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Analyzing the Relationship Between Arabian Stock Exchange Indices, Oil, and Gold Prices Using DCC and MST Models

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Abstract: - This study investigates the correlation among stock exchange indices in Arabian countries (United Arab Emirates, Egypt, Saudi Arabia, and Iraq), gold prices, crude oil prices, the index of non-fuel commodities, and major global stock market indices (USA, Germany, UK, Japan, and China) from January 6, 2010, to February 20, 2024, using daily data. The analysis employs Dynamic Conditional Correlation (DCC) and Minimum Spanning Tree (MST) models. Results reveal that the stock markets in Saudi Arabia (Tadawul), Egypt (EGX), and the United Arab Emirates (DFM) show a weak negative correlation with oil prices, while Iraq's stock market (ISX) also demonstrates a weak negative correlation. Additionally, ISX, Tadawul, and DFM indices, with the exception of EGX, have negative correlations with gold. MST analysis highlights gold's significant role in financial networks as a central asset that influences other markets. The presence of multiple connections to gold underscores its value as a protective asset during market fluctuations.

Keywords: Oil Price, Gold, Stock Market, Dynamic Conditional Correlation, Minimum Spanning Tree

I. INTRODUCTION

Following the 2008 financial crisis, significant attention was directed toward stabilizing financial systems by governments, universities, and regulatory agencies. Kaufman and Scott (2003) define systemic risk as “the risk that the entire system may break down, as opposed to the breakdowns in individual parts or components, which occurs as a domino effect.” Organizations such as the International Monetary Fund (IMF), Financial Stability Board (FSB), and Bank for International Settlements (BIS) classify systemic risk as a threat that can adversely affect the financial system, leading to disruptions in financial services and serious repercussions for the real economy (Long et al., 2017; Brunnermeier et al., 2009). Research indicates that the impacts of systemic risks can have far-reaching consequences, necessitating robust frameworks for monitoring and mitigating these risks (Elliott et al., 2014).

Financial markets are complex ecosystems where key participants manage risks through various financial correlations. Network theory provides a valuable framework for analyzing the intricate structures of these systems, enabling the study of contagion effects and systemic vulnerabilities (Newman, 2003). Numerous researchers have examined banking networks, focusing on the dynamics of risk transfer among financial institutions. These networks encompass interbank lending, payment systems, and the flow of credit between businesses, utilizing empirical methods and simulations to assess the potential impacts of institutional failures (Markose et al., 2012).

Research by Allen and Gale (2000) indicates that networks with a complete structure demonstrate greater stability compared to those with incomplete structures. While the literature on network analysis typically emphasizes how the overall architecture of a network influences systemic risk, there has been a notable lack of focus on how the local structure of the network contributes to systemic risk (Hautsch et al., 2015). Understanding both the global and local dynamics of these networks is crucial for a comprehensive evaluation of systemic risk in the financial sector.

Network theory has gained significant attention in recent years for systematic risk analysis. Systematic risk, often referred to as market risk, encompasses hazards associated with financial fluctuations and can arise from sequential defaults on obligations such as liabilities, derivatives, business credits, loans, and deposits. It can also be triggered by cross-correlations between financial assets (Jorion, 2007). Many researchers have explored the

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interconnections between financial institutions, allowing for the design of financial networks that facilitate the analysis of their topological features and hierarchical structures (Brunnermeier & Pedersen, 2009).

Studies indicate that network communications have heightened the correlation of stock returns, revealing that these financial networks can depict systematic risk more effectively than traditional physical networks (Diebold & Yilmaz, 2014). Furthermore, the structure of correlation networks is particularly vulnerable to macroeconomic shocks, as evidenced by the disruption that can arise during financial crises (Huang et al., 2009). Despite these insights, the measurement of systematic risk and the construction of stock correlation networks have primarily focused on the perspectives of financial institutions, often neglecting the broader implications of market behavior and individual investor actions (Podivinsky et al., 2020).

