Integration, Contagion and Turmoils; Evidence from Emerging markets

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Abstract

Purpose – Based on weekly data from 2012 to 2024, this paper aims to evaluate empirically the integration and contagion properties of some emerging stock markets from North Africa including Morocco, Tunisia and Egypt, and to deepen the understanding of the linkage between them during stable and turmoil periods (Covid 19, Ukrainian war and Gazza war).

Design/methodology/approach – Besides traditional Granger causality (GC) test (Granger, 1969), the (Shi, Hurn, & Phillips, 2020)' time-varying (TV) GC test, the (Song & Taamouti, 2020)' quantiles GC test, and the (Breitung-Candelon, 2006)' frequency domain (FD) GC tests are used for the *contagion* (diversification) check between market *volatility* (returns). Then, the *returns* DCC- GARCH specifications are used for the *integration* investigations. Then, based on the *returns* DCC dynamic regressions, the *contagion* analysis between considered markets that are related to the unexpected events is done.

Findings – As the results from the standard GC, all considered tests reveal that in mean, Tunisian returns R_T and Egyptian R_E are predictable by Moroccan R_M. Only Tunisian and Egyptian return can play then the role of diversifier. Results from these causality tests detect some contagion in variance between markets, which was denied from dynamic DDC regression regressions in returns. From dynamic DCC-GARCH model, our empirical results show a weak integration between returns.

Originality/value – Via the dynamic DCC ARCH and the DCC quantile regression, the time varying GC, the quantile GC, and the spectral GC tests, this paper provides a deeper understanding of North African marginal stock market behavior and linkage.

Key words: MASI, TUNINDEX, and EGX30 indexes; Time varying (TV), quantile (Q) and frequency domain (FD) GC tests; Dynamic conditional correlation (DCC)- GARCH model; DCC quantile regression; Contagion, hedges/diversifiers, Safe Havens properties.

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1. Introduction

Portfolio diversification and risk management remain central concerns for investors, as correlations between financial assets can change over time and in response to market conditions (Isogai, 2017; Hess, 2006; Loretan & English, 2000). This variability drives market players to constantly identify and monitor the performance of hedge and safe-haven assets, whether under "normal" market conditions or during major crises (such as the Covid-19 pandemic, the Ukrainian and Gazza war declarations). Furthermore, the ongoing evolution of developed and emerging markets means that the characteristics of the assets used for risk management vary according to the context of each market. For example, some emerging markets, heavily dependent on commodity prices, remain particularly vulnerable to shocks from the global economy due to specific structural and institutional constraints (Lane & Milesi-Ferretti, 2010; Raza et al., 2016; Mühleisen, Gudmundsson & Ward, 2020).

Attention has focused on the concept of integration between stock markets, given its profound influence on portfolio diversification. To achieve favorable portfolio performance, domestic investors need to understand the relationship between international financial markets and their domestic counterparts. Growing stock market integration reduces the effect of diversification even further, forcing foreign investors to understand how North African's stock markets react to global shocks. An index is classified as diversifier if it is positively, but weakly correlated, with another index or portfolio on average. The study of stock market integration has attracted a great deal of interest over the past decade (Saleem, 2013; Chebbi & Hedhli, 2014). More recently, Nguyen et al., (2022) suggested that the increasing level of integration between developed markets has reduced portfolio diversification opportunities, prompting investors to explore emerging markets to optimize their diversification strategies. These authors thus suggest that emerging stock markets should be included as a lever to reduce the risks associated with investment portfolios.

In a multivariate framework, volatility shocks in one market can simultaneously affect the risk and return of other markets. Consequently, volatility modeling relies on the study of the dynamics of return volatilities. Some research interprets these co-movements as a reflection of market integration or interdependence, while others associate them with volatility contagion or transmission phenomena (El Ghini & Saidi, 2015; Anyikwa & Le Roux, 2020; Nguyen et al,. 2022; Bugan et al.,2022; Jana & Sahu, 2024), particularly pronounced in times of crisis such as the studies of (Anyikwa & Le Roux ,2020; Nguyen et al., 2022; Bello et al., 2022). Furthermore, investigating the degree of interdependence between stock markets around the world can help improve decision-making and provide better strategies for international investors.

In the literature, the concept of contagion is commonly used to refer to the cross-border transmission of financial crises. In this study, we present two definitions of contagion; the first definition states that contagion is a significant increase in the correlation between markets observed during periods of crisis. Whereas, the second definition which is based on Granger causality test indicate the presence of the causality-in-variance between the series to indicate the existence contagion effects (Çevik, et al., 2018).

Although portfolio diversification generally enables investors to limit the risk of major losses, periods of financial market turbulence are often characterized by increased correlation between different asset classes. This phenomenon occurs even when macroeconomic fundamentals do not justify a marked interdependence (Dornbusch et al., 2000; Forbes & Rigobon, 2002). These phenomena of contagion and increased co-movements between asset classes during periods of crisis prompt investors to seek out safe-haven assets. These assets are distinguished by their ability to preserve their value and evolve independently of other assets during such episodes.

Empirically, a safe-haven asset can be defined as one that displays zero or negative correlation with other asset classes, such as equities, in specific contexts, notably during sharp falls in stock markets (Baur & Lucey, 2009).

Historically, hedge/diversifier or safe-haven investments have taken an important strategic role in economics, investment and portfolio management. A hedge is an index that is uncorrelated (weak hedge) or negatively correlated (strong hedge) with another index or portfolio on average in times of turmoil. A hedge may not reduce losses during times of market stress or turbulence, as the index may show positive correlations with other indexes during some periods, and negative correlations during other periods, resulting in a negative correlation on average.

Interactions between global stock markets have been extensively studied for developed markets, as well as for emerging markets in Asia, the Middle East, Western Europe and Latin America. In contrast, research into the links between emerging markets in North Africa remains limited. Recently, these markets have attracted increasing attention due to their relatively rapid growth. This paper contributes to the literature by examining the integration and contagion effects and the hedging/safe-haven among the North Africa emerging markets (including Morocco, Tunisia and Egypt) during the 2012-2024 using DCC-GARCH models and DCC quantile regressions during the recent Covid-19 pandemic, the Ukrainian and Gazza war declarations. This paper fills the gap in the literature by empirically investigating the dynamic co-movements of returns of some North African emergent stock markets. The stock markets of Tunisia, Morocco and Egypt were selected for their close commercial connectivity and strategic geographical location in North Africa, which facilitate regional economic exchanges and financial flows [1].

When diversifying funds, it is important for investors and portfolio managers to examine the level of integration of stock markets, as diversifying funds from one country to another is pointless if the stock markets of those countries are integrated. Moreover, the study of contagion and safe haven assets presents a significant practical interest for investors and economic decision-makers, particularly in times of financial crisis. Understanding the dynamics of contagion makes it possible to anticipate the propagation of shocks between markets and to adopt strategies to limit potential losses. The identification of safe-haven assets, characterized by their low or negative correlation with other assets during crises, helps investors to protect their portfolios against turbulence, while effectively diversifying their investments. Such information would also be invaluable to regulators seeking to strengthen market resilience, to academic research exploring emerging market dynamics, and to professional fund managers and institutional investors in their decision-making. The practical interest of this study is to provide international investors, multinationals and portfolio managers with a better understanding of the interdependent nature of Africa North's stock markets, in order to minimize their exposure to financial risk.

The paper proceeds as follows: Section 2 discusses previous empirical studies. Section 3 clarifies the empirical methodology and models. Practically, we have two subsections: the first presents data analysis, the second presents the mean connectedness using DCC-GARCH model and DCC quantile regression. Section 4 presents the empirical investigation in two subsections. The first concerns Granger type causality test results, while the second present models estimation. Section 5 synthesizes all the results and concludes.

2. Literature review

The theory of financial integration suggests that economic integration can offer significant potential benefits, such as increasing investors' chances of portfolio diversification, as well as the potential for higher abnormal returns (Agénor, 2003; Goetzmann et al., 2005). Thus, the integration of stock markets has attracted a great deal of attention and generated a desire to answer the question of how different financial markets with different volatilities relate to each other. The modern fundamental portfolio theory of Markowitz (1952) and Grubel (1968) proposes that investors prefer to diversify into less integrated markets. On the other hand, financial contagion refers to the process by which turbulence in one market or asset spreads to other assets, resulting in increased downward correlation and amplified losses.

