Cointegration, Causality and International Portfolio Diversification: An Investigation of Diversification Opportunities in the MENA Markets.

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Abstract:

This paper empirically examines the stock market integration and possible diversification opportunities across the MENA and the U.S. stock markets by using a sample of monthly data from 2010 to 2020. The paper investigates stock market interdependence from two perspectives which are 'long-term' and 'short-term'. For long for long-run interdependence, the cointegration approaches of Johansen (1988) and Gregory and Hansen (1996) were used. Regarding the short-run interdependence, the Granger causality test proposed by Granger (1969) has been employed.

Results under both cointegration approaches indicate no evidence of long-run relationships between the MENA and the U.S. stock markets, except for the stock market of Jordan, which suggests potential benefits from investments in the MENA markets for U.S. investors. On the other hand, only Bahrain and the UAE stock markets are cointegrated within the MENA markets, indicating substantial benefits for investors wishing to diversify across the MENA markets. The Granger causality test provides evidence of no short-run relationships between the MENA stock markets and the U.S. stock market; therefore, variations in the U.S. stock index are not transmitted to the MENA stock indices and vice versa. Alternatively, Granger causality tests reveal strong evidence of short-run causal linkages among MENA stock markets. Results show unidirectional Granger causality running from the stock market of Morocco to Egypt and Jordan stock markets. Additionally, unidirectional causality was detected from Egypt and Qatar's stock markets to Bahrain and Oman stock markets, respectively.

Key Words*: Cointegration, Causality, MENA, U.S, Stock Markets.*

1. Introduction:

International stock markets have experienced a large wave of radical changes in recent decades. Stock markets worldwide have become more integrated than ever; the rise in integration between financial markets worldwide has resulted in a high degree of interdependence, fuelled by advancements in information technology and the removal of foreign ownership restrictions. The recent financial crisis has demonstrated the high degree of interdependence that international stock markets persist, resulting in a worldwide financial market collapse.

Since portfolio diversification crucially depends on the degree of interdependence between asset returns and given the current environment of cross-interrelation between stock markets, information and price movements are transmitted instantly from one market to another, reaping the benefits of portfolio diversification is questionable. This raise concerns not only for researchers but also for investors. The main concern is whether the strong market linkages are only a short-run phenomenon or a long-run equilibrium relationship between stock markets. The presence of a long-run relationship between stock markets would imply a strong form of predictability among stock markets, known as cointegration. The existence of cointegration between stock markets would enable both researchers and investors to use information in one market to predict the long-run performance of another stock market in the long run.

The existence of cointegration is an important issue and has many implications in both theoretical finance and portfolio management. With regard to theoretical finance, the existence of cointegration between stock markets would imply that stock returns are predictable, which is prohibited under the efficient market hypothesis (EMH) since all of its three forms argue that stock returns are unpredictable. Thus, the existence of cointegration between stock markets clearly violates the EMH, allowing us to predict the future value of one market using information obtained from another market.

Similarly, the presence of stock markets cointegration has consequences for international investors. Since the main objective of portfolio diversification is to hedge against risks by investing in traded assets in different stock markets, which allows investors to inject different stocks into their portfolio given that there are not perfectly correlated, however, when stock markets share a long-run equilibrium relationship, then the benefits of international diversification will be limited. Therefore, the presence of a common stochastic trend between stock markets will result in returns that are similar in the long-run, meaning that there are no long term benefits from international diversification; hence a loss in one market would not be offset by a gain in another market (Kasa, 1992).

This paper aims to examine primarily whether stock markets in the Middle East and North Africa (MENA) region would still offer possible diversification opportunities for investors in the United States (U.S.) by investigating the cointegration relationship between the U.S. and the MENA region using the cointegration framework. However, we also investigate whether stock markets in the MENA region are cointegrated regionally. The paper expands on previous studies by Hassan (2003), Al-Khazali *et al*. (2006) and Elfakhani *et al*. (2008) in several ways. First, we use a longer and recent data sample, which allows us to consider recent developments in the MENA region. Secondly, as well as using the standard Augmented Dickey-Fuller (ADF) tests for unit root, we enhance our analysis by employing the unit root tests developed by Elliott *et al*. (1996) and Zivot and Andrews (1992). Thirdly, in addition to applying the Johansen approach of cointegration, we add to the analysis using the cointegration methodology of Gregory and Hansen (1996). Fourthly, Granger causality test has been employed to examine the short-run relations between the stock markets of the MENA regionally and with the U.S. stock market.

