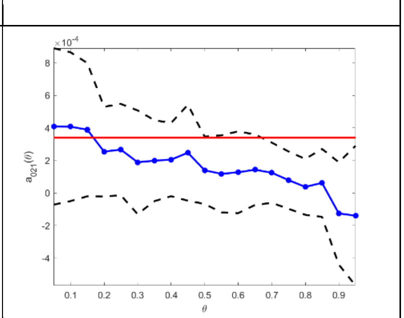
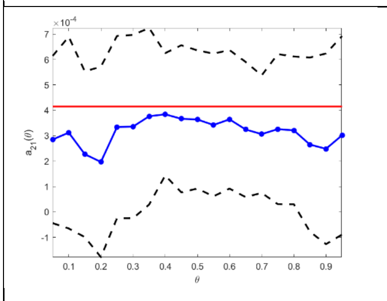
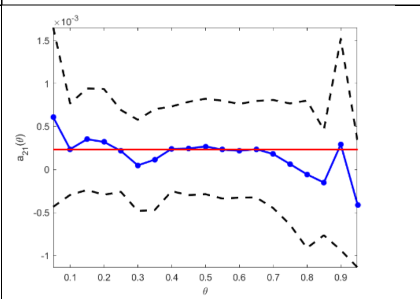
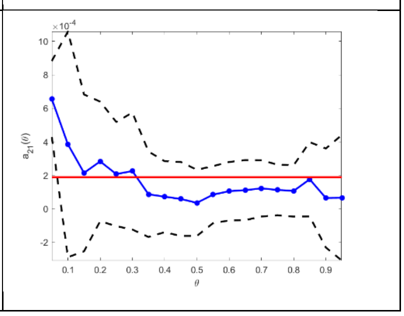
Following Chavleishvili and Manganelli (2024), the following equations express a conditional quantile VAR system in which, the oil price index (Y_{1t}) and the financial variables-stock price index of studied countries (Y_{2t}) have been modeled as a function of the quantile (θ):

$$Y_{1t} = w_1(\theta_1) + \qquad a_{11}(\theta_1)Y_{1,t-1} + a_{12}(\theta_1)Y_{2,t-1} + \varepsilon_{1t}(\theta_1) \tag{4}$$

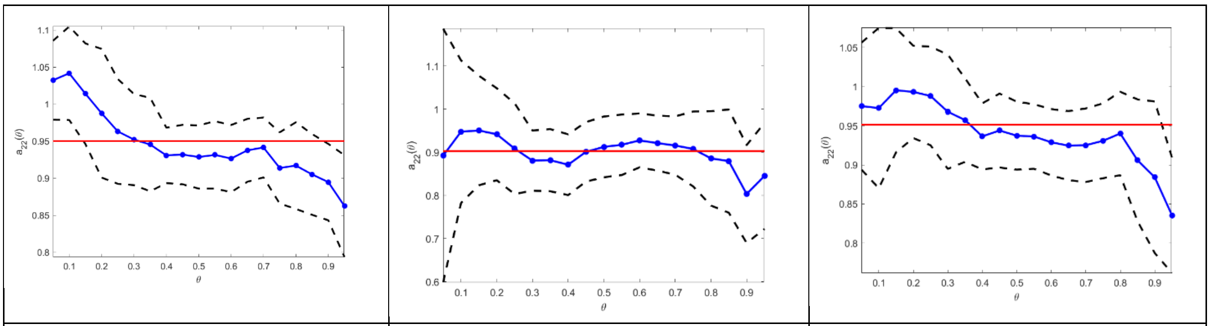
$$Y_{2t} = w_2(\theta_2) + a_{021}(\theta_2)Y_{1,t-1} + a_{21}(\theta_2)Y_{1,t-1} + a_{22}(\theta_2)Y_{2,t-1} + \varepsilon_{2t}(\theta_2) \tag{5}$$

The implicit hypothesis in the design of the model above is that shocks of real variables, such as oil price shocks can instantly affect the financial variables (due to the high speed of financial markets' response to news and information changes), but the financial shocks can affect the real variables with a lag.

The following diagrams demonstrate the estimated quantile coefficients of the models mentioned above with 95% confidence intervals of relevant OLS estimates. In these diagrams, the blue line represents QVAR estimates, the red line shows the OLS estimate, and the black dotted line indicates the 95% confidence intervals. In comparison between the estimated results of QVAR and conventional VAR, considerable asymmetries can be found in the coefficients estimated through the QVAR model.

