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Spillover effects of volatility between the Chinese stock market and selected emerging economies in the middle east: A conditional correlation analysis with portfolio optimization perspective

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A B S T R A C T

In recent years, the rapid transmission of information and interconnectedness of global financial markets have amplified the convergence and influence among them. Consequently, the occurrence of spillover effects in one market can significantly impact other markets. Accurately identifying and understanding these spillover effects is crucial for effectively managing and controlling market fluctuations. This research aims to measure and analyze the spillover effects between China's stock market and selected emerging economies in the Middle East, with a focus on exploring diversification opportunities. The analysis encompasses three distinct time periods, including the overall period from May 1, 2005, to May 31, 2023. The sub-periods consist of the first sub-period from May 1, 2005, to October 31, 2009, and the second sub-period from December 1, 2010, to May 31, 2023. Multivariate Generalized Heterogeneous Autoregression (MGARCH) is employed in this study to examine the spillover effects between China's economy and the emerging economies under consideration. The Granger causality analysis reveals a unidirectional causality running from the Chinese stock market to Jordan, as well as from the UAE to China throughout the entire observation period. However, no spillover effects are found between China and Saudi Arabia in either direction during any of the periods. Notably, a two-way causality is detected between the Chinese and UAE markets in the second sub-period. Furthermore, MGARCH results indicate no spillover effects from China to the emerging economies during the overall period, first sub-period, or second sub-period. The findings of this research offer valuable insights for investment portfolio managers in the Chinese economy, who may consider the examined emerging economies as potential destinations for risk diversification.

1. Introduction

In recent times, the growth of interconnectedness among financial markets has sparked the attention of economic and financial researchers. They have taken a keen interest in studying the relationships between financial assets, deciphering the mechanisms through which turbulence and fluctuations are transmitted among these assets, and examining the dynamics of interactions between different financial markets. The increased interconnectedness has resulted in a notable correlation in the price movements or returns of stocks and other assets across various markets. This correlation is characterized by the occurrence of waves of price increases or decreases that typically originate in one or more sectors and then spread to other sectors through market linkages.(Yin et al., 2020) .The interconnectedness between markets is also significant in terms of risk assessment. The risk of contagion, which refers to the transmission of fluctuations or turbulence from one market to

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another, is regarded as a crucial form of risk in financial markets. (Jafari et al., 2018). The problem of time series analysis in investment management has received significant attention from researchers, with studies examining various aspects of the market and decision-making processes (Ghousi, 2015; Touni et al., 2019). When hedging a portfolio of stocks against risk, the spillover effect of turbulence becomes crucial. If there is a spillover effect between markets, it implies a higher level of risk in those markets. Turbulence and fluctuations from one market can impact other markets, leading to uncertainty among financial investors (Chang & Tsay, 2010). Different markets exhibit varying relationships with each other. Some markets move in sync and are highly influenced by each other, while others show negative correlation with shocking events. There are also cases of neutral relationships among market movements (Bekaert, 1995; Huang et al., 2000; Lucey & Zhang, 2010; Beirne et al., 2010). The dynamic links and spillovers among different markets provide opportunities for creating a global investment portfolio rather than being limited to a single country's sectors. Investing in different countries can help protect the investment portfolio against specific risks associated with each country.

Studies have shown an increasing trend in investment in emerging markets and economies over the past two decades due to their high returns and risk characteristics (Delios & Henisz, 2000). Therefore, examining the volatility spillover effect from China and selecting emerging markets for investment portfolio formation becomes essential. Emerging economies are more susceptible to international vulnerabilities, including financial crises and political factors. Previous studies have explored the optimization of stock portfolios by selecting emerging economies among developing countries' indices or stocks (Dimitriou et al., 2013; Gulzar et al., 2019; Hoseini Ebrahimabad et al., 2019). The transmission of information between emerging and developing economies can occur through returns and volatility. Strong interdependence between financial markets can significantly impact investors' perception of foreign financial news, leading to increased correlation in stock returns and volatility across markets (Hamao, Masulis, & Ng, 1991). This study focuses on the relationship between China and other emerging economies, specifically Jordan, UAE, and Saudi Arabia, during the financial crisis. China, as the second-largest economy globally, plays a vital role among emerging countries and is considered an attractive investment destination (Stoian, 2013).

The objective of this article is to analyze the spillover effect of turbulence and fluctuations in the Chinese market on the selected emerging economies in the Middle East region. The study utilizes data from May 1, 2005, to May 31, 2023, divided into two sub-periods. The empirical analysis employs Granger causality and DCC dynamic conditional correlation techniques, revealing spillover effects from the Chinese market to the Indonesian stock market.

The results of this study have implications for foreign portfolio investors interested in the Middle East region's selected emerging economies. The paper offers portfolio strategies across different scenarios and contributes to existing literature by examining volatility spillover effects and accounting for structural failures, such as financial crises.

The following sections of the paper include an extensive review of literature on spillovers among different asset classes, discussion of data and econometric models used, empirical results, and concluding remarks with policy implications.