The paper is organised as follows; section two review previous literature related to cointegration of stock markets. In section three, we give a description of the data used in our study. Subsequently, a review of the econometrics techniques used is presented in section four. Section five provides a detailed analysis of the empirical results. Concluding remarks and suggestions for further research are presented in section six.

2. Literature Review:

Over four decades now since the introduction of the cointegration concept by Granger (1981) and Granger and Weiss (1983). They identify cointegration as a statistical property of long-run dependent time series. However, it was not until the pioneering work by Engle and Granger (1987) which enabled researchers to test for the presence of cointegration in financial time series. Engle and Granger (1987) extended the theory of cointegration and presented a two-step procedure for testing cointegration among time series. The further methodologyical framework was introduced by Johansen (1988), Johansen and Juselius (1990), which allowed to test for the presence of more than one cointegrating vector based on the vector autoregressive (VAR) framework.

These essential developments allowed for a substantial amount of papers to be produced by researchers examining the cointegration relationships between various economic variables. For example, Kasa (1992) tests for cointegration between stock markets in developed countries from 1974 to 1990 using a long VAR specification finds a strong rejection of the null hypothesis of no cointegration in the Johansen system and argues that stock indices in Japan, the U.S., the U.K., Germany and Canada are cointegrated around a single common stochastic trend. Following the same route, Corhay *et al*. (1993) investigate the hypothesis of cointegration between five European stock markets using both procedures of Engle and Granger (1987), and Johansen (1988) provide evidence of a long-run equilibrium relationship. Furthermore, Choudhry (1997) finds a significant long-run equilibrium relationship between the U.S. stock market and six Latin American stock markets using the Johansen (1988) methodology and data from 1989 to 1993. A study by Blackman *et al*. (1994) investigated the long-run relationship before and after the global financial developments in the 1980s find that there are more cointegrating vectors between the 16 OECD equity markets after but not before the 1980s. They further argue that these developments have resulted in stock markets worldwide becoming homogeneous, resulting in limited diversification opportunities. Contrary to previous findings, Masih and Masih (2002) provide stock market interdependencies between six primary international stock markets using the Johansen (1988) method during the pre and post globalisation era.

Proponents of integration between international stock markets tend to argue that cointegration and diminishing diversification opportunities between global stock markets can be attributed to globalisation, which has triggered changes in the global economic environment. These changes include the rise in capital flow across national borders due to the relaxation of controls on the financial market transactions and advancements in the transmission of information, and the reduction in transaction costs (Taylor and Tonks,1989), (Masih and Masih, 2002).

However, these arguments and findings are, without a doubt, challenged. For instance, Stengos and Panas (1992), following the methodology suggested by Engle and Granger (1987) and data sample spanning from 1985 to 1988, present no cointegration between various stocks listed in the Athens stock exchange. Kanas (1998) re-examines the claims that the U.S. stock market and European stock markets share a long-run equilibrium relationship and shows that these markets are not cointegrated, indicating risk reduction benefits of diversification. Concerning the Latin American stock markets, Tabak and Lima (2003) showed evidence of short-run but no long-run relationship between the U.S. stock market and the seven Latin American stock markets based on a sample of daily prices 1995 to 2001. A richer comprehensive analysis was presented by Richards (1995). He argues that previous findings of cointegration suffer from statistical biases; these biases tend to suggest cointegration when, in reality, there may be none. In particular, Richards (1995) focuses and examines the previous empirical work by Kasa (1992) and finds that the failure of taking into account the small sample critical values lead to rejection of the null hypothesis of no cointegration relationship; moreover, Richards (1995) finds that cointegration results are sensitive to the length of lags used in the VAR and that Kasa's long lag structure is inappropriate to remove nonnormality. By adjusting the critical values to account for small sample properties and employing the appropriate number of lags, Richards (1995) finds that cointegration no longer exists between the 16 international stock markets based on data sample from 1969 to 1994.