Saudi Arabi	Iraq	**Egypt**
		
		
		

[3] For further study on the QVAR model, how to forecast with the QVAR model and quantile impulse response functions, see the studies conducted by Chavleishvili and Manganelli (2021) and Chavleishvili and Manganelli (2024).



	Qatar	Oman

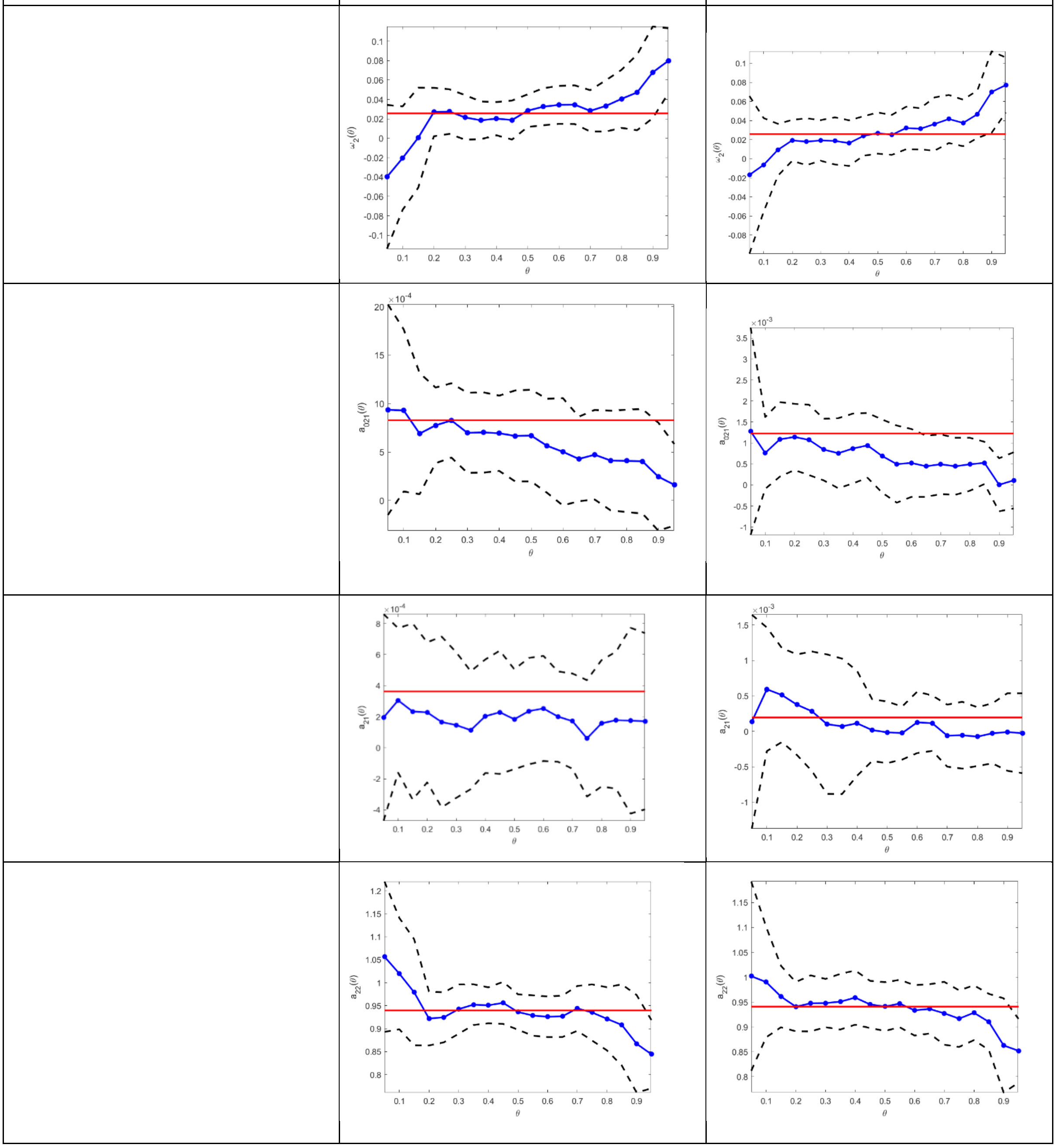


Figure 1. Comparison between QVAR and VAR estimates

These diagrams show that QVAR models can identify heterogeneous differences that are not detectable by OLS models. These differences reveal the heterogeneity in the effects of various variables within the data distribution. In particular, the effects of financial variables on the distribution of industrial production data are different in various quantiles, which are well identified, by using QVAR models. It means that the influence of a variable in lower values of the dependent variable (e.g., in 10% quantile) may differ from its influence in greater values (e.g., in 90% quantile). Heterogeneity in the effects means that independent variables do not have constant and monotonic effects, but these effects vary depending on the situation in data distribution. This characteristic is not well-detectable in the OLS model, but it can be found when QVAR models are used.

The impulse response functions are among the outputs of VAR model estimates that can be used and analyzed. Thus, the diagrams of stock index quantiles' impulse response to the changes resulting from a standard shock on the oil price variable are presented. For better visual understanding, the 3D quantile impulse response functions are reported. The advantage of these diagrams is seen in showing how any quantile of the stock market index responds to an oil price shock.