Furthermore, various studies have examined changes in dynamic correlations among industry indices from the perspective of publicly listed sectors on the stock exchange. A common finding across these studies is that the topology of the correlation network for industry indices alters during periods of crisis (Li et al., 2018). This underscores the relevance of studying systematic risk from the viewpoint of an industry index network.

Here's the rewritten text with integrated scientific sources:

Despite the wealth of research in financial risk, there is a scarcity of studies that specifically focus on measuring the contribution of systematic risk from the perspective of individual industries or on constructing networks of industry indices. Current research has struggled to elucidate the relationship between systematic risk contributions from specific industries and the corresponding local structures of these networks (Bartram et al., 2020).

On one hand, the flow of information—including both public and private data—can effectively elucidate the impact of stock linkages. The emergence of shared information, such as macroeconomic indicators, can cause simultaneous fluctuations in stock indices across various industries (Dungey et al., 2005). When private information becomes relevant, the behavior surrounding asset transfers between industries may further contribute to correlations among them (Chen et al., 2016).

On the other hand, the interconnected relationships between different industries—as revealed through correlations in their indices—also warrant consideration. The impact of each industry is conveyed through these inter-industry correlations, indicating that the measurement of systematic risk allocation is crucial when viewed through the lens of individual industries. Consequently, developing a network of industry indices is essential for exploring the relationship between an industry's contribution to systematic risk and its local network structure (Raddant & Kenett, 2021).

The characteristics of the global economy are dynamic, significantly influenced by the distinct economic structures of countries across various regions. Notably, the size and concentration of industries in different stock markets can lead to stronger interdependencies among economies. This enhanced integration has raised concerns about systemic global risk and the potential for contagion effects, where financial disturbances in one market can spill over into others (Coval & Stafford, 2007). Such risks tend to be exacerbated during financial crises, highlighting the vulnerabilities inherent in interconnected markets.

Consequently, individuals—ranging from ordinary citizens to investors and policymakers—must exercise caution due to the looming threat of another severe recession. The financial landscape remains susceptible to excessive risk-taking, which may necessitate taxpayer-funded interventions during crises (Shahzad et al., 2018; Laeven & Valencia, 2018). Addressing the structural aspects of stock market networks is essential for understanding financial integrity and mitigating the impact of systemic risks.

In light of the points discussed, this study seeks to examine the correlation structure among the overall stock market indices of select Arab countries—specifically the United Arab Emirates, Egypt, Saudi Arabia, and Iraq—alongside gold prices, crude oil prices, non-fuel commodity indices, and indices of prominent global stock markets, including those of the USA, Germany, the UK, Japan, and China. The analysis will utilize daily data spanning from January 6, 2010, to February 20, 2024.

II. THEORETICAL FOUNDATIONS

There are many views about how shocks are spread and transferred between countries, which are somewhat affected by the different definitions of contagion. Various theories have been proposed about the shock transfer channels and contagion incidence, which can be addressed within two general groups. One group of theories focuses on the fundamental factors (e.g., public shocks, business relationships, and financial relationships), and another group explains contagion occurrence based on the behavior of investors (including issues caused by Liquidity and Incentive Problems, Informational Asymmetries, Market Coordination Problem, and Investor Reassessment).

An increasing interest in modeling complex systems using network theory has occurred over recent years. Complex networks may consist of technological and biological systems (Newman, 2003), social networks (Toivonen et al., 2006), and financial markets (Allen and Gale, 2000; Bonanno et al., 2004). In particular, network-based approaches have become common for studying complex systems in Econophysics as an interdisciplinary research field that studies economic and financial phenomena.

Correlation-based networks are among the scopes that experienced considerable progress. The function of network theory for systematic risk analysis has drawn great attention in economics and financial studies over recent years. These networks can be used to decrease the complexity of financial dependencies and understand and predict dynamism in financial markets. One of the underlying and significant problems in this approach is to transfer the most relevant information from financial networks. Therefore, traditional algorithms have been adopted from network theory and some new techniques have been introduced. In this regard, Mantegna (1999) introduced a method for determining a hierarchical arrangement for a portfolio by extracting MST and using a full network of correlations of the US's stock price return.