Regarding the MENA region, the investigation into the cointegration relationship between stock markets has only been recent. One of the main conclusions usually drawn from the analysis of the MENA integration with global stock markets is that the MENA has a low correlation with foreign markets and is more segmented, which provides investors with diversification opportunities (Girard *et al*. 2003). Darrat *et al*. (2000), by employing the Johansen framework to investigate the cointegration relationship between MENA stock markets, confirms the existence of a high degree of integration between Jordan, Egypt, and Morocco stock markets data sample from 1996 to 1999. Alternatively, Hassan (2003) uses weekly data from 1994 to 2001. Also, he uses Granger causality test and Johansen procedure to examine the short and long-run relationship between stock markets of three countries who are members of the Gulf Cooperation Council (GCC), namely Bahrain, Kuwait and Oman. He finds evidence of cointegration only between Bahrain and Kuwait's stock markets, indicating that investors in Bahrain can benefit from the information in the Kuwaiti stock market to predict the long-run performance of the Bahraini stock market and vice versa. Concentrating only on stock markets in the GCC region, Assaf (2003) provides strong evidence of interdependence and causality among the GCC stock markets using weekly prices from 1997 to 2000. He further shows that these markets are not entirely efficient due to the slow response to regional news.

Additionally, Al-Khazali *et al*. (2006) show evidence of cointegration based on the Johansen framework between most of the GCC stock markets of Saudi Arabia, Kuwait, Bahrain and Oman from 1994 to 2003, in particular, they find that the economic liberalisation in 1997 to unify the stock markets in the Gulf region has strengthened the degree of integration between the four countries as compared to the pre-liberalisation period. Hammoudeh and Choi (2004), by using weekly prices data from 1994 to 2001, show that most of the GCC region's stock returns tend to move in the same direction and are influenced by the same mutual factors as political stability or oil prices. To investigate the long-run relationship between stock markets of the MENA and the U.S., Lagoarde-Segot and Lucey (2007) use combinations of alternative cointegration methodologies and daily prices from 1998 to 2004, show significant evidence of stock markets integration among the MENA but fail to reject the hypothesis of no cointegration between the stock markets of the MENA and the U.S. However, these findings were challenged by Elfakhani *et al*. (2008) where they examine the integration of ten MENA stock markets with each other and with the U.S. stock market using monthly data from 1997 to 2002 and the Johansen methodology. They report that only three countries stock markets of the MENA, namely Jordan, Kuwait and Morocco, are cointegrated with the U.S. stock market. However, they find weak evidence in support of the hypothesis of integration within the MENA region. By focusing only on short-run linkages, Genc *et al*. (2010) examine the short-run relationships between the GCC stock markets and the U.S. stock market through applying Granger causality test, find significant causality between stock markets of the U.S., Saudi Arabia and the UAE;

mainly, they find unidirectional causality stemming from the U.S. stock market to both Saudi and Emirati stock markets.

Recent evidence regarding the financial integration between the MENA stock markets and the U.S. stock market was provided by Paskelian *et al*. (2013), where they show that both of these markets are not yet cointegrated; however, they find strong bidirectional causality exists between several MENA stock markets, but no causality was detected between the U.S. stock market and the MENA stock markets. Assaf (2016) examines the financial integration before and after the global financial crisis of 2008 between stock markets of the MENA and the U.S. and shows that the low integration of the MENA with foreign stock markets has minimised the downturn on MENA's stock markets as compared to more integrated stock markets. Furthermore, Almohamad *et al*. (2018) examine both short and long-run relationship between the MENA, Chinese, the U.S. and the U.K. stock markets. They use weekly stock prices and considered two sub-periods of pre and post the global financial crisis of 2008; and concluded that integration between those stock markets had risen significantly in the post-crisis compared to the pre-crisis period. Moreover, the authors show strong evidence of short-run causality among stock markets in the post-crisis period. This implies that the relationship between MENA stock markets and foreign stock markets has deteriorated significantly after the global financial crisis; based on these results, we can conclude that diversification opportunities in the MENA markets are no longer available.

