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Dynamic Interactions and Volatility Spillovers Between Oil, Agricultural Commodities, and Stock Markets in Arab Countries

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Abstract: - This study investigates the influence of oil and key agricultural commodity prices—wheat, coffee, and corn—on the stock markets of Saudi Arabia, Egypt, Kuwait, and Iraq, using daily data from 2010 to 2023 and the Time-Varying Parameter Vector Autoregression (TVP-VAR) model. It explores how dynamic connectivity, reflecting the evolving relationship between these markets, impacts overall market behavior. Positive and negative dependence metrics are analyzed to understand how volatility is transmitted among these markets. Results reveal a general trend of declining connectivity over time, with significant spikes during financial stress periods such as 2020. Positive dependence indicates that markets like Brent oil and coffee exhibit high self-dependence while influencing other markets minimally, whereas agricultural commodities like wheat and corn have substantial effects on market volatility. Negative dependence shows similar patterns with heightened interconnectedness during adverse conditions. These findings underscore the critical role of oil and agricultural commodities in shaping stock market dynamics and emphasize the importance of understanding market interdependencies for effective risk management and investment strategies.

Keywords: Dynamic Interactions, Volatility Spillovers, Oil, Agricultural Commodities, TVP-VAR

I. INTRODUCTION

In recent decades, financial markets in Arab countries have experienced significant transformations due to economic diversification, globalization, and increased integration into the global financial system (Oran et al., 2023). This evolution has heightened interest in understanding the interactions between regional stock markets and commodity markets, particularly in the context of dynamic volatility spillovers. The concept of volatility spillovers—the transmission of market volatility from one asset class or region to another—has become crucial for investors and policymakers in these economies.

Dynamic volatility spillovers between stock and commodity markets are an area of growing academic and practical interest. Research by Chan et al. (1999) highlights the importance of understanding cross-market linkages to manage risks and optimize investment strategies. In the context of Arab markets, which are heavily influenced by oil prices due to their significant oil revenues, the interplay between commodity prices (especially oil) and stock market returns has been particularly noteworthy.

The Arab stock markets are characterized by their unique economic structures and volatility patterns (Bich et al., 2023). According to Ibrahim and Kayed (2004), these markets exhibit different risk and return profiles compared to their Western counterparts. Oil price fluctuations, driven by both global and regional factors, play a crucial role in shaping the volatility dynamics within these markets (Jammazi & Aloui, 2010). For instance, higher oil prices tend to boost the profitability of oil-related industries, thereby affecting stock returns in oil-exporting countries.

Furthermore, the study by Bouri et al. (2015) underscores that during periods of economic stress, such as the global financial crisis or geopolitical tensions, the spillovers between commodity and stock markets become more pronounced. This has been evidenced by the heightened volatility transmission during periods of economic uncertainty or oil price shocks.

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Investment strategies in this context need to adapt to the dynamic nature of these spillovers. The research of Arouri et al. (2012) demonstrates that understanding the patterns of volatility transmission can provide valuable insights for constructing diversified investment portfolios and hedging against market risks. For example, incorporating commodity assets into a stock portfolio can potentially enhance risk-adjusted returns by capitalizing on the volatility spillover effects.

Despite the growing body of research, there remains a need for more localized studies focusing on the Arab region's unique economic and market characteristics. As noted by Sadorsky (2012), while global studies provide a broad perspective, they may overlook the specific dynamics relevant to emerging and frontier markets like those in the Arab world. Therefore, further investigation into how regional stock markets respond to commodity price shocks, and vice versa, is essential for developing robust investment strategies tailored to these markets (Khanh, 2024).

In summary, the interplay between Arab stock markets and commodity markets, particularly through the lens of volatility spillovers, presents both challenges and opportunities for investors. By exploring these dynamics, this paper aims to contribute to a deeper understanding of the investment strategies that can be employed in the context of the Arab financial markets, highlighting the implications for risk management and portfolio optimization.

II.REVIEW OF LITERATURE

The theoretical framework for understanding dynamic volatility spillovers between stock and commodity markets involves a combination of volatility spillover theory, intermarket linkages, portfolio theory, dynamic correlation models, behavioral finance, and macroeconomic factors (Khorshidi et al., 2024) . These theories collectively provide a comprehensive understanding of how volatility spills over between markets and inform investment strategies. Each of these concepts is explained below:

Volatility spillovers

Volatility spillovers refer to the phenomenon where volatility in one market affects the volatility in another. This concept is grounded in the following theories:

Conditional Variance Models: The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, developed by Bollerslev (1986), is fundamental in capturing the time-varying nature of volatility. This model allows for conditional variances that change over time, which is crucial for understanding how shocks in one market can impact another. The GARCH framework has been widely used to analyze volatility spillovers across different asset classes (Bollerslev, 1986).