Network structures provide an appropriate field for systematic risk assessment that is caused by specific interactions between various factors of financial risk affecting the stock markets. Moreover, an accurate assessment of network structures provides important insights into the cross-correlation power, directing spillovers, and transfer or receiving spillovers between financial risk factors under different market conditions.

III. EMPIRICAL STUDIES

Eryigit and Eryigit (2009) reported the results of a study on the properties of networks formed by cross-correlation among stock market indices. Their analysis showed that markets of North America and Europe show stronger correlations compared to the case of integration with other geographical areas. Similar antecedents were found by Brida and Risso (2010) and Kantar et al. (2011).

Sensoy and Tabak (2014) suggested a dynamic spanning tree created through the ARMA-FIEGARCH-DCC process for the assessment of cross-correlations between the stock markets of Asia and the Asia Pacific. They concluded that this network shrinks through time and Hong Kong's marker is its main actor.

Qiao et al. (2015) modeled the currency network by using the Real Effective Exchange Rate (REER). Using the MST (Minimum Spanning Tree) approach and rolling-window method, they constructed time-varying correlation-based networks with which they investigated the linkage effects between different currencies. This study demonstrated that linkage effects existed between currency networks and the euro (EUR) which is confirmed as the predominant world currency.

Tang et al. (2018) studied two major markets of the most influential economies, China and the United States, systematically from the perspective of financial network analysis. Results indicate that the network properties and hierarchical structures are fundamentally different for the two stock markets. The patterns included in the price movements are revealed and clear the market dynamics. Financial policymakers and regulators can be inspired by these findings for application in policymaking, regulations design, portfolio management, risk management, and trading.

Lee et al. (2019) studied the application of financial network indicators in designing global stock market investment strategies. They examined the effect and usefulness of network indicators by using them as input to determine strategies through several machine learning approaches (including logistic regression and support vector machine). Their results indicated the importance of networks as supplementary indicators for predicting the global stock market. In particular, these indicators were more effective during market crisis periods.

Zhang et al. (2020) studied the systematic risk spillovers and connectedness in the sectoral tail network of the Chinese stock market and the mechanism of transferring systematic risk spillovers using block models. According to the conditional value at risk (CoVaR) and single index model (SIM) quantile regression technique, they analyzed the tail risk connectedness and found that the stock market is exposed to more systematic risk and more connectedness during market fall. In addition, the orthogonal pulse function shows that the Herfindahl-Hirschman Index (HHI) of the edges has a significant positive effect on systematic risk, but indicates the impact of a certain lag feature. Moreover, the connectedness of sectors' direction shows that systematic risk receivers and enders vary through time and adopt page rank index to identify important systematic sectors released by companies and financial sectors. Finally, the block models indicate that the tail risk network of Chinese sectors can be divided into four different spillover function blocks. The role of blocks and the spatial spillover transmission path between risk blocks are time-varying. Our results provide useful and positive implications for market participants and policymakers who deal with investment diversification and tracing the paths of risk shock transmission.

Laborda and Olmo (2021) studied volatility spillover between seven different economic sectors of the USA using Diebold and Yilmaz's (2012) approach. Their results showed that banking and insurance, energy, technology, and biotechnology are the main channels through which shocks propagate to the rest of the economy.

Vié and Morales (2021) proposed a model to study the effects of network structure on the behavior of economic systems by changing the density and centralization of connections among agents. Production complexity increases regarding the combinatorial explosion of parts and products. Emergent systematic risks occur when connections increase vulnerabilities. Their results indicate a universal description of economic collapse provided in the emergence of peaks and phase transmission in the relationship between network structure and risk of individual failure. It seems that this relationship follows a sigmodal form in terms of centralized or denser networks. This model sheds new light on the relevance of policies for economic complexity growth and highlights the tradeoff between increasing the potential production of the system and its strength to collapse. They discussed the implications of policy for intervening in the organization of connections and system features and emphasized how different structures of the network and node characteristics indicate various directions for promoting complex and robust economic systems.