In summary, all the previous literature regarding the MENA stock markets integration has ignored crucial issues that arise in testing for a meaningful long-run relationship among stock markets. The first issue is about the unit root testing procedure; the Augmented Dickey-Fuller (ADF) test suffers biases such as poor size and power properties. These biases tend to lead to the wrong conclusion regarding the data generating process (DGP) (Stock,1994). Moreover, given that most of the countries in the MENA region are major oil-exporting countries and are affected by common factors, the shocks in oil prices tend to influence the stock markets of the producing countries (Degiannakis *et al*. 2017). These shocks tend to create structural breaks in the DGP, which is not considered under the conventional ADF. When structural breaks occur in the DGP, statistical inferences based on the ADF are biased towards the non-rejection of the null hypothesis (Perron, 1989).

The second issue is regarding testing for cointegration in the presence of structural breaks. It is well known that the cointegration relationship is subject to structural breaks. The Johansen methodology does not allow for a structural break in the cointegration relationship, the apparent findings by previous literature in the MENA regarding the financial integration are questionable. In particular, Elfakhani *et al.* (2008) found that only some of the MENA stock markets are cointegrated with the U.S. stock market using data from 1997 to 2002. However, given the oil crisis in early 1998, which has led to significant price falls for oil-exporting countries, such a crisis can lead to shocks that create a structural break in the cointegration relationship. This may explain the failure to detect more cointegrating relationships by Elfakhani *et al*. (2008) since the authors' Johansen methodology does not allow for structural breaks in testing for long-run relationship.

The effect of structural breaks on cointegration test results is well documented. For example, Davies (2006), who uses the two-regime Markov model, which incorporates structural breaks to test for cointegration relationship between mature stock markets similar to those used by Kasa (1992) and Richards (1995), finds significant evidence of a long-run relationship between stock markets. This explains Richards (1995) failure to detect cointegration since he does not consider the possibility of structural breaks when testing for cointegration. Additionally, Khan (2011) examines the long-run relationship between the U.S. and 22 developed and developing stock markets using the framework of Johansen (1988) and Gregory and Hansen (1996). The author finds that while the

Johansen methodology detects no cointegration, the Gregory and Hansen test reveals strong cointegration between most stock markets.

Therefore, this paper aims to fill the gaps in the literature of cointegration among the stock markets of the MENA and the U.S. by using the latest data and robust methodologies; we aim to provide consistent results that allow for both researchers and investors to draw reliable conclusions concerning the integrity of the MENA region with the U.S. stock markets.

3. Data:

In this paper, we use stock price indices data of ten stock markets from the MENA region and the United States (U.S.) stock market; the ten stock indices from the MENA repressent Bahrain, Egypt, Jordan, Kingdom of Saudi Arabia (KSA), Lebanon, Morocco, Oman, Qatar, Tunisia and the United Arab Emirates (UAE). The data on the 11 indices were collected from Refinitiv Eikon Data Stream, where each of these indices represents the country's benchmark and are summarised in Table 1.