In the related literature to integration and contagion between stock markets, the majority of the previous studies have considered developed markets, as well as for emerging markets in Asia, the Middle East, Western Europe and Latin America. The more recent researches are

- Youssef et al. (2021) examined the relationship between stock markets during the COVID-19 pandemic for the following countries: China, France, Germany, Italy, Russia, Spain, the United Kingdom and the United States. Results find the presence of a progressive integration of the four stock markets, leading to increasing co-movements in prices, returns, volatilities and correlations.
- Uddin et al., (2022) investigated the interdependence dynamics of Asian and global financial markets touched by the coronavirus epidemic (COVID-19). Findings indicated increasing global connectivity among underlying assets driven by the COVID-19 epidemic. Furthermore, the results indicate increasing dependency between underlying assets as frequency horizons increase [2].
- Based on the DCC-EGARCH model, Nguyen et al., (2022) studied financial contagion from US, Japanese and Chinese stock markets to Asian markets during the global financial crisis and the Covid-19 pandemic crisis. They indicated that contagion impacts are not highly associated with the level of global integration, and that Asian markets tend to be more affected by contagion from Japan and China.
- Sher et al., (2024) studied the integration dynamics between the Chinese stock market and its principal developed counterparts (Australia, Germany, Japan, the UK and the USA), focusing on portfolio diversification. Based on the Granger Causality tests they showed the presence of modest integration, implying diversified portfolios for developed-country investors due to higher returns in China with acceptable risk.
- Endri et al., (2024) investigated the integration of the Indian stock market with eight major trading partner countries. They found a *weak integration* between the Indonesian stock market and those of its main trading partners over the long-term, which enables investors from the eight main trading partner countries to diversify their international investment portfolios via the Indonesian stock market, and vice versa. In the short-term, the integration is found between Indonesian stock markets along those of its main trading partners, except for China. As a result, the Chinese stock market has become more attractive to Indonesian investors seeking diversification, and vice versa.
- Eronimus & Reetika., (2024) studied the dynamics of the integration relationship between the Indian and Chinese stock markets. Based on the cointegration test and the Granger causality test, integration between these two markets is proved, implying that

diversifying investments across these markets cannot provide fruitful returns for investors in the long-term.

Besides the integration and contagion properties between stock markets, researchers are increasingly interested in the potential of various asset classes to protect against market downturns. This is particularly evident in crises, when investors seek to divest themselves of risky assets in favor of safer ones. A safe haven is as an asset that is uncorrelated to stocks and bonds during periods of stress or turbulence in the stock markets. It is offset by a hedge, described as a security that is uncorrelated on average to stocks or bonds. In this regards, we present the following papers:

- Based on unconditional quantile regression (UQR), Chang et al., (2023) examined the hedging and safe-haven ability of gold, the US dollar, bonds, crude oil and bitcoin against stocks markets. They revealed that the hedging (safe-haven) effect generally decreases (increases) with the quantiles of asset returns and indicated the presence of asymmetric contagion between equities and gold, equities and bonds, and equities and oil.
- Tarchella et al., (2024) studied the safe-haven, hedge and diversification properties of oil, gold and two crypto-currencies (bitcoin and ethereum) against equity investments in the G7 economies. In times of stress, bitcoin is found to offer the best hedge for European G7 and UK equities, Ethereum is the optimal hedge for the USA and Canada, and oil is a superior hedge for Japanese equities in all market conditions.
- Chkili (2024) analyzed the potential safe-haven assets for stock markets in the Middle East and North Africa (MENA) during the uncertainty of the COVID-19 pandemic. He showed that gold retains its traditional role as a safe haven for MENA stock markets during the pandemic, while Bitcoin is unable to provide this property.
- Ibrahim et al., (2024) examined how much volatility from the bitcoin market has contagion to traditional markets, focusing on gold and six major stock markets. They showed the presence of the long-term volatility contagion between bitcoin and gold (and bitcoin and all six stock markets), and the short-term contagion during turbulent and uncertain periods. In the short-term contagion is observed on the Chinese and Japanese markets during COVID-19 [3].
- Jana & Sahu (2024) analyzed the interconnection between crypto-currencies and the Indian stock market, and explored the diversification, hedging and safe-haven potential of the crypto-currencies. They deduced that in times of financial turbulence, Bitcoin, Ethereum and Cardano are positively correlated with the stock market. In addition, Bitcoin, Ethereum, Dogecoin and Cardano are qualified to provide diversification or hedging opportunities in normal economic situations, while only Dogecoin can act as a safe-haven asset during periods of financial stress.
- For ten of the countries most affected by the coronavirus, Bahloul et al., (2023) studied the hedging, safe-haven and diversification properties of Islamic indices, bitcoin and gold. The Islamic indices are found to be not qualified as hedging assets for the conventional market in all the studied countries during the pandemic crisis period, while gold represented a solid hedge in all countries, with the exception of Brazil and Malaysia (Bitcoin is a solid hedge for the USA and is a solid hedge and safe haven for China).
- In order to determine whether Islamic financial markets offer advantages in terms of portfolio diversification and safe havens in turbulent times, Bugan et al., (2024)

analyzed relationships between Islamic and conventional stock market returns. Based on the Causality tests in variance, they showed that Islamic markets offer limited safe havens and from time-varying conditional correlations and hedge ratios, a limited portfolio diversification benefits are offered by Islamic equity markets.

In the previous studies, no paper pay attention to North Africa emerging market except (Chkili, 2024) which considered the MENA Era. However, from the North Africa side, only three (four) papers which did consider Tunisia and/or Morocco among others (Tunisia and Morocco and Egypt) stock markets for analysis. The first three papers are the follow:

- Based on time-varying copula model to capture the dependency structure and the temporal dynamics between Tunindex and three stock market indices (American, French and Moroccan), Chebbi & Hedhli, (2014) concluded that the Tunisian and the US stock markets are the most dependent on the French market.
- Later, using the DCC-GARCH, El Ghini & Saidi, (2015) analyzed the contagion impacts of the global financial crisis between Morocco and the four principal developed stock markets (France, Germany, the United Kingdom and the United States). They indicated that the global financial crisis increase the financial links between the Moroccan stock market and the other markets under consideration and then bad news about economic partners of Morocco can generate contagion in the local stock market [4].
- Then, El Ghini & Saidi (2017) reconsidered the Moroccan stock market and its relation with the US and the three European stock markets before and during the financial crisis (GFC). Based on the bivariate model VAR-BEKK GARCH, they found a varying degree of interdependence and spillover effects between the four major stock markets and the Moroccan stock pre and post the GFC.

Few studies have focused on the three North African countries: Egypt, Morocco and Tunisia with or without additional markets (namely Ibrahim, 2009; Saleem, 2013; Anyikwa & Le Roux, 2020; Bello et al., 2022) as follow:

- Ibrahim (2009) studied the long-term relationship between the stock markets of the three North African countries (Egypt, Morocco and Tunisia). The multivariate and bivariate long-term non-linear cointegrating relationship between these markets was proved, implying that portfolios in these markets are *inefficient* (systematic risk cannot be diversified).
- Later, Saleem (2013) had analyzed the stock markets of South Africa, Nigeria and Kenya, which represent South, East and West Africa respectively, as well as the Egyptian, Moroccan and Tunisian stock markets. Attempting to determine the level of integration within these emerging markets, he indicated that the stock markets of North Africa (represented by Egypt, Morocco and Tunisia) have *common influences* in terms of both returns and volatility.
- More recently, based on the ARDL and DCC-GJR-GARCH models, Anyikwa & Le Roux (2020) examined the evidence of integration and contagion in the generation of co-movements between the African stock markets namely; Egypt, Kenya, Mauritius, Nigeria, South Africa, Tunisia and Morocco and the developed stock markets. A limited integration between stock markets was showed, while from the dynamic correlation analysis a substantial evidence of *contagion during crisis periods was proved*.

- Recently, Bello et al., (2022) investigated financial contagion in individual stock markets for 11 countries including Tunisia, Egypt and Morocco, during major crises. *No significant evidence of contagion* during the global financial crisis from a regional perspective was showed.

As can be seen, using different context, different data frequency, different period of the study, and different methodology, there is no consensus about integration and contagion properties results (see Table in Annex for more details). Also, a limited number of studies was done for the North Africa case. However, in this literature, only conventional and time varying GC tests are applied regardless the nonlinearity or the extreme max and min value of the considered process. In addition, the more considered model is the DCC-GARCH model.

In this paper, besides the quantile GC test and the frequency domain GC test and the DCC-GARCH model, we'll consider the DCC quantile and DCC regression to analyze three emerging North African markets with weekly data from 2012 to 2024 covering three major turbulent events (Covid 19 outbreak; Ukrainian war, and Gazza war).

3. Methodology

3.1 Data Analysis

This study covers a total of $k = 3$ North African stock index series (the Moroccan All Shares index (MASI), the TUNINDEX, and the Egyptian EGX30 index). The weekly data are collected from investing.com for the period from 3/18/2012 to 10/13/2024 (T= 655 observations) covering the Covid 19 outbreak period and the Ukrainian and Gazza war declarations. Figure 1 illustrates the development of the three stock index in log. We could see from the graph that there is strong similarity between them.

The data expressed in logarithms are taken in the first difference. Returns of stock indices are calculated as;

$$R_{\_it} = \log\left(\frac{SP_{\_it}}{SP_{it-1}}\right), t = 1, \dots, T = 655,$$

where

$SP_{\_it}$: stock price for Market $\mathrm{i = m, t, and\ e}$ for Morocco, Tunisia and Egypt respectively.

Table 1 Panel A presents some sample distributional statistics for the stock market returns included in this paper. Statistics consist of the weekly sample mean returns, standard deviation, minimum returns and maximum returns, and Normality Jarque-Bera (JB) test results. It presents also ARCH-LM test results. In Panel B and Panel C, correlation matrix and the (Brock, Dechert, Scheinkman, & LeBaron, 1996) independence test results (BDS test) are given respectively.

As measured by the standard deviation, market return volatility of North Africa country is highest in Egypt, followed by Morocco and Tunisia. In terms of skewness, all considered returns are skewed to the left. All series exhibit excessive kurtosis. The Jarque–Bera statistic rejects the null hypothesis of normality for all return series (see Table 1 Panel A).