Ding and Zhang (2021) adopted empirical mode decomposition and STVAR model with the base data of optimized original sample interval. Moreover, they maintained the mature studies on the multiscale systematic risk under the frequency and divided the systematic risk dimension into two states. When frequency is combined with states, the risk spillover center is affected by disruptive changes, particularly in the long term, and metals become the risk spillover center, substituting the energy commodity provided that compositions with extraordinary value can increase persuasive power for long-term perspective. They also recommended that joint fluctuations of agricultural commodities and energy commodities be converted to other important risk spillover points. For investors, the holding period and portfolio both must be considered.

Lai and Hu (2021) estimated Granger causalities of stock markets of 20 different countries from August 2019 to March 2020. Also, the complex network of global stock markets is created based on the data. Financial risks are identified by comparing the various characteristics of the topology of a complex financial network and the centrality of the stabilization and fluctuation periods. The results indicate that COVID-19 leads to close relationships of financial connections between various countries, its impact spreads in a shorter distance, and crisis transmission is faster. In general, financial crises can be identified using network topological structure and centrality analysis based on network connectivity measurements. The Granger complex network can be used for measuring and warning the systematic risk.

Namaki et al. (2023) investigated the effect of banks' network topology on banks' systematic risk in the Tehran Stock Exchange by using daily stock returns from 2011 to 2013. First, systematic risk is measured and decomposed by using the EVT approach and then this index is divided into two dimensions: bank tail risk and systematic linkage. Then, the network between banks listed in the banking industry of the Tehran Stock Exchange is created based on the dynamic conditional correlations (DCC) by using the minimum spanning tree (MST) approach, and bank network topology is measured. Finally, the relationship between the systematic risk of banks and its dimensions with banks' network topology is assessed by using panel data regression. According to the results, Post-Bank, Tejarat, and Saderat banks showed the highest, and Karafarin and Eghtesad-Novin Banks had the lowest systematic risk. Also, the regression results showed that there is a positive and significant relationship between the variables of node strength, inbetweenness centrality, and size with the bank's systematic risk, and a negative and significant relationship between the variables of node degree and liquidity with the banks' systematic risk.

IV. ESTIMATION METHOD

Dynamic Conditional Correlation model (DCC)

DCC has been proposed by Engle (2002) and is a direct generalization of Constant Conditional Correlation (CCC) that was introduced by Bollerslev (1990). This model is used to estimate time-varying correlations between multiple time series. It is assumed in this model that vector *K*1* includes returns r_t having a normal conditional distribution with zero mean value and covariance matrix of H_t.

(1) $$r_t | F_{t-1} \sim N(0, H_t)$$

where F_{t-1} represents information collection in time *t-1*. Covariance matrix H_t can be presented as $H_t=D_tR_tD_t$ in which, $D_t=diag\{\sigma_{it}\}$ and is a diagonal matrix that its *i*th diagonal component is matched with conditional standard deviation of *i*th asset and $R_t=\{\rho_{ij,t}\}$ is *t* time-varying correlation matrix. Estimate of such a model is a three-stage process (Engle and Sheppard, 2001; Engle, 2002). In the first step, a univariate GARCH model is fit for each time series. Then, the non-conditional correlation matrix of standardized returns ($\bar{R}$) and the non-conditional covariance matrix of negative standardized returns ($\bar{N}$) are estimated by using torques. In the last step, those parameters then control correlation dynamism by using the quasi-maximum likelihood method. Correlation dynamisms are determined based on the equation below:

(2) $$Q_t = (1-\sum_{m=1}^{M}\theta_m - \sum_{n=1}^{N}\varphi_n)\bar{R} + \sum_{m=1}^{M}\theta_m(\in_{t-m}\in'_{t-m}) + \sum_{n=1}^{N}\varphi_n Q_{t-n}$$

(3) $$R_t = Q_t^* Q_t Q_t^*$$

where $\in_t = D_t^{-1} r_t$ is a vector of standardized returns and $\bar{R} = E[\in_t \in'_t]$ represents a nonconditional correlation matrix $\in_t$. Multiplication by $Q_t^* = (Q \otimes I_k)^{-1/2}$ term ensures that R_t is a correlational matrix with values one on the main diameter and values ≤1 for components outside of the main diameter.