2. Review of literature and rationale of the study

Understanding turbulence characteristics and transmission mechanisms in financial markets is crucial for investors. It has significant implications for stock portfolio management, enabling the selection of optimal stock combinations to reduce risk. Turbulence analysis is also necessary for various tasks such as option pricing, investment portfolio optimization, value at risk calculation, and risk hedging. Additionally, the spillover effects of turbulence between markets in different countries have been highlighted as a factor justifying economic policy coordination among nations. Economic policy decisions, particularly financial ones, are expected to spread to other countries' markets as internal shocks in one country often impact beyond its domestic economy. Research on volatility spillover analysis was initially introduced by Engle III et al. (1988) and Engle et al. (1990). Subsequent studies examined volatility spillovers between the US and Japanese stock markets (Lin et al., 1994), explored spillover effects of volatility in different financial markets using similar models (Bekaert & Harvey, 1997; Ng, 2000), and distinguished between global and domestic shocks in the volatility of emerging stock markets, including European stock markets (Balli et al., 2015). Furthermore, studies have identified significant return fluctuations spillover from developed markets to emerging markets (Brana et al., 2012). Assessing liquidity creation and vulnerability of emerging markets under accommodative monetary policy highlighted the impact of surplus liquidity on developing countries (Majdoub & Mansour, 2014). Conditional correlation between the US and five emerging Islamic countries was examined, where weak correlation was observed within the studied period, providing valuable insights for international investment portfolio investors (Abbas et al., 2013).

Multiple studies explored the spillover effects of volatility among Asian countries (Li & Giles, 2015), the impact of US and UK turbulence on selected emerging markets, with significant correlation found between Egypt, Israel, and the US stock market (Abou-Zaid, 2011). Volatility and its effects from developed markets to emerging markets have also been extensively studied (Beirne et al., 2013). Additionally, the dynamic correlation between exchange rates and stock markets of emerging countries has been investigated, shedding light on turbulence spillover between these two asset classes (Chkili, 2012).

These studies have contributed to literature on market volatility, offering insights into diversification, hedging, and enabling institutional investors to diversify their portfolios across different asset classes to mitigate potential risks. While there is a considerable body of literature on volatility spillovers between various markets and asset classes, research on China and other emerging markets remains limited. Investors seeking to reduce portfolio risks, particularly related to the Chinese stock market and emerging markets, would benefit from studies addressing turbulence spillover effects between selected countries in the Middle East region.

3. Data and Econometric Models

3.1 Data description

In this research, the aim was to study the impact of China's stock market on selected emerging economies in the Middle East region. Specifically, the focus was on the stock markets of Saudi Arabia, Jordan, and the United Arab Emirates. The data used in this study included the prices of shares in the Shanghai Stock Exchange (SSE) in China, the Riyadh Stock Exchange (TASI) in Saudi Arabia, the Oman Stock Exchange (ASE) in Jordan, and the Abu Dhabi Stock Exchange (ADX) in the United Arab Emirates. The data was obtained from Investing.com and consisted of 4585 observations. The research covered the period from May 1, 2005, to May 31, 2023. By analyzing the data, daily returns were calculated using equation (1), where p_t and p_{t-1} represent the stock prices in periods t and t-1, respectively. The results of the analysis were analyzed for different periods, including the full period from May 1, 2005, to May 31, 2023, the first sub-period from May 1, 2005, to October 18, 2009, and the second sub-period from October 19, 2009, to May 31, 2023.

$$r_t = Ln(\frac{p_t}{p_{t-1}}) \tag{1}$$

3.2 Econometric Models

Due to the wide role of turbulence (variability) and their spillover effects in economic theories, the quantification and numerical analysis of instability in the empirical domain of economics is of particular importance. A view that is proposed in the field of econometrics to measure and quantitatively investigate uncertainty and turbulence is the use of ARCH autoregressive conditional heteroskedasticity variance model, which was first proposed by (Engle, 1982) and has been developed and expanded over time. After the introduction of these models by Engel, turbulence modeling in financial time series attracted a lot of attention, and depending on the objectives of various studies, different GARCH models have been introduced, but one of the interesting and practical issues that is very It is aimed at the accurate modeling of turbulence, understanding the transfer and spillover of returns of financial assets to each other. In this research, by using dynamic conditional correlation and using a multivariable model, the spillover effect of turbulence from the Chinese stock market on selected emerging economies in the Middle East is investigated. Dynamic Conditional Correlation (DCC) is one of the best tools to capture information transfer or spillover from one market to another market (Pandey et al., 1982). These models are briefly described below.