The BDS test on the residuals of the regression model is performed to examine the nonlinear behavior of the process. This test is conducted on the residuals of the lag-augmented VAR (LA-VAR (2)) model regarding stock returns. Based on the results presented in Table 1 Panel C, the null hypothesis is rejected at all embedding dimensions (m), implying that nonlinear models can be appropriate to investigate the relationship between stock returns.

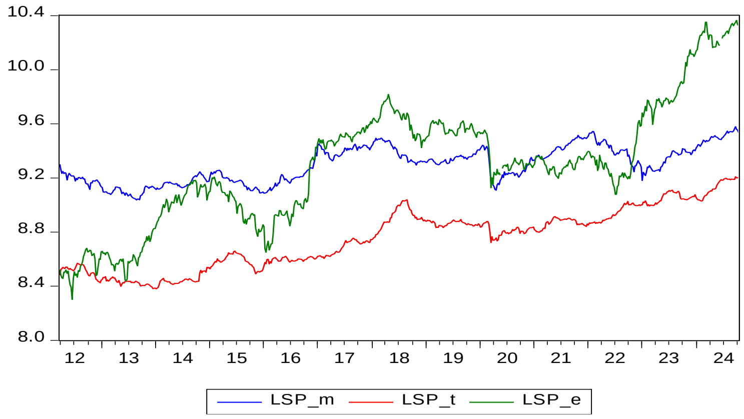


Figure 1: The movements of the stock indices in log.

Note: M, T, and E indicate respectively Morocco, Tunisia and Egypt.

Source: Author's own work

From correlation matrix in Table 1 panel B, it is clear that all returns are positively correlated that may indicating some *weak* market linkage which can offer potential gains from international portfolio diversification. More rigorous statistic investigations are needed for this dissertation. Motivated by the literature, the framework for this study will designed to account for the role of integration and contagion in generating co-movements. Dynamic conditional correlation models and GARCH models emerge as valuable tools for gaining insights into the evolving correlations over time. These frameworks are presented below. Individual volatility behavior investigation will take place in a first step.

Table 1:

Panel A: descriptive statistics

	Mean	Max	Min	Std. Dev.	J-B	ARCH-LM
R_M	0.000349	0.076737	-0.098156	0.015932	1202.772(0.00)	97.66848(0.00)
R_T	0.001107	0.062256	-0.075964	0.011648	906.5401(0.00)	87.71171(0.00)
R_E	0.002723	0.193191	-0.195579	0.034744	650.6943(0.00)	12.49559(0.00)

Panel B : Correlation matrix

Probability	R_M	R_T	R_E
R_M	1.0000		
R_T	0.148043 (0.0001)	1.0000	
R_E	0.175660(0.0000)	0.106937(0.0062)	1.000

Panel C: BDS test for nonlinearity

		Dimension				
Variables		$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$
R_M	BDS Statistic	0.014534 (0.0000)	0.028490 (0.0000)	0.036229 (0.0000)	0.039850 (0.0000)	0.040364 (0.0000)
R_T	BDS Statistic	0.022619 (0.0000)	0.039325 (0.0000)	0.049913 (0.0000)	0.057035 (0.0000)	0.058437 (0.0000)
R_E	BDS Statistic	0.014576 (0.0000)	0.024830 (0.0000)	0.028891 (0.0000)	0.029124 (0.0000)	0.029569 (0.0000)

Note: (.): p-Values are presented in the parentheses. The BDS test, named after the three authors (Brock, Dechert, Scheinkman, & LeBaron, 1996) who first developed it, is a portmanteau test for time based dependence in a series. It can be used for testing against a variety of possible deviations from independence including linear dependence, non-linear dependence, or chaos.
Source: Author's calculations

3.3. The mean connectedness Analysis

Based on the DCC-GARCH model (El Ghini & Saidi, 2017; Anyikwa & Le Roux, 2020; Uddin, et al., 2022; Nguyen, et al., 2022; Bello, et al., 2022; Tarchella, et al., 2024; Bahloul, et al., 2023; Chkili, 2024; Ibrahim, et al., 2024; Jana & Sahu, 2024) and the DCC quantile regression (Ratner & Chiu, 2013; Akhtaruzzaman & Sensoy, 2021; Bahloul, et al., 2023), several properties will be revealed as the integration, contagion, diversifier, hedge and safe haven.

3.3.1 The DCC-GARCH model and Integration

To characterize volatility and time-varying dynamic conditional correlations (DCC) between variables, this paper uses the DCC-MGARCH (1, 1) proposed by Engle (2002) and Tse and Tsui (2002). So, the following model will be considered

$$R_t = \mu_t + \sigma_t \varepsilon_t,\ \varepsilon_t \sim (0, H_t), \tag{1}$$

where

$R_t = (R_{1t}, R_{2t})'$ be a vector of returns,
$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t},)'$ is the shock or innovation vector of the series at time t,
$\mu_t = E[R_t/\Psi_{t-1}]$ is the conditional expectation of R_t given the past information Ψ_{t-1}.

This model assumed the normally distributed with a zero mean and conditional variance–covariance matrix (H_t):

$$\mathrm{H}_t = \Gamma_t \mathrm{W}_t \Gamma_t,$$

where H_t represents the conditional variance–covariance matrix, Γ_t is a 2×2 diagonal matrix, and W_t is a 2×2 conditional correlation matrix. Based on a univariate GARCH (1, 1) process, the time-varying standard deviation matrix is calculated as follows:

$$\Gamma_t = diag(h_{11,t}^{-1/2}, h_{22,t}^{-1/2})$$

$$h_{ii,t} = c_i + \alpha_i {\varepsilon^2}_{i,t-1} + \beta_i h_{ii,t-1},\ i = 1, 2,$$

where

$h_{ii,t-1}$ is the conditional variance,
α and β are non-negative scalar parameters satisfying $0 < \alpha + \beta < 1$.

As Engle (2002) proposed a dynamic correlation structure, the matrix W_t is defined by a multivariate GARCH (1, 1) process as follows:

$$\mathrm{W}_t = (1 - \alpha - \beta)\mathrm{W} + \alpha a_{t-1} {a'}_{t-1} + \beta \mathrm{W}_{t-1}$$

where

a_t is the standardized innovation vector with elements $a_{it} = \varepsilon_{it}/\sqrt{{\sigma^2}_{i,t}}$
W_t is a symmetric time-varying covariance matrix and W is an unconditional variance matrix of ε_{it}.

Then, the dynamic conditional correlation coefficient, $\rho_{ij,t}$, is defined as follows

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t} h_{jj,t}}},\ i, j = 1, 2, 3. \tag{2}$$

The parameter β in the model indicates the conditional correlation effect of the previous period on the current period conditional correlation.

3.3.2. The DCC Quantile regression

3.3.2.1. Diversifier or Hedge properties

Referring to Ratner & Chiu (2013), Akhtaruzzaman, et al. (2021), and Bahloul, et al., (2023), we consider the regression of the DCC_{ijt} on some dummy variables representing market turmoil (extreme movements) to test the presence of a significant decrease in the mean of the CC. To test if stock market i can be a diversifier/hedge and/or a safe haven against stock market j, the following regression model for extreme downward movements is considered

$$DCC_{ijt} = \theta_0 + \phi DCC_{ijt-1} + \theta_1 . D(r_j q_{10}) + \theta_2 D(r_j q_5) + \theta_3 D(r_j q_1) + u_t, \qquad (3)$$

where

- DCC_{ijt} is the pairwise CC between the stock market i and stock market j;
- $D(r_j q_p)$ is a dummy variable that represents extreme movements and is equal to one if the assets return j exceeds a certain threshold given by the lower $p = 10^{\text{th}}$, 5^{th}, and 1^{ts} percentile of the return distribution and zero if not;
- r_j is the return of the stock market j.

In line with Ratner and Chiu (2013), we use *t*-tests to verify if there is *no correlation* [5]. The test hypotheses are

$$H_{00}: \theta_0 = 0 \ (\textit{weak hedge}) \text{ vs } \begin{cases} H_{10}^{-}: \theta_0 < 0 \ (strong\ hedge) \\ H_{10}^{+}: \theta_0 > 0 \ (diversifier) \end{cases}$$

The decision rules are defined as follows:

i) we consider a stock market indexes i is a *diversifier* for the stock market j if θ_0 is *significantly positive* (not equal to 1).

ii) A stock market index i is a *weak hedge* for the stock market index j if θ_0 is *significantly* equal to zero, or a *strong hedge* if θ_0 is significantly *negative*.

3.3.2.2 The Turmoils and Contagion Effect Discussion

Contagion can be generated if the correlation between two markets is moderated during stable periods while a shock to one market leads to a surge in the market co-movement. In this paper, the definition of contagion is based on (Forbes & Rigobon, 2002 and Ratner & Chiu, 2013) expressing a significant rise in the conditional cross-market correlation during the crisis periods.