Creation of Minimum Spanning Tree (MST)

According to the approach proposed by Mantegna (1999), the equation below is used to convert extracted correlations to criteria of interval between each pair of indicators:

(4) $$d_{ij}^t = \sqrt{2(1-\rho_{ij}^t)}$$

Also, one can examine the relationship between considered indicators by applying a simple conversion from elements of the return correlation matrix into the interval. Therefore, a connected graph is built in which, nodes are related to indicators, and intervals or edges between them are obtained from the proper conversion of correlation coefficients. This formula estimates interval requirements. Then, the N×N interval index is used to determine MST that is created using Kruskal's algorithm (1959).

V. DATA AND ESTIMATE RESULTS

The table below reports the variables and indicators used in this study. The period of this research is from 2010/01/06 to 2024/02/20 and daily data are used.

Table 1: variables and indicators

Title	Index
Crude oil	Brent Oil (Brent Oil Futures)
Commodities market	DAW Jones (Dow Jones Commodity)
Gold market	Gold (Gold Futures)
Stock market of the USA	SP (S&P 500)
Stock market of Germany	DAX (Frankfurt Stock Exchange)
Stock market of London	FTSE (FTSE 100)
Stock market of Japan	Nikkei (Nikkei 225)
Stock market of China	Shanghai (Shanghai Composite)
Stock market of Iraq	ISX (ISX Main 60)
Stock market of United Arab Emirates	DFM (DFM General)
Stock market of Saudi Arabia	Tadawul (Tadawul All Share)
The stock market of the whole world	MSCI (MSCI World)

Based on the univariate model of the DCC-GARCH approach, a GARCH model was first fit in this study for each return on the system entrance separately and then a DCC model was fit for cross-correlation between two time series. In addition, Threshold GARCH (TGARCH) was used to consider stock volatility asymmetry in a better way. The heat map was then used to interpret the results of the DCC model estimate. The heat map indicates the average rate of conditional correlations for a set of data that is calculated using the DCC model. Therefore, each cell in this map represents the mean value of paired conditional correlations between datasets.

To show the power and direction of correlations, the heat map uses a color gradient in which, red color expresses a high positive correlation (near +1), blue expresses a high negative correlation (near -1), and white/bright blue indicates low or lack of correlation (near 0). The elements on the main diameter all equal 1, which represents the full correlation of each dataset with itself.

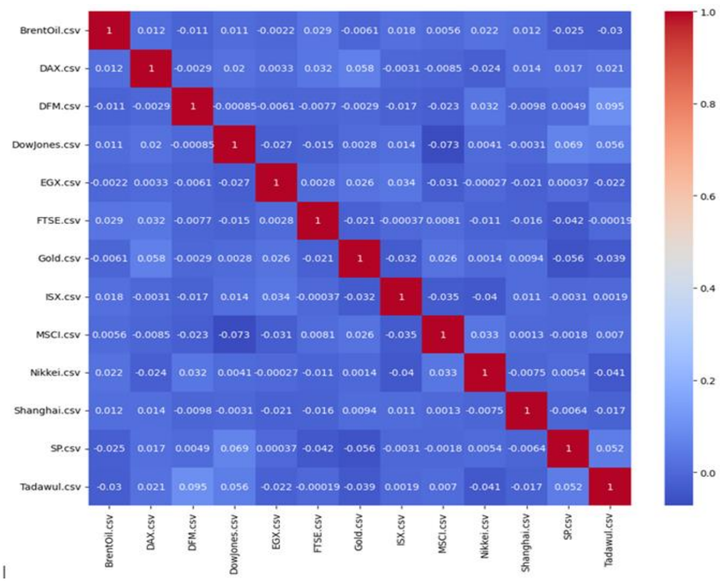

Fig 1. Heat map for dynamic conditional correlations

According to the heat map shown above, Brent Oil indicates an average positive correlation with DAX (0.012) and FTSE (0.029) within the daily timeframe. Furthermore, a weak negative correlation exists between future oil prices with Gold (-0.0061) and SP (-0.025). There is a negative correlation between Gold and SP. Also, there is a weak negative correlation between oil prices and the stock markets of Saudi Arabia, Egypt, and the United Arab Emirates, except for Iraq.