Table 1: Data Summary

Stock Market	Index Name	Datastream Code
Bahrain	Bahrain All Share Index	BASI
Egypt	Egyptian Exchange Price Index	EGX30
Jordan	Amman Stock Exchange All Share Index	.AMMAN
KSA	Tadawul All Share Index	TASI
Lebanon	Lebanon BLOM Stock Index	BLSI
Morocco	Moroccan All Shares Index	MASI
Oman	Muscat Stock Exchange General Index	MSI
Qatar	Qatar Stock Exchange General Index	QSI
Tunisia	Tunis Stock Exchange Index	Tunindex
U.S.	Standard and Poor's 500 Index	SPX
UAE	Abu Dhabi Securities Exchange General Index	.ADI

The data sample of the stock price indices has been collected monthly from January 2010 to January 2020 to provide a more robust analysis since using daily, and weekly data is likely to suffer from heteroscedastic and serially correlated residuals. Therefore, sampling at a monthly frequency eliminates these issues, which affects cointegration analysis. However, one main issue we encountered during the data collection was the different end-month dates between countries. To uniformise dates, we first collect daily data of each country's stock index price, and when a missing day value is found, we use the previous day closing price. Moreover, we set the S&P 500 index dates as the reference date for all other stock market indices. After that, we aggregate the daily data to monthly averages. Thus, using this technique allows us to harmonise the time series data across the 11 stock markets.

The natural logarithm is applied to transform each stock price index in order to smooth the data. Then, the first difference of natural logarithm of the 11 indices is used to obtain the monthly returns, calculated as follows:

$$R_{it} = ln\left(\frac{P_{it}}{P_{it-1}}\right) \quad (1)$$

Where R_{it} is the return of market i on date t and P_{it} is the closing price of market i on date t.

The statistical properties of each stock market return, including the mean, median, standard deviation, skewness, kurtosis, and the Jarque-Bera test of normality, are presented in Table 2. Lastly, a correlation matrix between the 11 stock markets monthly returns are presented in Table 3.

Table 2: Descriptive Statistics for Monthly Stock Index Returns

Stock Market	Mean(%)	Median(%)	Std.Dev(%)	Skewness	Kurtosis	Jarque-Bera
Bahrain	0.088	-0.256	2.417	-0.076	3.879	5.978
Egypt	-0.281	-0.271	6.633	-0.790	6.875	30.542**
Jordan	-0.370	-0.444	2.262	0.119	3.043	0.583
KSA	0.234	0.766	4.341	-0.534	4.840	13.203**
Lebanon	-0.629	-0.546	1.914	-0.179	3.274	1.635
Morocco	-0.047	-0.436	2.980	0.614	3.998	7.671**
Oman	-0.399	0.080	2.988	-0.811	4.473	11.796**
Qatar	0.360	0.675	4.018	-0.388	3.086	3.211
Tunisia	-0.269	-0.279	3.007	-0.047	3.489	2.705
U.S.	0.892	1.393	2.769	-1.162	5.364	23.046**
UAE	0.539	0.242	3.281	0.106	3.563	3.264

Notes: ** indicate significance at the 5% level

The results in Table 2 suggest that the U.S. market, on average, offers the highest mean return during the sample period, followed by the Emirati market. At the same time, the highest median returns are offered by the U.S. and the Saudi markets. However, in terms of riskiness, the Egyptian market has the highest risk approximated by the standard deviation (6.63%). In comparison, the Lebanese market exhibits the lowest risk as it has the lowest standard deviation (1.91%). Regarding the skewness(1) of monthly market returns, all stock indices display negative skewness. The U.S market has the highest negative skewness, and the Tunisian market has the lowest; however, only the Jordanian, Moroccan and Emirati markets have positive skewness. Negative skewness means that there is a high probability of negative gains than positive ones.

In contrast, positive skewness means a higher probability of achieving positive gains than negative gains. This means, for instance, that investors would obtain positive returns from the Jordanian, Moroccan and Emirati markets compared to other markets in the sample. Regarding kurtosis(2) measure, all the markets tend to have a kurtosis larger than 3, which means that the distribution in these markets is leptokurtic.

This suggests that the returns in these markets have less extreme outcome compared to normal distribution. The Jarque-Bera test for normality shows that we can reject the null hypothesis of normality at a 5% significance level for indices returns of Egypt, KSA, Morocco, Oman and the U.S.; this indicates that monthly returns in these markets demonstrate non-normal error terms.