3.2.1 Granger Causality Test

Granger (1969) introduced the *Granger causality test* to detect the causal connection between variables. This test assesses the impact of changes in one series on changes in another series to determine causality. In essence, in the context of Granger causality, if we regard *x* as a determinant of *y*, we can interpret *x* as the cause of *y*. This implies that *x* can forecast y by considering past values.

$$X_{(t)} = \sum_{J=1}^{P} A_{11.j} \underset{w}{\;} ; X_{(t-j)} + \sum_{j=1}^{p} A_{12.J} ; Y_{(t-j)} + \boldsymbol{\epsilon_{1(t)}} \tag{2}$$

$$Y_{(t)} = \sum_{J=1}^{P} A_{21.j} \underset{w}{\;} ; X_{(t-j)} + \sum_{j=1}^{p} A_{22.J} ; Y_{(t-j)} + \boldsymbol{\epsilon_{2(t)}} \tag{3}$$

In Eq. (1) and Eq. (2), the variable p represents the maximum number of observation delays. Granger causality is a method used by researchers to determine the direct influence of one series on another series without any prior assumptions. This test is rooted in two fundamental principles: firstly, that the cause precedes its effect, and secondly, that the cause provides unique information about future values. The test is applied to fixed series data. Therefore, if two or more series have constant values, the test is applied to stationary data (I(0)). On the other hand, if the series is non-stationary, it is transformed into stationary data before conducting the Granger causality test.

3.2.2 Multivariate GARCH model

The MGARCH model (multivariate GARCH) is commonly employed in financial econometrics to measure fluctuations in both univariate and multivariate settings. Research suggests that there are financial spillover effects over time between different markets and assets, highlighting the importance of considering interdependence through multivariate models. By utilizing multivariate models, the financial industry can make better decisions regarding asset pricing, portfolio optimization, risk hedging, and risk management. In this study, the volatility of China and three selected emerging countries in the Middle East is analyzed, making the MGARCH model the most suitable choice. In financial econometrics literature, there are four types of multivariate GARCH models, including the VECH model proposed by Bollerslev et al. (1988), the BEKK model, and the DCC model. The VECH model directly extends the univariate GARCH to multiple dimensions, while Bekk (1995) reduced the parameters of the VECH model. The DCC model provides further simplification to the BEKK model, resulting in a reduction of unknown parameters and making it a superior model to BEKK (Huang et al., 2010). MGARCH models capture the simultaneous variability of two or more variables, where the variability of each variable can affect the others. The multivariate GARCH model involves several parameters, making their estimation challenging. To address this issue, diagonal multivariate GARCH models are employed, rewriting the univariate GARCH equation as follows.

$$H_{11t} = C_1 + [u_{1t-1} \ \ u_{2t-1}] \begin{bmatrix} a_{11} & \frac{a_{12}}{2} \\ \frac{a_{12}}{2} & a_{22} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} + E_{t-2} \left\{ [u_{1t-1} \quad u_{2t-1}] \begin{bmatrix} g_{11} & \frac{g_{12}}{2} \\ \frac{g_{12}}{2} & g_{13} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} \right\} \tag{4}$$

where

$$h_{iit-1} = E_{t-2}(u_{it-1}^2) \tag{5}$$

and

$$h_{12t-1} = E_{t-2}(u_{1t-1} \quad u_{2t-1}) \tag{6}$$

is

$$H_{12t} = C_2 + [u_{1t-1} \ \ u_{2t-1}] \begin{bmatrix} a_{21} & \frac{a_{22}}{2} \\ \frac{a_{22}}{2} & a_{23} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} + E_{t-2} \left\{ [u_{1t-1} \quad u_{2t-1}] \begin{bmatrix} g_{21} & \frac{g_{22}}{2} \\ \frac{g_{22}}{2} & g_{23} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} \right\} \tag{7}$$

and

$$H_{22t} = C_3 + [u_{1t-1} \ \ u_{2t-1}] \begin{bmatrix} a_{31} & \frac{a_{32}}{2} \\ \frac{a_{32}}{2} & a_{33} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} + E_{t-2} \left\{ [u_{1t-1} \quad u_{2t-1}] \begin{bmatrix} g_{31} & \frac{g_{32}}{2} \\ \frac{g_{32}}{2} & g_{33} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} \right\} \tag{8}$$

The matrix representation of the equations would be as follows:

$$\begin{aligned} H_t = \begin{bmatrix} C_1 & C_2 \\ C_2 & C_3 \end{bmatrix} + \begin{bmatrix} u_{1t-1} & u_{2t-1} & 0 & 0 \\ 0 & 0 & u_{1t-1} & u_{2t-1} \end{bmatrix} \begin{bmatrix} a_{11} & \frac{a_{12}}{2} & a_{21} & \frac{a_{22}}{2} \\ \frac{a_{12}}{2} & a_{13} & \frac{a_{22}}{2} & a_{23} \\ a_{21} & \frac{a_{22}}{2} & a_{31} & \frac{a_{32}}{2} \\ \frac{a_{22}}{2} & a_{23} & \frac{a_{32}}{2} & a_{33} \end{bmatrix} \begin{bmatrix} u_{1t-1} & 0 \\ u_{2t-1} & 0 \\ 0 & u_{1t-1} \\ 0 & u_{2t-1} \end{bmatrix} \\ + E_{t-2} \left\{ \begin{bmatrix} u_{1t-1} & u_{2t-1} & 0 & 0 \\ 0 & 0 & u_{1t-1} & u_{2t-1} \end{bmatrix} \begin{bmatrix} g_{11} & \frac{g_{12}}{2} & g_{21} & \frac{g_{22}}{2} \\ \frac{g_{12}}{2} & g_{13} & \frac{g_{22}}{2} & g_{23} \\ g_{21} & \frac{g_{22}}{2} & g_{31} & \frac{g_{32}}{2} \\ \frac{g_{22}}{2} & g_{23} & \frac{g_{32}}{2} & g_{33} \end{bmatrix} \begin{bmatrix} u_{1t-1} & 0 \\ u_{2t-1} & 0 \\ 0 & u_{1t-1} \\ 0 & u_{2t-1} \end{bmatrix} \right\} \end{aligned} \tag{9}$$