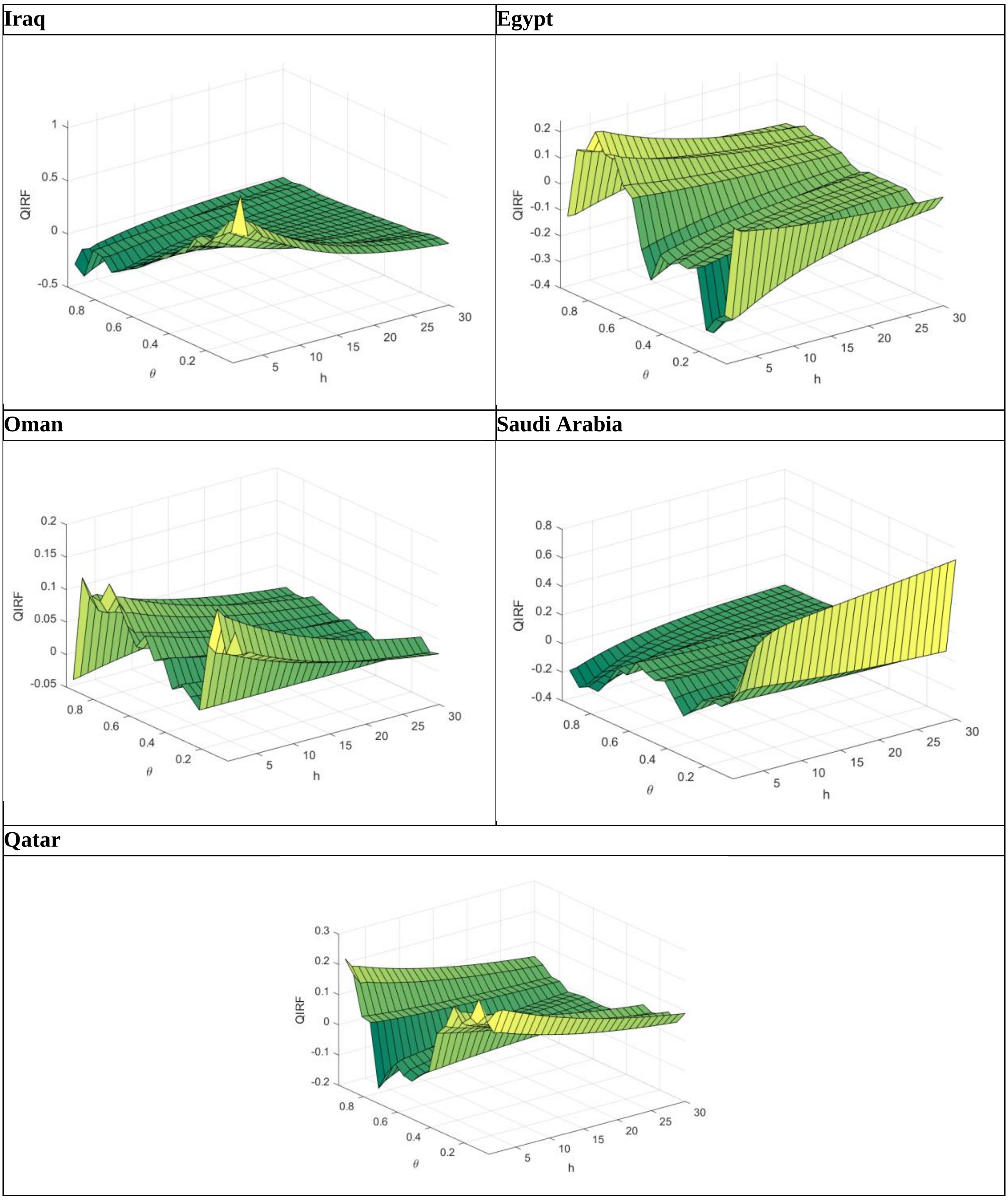


Figure 2: stock index 3D quantile impulse response

The diagrams shown above indicate the effect of oil shocks on different quantiles of the stock market index in the studied countries within different timelines. The vertical axis represents the severity of responses to the shock, and the horizontal axis indicates the time for which, the response has been measured. The θ axis also consists of quantiles (e.g., 0.05, 0.1, etc.). The diagram depicts how different quantiles of the stock market index respond to an oil shock. If the OLS VAR model could reveal the dynamic interactions between real and financial variables accurately, it was expected that all details of the 3D diagram move parallelly with a similar size between various quantiles. The reason is that changes in forecast distribution are completely directed with forecast mean variations in an OLS VAR model. However, this does not occur, implying that the OLS VAR model may not provide precise results when the analysis is far from the central tendency of the distribution. The diagram indicates that the shock effect disappears for all considered quantiles after around 24 months.

For instance, the quantile impulse response function in the stock market of Egypt indicates how various quantiles of the stock market show different responses to oil shocks. For lower quantiles, the responses may be more negative, while being more positive for upper ones. When time (h) increases, the effect of shock on the stock market will vary. There might be stronger responses in the early phases, which gradually decline.

In the case of Iraq, the response of Iraq's stock market to the shock is highly strong in the early stage (around time 5), and a peak is observed in the responses' intensity. This diagram depicts the asymmetric effects on different parts of the distribution. Various quantiles show different responses to the shock at varying times. Following the initial shock, through time, the impact of shock declines gradually, reaching more stable levels. This diagram clearly shows that oil shock can leave strong and rapid effects of the stock market, especially within initial post-shock times.