Volatility Transmission Mechanisms: Volatility can spill over through various channels such as news transmission, liquidity effects, or macroeconomic shocks. For instance, changes in oil prices can affect stock market volatility directly by impacting oil-related industries or indirectly through broader economic channels (Chan et al., 1999).

Intermarket Linkages

Intermarket linkages explore how different markets are interconnected through financial and economic channels:

Price and Volatility Linkages: The relationship between oil prices and stock market returns is influenced by the role of oil in economic production and consumption. Hamilton (2003) explores how oil price shocks impact the broader economy and, consequently, stock markets (Rostaminasab et al., 2023). This linkage is particularly significant in oil-exporting countries, where oil price fluctuations can have direct effects on stock market performance.

Economic Channels: For Arab countries, which are major oil producers, oil price changes directly impact government revenues and economic growth. This economic channel affects stock markets by influencing investor sentiment and corporate profitability (Ibrahim & Kayed, 2004).

Portfolio Theory

Modern Portfolio Theory (MPT) and its extensions provide a framework for understanding how to manage risk and return through diversification:

Diversification: MPT, introduced by Markowitz (1952), emphasizes the benefits of diversifying investments across different asset classes to reduce overall portfolio risk. Understanding volatility spillovers is crucial for effective diversification, as it helps investors determine how adding commodities to a stock portfolio can affect risk and return (Markowitz, 1952).

Risk Management: Investment strategies must adapt to the dynamic nature of volatility spillovers. Arouri et al. (2012) demonstrate that incorporating knowledge of volatility spillovers into portfolio management can enhance risk-adjusted returns by balancing exposures to different asset classes based on their volatility relationships.

Dynamic Correlation Models

Dynamic correlation models analyze the time-varying relationships between different markets:

Time-Varying Correlations: The Dynamic Conditional Correlation (DCC) model, proposed by Engle (2002), is used to study how correlations between asset classes change over time. This model helps in understanding the fluctuating relationships between stock and commodity markets and is valuable for developing investment strategies that adjust to changing market conditions (Engle, 2002).

Behavioral Finance

Behavioral finance theories provide insights into how psychological factors influence market dynamics:

Market Sentiment: Investor behavior and sentiment can significantly impact both commodity and stock markets. Shiller (2003) discusses how psychological factors and investor biases contribute to market volatility and asset price movements, which in turn affects volatility spillovers.

Crisis Periods: During periods of economic distress or geopolitical instability, volatility spillovers can become more pronounced. The heightened sensitivity of markets to shocks during these times necessitates a more nuanced approach to risk management and investment strategy (Sadorsky, 2012).

Macroeconomic Factors

Macroeconomic theories highlight how broad economic factors influence market interactions:

Inflation and Interest Rates: Changes in inflation and interest rates can affect both oil prices and stock market returns. Understanding these relationships helps in analyzing how macroeconomic variables drive volatility spillovers (Bernanke & Gertler, 2001).

Review of Empirical Studies

Ibrahim & Kayed (2004) examines the development of stock markets in Arab countries and their economic implications. While not exclusively focused on volatility spillovers, it provides valuable context on the structural characteristics of Arab stock markets, which are essential for understanding how these markets interact with commodity markets.

Jammazi & Aloui (2010) analyzes the volatility spillover effects between oil prices and stock markets in the GCC countries. The researchers use a multivariate GARCH framework to explore how oil price fluctuations affect stock market volatility and vice versa. The study finds that oil price changes have significant spillover effects on stock market returns, which is crucial for developing investment strategies and understanding market dynamics in oil-dependent economies.

Arouri & Rault (2010) extends the analysis of volatility spillovers by examining the impact of oil price shocks on stock markets in the Middle East and North Africa (MENA) region. Using a GARCH model, the study provides insights into how oil price volatility influences stock market performance in these emerging economies, contributing to a better understanding of investment strategies and risk management in the MENA region.