To test the alternative stock market's contagion during the crisis: COVID-19 pandemic period, Ukraine-Russia War period and Gazza-Israel war period, we estimate the following model:

$$DCC_{ij,t} = \theta_0 + \phi DCC_{ij,t-1} + \theta_1 . D_{Covid} + \theta_2 D_{Ukraine} + \theta_3 D_{Gazza} + u_t, \qquad (4)$$

where $DCC_{ij,t}$ is the pair conditional correlation between the conventional stock market indices, the dummy variables:

- D_{Covid} represents the COVID-19 pandemic crisis that is equal to one between 16 November 2019 and 5 May 2023 and zero otherwise.
- $D_{Ukraine}$ represents the Ukrainian War crisis that takes one from 24 February 2022 and zero otherwise.
- D_{Gazza} represents the Gazza war period that is equal to one from 7 October 2023 and zero otherwise.
- ρ: θ_0 is the conditional correlation in average during the stable period.
- $ρ^t: \theta_0 + \theta_1$ is the conditional correlation in average during the turmoil (high volatility) due to the Covid event.
- $ρ^t: \theta_0 + \theta_2$ is the conditional correlation in average during the turmoil due to the Ukrainian war.
- $ρ^t: \theta_0 + \theta_3$ is the conditional correlation in average during the turmoil due to the Gazza war.

In line with (Nguyen et al., 2022 and Anyikwa & Le Roux, 2020), we use *t*-tests to verify if there is a significant increase in the mean of the correlation coefficients, which implies the contagion effect. The test hypotheses are

$$H_0: \rho > ρ^t \text{ (no contagion) vs } H_1: \rho < ρ^t \text{ (contagion)},$$

or equivalently,

$$H_{0k}: \theta_k = 0 \text{ (no contagion) vs } H_{1k}: \theta_k > 0 \text{ (contagion)}, k = 1, 2, 3,$$

The alternative hypothesis H_{1k} implies a significant increase in the mean of the conditional correlation during a crisis period, meaning that contagion effect exists.

4 Empirical results

4.2 The Causality discussion based on GC type tests

Besides the standard GC test (Chang et al., 2023; Sher, et al., 2024; Endri, et al., 2024; Eronimus & Reetika, 2024), other causality tests can be applied to investigate the causal links of returns more accurately in the time domain, in the quantiles and in the target return's frequency (Yilanci & Kilci, 2021, Bugan, et al., 2022, Ozcelebi & Tevfik Izgi, 2023, and Ashena, et al., 2024). Therefore, this study uses in a second step the *time-varying* form of the causality test, which can exhibit changes in the causality relationship over time. In the third step, we consider the Quantile GC test as a nonparametric approach (Troster et al., 2018; Ahmed et al., 2022) which detect and quantify *both linear and nonlinear causal effects between variables* and locate the causality for extreme-low and -hight return. In the forth step we apply the Frequency domain (FD) GC test to see if the causality is present in short-, medium-, or long-run.
In the context of the present paper, we consider the causality-in-mean and the causality-in-variance verification.

4.2.1. Causality In-Mean and diversification

Table 2 Panel A reports the traditional GC test. The standard GC estimation results demonstrate unidirectional causality only from Morocco return to Egyptian and to Tunisian returns. The non causality between Tunisian return and Egyptian return implies the existence of long-term gains from the international *diversification* in these markets.

The results of the (Shi, et al., 2020)' *time-varying causality* tests based on the rolling window procedure are reported in Figure 2 at 5% and 10% significance levels. Both procedure give the same results. Figure 2 displays the test statistic sequences and their corresponding bootstrapped 5% and 10% critical values. A sum up of the Figure 2 results are given at Table 2 Panel B.

In a third step, the *causal relationship at different quantiles* of the conditional distribution can provide a more accurate understating of the relationship between returns as proposed by (Song & Taamouti, 2020) [6]. Figure 3 shows the causality results of the QGC tests between returns across quantiles regarding test statistics and critical values. The results are summed up at Table 2 Panel C.

Table 2: Granger causality type tests results

Panel A: The Traditional GC tests results

Null Hypothesis:	F-Statistics	Prob.	Conclusion
R_M ⇸ R_E	3.90577	(0.0206)	R_M $\rightarrow_{GC}$ R_E
R_E ⇸R_M	1.96028	(0.1417)	
R_T ⇸ R_E	0.49605	(0.6092)	
R_E ⇸ R_T	0.70161	(0.4962)	
R_T ⇸ R_M	1.11597	(0.3282)	
R_M ⇸ R_T	3.73392	(0.0244)	R_M $\rightarrow_{GC}$ R_T

Panel B: TVGC test (see Figure 2)

Conclusion: Causality only during Covid period

R_M $\rightarrow_{TVGC}$ R_T (temporarily) ; R_T $\rightarrow_{TVGC}$ R_E ; and R_M $\rightarrow_{TVGC}$ R_E

Panel C: QGC test (see Figure 3)

Conclusion:

Extra low returns: R_T $\rightarrow_{QGC}$ R_M; R_E $\leftrightarrows_{QGC}$ R_T; R_M $\rightarrow_{QGC}$ R_T

Extra hight returns: R_M $\rightarrow_{QGC}$ R_T;

Central return: R_M $\leftrightarrows_{QGC}$ R_E

Panel D: FDGC test results (see Figure 4)

Direction of Causality	**Conclusion**	**Short -term** ωi=0.05	**Medium-term** ωi=1.50	**Long -term** ωi=2.50
R_T$\rightarrow_{DFGC}$ R_M		0.1977	2.2521	2.0461
		(0.9059)	(0.3243)	(0.3595)
R_M$\rightarrow_{DFGC}$ R_T	**Yes**	**7.7524****	**11.3031*****	**9.2931*****
		(0.0207)	**(0.0035)**	**(0.0096)**
R_E $\rightarrow_{DFGC}$ R_T		0.3010	0.7951	1.4215
		(0.8603)	(0.6720)	(0.4913)
R_T$\rightarrow_{DFGC}$ R_E		1.0849	0.9343	1.1361
		(0.5813)	(0.6268)	(0.5666)
R_E$\rightarrow_{DFGC}$ R_M		1.5665	3.6853	2.4488
		(0.4569)	(0.1584)	(0.2939)
R_M $\rightarrow_{DFGC}$ R_E	**Yes**	**8.3617****	**9.9868*****	**6.8713****
		(0.0153)	**(0.0068)**	**(0.0322)**

Note: ⇸: does not Granger Cause. p-values are presented in the parentheses. In testing for standard Granger causality for two stationary variables Y_t and X_t , we consider the following model Y_t = a + $\sum_{j=1}^{p} C_j Y_{t-j} + \sum_{j=1}^{p} D_j X_{t-j} + \varepsilon_t$. X does not Granger cause Y if $D_j = 0$ for all $j = 1, \ldots, p$. The non-causality from X_t to Y_t refers to the situation that the predictions of Y_t conditional on its own history cannot be improved by incorporating the past of X_t in the model. *, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively. (.) is the p-value.

H_0: No Granger-causality from X to Y at frequency w. ($\rightarrow_{GC}$): unidirectional Granger cause. ($\rightarrow_{TVGC}$: unidirectional TVGC; ($\rightarrow_{QGC}$): unidirectional QGC; ($\leftrightarrows_{QGC}$): bidirectional QGC; ($\rightarrow_{DFGC}$): unidirectional FDGC.
Source Authors' calculations

In the fourth step, the FD GC approach is used to explore the direction of causality between returns in different frequency (short-, medium- and long-run). Table 2 Panel D shows that only R_M which Granger-cause R_T and Granger-cause R_E in all frequencies [see also figure 4 (b) and figure 4 (f)].

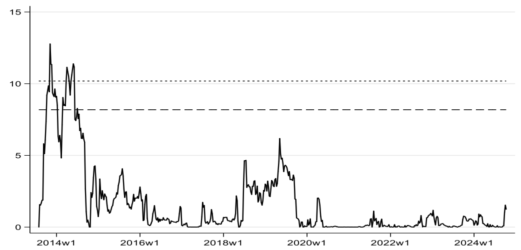
The time-varying causality test approach allows the detection of a causal relationship that prevails in sub-periods. Looking at Figure 2, it is found that the R_M is TVG caused by R_T only in 2014 and 2015, respectively. On the contrary, it can be seen that in the beginning of the Covid 19 outbreak spread (2019), R_T and R_E are temporary caused by R_M. Considering the R_T behavior, it is found that R_T has a TVG causal effect on R_E in more time during the pre and post Ukrainian war announcement.

Looking at Figure 3 (a) and (b), considering causality from R_T to R_M as well as in the opposite direction, the H_0 test of the no causality test is not rejected just in the extreme quantiles (causal independence was observed in most quantiles). This result implies that there is a bidirectional causality between R_T and R_M.

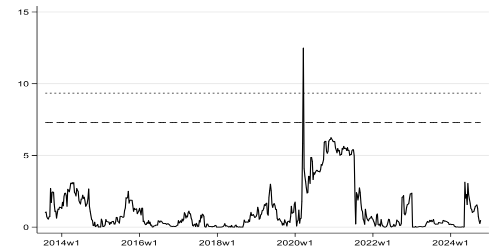
From figures 3 (c) and (d), the null hypothesis of no causality between R_E and R_M is rejected at the 5% significance level in most quantiles and a bidirectional causality is then confirmed between R_E and R_M.