Table 3: Correlation Matrix of the Monthly Stock Index Returns

Stock Market	Bahrain	Egypt	Jordan	KSA	Lebanon	Morocco	Oman	Qatar	Tunisia	UAE	U.S.
Bahrain	1										
Egypt	0.226	1									
Jordan	0.350	0.254	1								
KSA	0.357	0.213	0.291	1							
Lebanon	0.217	0.158	0.439	0.277	1						
Morocco	0.185	0.279	0.245	0.212	0.148	1					
Oman	0.291	0.237	0.248	0.453	0.154	0.221	1				
Qatar	0.370	0.307	0.231	0.473	0.111	0.168	0.478	1			
Tunisia	0.128	0.193	0.177	0.129	-0.043	0.139	-0.060	0.090	1		
UAE	0.468	0.348	0.284	0.518	0.179	0.211	0.505	0.625	0.138	1	
U.S.	0.316	0.327	0.263	0.478	0.231	0.173	0.358	0.375	-0.030	0.375	1

Table 3 reports the correlate-ion matrix between the 11 stock markets returns during the sample period. Concentrating on the correlation between the U.S. and MENA markets shows that the Saudi and the U.S. market display the highest positive correlation (0.48). In contrast, the Tunisian market has the lowest correlation (-0.03) with the U.S. market compared with other MENA countries. Within the MENA markets, correlation is the highest between UAE and Qatar, whereas Tunisia and Oman have the lowest correlation. Moreover, GCC countries display higher monthly returns correlation regionally than markets in Northern Africa and the Levant region. The negative correlation between Tunisia and the U.S. and between Tunisia and Lebanon, Tunisia and Oman illustrate the benefit of short-term diversification between these markets. For instance, a portfolio that includes stocks from Tunisia and the U.S. will have lower variance, which reduces the risk faced by international investors.

4. Empirical Methodology:

Our methodology is divided into four main parts: Firstly, we test the unit root hypothesis for stationarity using the Augmented Dickey-Fuller (ADF) test, DF-GLS test and Zivot and

Andrews test. Secondly, we employ the Johansen Approach (J.A.) test and Gregory and Hansen test to examine the co-integration among market indices under consideration. Thirdly, we employ Granger Causality test to scrutinise the direction of causal relationships (if any) among stock indices.

a) Unit Root Tests:

We initially perform the Augmented Dickey-Fuller (ADF) unit root test to examine the data's rime series properties without accounting for any structural breaks. The ADF conducted using the following equations:

$$\Delta y_t = \mu + \phi y_{t-1} + \sum_{i=1}^{k} \psi_i \, \Delta y_{t-i} + \varepsilon_t \quad (2)$$

$$\Delta y_t = \mu + \beta t + \phi y_{t-1} + \sum_{i=1}^{k} \psi_i \, \Delta y_{t-i} + \varepsilon_t \quad (3)$$

Where y_t denotes being tested, Δ is the first different operator, t is a time trend term, k denotes the optimal lag length and $\varepsilon_t$is a white noise disturbance term. In this paper, the lowest value of the Akaike Information Criteria (AIC) has been used as a guide to determine the optimal number of lags in the ADF regression. The maximum number of lags has been set, according to Schwert (1989).

The DF-GLS unit root test has been used since the ADF test tends to suffer from low power; thus, the test fails to reject a false null hypothesis of a unit root (Byrne and Perman, 2007). The DF-GLS test is constructed into two steps. Suppose we want to test for the presence of unit root in the series y_t, the first step in constructing the DF-GLS is to remove the deterministic terms from the series y_t using the GLS as follows:

$$\tilde{y}_t =. \beta_{GLS}' \, V_t + \varepsilon_t. \quad (4)$$

$$y_t^d =. y_t - \hat{\beta}_{GLS}' \, V_t. \quad (5)$$

Where V_t represents a vector of deterministic components (intercept, trend).