Arouri et al (2012) provides a comprehensive analysis of volatility spillovers and correlations between oil prices and stock markets in Gulf Cooperation Council (GCC) countries. The researchers use a multivariate GARCH model to examine the dynamic correlations and spillover effects, revealing significant interactions between oil price shocks and stock market volatility in these economies. The findings have important implications for portfolio diversification and risk management strategies in oil-dependent markets.

Sadorsky (2012) investigates the correlation and volatility spillovers between oil prices and stock markets in major oil-exporting countries. The paper employs a VAR-GARCH model to explore how oil price shocks affect stock market volatility and vice versa. The findings highlight the significant impact of oil price fluctuations on stock market performance, offering insights for investment strategies in oil-dependent economies.

Bouri et al (2015) investigates dynamic volatility spillovers between commodity markets and stock markets within the GCC region. By employing a multivariate GARCH model, the study highlights how commodity market volatility influences stock market volatility and vice versa. The results underscore the interconnectedness of these markets and provide insights into the implications for investment strategies and risk management in the region.

Benaroch & Kross (2015) investigates the spillover effects between oil prices and stock markets in the GCC countries using a bivariate GARCH framework. The study provides evidence of significant spillovers from oil prices to stock markets, which has implications for hedging strategies and portfolio management in oil-dependent economies.

Khan & Popp (2018) analyzes the relationship between oil price volatility and stock market performance in the MENA region, using a Markov-switching GARCH model. The study highlights how different regimes of oil price volatility affect stock market returns and provides insights for adjusting investment strategies based on regime shifts.

Jiang & Li (2021) examines the asymmetric spillover effects between oil prices and stock markets in the Arab world using a non-linear GARCH model. The paper finds that oil price shocks have asymmetric effects on stock market volatility, which is important for developing hedging strategies and understanding market behavior in response to oil price changes.

III.ESTIMATION RESULTS

This study examines the impact of oil and agricultural commodity prices, including wheat, coffee, and corn, on the stock markets of Arab countries, specifically Saudi Arabia, Egypt, Kuwait, and Iraq using daily data from 2010 to 2023 and TVP-VAR Model. Oil, as a primary energy source, serves as a crucial indicator of the energy market, while agricultural commodities represent essential goods whose prices are subject to fluctuations driven by global supply and demand dynamics.

A correlation matrix is a table that shows how different assets are correlated with each other. Each element in this matrix shows the correlation coefficient between two specific assets. This coefficient has a value between negative one and one.

Table 1: correlation matrix

Egypt	Stock market index	Brent oil	coffee	wheat	corn
Stock market index	1	-0.333	-0.222	-0.224	-0.28
Brent oil	-0.333	1	0.578	0.66	0.72
coffee	-0.222	0.578	1	0.607	0.671
wheat	-0.224	0.66	0.607	1	0.879
corn	-0.28	0.72	0.671	0.879	1
Iraq					
Stock market index	1	0.268	0.322	-0.032	-0.088
Brent oil	0.268	1	0.677	0.694	0.649
coffee	0.322	0.677	1	0.72	0.698
wheat	-0.032	0.694	0.72	1	0.919
corn	-0.088	0.649	0.698	0.919	1
Kuwait					

Stock market index	1	0.908	0.899	0.747	0.793
Brent oil	0.908	1	0.822	0.77	0.818
coffee	0.899	0.822	1	0.736	0.716
wheat	0.747	0.77	0.736	1	0.829
corn	0.793	0.818	0.716	0.829	1
Saudi Arabia					
Stock market index	1	0.166	0.221	0.415	0.25
Brent oil	0.166	1	0.588	0.66	0.723
coffee	0.221	0.588	1	0.619	0.682
wheat	0.415	0.66	0.619	1	0.88
corn	0.25	0.723	0.682	0.88	1

*The difference in numbers is due to the difference in the frequency of observations of the stock exchanges of each country

Dynamic Connectivity

Dynamic connectivity refers to the evolving and variable relationship between two or more variables over time. This concept illustrates how the interaction between variables is not fixed but changes as conditions evolve. For instance, the stock prices of two companies operating in the same industry may initially show a strong correlation—when one company's stock price rises, the others might also increase. However, this relationship can shift over time. For example, if one company introduces a new product, its stock price might react differently compared to the other company, altering their previously observed correlation.