The results of the no causality test from R_E to R_T indicates that R_E leads to shocks to the R_T. Moreover, the no causality test in the opposite direction is rejected across some quantiles indicating unidirectional causality from R_T to R_E (see Figure 3 (e) and (f)).

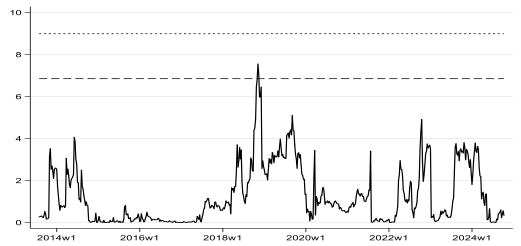
The empirical results show that the R_E (R_M) has a strong predictive power for predicting R_M (R_E) when compared to that of the predictive power of the R_T. In particular, the R_E (R_T) is able to predict the lower quantiles of the distribution of the R_T (R_E). However, R_T (R_M) predicts only the lower and upper quantiles.



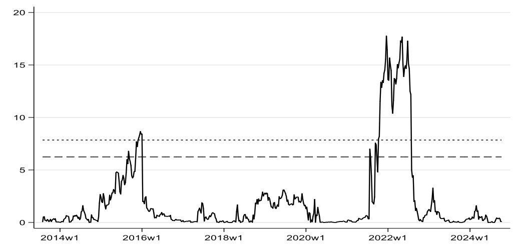
R_T →? R_M



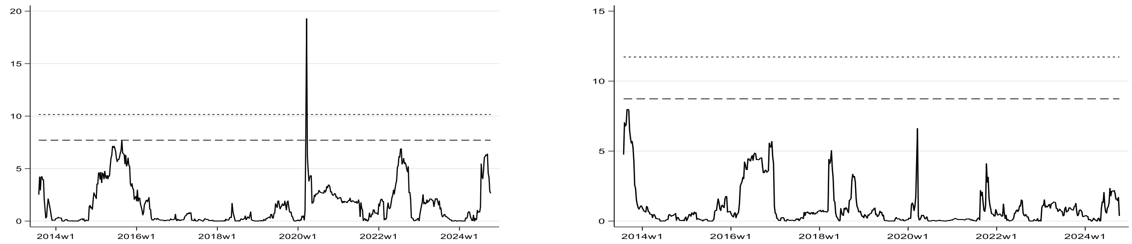
R_M →? R_T



R_E →? R_T



R_T →? R_E

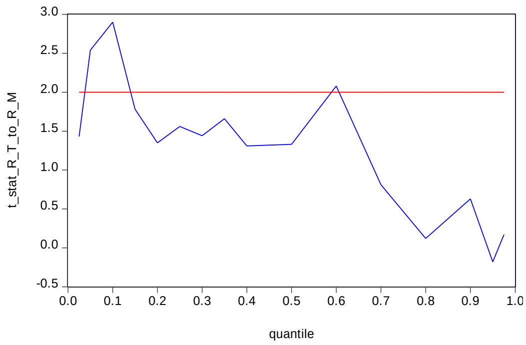


R_M →? R_E R_E →? R_M

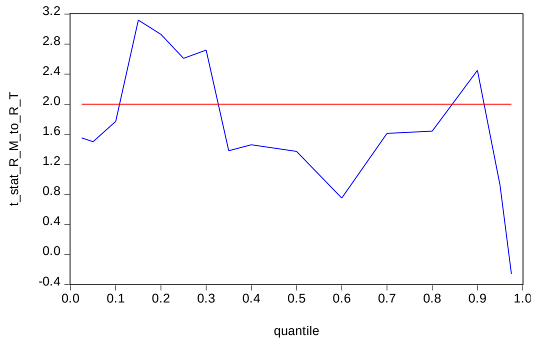
Figure 2: Results of *time varying causality* in mean based on *Rolling window* [7]

Source: Author's calculations.

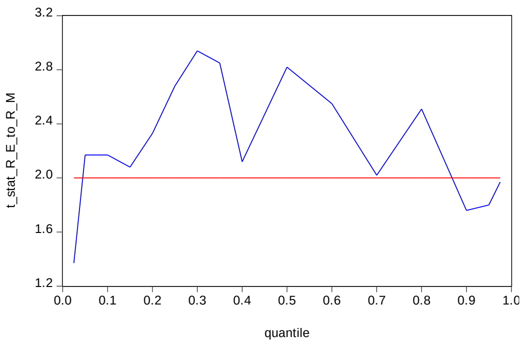
Note: lines indicated by … and ---- are respectively the bootstrapped 5% and 10% critical values. We reject the non-causality hypothesis for value above the considered line.



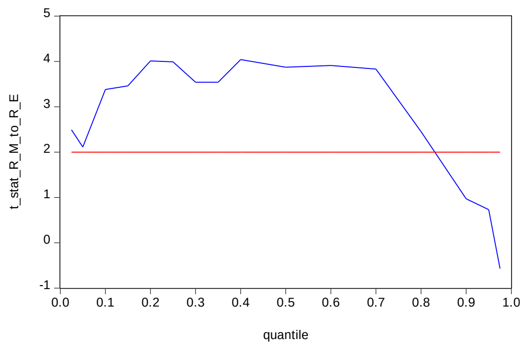
(a) R_T →? R_M



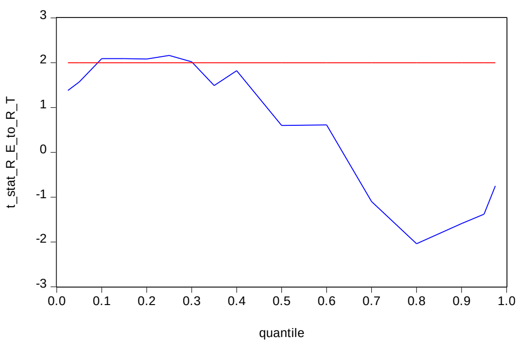
(b) R_M →? R_T



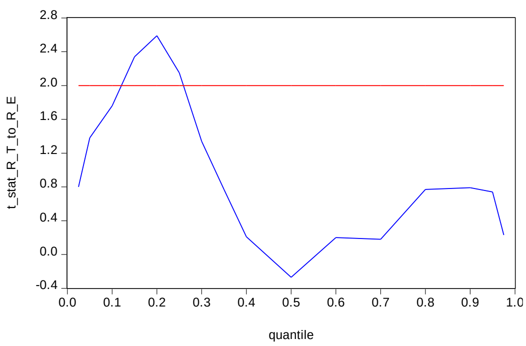
(c) R_E →? R_M



(d) R_M →? R_E



(e) R_E →? R_T

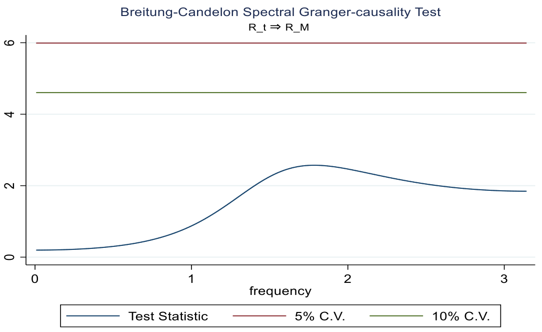


(f) R_T →? R_E

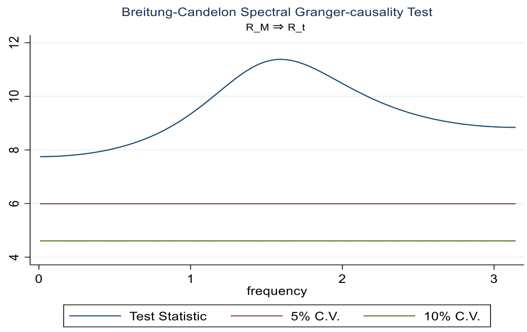
Figure 3: Results of GC *in quantile*

Source: Author's calculations

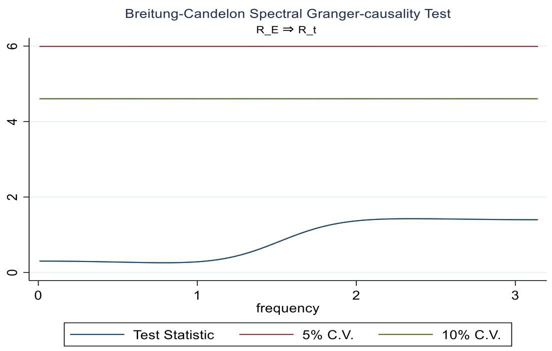
Note: for positive (negative) statistics critical value is equal to (-) 2 (red line). We reject the non-causality hypothesis for value above (below) the red line.