When Eq. (9) is condensed, it becomes:

$$H_t = C + (I_2 \otimes \acute{u}_{t-1})\tilde{A}(I_2 \otimes u_{t-1}) + E_{t-2}\left|(I_2 \otimes \acute{u}_{t-1})\tilde{G}(I_2 \otimes u_{t-1})\right| \tag{10}$$

As a result, the matrix H_t will assume a quadratic structure.

4. Empirical results and discussion

In this article, the authors aim to examine the spillover effect of fluctuations between the Chinese stock market (SSE) and three emerging markets in the Middle East: the Saudi Arabian stock market (TASI), the Jordanian stock market (ASE), and the United Arab Emirates stock market (ADX). The research is conducted over three time periods: the full period from May 1, 2005, to May 31, 2023, the pre-financial crisis period from May 1, 2005, to October 18, 2009, and the post-financial crisis period from October 19, 2009, to May 31, 2023.

Table 1 presents the descriptive statistics for the entire period, highlighting that the Chinese stock market (SSE) had the highest return (0.2394), followed by the Jordanian stock market (ASE) (0.1844), and the Saudi Arabian stock market (TASI) (0.1739). Conversely, the United Arab Emirates stock market (ADX) had the lowest positive return (0.1672). The return distribution of the Chinese, Saudi Arabian, and United Arab Emirates stock markets exhibited negative deviation, suggesting the possibility of low returns at a high level. However, the Jordanian stock market demonstrated positive deviation (0.1191) and had a high volatility level (6.7716), indicating a high probability of generating very large or very small future returns. The returns of the three markets were found to be non-normally distributed according to the Jarque-Bera test. The generalized Dickey-Fuller test confirmed the constancy of the return mean value, implying predictability and generalizability. Furthermore, the ARCH-LM test showed volatility clustering in each log series.

Table 2 and Table 3 provide the descriptive statistics for the pre- and post-financial crisis periods, respectively. During the pre-financial crisis period, the Chinese stock market (SSE) exhibited lower average return compared to other stock markets (-186.02 e), with higher volatility (standard deviation of 0.1107). Similar stability and reliability were observed through the ADF and ARCH-LM tests. In the post-financial crisis period, the Chinese stock market (SSE) and the Saudi Arabian stock market (TASI) had the highest average returns (-208.46 e and -181.92 e, respectively) among the analyzed markets. The United Arab Emirates and the Jordanian stock markets had negative average returns, with Jordan experiencing the lowest average return (-198.62 e). The Chinese stock market displayed higher risk (standard deviation of 0.0549) compared to other markets, while Jordan's stock market had the lowest risk. The distribution of returns for the Saudi Arabian and United Arab Emirates stock markets exhibited negative skewness, indicating the possibility of low returns at a high level. On the other hand, the Chinese and Jordanian stock markets showed positive skewness, suggesting a high probability of generating very large or very small future returns. The Jarque-Bera test confirmed the non-normal distribution of all series in the post-financial crisis period. Stationarity was found in all series, and the ARCH-LM test confirmed the presence of an ARCH effect.

In summary, the article investigates the spillover effect between the Chinese stock market and selected Middle Eastern emerging markets. The findings reveal variations in returns, volatility, skewness, and distribution patterns across different time periods and markets.

Table 1
Descriptive statistics (monthly yield data: May 1, 2005 to May 31, 2023)

Descriptive Statistics	SSE	TASI	ASE	ADX
Stdev	0.0726	0.0683	0.0476	0.0562
ARCH LM-test	0.00	0.00	0.00	0.00
Jarque Bera	53.2745	31.3013	130.3260	98.5659
ADF Test	0.0100	0.0100	0.0100	0.0100
sig. value	0.00	0.00	0.00	0.00
Nobs	4585	4585	4585	4585
Skewness	-0.4606	-0.6440	0.1191	-0.8314
Minimum	-0.2625	-0.2508	-0.2504	-0.2353
Maximum	0.2394	0.1739	0.1844	0.1672
Kurtosis	5.2457	4.3426	6.7716	5.8523
Mean	-1.28 e-19	3.23 e-18	3.22 e-18	3.39 e-18
Median	0.0036	0.0088	-0.0026	0.0028

Tabe 2
Descriptive statistics (monthly yield data: May 1, 2005 to October 18, 2009)