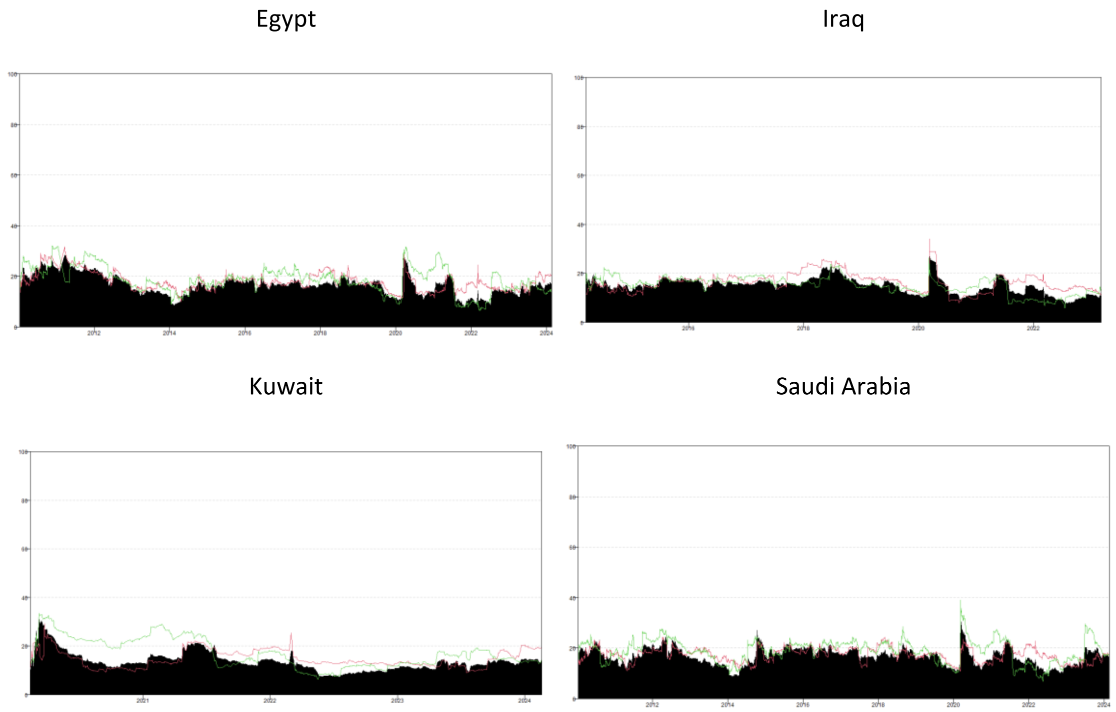

Figure 1: Dynamic connectivity of Selected Stock Exchange

The green and red lines illustrate how connectivity due to positive and negative returns has evolved over time. The green line represents connectivity driven by positive returns, which varies over time, with periods of increase and decrease. Similarly, the red line depicts connectivity driven by negative returns, which also fluctuates significantly.

Overall, both lines exhibit a declining trend over time. However, during critical market conditions, both lines experience sharp increases. Notably, the red line, representing negative returns, shows a dramatic rise during periods of intense financial stress, such as in 2020. This surge highlights the heightened impact of negative returns during times of uncertainty and financial strain.

In summary, the analysis reveals that during critical periods, such as 2020, the overall connectivity, as indicated by both the green and red lines, intensifies. This suggests that the influence of both positive and negative returns on overall market connectivity becomes more pronounced during times of significant financial stress.

General Connectedness of Positive and Negative Returns

Connectedness in financial markets refers to the degree of interaction and dependence between variables over time. This concept helps analyze market fluctuations and how shocks are transmitted across markets. The following table provides an analysis of both positive and negative correlations between five markets: Selected stock market index, Brent crude oil, coffee, wheat, and corn. The table is divided into two sections: positive dependence and negative dependence .In the following, the interpretation of the table is presented only for the country of Egypt, and a similar interpretation can be made for other countries.