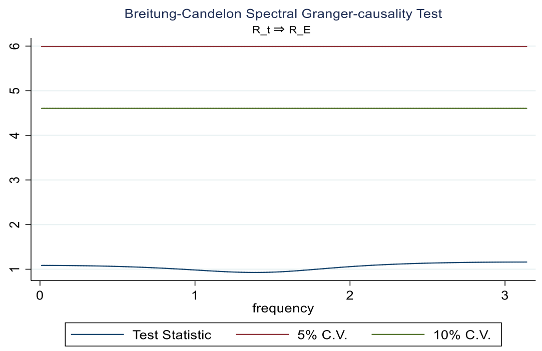
(a) R_T →? R_M



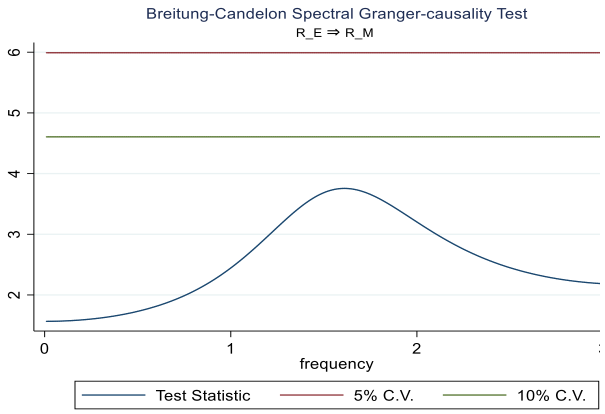
(b) R_M →? R_T



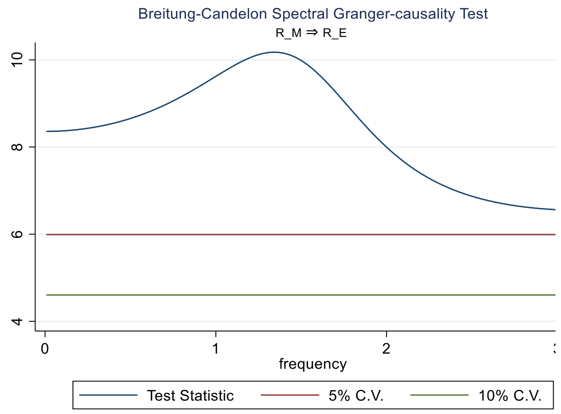
(c) R_E →? R_T



(a) R_T →? R_E



(b) R_E →? R_M



(c) R_M →? R_E

Figure 4: Frequency domain GC test results

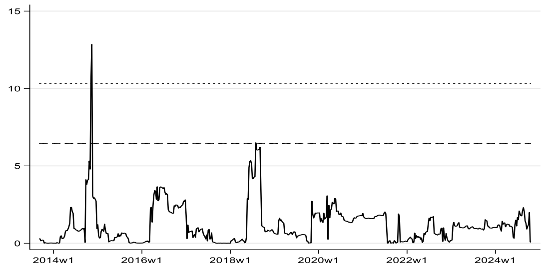
Source: Author's calculations.

Note: green and red lines are respectively the 5% and 10% critical values. We reject the non-causality hypothesis for value above the considered line.

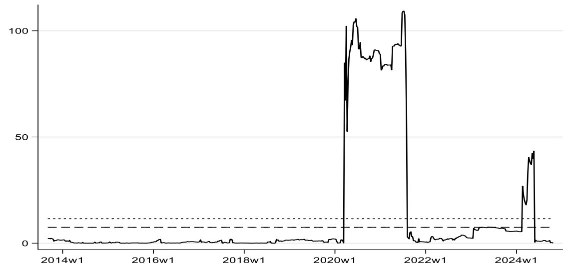
4.2.2. Causality-In-Variance and contagion

The causality-in-variance between the series indicates the existence of volatility contagion effects (Çevik, et al., 2018). The results of the causality-in-variance tests are displayed in Figure 5 for Time-varying Granger-causality (TVGC) test and Figure 6 for FDGC test.

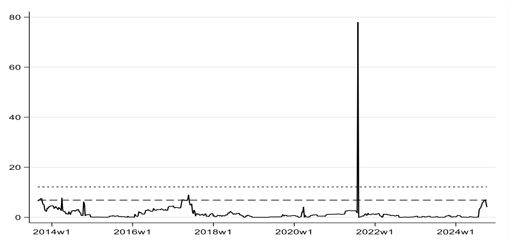
The TVGC -in-variance test results indicate evidence of causal linkages among stock market volatility that are specific only to certain time periods (Figure 5), especially during the Covid 19 outbreak from Vol_RM to Vol_RT and from Vol_RE to Vol_RM.



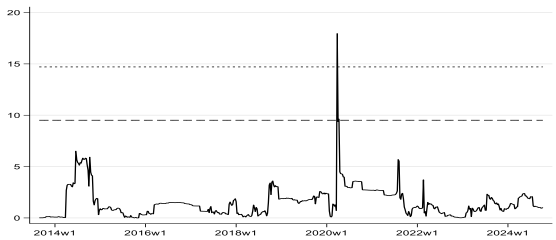
(a) Vol_RT →? Vol_RM



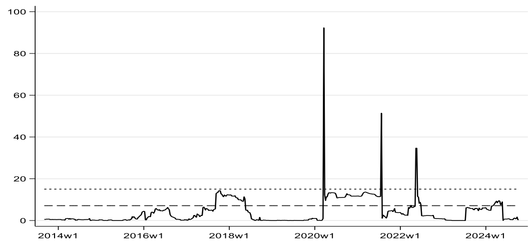
(b) Vol_RM →? Vol_RT



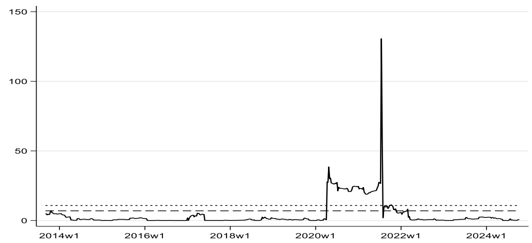
(c) Vol_RE →? Vol_RT



(d) Vol_RT →? Vol_RE



(e) Vol_RM →? Vol_RE

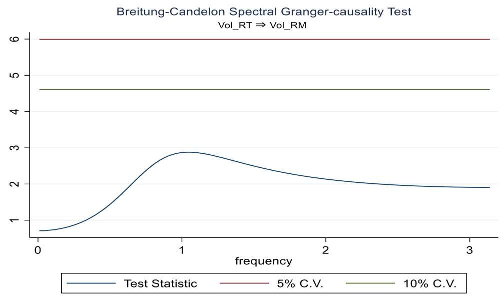


(f) Vol_RE →? Vol_RM

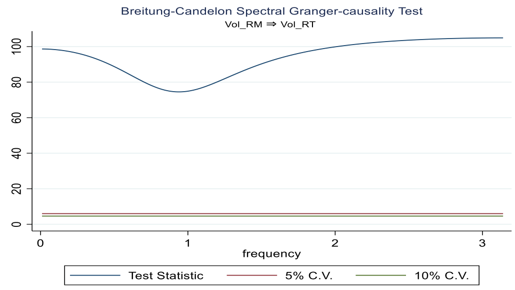
Figure 5: Results of *time varying causality* in variance based on *Rolling window*
Source: Author's calculations.

Note: lines indicated by … and ---- are respectively the bootstrapped 5% and 10% critical values. We reject the non-causality hypothesis for value above the considered line.

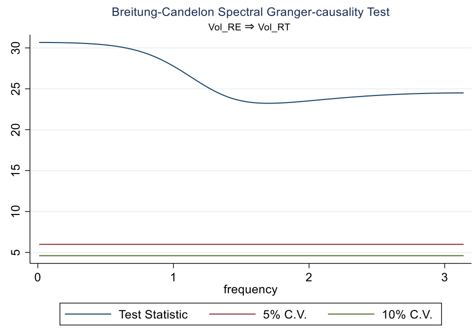
Figure 6 shows that Vol_RM unidirectional Granger-cause Vol_RT and Vol_RE [see fig (b) and (e)] in all frequencies, while bidirectional Granger-causality exist between Vol_RE and Vol_RT in all frequencies [see fig (c) and (d)].



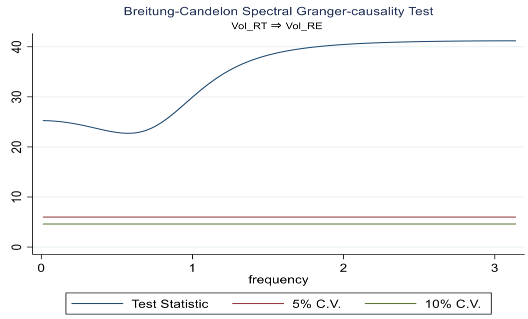
(a) Vol_RT →? Vol_RM



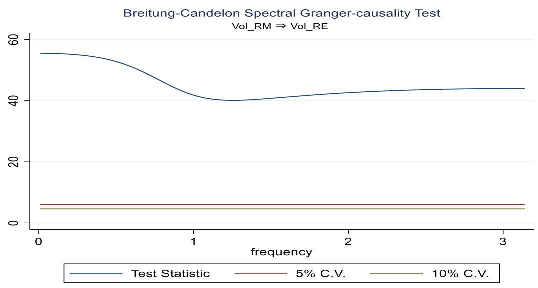
(b) Vol_RM →? Vol_RT



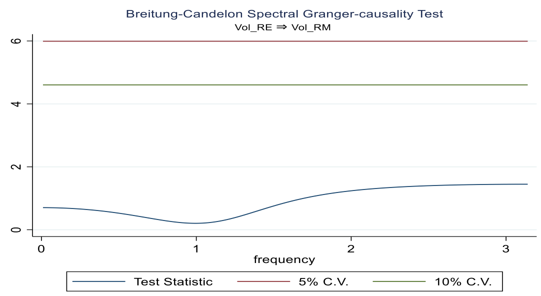
(c) Vol_RE →? Vol_RT



(d) Vol_RT → ? Vol_RE



(e) Vol_RM →? Vol_RE



(f) Vol_RE →? Vol_RM

Figure 6: Frequency domain GC test results

Source: Author's calculations.