Descriptive Statistics	SSE	TASI	ASE	ADX
Stdev	1106	1187	1186	1194
ARCH LM-test	-6.02 e-18	e-197.07	-4.49 e-18	-5.98 e-18
Jarque Bera	0.0211	0.0131	0.0051	0.0027
ADF Test	0.2276	0.1822	0.1823	0.1848
sig. value	-0.2743	-0.2308	-0.2075	-0.1865
Nobs	0.1107	0.1024	0.0750	0.0811
Skewness	-0.8391	-0.3586	-0.1437	-0.2184
Minimum	3.5672	2.3963	3.4139	3.1148
Maximum	6.9303	1.9779	0.6138	0.4593
Kurtosis	0.00	0.00	0.00	0.00
Mean	0.0100	0.0100	0.0100	0.0100
Median	0.00	0.00	0.00	0.00

Table 3
Descriptive statistics (monthly yield data: October 19, 2009 to May 31, 2023)

Descriptive Statistics	SSE	TASI	ASE	ADX
Stdev	3479	3407	3399	3391
ARCH LM-test	8.46 e-20	1.92 e-18	-8.62 e-19	-1.98 e-18
Jarque Bera	-0.0001	0.0036	-0.0018	-0.0011
ADF Test	0.1898	0.1660	0.1749	0.1156
sig. value	-0.1837	-0.1613	-0.1247	-0.2411
Nobs	0.0549	0.0538	0.0329	0.0483
Skewness	0.1375	-0.2347	0.8112	-0.9123
Minimum	4.2290	3.9021	8.2036	7.8697
Maximum	10.8392	7.0248	199.3096	183.6766
Kurtosis	0.00	0.00	0.00	0.00
Mean	0.0100	0.0100	0.0100	0.0100
Median	0.00	0.00	0.00	0.00

After analyzing descriptive statistics, researchers used the Granger method to examine information flow in stock exchanges and test the flow of information between different financial markets. This method helps detect the direction of economic fluctuations between countries (Gupta & Guidi, 2012; Huang et al., 2000). The results of the Granger causality test, presented in Tables 4, 5, and 6, reveal interesting findings. In the overall period, it shows a one-way causality from China's Shanghai Stock Exchange to Jordan's Oman Stock Exchange, indicating the flow of causality from China to Jordan. However, there is no evidence of causality flow from the Jordanian stock market to the Chinese stock market. Furthermore, at a 5% significance level, there is a one-way causality flow from the UAE's Abu Dhabi Stock Exchange to China's Shanghai Stock Exchange. The analysis indicates no causality flow between Saudi Arabia and China, in either direction. Looking at the first sub-period (January 3, 2000, to October 18, 2009) in Table 5, there is no bilateral or unilateral causality between China and Saudi Arabia or China and Jordan. However, there is a two-way flow of information from China's Shanghai Stock Exchange to the UAE's Abu Dhabi Stock Exchange.

Table 6 summarizes the results of the Granger causality test for the second sub-period (October 19, 2009, to May 31, 2023). It does not indicate any causality flow from the sampled countries' stock markets to the Chinese market, or vice versa.

Table 4
Granger causality test results (monthly return data: May 1, 2005 to May 31, 2023)

Null Hypothesis (H0)	F-value	P-value
No Granger Causality flows from TASI to SSE	1.6844	0.1715
No Granger Causality flows from SSE to TASI	1.8555	0.1383
No Granger Causality flows from ASE to SSE	2.5523	0.0566
No Granger Causality flows from SSE to ASE	5.1021	0.0020
No Granger Causality flows from ADX to SSE	5.0081	0.0023
No Granger Causality flows from SSE to ADX	4.3268	0.0055

Table 5
Granger causality test results (monthly yield data: May 1, 2005 to October 18, 2009)

Null Hypothesis (H0)	F-value	P-value
No Granger Causality flows from TASI to SSE	0.6920	0.5618
No Granger Causality flows from SSE to TASI	0.6477	0.5885
No Granger Causality flows from ASE to SSE	1.1833	0.3270
No Granger Causality flows from SSE to ASE	2.2611	0.0946
No Granger Causality flows from ADX to SSE	3.3041	0.0288
No Granger Causality flows from SSE to ADX	3.1758	0.0333

Table 6
Granger causality test results (monthly return data: October 19, 2009 to May 31, 2023)

Null Hypothesis (H0)	F-value	P-value
No Granger Causality flows from TASI to SSE	0.7119	0.5427
No Granger Causality flows from SSE to TASI	2.3055	0.0790
No Granger Causality flows from ASE to SSE	0.537	0.6576
No Granger Causality flows from SSE to ASE	2.2905	0.0806
No Granger Causality flows from ADX to SSE	2.1432	0.0971
No Granger Causality flows from SSE to ADX	1.5165	0.2125

Tables 7 to 9 provide the results of the heterogeneity of autoregressive correlation of stock returns for the sampled countries. These tables assess the transfer of information from the Chinese stock market to the markets of Saudi Arabia, Jordan, and the United Arab Emirates. The findings suggest no information transfer or spillover from the Chinese market to the stock markets of Jordan, UAE, and especially Saudi Arabia, based on the ARCH and MGARCH results. Thus, investors in the Chinese stock market can diversify their stock portfolios in these countries' markets as they are not influenced by the Chinese market.