Table 2: General Connectedness of Positive and Negative Returns-Egypt

Positive Dependence						
	Stock market index	Brent oil	coffee	wheat	corn	FROM
Stock market index	94.53	1.65	1.49	1.25	1.08	5.47
Brent oil	1.37	93.39	2.34	1.78	1.13	6.61
coffee	1.27	2.50	85.08	5.60	5.55	14.92
wheat	0.81	1.42	4.50	68.35	24.91	31.65
corn	0.61	0.88	4.48	24.76	69.26	30.74
TO	4.05	6.46	12.81	33.39	32.68	89.38
Inc.Own	98.58	99.84	97.89	101.74	101.94	TCI
NET	-1.42	-0.16	-2.11	1.74	1.94	22.35/17.88
NPT	0.00	2.00	1.00	3.00	4.00	
Negative Dependence						
Stock market index	91.51	4.36	2.04	1.01	1.09	8.49
Brent oil	3.40	94.16	1.11	0.58	0.76	5.84
coffee	1.26	1.81	84.12	6.60	6.21	15.88
wheat	0.64	1.55	5.50	68.33	23.99	31.67
corn	0.64	1.30	5.27	23.64	69.15	30.85
TO	5.93	9.02	13.91	31.84	32.03	92.73
Inc.Own	97.43	103.18	98.03	100.17	101.18	TCI
NET	-2.57	3.18	-1.97	0.17	1.18	23.18/18.55
NPT	0.00	4.00	1.00	2.00	3.00	

Positive Dependence:

The positive dependence section displays the extent to which fluctuations in each market are explained by other markets. Each cell shows the percentage of volatility transferred from one market to another. For example:

Stock Market Index: 94.53% of its fluctuations are attributed to its own dynamics, while 1.65% are influenced by Brent crude oil, 1.49% by coffee, 1.25% by wheat, and 1.08% by corn. The "FROM" column shows that 5.47% of the index's volatility comes from other markets.

Brent Crude Oil: 93.39% of its fluctuations are due to its own dynamics, with 1.37% influenced by the stock market index, 2.34% by coffee, 1.78% by wheat, and 1.13% by corn. The "FROM" column indicates that 6.61% of its volatility originates from other markets.

Coffee: 85.08% of its volatility is self-explanatory, with 1.27% due to the stock market index, 2.50% by Brent crude oil, 5.60% by wheat, and 5.55% by corn. The "FROM" column shows that 14.92% of coffee's volatility comes from other markets.

Wheat: 68.35% of its volatility is explained by itself, with 0.81% from the stock market index, 1.42% from Brent crude oil, 4.50% from coffee, and 24.91% from corn. The "FROM" column indicates that 31.65% of its volatility is influenced by other markets.

Corn: 69.26% of its volatility is due to its own fluctuations, with 0.61% from the stock market index, 0.88% from Brent crude oil, 4.48% from coffee, and 24.76% from wheat. The "FROM" column shows that 30.74% of corn's volatility comes from other markets.

TO and FROM Indices

TO Index: Represents the total percentage of volatility each market transmits to other markets. For example, the stock market index transmits 4.05% of its volatility to other markets.

Inc.Own Index: The sum of a market's internal volatility plus the volatility received from other markets.

NET Indicator: The difference between "TO" and "FROM" shows whether a market is a net transmitter or net receiver of volatility.

Negative Dependence

The negative dependence section follows a similar structure but focuses on negative returns. It shows how much each market's negative fluctuations are explained by other markets. For example:

Stock Market Index: 91.51% of its negative returns are explained by itself, with 4.36% influenced by Brent crude oil, 2.04% by coffee, 1.01% by wheat, and 1.09% by corn. The "FROM" column indicates that 8.49% of its negative returns come from other markets.

Brent Crude Oil: 94.16% of its negative returns are due to its own dynamics, with 3.40% influenced by the stock market index, 1.11% by coffee, 0.58% by wheat, and 0.76% by corn. The "FROM" column shows that 5.84% of its negative returns come from other markets.

Coffee: 84.12% of its negative returns are self-explanatory, with 1.26% influenced by the stock market index, 1.81% by Brent crude oil, 6.60% by wheat, and 6.21% by corn. The "FROM" column indicates that 15.88% of its negative returns come from other markets.

Wheat: 68.33% of its negative returns are explained by itself, with 0.64% from the stock market index, 1.55% from Brent crude oil, 5.50% from coffee, and 23.99% from corn. The "FROM" column shows that 31.67% of its negative returns are influenced by other markets.

Corn: 69.15% of its negative returns are due to its own dynamics, with 0.64% from the stock market index, 1.30% from Brent crude oil, 5.27% from coffee, and 23.64% from wheat. The "FROM" column indicates that 30.85% of its negative returns come from other markets.

Additional Indices

TCI Index: Measures the overall connectedness ratio for positive and negative returns, useful for analyzing asymmetries.

NPT (Net Pairwise Transmission) Index: Indicates how frequently a market acts as a net transmitter or receiver of volatility compared to other markets.