Note: green and red lines are respectively the 5% and 10% critical values. We reject the non-causality hypothesis for value above the considered line

4.3. The DCC-GARCH and DCC Quantile model results

A GARCH model is selected for the conditional variance that is followed by calculating the conditional correlation matrix based on the conditional variance. Considering the Akaike and Schwarz–Bayesian criteria, the optimal mean and variance equations are chosen. The DCC-GARCH results are displayed in the following Table 3.

The trend of the dynamic conditional correlation (DCC) between each couple of the considered returns is presented in Figure 7 (a), (b) and (c) respectively between the R_E and R_M, between R_E and R_T, and between R_T and R_M. Clearly, dynamic conditional correlation coefficients vary considerably over time. The fluctuating range of the dynamic relationship between the R_E and R_M is between_ -0.357449 and 0.518984, between R_E and R_T is between -0.308074 and 0.573894, and between R_T and R_M is between -0.352452 and 0.576563.

Table 3: DCC-GARCH (1, 1) Results from Eq. (2)

variables	R_M	R_T	R_E	DCC_GARCH
ARCH (α)	0.15 (0.02)	0.12(0,12)	0.14(0,03)	0,06(0.03)
GARCH(β)	0.72(0,00)	0.60(0,08)	0.61(0,00)	0.33(0,23)
α+β	0.87	0.72	0.75	0.39

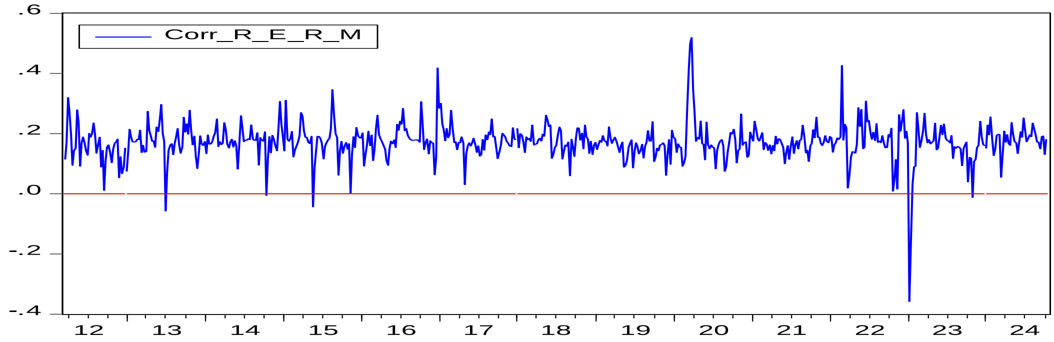
Note: (.) is the p-value.

Source: Authors' own work.

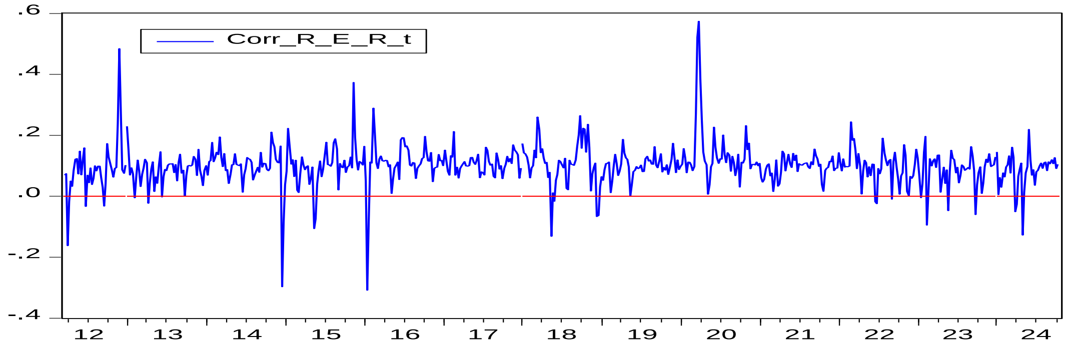
Based on these results, α and β parameters are non-negatively significant for Morocco and Egypt at 5% level (for Tunisia β, is significant at 10% level). The α + β values are not close to 1 (except for Morocco), indicating the variables' *sustainability* is not significant for considered countries.

The DCC between returns is positive with some exceptions. The relationship between returns exhibited substantial positive and negative fluctuations from the beginning until the end of the considered period. The DCC between returns demonstrate nor upward neither downward trend. However, in the end of 2019 (beginning of 2022/end of 2023), concurrent with the Covid19 outbreak crisis (Ukrainian /Gazza war declarations), the correlation between returns increased (decreased) and eventually reached its maximum value (negative value), while with the beginning of the Ukrainian war, the correlation between R_E and R_M reach its minim value.

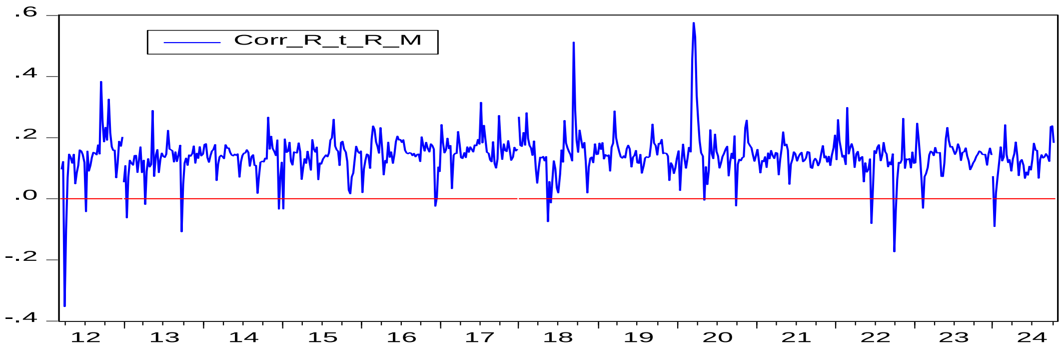
The existence of such positive correlation implies a certain degree of *integration* between returns which negatively affects the potential gains from long-term to investor in these markets [8].



(a) Between Egypt and Morocco



(b) Between Egypt and Tunisia



(c) Between Tunisia and Morocco

Figure 7: Dynamic *conditional correlation* between returns
Source: Author's calculations.

This paper calculated the time-varying conditional correlations between conventional stock indexes using the DCC-GARCH models. Although the DCC-GARCH results indicate the existence of positive relationships between stock returns, the DCC-GARCH models cannot provide a full description of the financial assets' properties as diversifiers/weak hedges, contagion, or safe havens. Then, we use Ratner & Chiu (2013) methodology to obtain a full description of financial asset classes diversification/weak hedge and safe haven or contagion properties. Table 4 presents the effect of stock market indexes during extreme financial market volatility. Table 4 (first column) shows *diversification property* for all studied stock markets index since each coefficient θ_0 is positive, far from one, and significant at 1% level [9].

Table 5 presents the *contagion* effect of the stock market indexes during turmoils (COVID-19 pandemic and Ukrainian and Gazza wars). Table 5 shows no contagion between considered stock markets.

Table 4: Estimation results for Diversifier and safe haven properties

Panel A: j: MASI

	Diversifier?	Market turmoils		
	Average of CC (θ_0)	10% quantile (θ_1)	5% quantile (θ_2)	1% quantile (θ_3)
i: Tunindex	0.0754***(0.000)	-0.0105 (0.3208)	-0.0059 (0.6991)	0.0526**(0.0346)
i: EGX30	0.0927***(0.000)	-0.0017 (0.8532)	0.0296**(0.0352)	-0.0487**(0.0317)

Panel B: j: EGX30

	Average of CC (θ_0)	10% quantile(θ_1)	5% quantile(θ_2)	1% quantile(θ_3)
i: MASI	0.0944***(0.000)	-0.0132 (0.1678)	0.0296**(0.0340)	0.0569**(0.0115)
i: Tunindex	0.0489***(0.000)	0.0068 (0.5137)	0.0108 (0.4743)	0.0626**(0.0100)

Panel C: j: Tunindex

	Average of CC (θ_0)	10% quantile(θ_1)	5% quantile(θ_2)	1% quantile(θ_3)
i: MASI	0.0741***(0.000)	0.0117 (0.2598)	-0.0186 (0.2229)	0.0629**(0.0114)
i: EGX30	0.0492***(0.000)	0.0139 (0.1767)	-0.0291**(0.0538)	0.0531**(0.0297)

Note: This table presents the estimation results from Eq. (3) for stock indices i and j. '***', '**' and '*' indicate statistical significance at the 1%. 5% and 10% levels, respectively. (.) is the p-value. Source: Authors' own work.

Table 5: t-Test results for contagion properties

Between	COVID-19	Contagion?	Ukrainian War	Contagion?	Gazza war	Contagion?
(R_E, R_M)	0.00104 (0.8393)	N	-0.0042(0.5377)	N	0.0026(0.799)	N
(R_E, R_T)	0.0090(0.1052)	N	-0.01286*(0.081)	N	0.0061(0.5737)	N
(R_T, R_M)	0.0009(0.8747)	N	-0.0087(0.247)	N	0.0013(0.907)	N

Note: This table presents the estimation results from Eq. (4). '***,' '**', and '*' indicate statistical significance at the 1%. 5% and 10% levels, respectively. (.) is the p-value. N: no significant contagion. Source: Authors' own work.