The diagram respective to Oman indicates that the stock market provides oscillations with certain considerable peaks and valleys when responding to oil shocks. In some points, QIRF (Quantile Impulse Response Function) reaches positive levels, while reaches negative levels in other ones, indicating conflicting responses of the stock market. This reveals the asymmetric effects existing in different quantiles. An increase in time (h) leads to a gradual decrease in responses, but volatilities still exist. This explains that the stock market of Oman may differently respond to oil shocks at different times. There are also conflicting responses and volatilities in the rest of the diagrams. This indicates the complexity of the stock market against oil shocks, so considerable differences are observed in the response of various quantiles.

IV. CONCLUSION

This study examines how stock markets in selected Arab countries—specifically Saudi Arabia, Egypt, Qatar, Iraq, and Oman—respond to oil shocks. To carry out this analysis, a bivariate Quantile Vector Autoregression (QVAR) model is employed alongside time-series data on oil prices and the stock markets of these countries, covering the period from early 2011 to the end of 2023 at a daily frequency.

The findings indicate that both financial and real shocks have asymmetric effects on the distribution of industrial production. This suggests that analyses based solely on forecast averages may overlook critical and complex aspects of the economic system. Utilizing a coherent and dynamic model that accounts for the interactions between real and financial variables over time enhances the accuracy and comprehensiveness of the analysis.

This approach is particularly valuable for policymaking and economic decision-making, as it allows for a detailed examination of shock effects across various timeframes and contexts. Furthermore, the results from the structural Impulse Response Functions (IRF) reveal that stock market reactions to oil shocks vary by quantile, indicating that these markets may respond differently—sometimes even contradictorily—to oil price fluctuations depending on the timing and context.

The insights gained from this study offer practical implications for economic policymakers and analysts. A deeper understanding of how various economic sectors respond to real and financial shocks can inform the design and implementation of effective economic policies, reduce volatility, and bolster overall economic stability.

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