The stock market of Iraq shows a negative correlation with all indicators except for EGX, Shanghai, and Dow Jones.

Except for the EGX index, Tadawul and DMF indicators indicate a negative correlation with Gold.

Analysis of the graph obtained from the MST model is presented herein. This graph is an important tool used for analyzing financial networks. This model allows us to create a simple and useful graph for a better understanding of the structure and connections between assets by using correlations between them. In this graph, each vertex represents an asset and each edge indicates a minimum correlation between two assets.

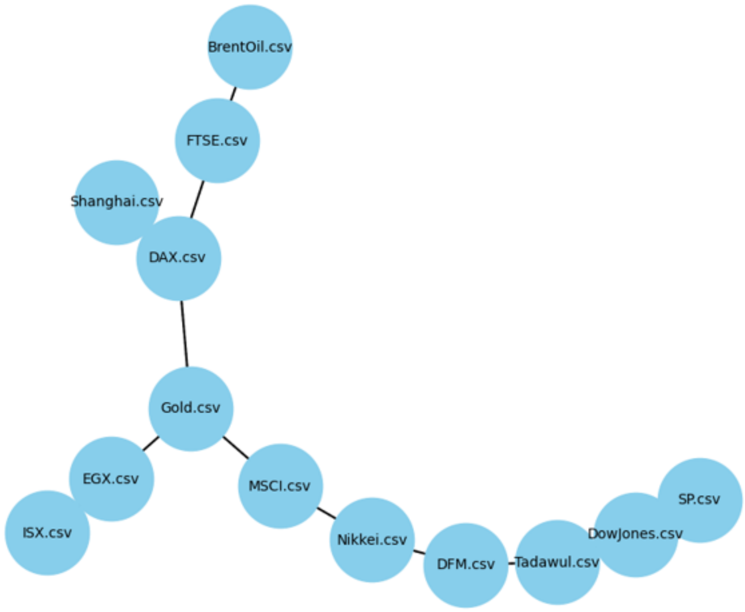

Fig 2. Minimum Spanning Tree (MST)

main results of the graph shown above can be expressed as follows:

1. The centrality of nodes:

- Gold node appears as a central node that is connected to several other nodes. This indicates the high importance of gold in the financial network showing that gold is a central asset with high influence.

2. Relevant markets:

- DAX node appears as an important node in the network that is connected to other nodes such as FTSE and Shanghai. This indicates the impact of European and Asian markets on each other.

3. Connection paths:

- Various paths from different nodes connect to the Gold which implies the importance of gold as a protective asset in market volatilities.

- Longer paths such as SP →…→ Tadawul → DFM → … → Gold indicates more complex and less direct relationships between assets.

VI. CONCLUSION

The DCC model's capability to assess time-varying correlations is underpinned by several key factors. First, understanding how correlations fluctuate over time is essential for evaluating systematic risk and enhancing portfolio diversification. For example, correlations between assets typically increase during market downturns, which elevates systematic risk and informs risk management strategies. Second, dynamic correlations allow for more precise estimates of risk and return swaps, thereby improving portfolio allocation decisions through better optimization. Third, the DCC model offers valuable insights into the interconnections between global financial markets, aiding policymakers and investors in understanding how shocks in one market can affect others through cross-correlation.

Given these advantages, this study aims to estimate the conditional correlations among selected stock markets in Arabian, European, East Asian, and U.S. countries, along with oil prices, gold prices, and commodity indicators. The findings will be presented using heat maps and minimum spanning tree (MST) graphs. Analyzing conditional correlations and the structural connections between the markets can be beneficial for various applications, such as predicting market movements, constructing portfolios, diversifying investments, and managing risk, ultimately leading to more informed and effective decision-making in risk management and investment strategies.

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