5 Conclusion

The integration and contagion properties of groups of stock returns have been the subject of extensive study by several financial economists around the world. The empirical results in the literature are mixed. Some studies conclude about integration and /or contagion while others found the opposite depending on the context (from G7, BRICS, MENA, North Africa, GCC, …), the methodology adopted (linear/nonlinear, static/dynamic model, …), the frequency of the data (daily, weekly, monthly, …) and the period of study (see Annex for more details).

This paper contributes to the literature by examining the integration and contagion properties among the North Africa emerging markets (including Morocco, Tunisia and Egypt) using weekly data from January 2012 to October 2024. Besides the conventional GC test and the DCC-GARCH model, our results are based on the TVGC, QGC and FDGC tests, on the DCC quantile regressions, and on the DCC regressions for a period covering the three major recent turmoils (the Covid-19 pandemic, the Ukrainian and the Gazza war declarations).

As the standard GC results, all considered GC type tests reveal that in mean, returns R_T for Tunisia and R_E for Egypt are predictable by R_M for Morocco. Only Tunisian and Egyptian return can play the role of diversifier. Results from these causality tests detect in variance some contagion between markets (Anyikwa & Le Roux, 2020) which is denied from dynamic DDC regression regressions in returns (Bello et al., 2022). The DCC between returns is positive with some exceptions. The existence of such positive correlation implies a certain degree of *integration* between returns (Anyikwa & Le Roux, 2020), which negatively affects the potential gains from long-term to investor in these markets. Ratner & Chiu (2013) methodology results provide the presence of *diversification property* for all studied stock market indexes.

This study is of major practical interest to investors and economic decision-makers. These emerging markets, often subject to global and regional economic shocks, offer strategic opportunities for portfolio *diversification* and risk management. Stock market integration offers certain advantages in terms of market efficiency gains, but also may entail potential risks (Yousef, 2020).

Note:

1. These characteristics make it possible to explore the dynamics of interdependence and diversification in a region where trade and financial interactions are influenced by specific geopolitical and economic factors. Moreover, their inclusion in the analysis responds to a growing interest in North Africa's emerging markets, often neglected in global economic studies.

2. Policymakers face the challenge of developing a roadmap to unravel their respective financial markets' impact of uncertainty. International market players and investors should take account of extreme market conditions in their modelling, to formulate accurate and appropriate portfolio management decisions.
3. These findings have major implications for stock market investors and policy-makers, offering evidence of the potential use of crypto-currencies for hedging, diversification or as a safe haven.
4. This growing integration is being taken into account by international investors in their trading strategy, which consists of taking a position in one market while following the signals given by the volatility of another.
5. Or if there is a significant *decrease* in the correlation coefficients. The test hypotheses are $H_{0k}: \theta_k = 0$ (*weak safe haven*) vs $H_{1k}: \theta_k < 0$ (*strong safe haven*), $k = 1, 2, 3$. The alternative hypothesis H_{1k} implies a significant *decrease* in the mean of the conditional correlation. The decision rule is: a stock market index i is a *weak/strong safe haven* for the stock markets j if θ_1, θ_2, or θ_3 are significantly zero/negative.
6. Since the unit-root test reveals that all returns are stationary, all variables are then used at the level.
7. The Rollig GC tests calculate Wald statistics from subsamples of the data with 72 observations for the minimum window size. Lag order is assumed to be constant and selected using BIC with a maximum length of 12 for the whole sample period.
8. Since market integration has a profound impact on global trade and economy, it leads to greater synchronisation in price movements, a wider range of suppliers and commodities, and improved market efficiency.
9. Tunindex works as a weak save haven for MASI and EGX30 in the 1% quantile. EGX30 index works as a strong (weak) save haven for MASI and Tunindex in the 1% and 5% (5% and 1%) quantiles. In 10% quantile, Tunindex (EGX30) can serve as a weak safe haven for EGX30 (Tunindex). In 5% and 1% quantiles, MASI works as a weak save haven for EGX30 (see Table 4).

Annex

Table A1: Sum up of the literature review

Authors	**Variables**	**Model**	**Sample**	**Results**			
				Integration	**Diversifier/ Hedge**	**Contagion**	**Safe-Haven**
Ibrahim (2009)	-Closing price indices for Tunisia, Egypt, and Morocco stock markets	Johansen and Juseilus (1990). Nonlinear cointegration test of Breitung (2001)	2006-2022 Daily data	Yes	No diversifier	-----	------
Saleem (2013)	Return indices for Nigeria, Kenya, Morocco, Egypt, Mauritius and Tunisian markets.	A bivariate GARCH-BEKK model	2004-2011	Yes	-----	-----	-------
Chebbi & Hedhli (2014)	Stock market index for Tunisia, France, America and Morocco.	GJR-GARCH (1, 1) The GARCH-EVT-Copula model	2000-2013 Daily data	Yes	-----	------	--------
El Ghini and Saidi (2015)	MASI (Morocco), NASDAQ 100 (USA), CAC 40 (France), FTSE 100 (UK), and DAX 30 (Germany)	CCC-GARCH model and DCC-GARCH.	2002-2012 Daily data	Yes	----	Yes	-----
El Ghini & Saidi (2017)	MASI, CAC, DAX, FTSE and NASDAQ	VAR-BEKK GARCH model	2002-2012 Daily data	Yes	------	------	-------
Anyikwa & Le Roux (2020)	11 stock markets: Egypte, Kenya, Mauritius , Morocco, Nigeria, South Africa, Tunisia France, Germany, UK and US	ARDL and DCC-GJR-GARCH models	January 2003 to December 2018.	Yes (limited)	------	Yes	-----

			Weekly data				
Youssef et al. (2021)	Stock index for China, France, Germany, Italy, Russia, Spain, the United Kingdom and the United States	TVP-VAR-	2015-2020 Daily data	Yes	--------	-------	---------
Uddin et al.(2022)	-The stock return for Shanghai, Korea, World, Hang Seng, NIKKEI	Time-varying Dynamic Conditional correlation (DCC)-Student-t copula method	2018-2020 Daily data	Yes	--------	-------	--------
Nguyen et al,. (2022)	US, Japanese and Chinese stock markets indices.	DCC-EGARCH model	2005-2021 Daily data	Yes	-----	Yes	------
Bello and al.,(2022)	11 stock market indices, including Côte d'Ivoi, Egypt, Ghana, Kenya, Morocco, Mauritius, Nigeria, Tunisia, Tanzania, South Africa, Zambia. United States, United Kingdom, Greece and China.	DCC-GARCH model	2005-2020 Daily data	--------	---------	No	-------
Sher et al. (2024)	-stock markets index for China, Australia, Japan, Germany, the United States, and the United Kingdom	Granger Causality Tests Based on VECM	2012-2022 Daily data	Modest	Diversifier	--------	----------
Endri et al. (2024)	Stock market index for Indonesia, China, Japan, the United States, Malaysia, India, Singapore, the Philippines, and South Korea	VAR model, multivariate Johansen cointegration, and paired Granger causality test	2013-2024 Weekly data	Weak	Diversifier	---------	-------
Eronimus & Reetika (2024)	Stock index for Indian and China	Granger causality tests and Johansen Cointegration test	2002-2021 Daily data	Yes	No Diversifier	----------	-------
Chang et al. (2023)	-BRICS stock markets indices	-Granger causality tests. -Dynamic Conditional Independence.		-----	Hedge	Yes	Yes
Tarchella et al. (2024)	G7 stock market indices (France, Germany, Italy, United States, United Kingdom, Canada, Japan) and prices for oil, gold, bitcoin and ethereum	DCC-GARCH, ADCC-GARCH et GO-GARCH,	Daily data		Hedge	-----	Yes
Bahloul et al. (2023)	-Conventional and Islamic MSCI stock indexes for nine countries: the U.S., Brazil, the U.K., Italy, Spain, Germany, France, Russia and china. -Daily closing price of the gold spot price and bitcoin price index.	DCC-GARCH and quantile regression models	2015-2020 daily	------	Hedge	Yes	Yes
Chkili (2024)	Middle East and North Africa (MENA) stock indices	DCC-GARCH	2013-2021	------	------	Yes	Yes
Ibrahim et al. (2024)	Stock indices for Japon, États-Unis, Royaume-Uni, Chine, Allemagne et France.	DCC-GARCH	2011-2022 Daily data	------	Yes hedge	Yes	Yes
Bugan et al. (2024)	-Dow Jones Islamic Stock Market Index (DJIM). -13 major emerging stock markets indices for conventional stock markets, namely: Argentina, Brazil China, the Czech Republic, India, Indonesia, South Korea, Malaysia, Mexico, Poland, Russia, South Africa, and Turkey	-Granger Causality-in-variance. -Time-varying conditional correlations	1996-2020 Daily data	Yes	Hedge	Yes	Limited
Jana & Sahu (2024)	Indian stock market indices	Time-varying correlations	2017-2022 Daily data	Yes	Hedge	Yes	Yes

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