The estimated parameters in regression (4) are then used to remove the deterministic terms; this procedure is referred to as GLS detrending (Zivot and Wang, 2006). The final step involves using the detrended series y_t^d, to estimate the ADF test obtained from the following regression, which omits deterministic terms :

$$\Delta y_t^d = \phi y_{t-1}^d + \sum_{i=1}^{k} \psi_i \Delta y_{t-i}^d + \varepsilon_t \quad (6)$$

Then, we compute the hypotheses testing, where the null hypothesis of ($\phi = 0$) is tested against the alternative of ($\phi < 0$). Under the null hypothesis y_t is a random walk possibly with a drift, whereas under the alternative y_t follows a stationary process. As with the ADF tests' critical values, the critical values for DF-GLS depend on whether or not a time trend is included in the vector of deterministic terms. One of the main advantages of the DF-GLS test is that it improves the ability to distinguish between the null hypothesis of unit root and the alternative of stationarity (Stock and Watson, 2015).

An important shortcoming associated with the ADF and DF-GLS tests is that they do not allow for the effect of structural breaks. Perron (1989) shows that a structural change in a time series can largely influence the results of unit root tests. Zivot and Andrews (1992) have developed methods to search for a structural break in the data endogenously. We employ their model C, which allows for one structural break in both the intercept and slope coefficients in the following equation:

$$\Delta y_t = \mu + \beta t + \phi y_{t-1} + \theta DU_t + \gamma DT_t + \sum_{i=1}^{k} \psi_i \, \Delta y_{t-i} + \varepsilon_t \quad (7)$$

The regression is the same as the ADF unit root but includes dummy components. DU_t and DT_t are indicator dummy variable for a mean and a time trend shifts respectively, at a possible structural break date TB, and are described as follows:

$$DU_t = \begin{cases} 1, & if\ t > TB \\ 0, & otherwise \end{cases}$$

$$DT_t = \begin{cases} t - TB, & if\ t > TB \\ 0, & otherwise \end{cases}$$

The null hypothesis of a unit root with drift and no structural break (ϕ=0) is tested against the alternative of trend stationary at one-time unknown break (ϕ<0). The critical values for unit root test under a possible structural break are different from those under ADF and are provided (Zivot and Andrews,1992)

b) Cointegration:

The Johansen Approach (J.A.) is applied to detect the presence of one or more cointegrating vectors in a multivariate setup. The approach relies on VAR, which is an extension of the autoregressive(A.R.) model, wherein the model every single equation the dependent variable depends on its own and lagged values of other variables. Under the VAR framework, all variables are endogenous; therefore, no prior specifications are needed. This study will employ a bivariate VAR to test for cointegration among stock markets. To present the J.A., suppose that we have two variables y_t and x_t which are $I(1)$ and that might be cointegrated, the first step in the J.A. is to set up a VAR(k) model:

$$Z_t = \mu + A_1 Z_{t-1} + A_2 Z_{t-2} + \cdots + A_k Z_{t-k} + u_t \qquad (8)$$
$$u_t \sim IIN(0,\Sigma)$$

Where $\boldsymbol{Z_t}$= $[y_t, x_t]$ and $\boldsymbol{u_t}$ is a *2x1* vector of independent Gaussian error terms, $\boldsymbol{k}$ denotes the number of lags.

One of the main difficulties that arise when estimating the VAR model above is to choose the optimal number of lags; this is crucial because the choice of the lag length can have a significant impact on the result of the cointegration analysis. Therefore, we must ensure that we include enough lags in the above model such that the error term does not suffer from non-normality, heteroscedasticity and serial correlation (Asteriou and Hall, 2016). Emerson (2007) presents evidence where using different lag lengths can lead to a different conclusion regarding the cointegrating relationship. Moreover, Lee and Tse (1996) demonstrate that the presence of heteroskedasticity in the VAR model can lead to biased results of cointegration testing. In contrast, Juselius (2006) shows that statistical inferences in the cointegrated VAR are robust to heteroskedasticity but not non-normality.

Therefore, to ensure robust results, we include unrestricted impulse dummies in the VAR to handle non-normality to reach the correct specification. The impulse dummies are obtained by using the option large residuals in Autometrics at a 5% significance level to detect outliers and move closer to satisfying the normality assumption for the validity of employing the J.A. as residuals must be well behaved. After including the dummies in the VAR, we rely on the AIC to determine the optimal lag length.