Table 8 represents the MGARCH model results for the first sub-period (May 1, 2005, to October 18, 2009), which occurred before the Chinese financial crisis. It shows no information transfer between the Chinese market and the investigated countries' stock markets during this period, as indicated by insignificant ARCH and MGARCH parameters. Likewise, Table 9 summarizes the model results for the second sub-period (October 19, 2009, to May 31, 2023), which occurred after the Chinese financial crisis. The ARCH and MGARCH parameters for these countries' stock markets remain insignificant, indicating no spillover effect from the Chinese stock market during this period.

Table 7
ARCH and MGARCH model parameters (monthly return data: May 1, 2005 to May 31, 2023)

Variables	Estimates	ARCH	MGARCH
TASI	Coef	11.7627	0.0057
	Sig-Value	0.0000	0.1003
ASE	Coef	1.0442	0.0049
	Sig-Value	0.3739	0.0895
ADX	Coef	4.0044	0.0032
	Sig-Value	0.0084	0.0395

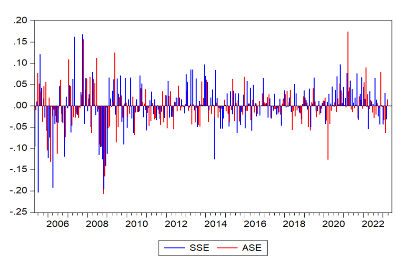
Table 8
ARCH and MGARCH model parameters (monthly return data: May 1, 2005 to October 18, 2009)

Variables	Estimates	ARCH	MGARCH
TASI	Coef	0.9800	-0.0063
	Sig-Value	0.4102	0.5013
ASE	Coef	1.1961	-0.0039
	Sig-Value	0.3215	0.7169
ADX	Coef	0.2230	-0.0152
	Sig-Value	0.8798	NA

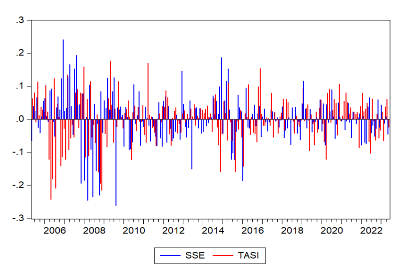
Table 9
ARCH and MGARCH model parameters (monthly return data: October 19, 2009 to May 31, 2023)

Variables	Estimates	ARCH	MGARCH
TASI	Coef	0.6080	0.0050
	Sig-Value	0.6107	0.2098
ASE	Coef	0.8098	-0.0017
	Sig-Value	0.3214	0.5494
ADX	Coef	2.3300	0.0086
	Sig-Value	0.0764	0.0073

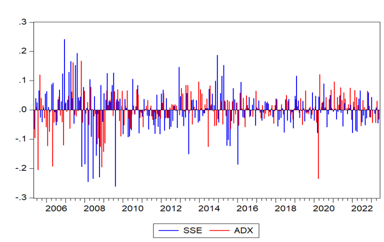
Fig. 1, Fig. 2, and Fig. 3 depict correlation charts between the Chinese stock market and the Saudi Arabian, Jordanian, and UAE markets. These figures demonstrate the correlation patterns across the general period, first sub-period, and second sub-period. The correlations range between -0.27 to 0.26 for Saudi Arabia, -0.2 to 0.16 for Jordan, and -0.27 to 0.25 for the UAE. Over time, the correlation pattern of the stock market fluctuates slightly and reverts to a long-term average.



Between China and Jordan stock market

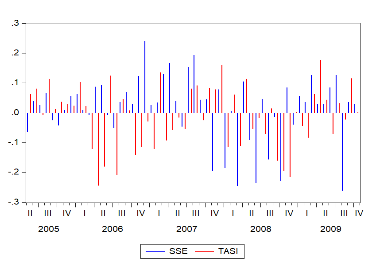


Between China and Saudi Arabia stock market

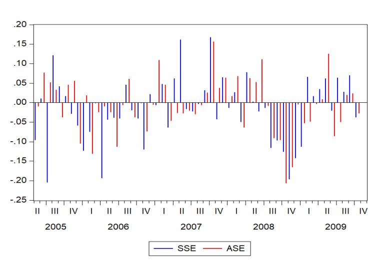


Between China and UAE stock market

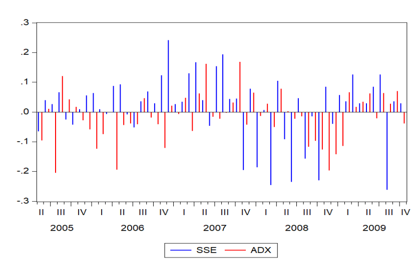
Fig. 1. Correlation between different stock markets (monthly return data: May 1, 2005 to May 31, 2023)