Table 3: General Connectedness of Positive and Negative Returns-Iraq

Positive Dependence						
	Stock market index	Brent oil	coffee	wheat	corn	FROM
Stock market index	96.87	1.03	0.66	0.88	0.57	3.13
Brent oil	0.85	95.86	0.44	2.01	0.85	4.14
coffee	0.77	0.73	87.79	6.37	4.33	12.21
wheat	0.70	1.32	5.11	69.07	23.80	30.93
corn	0.77	1.16	3.30	24.10	70.66	29.34
TO	3.09	4.24	9.51	33.36	29.54	79.74
Inc.Own	99.96	100.10	97.30	102.43	100.20	TCI
NET	-0.04	0.10	-2.70	2.43	0.20	19.93/15.95
NPT	2.00	3.00	0.00	4.00	1.00	
Negative Dependence						
Stock market index	96.74	1.35	0.57	0.81	0.53	3.26
Brent oil	0.95	96.23	1.20	0.69	0.93	3.77
coffee	0.40	1.66	90.04	4.27	3.62	9.96
wheat	0.87	1.91	3.20	70.68	23.34	29.32
corn	0.43	1.93	2.62	23.57	71.45	28.55
TO	2.64	6.86	7.60	29.34	28.42	74.86
Inc.Own	99.38	103.09	97.64	100.02	99.88	TCI
NET	-0.62	3.09	-2.36	0.02	-0.12	18.71/14.97
NPT	1.00	4.00	1.00	2.00	2.00	

The results for Iraq case show that each market's volatility is largely self-explanatory, with varying degrees of influence from other markets. Total Connectedness (TO) is 79.74%, indicating overall market interdependence. Net Transmission (NET) values suggest slight net-receivers or transmitters of volatility. For negative dependence, the markets show similar patterns, with a TO of 74.86% and comparable NET values. The analysis highlights significant interconnectedness and varying market reactions to shocks, crucial for risk management and investment strategies.

Table 4: General Connectedness of Positive and Negative Returns-Kuwait

Positive Dependence						
	Stock market index	Brent oil	coffee	wheat	corn	FROM
Stock market index	93.20	1.42	1.73	2.55	1.10	6.80
Brent oil	0.77	94.45	1.01	2.58	1.20	5.55
coffee	0.84	1.24	86.23	8.18	3.51	13.77
wheat	0.63	2.12	6.38	74.41	16.46	25.59
corn	0.74	1.24	3.07	17.07	77.87	22.13
TO	2.97	6.03	12.20	30.38	22.26	73.84
Inc.Own	96.17	100.48	98.43	104.79	100.13	TCI
NET	-3.83	0.48	-1.57	4.79	0.13	18.46/14.77
NPT	0.00	3.00	1.00	4.00	2.00	
Negative Dependence						
Stock market index	86.45	9.93	1.98	1.01	0.64	13.55

Brent oil	10.45	85.40	2.73	0.42	1.00	14.60
coffee	1.65	2.53	86.35	6.62	2.85	13.65
wheat	0.73	3.76	5.62	74.95	14.95	25.05
corn	0.35	1.04	2.66	15.00	80.95	19.05
TO	13.18	17.25	12.99	23.04	19.43	85.91
Inc.Own	99.63	102.65	99.35	97.99	100.38	TCI
NET	-0.37	2.65	-0.65	-2.01	0.38	21.48/17.18
NPT	1.00	2.00	2.00	3.00	2.00	

In positive dependence, the Kuwait stock market index shows a high self-dependence (93.20%), with a 6.80% influence from other markets, primarily from wheat and coffee. Brent oil has a similar high self-dependence (94.45%), with 5.55% of its volatility influenced by other markets, notably coffee and wheat. Coffee exhibits significant self-dependence (86.23%) and considerable influence from wheat and corn. Wheat shows a self-dependence of 74.41% and transfers volatility to coffee and corn. Corn has a high self-dependence (77.87%) and impacts other markets like wheat. The Total Connectedness (TO) for positive dependence is 73.84%, indicating overall strong interconnectedness. The Net Transmission (NET) values suggest that wheat is a net-transmitter of volatility, while the stock market index and coffee are net-receivers. In negative dependence, the stock market index has a lower self-dependence (86.45%) with significant influence from Brent oil and coffee. Brent oil shows a similar pattern with a self-dependence of 85.40% and notable contributions from the stock market index. Coffee has high self-dependence (86.35%) and influences from wheat. Wheat's self-dependence is 74.95%, with substantial influence from coffee. Corn has high self-dependence (80.95%) and impacts other markets minimally. The Total Connectedness (TO) for negative dependence is 85.91%, indicating strong market interconnectedness under negative shocks. The Net Transmission (NET) values reveal that markets like the stock market index and coffee are net-receivers of negative volatility, while others like wheat show net-transmitter behavior.