Between China and Jordan stock market

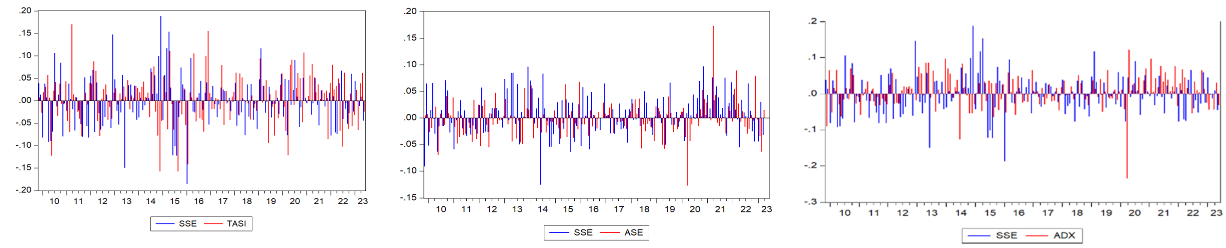


Between China and Saudi Arabia stock market



Between China and UAE stock market

Fig. 2. Correlation of stock markets (monthly return data: May 1, 2005 to October 18, 2009)



Between China and Jordan stock market | Between China and Saudi Arabia stock market | Between China and UAE stock market

Fig. 3. Correlation of stock markets (monthly return data: May 1, 2005 to May 31, 2023)

5. Conclusion

The aim of this research was to explore the spillover effect between the Chinese stock market and selected emerging economies in the Middle East region (Saudi Arabia, Jordan, and the United Arab Emirates). The study examines data from May 1, 2005, to May 31, 2023. Emerging economies, including the ones considered in this research, offer benefits to investors due to their similarities. The findings are based on empirical analysis and descriptive statistics. The research revealed a one-way causality from China's stock market (Shanghai Stock Exchange) to Jordan's stock market (Oman Stock Exchange), indicating that the causality flows from China to Jordan. However, there was no evidence of a causality flow from the Jordanian stock market to the Chinese stock market. Similarly, there is a one-way causality flow from the United Arab Emirates (Abu Dhabi Stock Exchange) to China's stock market. The analysis indicated no turbulence spillover effect between Saudi Arabia and China, and vice versa. The first sub-period (January 3, 2000, to October 18, 2009) shows no bilateral or unilateral relationship between China and Saudi Arabia and China and Jordan. However, there was a two-way flow of information from China's stock market to the UAE's stock market. In the second sub-period (October 19, 2009, to May 31, 2023), there was no causality flow from the sample countries' stock markets to the Chinese stock market, and vice versa. Thus, no two-way correlation was observed between the Chinese market and the studied countries. Moreover, the research revealed significant DCCα and DCCβ of the Chinese market and the studied countries throughout the entire period, indicating a spillover effect from the Chinese market to the stock market of these countries in the comprehensive period, both before and after the financial crisis. However, these findings did not confirm the information transfer between these financial markets. The research findings offer valuable insights for investment portfolio managers who aim to optimize returns and minimize investment risk through portfolio diversification. Volatility spillover serves as a technique to assess market integration. The research examines the opportunity to construct an investment portfolio using portfolio diversification in China, Saudi Arabia, the United Arab Emirates, and Jordan. It reveals that due to the lack of integration or information connection between the Chinese stock market, particularly Saudi Arabia, there is a significant advantage in diversifying investments in their market. This result holds true for Jordan's stock market and, to a lesser extent, the UAE's stock market. Future studies can be conducted by considering different economies in other countries and employing alternative time series models.

References

Abbas, Q., Khan, S., & Shah, S. Z. A. (2013). Volatility transmission in regional Asian stock markets. *Emerging Markets Review*, *16*, 66-77.

Abou-Zaid, A. S. (2011). Volatility spillover effects in emerging MENA stock markets. *Review of Applied Economics*.

Ahmed, S., Coulibaly, B., & Zlate, A. (2017). International financial spillovers to emerging market economies: How important are economic fundamentals? *Journal of International Money and Finance*, *76*, 133-152.

Baele, L. (2005 .(Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis*, *40*(2), 373-401.

Balli, F., Hajhoj, H. R., Basher, S. A., & Ghassan, H. B. (2015). An analysis of returns and volatility spillovers and their determinants in emerging Asian and Middle Eastern countries. *International Review of Economics & Finance*, *39*, 311-325.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., & Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review*, *11*(3), 250-260.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., & Spagnolo, N. (2013). Volatility spillovers and contagion from mature to emerging stock markets. *Review of International Economics*.

Bekaert, G. (1995). Market integration and investment barriers in emerging equity markets. *The World Bank Economic Review*, *9*(1), 75-107.

Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial economics*, *43*(1), 29-77.

Bekk, R. (1995). Cosmic consciousness. *Moscow, Odissey*.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of political Economy*, *96*(1), 116-131.

Brana, S., Djigbenou, M.-L., & Prat, S. (2012). Global excess liquidity and asset prices in emerging countries: A PVAR approach. *Emerging Markets Review*, *13*(3), 256-267.