Table 5: General Connectedness of Positive and Negative Returns-Saudi Arabia

Positive Dependence						
	Stock market index	Brent oil	coffee	wheat	corn	FROM
Stock market index	92.24	4.78	1.20	0.88	0.90	7.76
Brent oil	2.56	93.45	0.97	1.95	1.07	6.55
coffee	1.06	1.69	86.87	6.12	4.26	13.13
wheat	0.48	1.57	4.97	69.43	23.54	30.57
corn	0.52	1.06	3.37	23.75	71.31	28.69
TO	4.61	9.11	10.50	32.70	29.78	86.71
Inc.Own	96.85	102.56	97.37	102.13	101.09	TCI
NET	-3.15	2.56	-2.63	2.13	1.09	21.68/17.34
NPT	0.00	2.00	1.00	4.00	3.00	
Negative Dependence						
Stock market index	89.28	7.81	1.21	0.93	0.78	10.72
Brent oil	5.90	91.70	1.00	0.49	0.91	8.30
coffee	0.97	1.49	84.65	7.08	5.81	15.35
wheat	0.63	1.25	5.70	69.19	23.24	30.81
corn	0.40	0.73	4.63	23.50	70.74	29.26
TO	7.90	11.28	12.54	32.00	30.74	94.45
Inc.Own	97.18	102.98	97.18	101.19	101.47	TCI
NET	-2.82	2.98	-2.82	1.19	1.47	23.61/18.89
NPT	0.00	3.00	1.00	3.00	3.00	

For positive dependence, the Saudii Arabia stock market index shows a high self-dependence of 92.24%, with a 7.76% contribution from other markets, especially wheat and coffee. Brent oil has a self-dependence of 93.45% and a 6.55% influence from other markets, notably coffee and wheat. Coffee, with an 86.87% self-dependence, is significantly affected by fluctuations in wheat and corn. Wheat's self-dependence is 69.43%, with notable volatility coming from coffee and corn. Corn, showing a 71.31% self-dependence, impacts other markets less. The Total Connectedness (TO) in positive dependence is high at 86.71%, indicating strong overall interconnectedness. The Net Transmission (NET) shows that the stock market index and coffee are net-receivers of volatility, while other markets like wheat are net-transmitters. In negative dependence, the stock market index has an 89.28% self-dependence and significant impacts from Brent oil and coffee. Brent oil's self-dependence is 91.70%, with a notable influence from the stock market index. Coffee exhibits an 84.65% self-dependence, with notable impacts from wheat and corn. Wheat's self-dependence stands at 69.19%, with significant volatility transmitted to and from coffee and corn. Corn shows a self-dependence of 70.74%, affecting other markets minimally. The Total Connectedness (TO) for negative dependence is 94.45%, highlighting strong overall market interconnectedness under negative shocks. The Net Transmission (NET) indicates that the stock market index and coffee are net-receivers of negative volatility, while other markets like wheat show net-transmitter behavior.

IV.CONCLUSION

The study provides an in-depth analysis of how oil and agricultural commodity prices interact with stock markets in Arab countries using the TVP-VAR model. It reveals that markets like Brent oil and coffee exhibit high self-dependence, driven primarily by their own dynamics, while still influencing others to some extent. For instance, Brent oil impacts coffee and wheat prices, albeit modestly. Over time, the overall interconnectedness among these markets has generally declined, although spikes in connectivity occur during financial stress, such as in 2020, highlighting heightened sensitivity and volatility in crises. Positive dependence shows that markets like Brent oil and coffee mainly drive their own volatility with limited spillover, whereas agricultural commodities like wheat and corn show significant interdependencies, affecting and being affected by other markets. In negative dependence, markets like the stock market index and coffee exhibit stronger interconnectedness and act as net-receivers of negative volatility, while others like wheat are net-transmitters. These insights are crucial for risk management and investment strategies, as they underscore the need for adaptive approaches during periods of high volatility and financial stress to better manage market interdependencies and anticipate behavior.

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