Chang, C., & Tsay, R. S. (2010). Estimation of covariance matrix via the sparse Cholesky factor with lasso. *Journal of Statistical Planning and Inference*, *140*(12), 3858-3873.

Chkili, W. (2012). The dynamic relationship between exchange rates and stock returns in emerging countries: volatility spillover and portfolio management. *International Journal of Management Science and Engineering Management*, *7*(4), 253-262.

Delios, A., & Henisz, W. I. (2000). Japanese firms' investment strategies in emerging economies. *Academy of Management journal*, *43*(3), 305-323.

Dimitriou, D., Kenourgios, D., & Simos, T .(2013) .Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis*, *30*, 46-56.

Engle III, R. F., Ito, T., & Lin, W.-L. (1988). Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. In: National Bureau of Economic Research Cambridge, Mass., USA.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 987-1007.

Engle, R. F., Ng, V. K., & Rothschild, M. (1990). Asset pricing with a factor-ARCH covariance structure: Empirical estimates for treasury bills. *Journal of econometrics*, *45*(1-2), 213-237.

Ghousi, R.) 2015 .(Applying a decision support system for accident analysis by using data mining approach: A case study on one of the Iranian manufactures. *Journal of Industrial and Systems Engineering*, *8*(3), 59-76.

Graham, M., Kiviaho, J., & Nikkinen, J. (2012). Integration of 22 emerging stock markets: A three-dimensional analysis. *Global Finance Journal*, *23*(1), 34-47.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

Gulzar, S., Mujtaba Kayani, G., Xiaofen, H., Ayub, U., & Rafique, A. (2019). Financial cointegration and spillover effect of global financial crisis: A study of emerging Asian financial markets. *Economic research-Ekonomska istraživanja*,187-218 ,(1)32 .

Gupta, R., & Guidi, F. (2012). Cointegration relationship and time varying co-movements among Indian and Asian developed stock markets. *International Review of Financial Analysis*, *21*, 10-22.

Hoseini Ebrahimabad, S. A., Heidari, H., Jahangiri, K., & Ghaemi Asl, M. (2019). Using Bayesian Approach to Study the Time Varying Correlation among Selected Indices of Tehran Stock Exchange. *Financial Research Journal*, *21*(1), 59-78.

Huang, B.-N., Yang, C.-W., & Hu, J. W.-S. (2000). Causality and cointegration of stock markets among the United States, Japan and the South China Growth Triangle. *International Review of Financial Analysis*, *9*(3), 281-297.

Huang, Y., Su, W., & Li, X. (2010). Comparison of BEKK GARCH and DCC GARCH models: An empirical study. Advanced Data Mining and Applications: 6th International Conference, ADMA 2010, Chongqing, China, November 19-21, 2010, Proceedings, Part II 6,

Investing.com. https://www.investing.com/

Jafari, M., Shakeri, A., & Mohammadi, T. (2018). Impact of fluctuations in financial markets on oil prices and Iran's economic security. *Strategic Studies Quarterly*, *21*(80), 101-134.

Li, Y., & Giles, D. E. (2015). Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. *International Journal of Finance & Economics*, *20*(2), 155-177.

Lin, W.-L., Engle, R. F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of financial studies*, *7*(3), 507-538.

Lucey, B. M., & Zhang, Q. (2010). Does cultural distance matter in international stock market comovement? Evidence from emerging economies around the world. *Emerging Markets Review*, *11*(1), 62-78.

Majdoub, J., & Mansour, W. (2014). Islamic equity market integration and volatility spillover between emerging and US stock markets. *The North American Journal of Economics and Finance*, *29*, 452-470.

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific–Basin. *Journal of international money and finance*, *19*(2), 207-233.

Pandey, A., Singh, R., & Verma, V. (1982). Synthesis of N, N-disubstituted 3-oxo-2-phenyl-2, 3-dihydro-1, 2, 4-thiadiazoles: oxidative debenzylation and cyclization of 1, 1, 5-trisubstituted S-benzyl-2-thioisobiurets. *Synthesis*, *1982*(12), 1068-1070.

Stoian, C. (2013). Extending Dunning's Investment Development Path: The role of home country institutional determinants in explaining outward foreign direct investment. *International Business Review*, *22*(3), 615-637.

Touni, Z., Makui, A., & Mohammadi, E. (2019). A MCDM-based approach using UTA-STRAR method to discover behavioral aspects in stock selection problem. *International Journal of Industrial Engineering and Production Research*, *30*(1), 93-103.

Yadav, M. P., Sharma ,S., & Bhardwaj, I. (2023). Volatility spillover between Chinese stock market and selected emerging economies: a dynamic conditional correlation and portfolio optimization perspective. *Asia-Pacific Financial Markets*, *30*(2), 427-444.

Yin, K., Liu, Z., & Jin, X. (2020). Interindustry volatility spillover effects in China's stock market. *Physica A: Statistical Mechanics and its Applications*, *539*, 122936.