Therefore, using impulse dummy variables, the unrestricted VAR (k) model in (8) becomes:

$$Z_t = \mu + A_1 Z_{t-1} + A_2 Z_{t-2} + \cdots + A_k Z_{t-k} + \Phi D_t + u_t \qquad (9)$$
$$u_t \sim IIN\,(0, \Sigma)$$

Where $\boldsymbol{D_t}$ is a $\boldsymbol{dx1}$ vector of impulse dummy variables (0,0,0, 1,0….0).

The next step of the J.A. requires transforming the VAR (k) model in (9) to a Vector Error Correction Model (VECM):

$$\Delta Z_t = \Pi Z_{t-1} + \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \cdots + \Gamma_k \Delta Z_{t-k-1} + \Phi V_t + u_t \qquad (10)$$
$$u_t \sim IIN\,(0, \Sigma)$$

Where $\boldsymbol{\Pi} = -(\boldsymbol{I} - \sum_{i=1}^{k} \boldsymbol{A}_i)$, $\boldsymbol{\Gamma_i} = -\sum_{j=i+1}^{k} \boldsymbol{A_j}$, $i \in [1, k]$ and $\boldsymbol{V_t}$ Includes deterministic components constant, trend, impulse dummies that solved our misspecification issue. The parameters in (10) are estimated by the Maximum Likelihood Estimation (MLE) method. The J.A. relies on examining the behaviour of the matrix $\boldsymbol{\Pi}$ which contains information regarding the long-run relationship; the approach investigates the relationship between the rank $\boldsymbol{r}$ of the matrix $\boldsymbol{\Pi}$ to its characteristic roots referred to as eigenvalues $\boldsymbol{\lambda}$, that are statistically significant. The rank of $\boldsymbol{\Pi}$ is then determined by the number of non-zero eigenvalues, which are interpreted as cointegrating vectors. Johansen and Juselius (1990) highlight three possible cases based on the rank of $\boldsymbol{\Pi}$:

1. $\boldsymbol{\Pi}$ has a full rank ($\boldsymbol{r} = \boldsymbol{g}$); in this case, all eigenvalues are significantly different from zero, meaning that all variables are stationary and no cointegration exists.
2. $\boldsymbol{\Pi}$ has a zero rank ($\boldsymbol{r}$ =0); in this case, all eigenvalues are not significantly different from zero, meaning no linear combinations exist between variables, thus no cointegration.
3. $\boldsymbol{\Pi}$ **has** a reduced rank (0< $\boldsymbol{r}$ < $\boldsymbol{g}$); in this case, there exist $\boldsymbol{r}$ linear combination of stationary variables; hence cointegration exists with $\boldsymbol{r}$ cointegrating relationships.

To test for the cointegrating rank Johansen (1988), Johansen and Juselius (1990) developed two methods :

1. In the Maximum eigenvalue test (Max Test), under this test, the null hypothesis of rank ($\boldsymbol{\Pi}$)= $\boldsymbol{r}$ is tested against the alternative hypothesis that the rank is $\boldsymbol{r+1}$.

$$\lambda_{Max}(r, r+1) = -T ln\left(1-\hat{\lambda}_{r+1}\right) \qquad (11)$$

2. The Trace Test, under this test the null hypothesis of $\boldsymbol{r}$ or less than $\boldsymbol{r}$ cointegrating vectors is tested against the alternative of more than $\boldsymbol{r}$ cointegrating vectors.

$$\lambda_{Trace}(r) = -T\sum_{i=r+1}^{g} ln\,(1-\hat{\lambda}_i) \qquad (12)$$

In both tests r represents the number of cointegrating relationships, T is the number of observations and $\hat{\lambda}$ are the estimateed eigenvalues. Cheung and Lai (1993) show that the Trace test is more robust to the skewness and excess kurtosis than the Max Test. Therefore for our analysis, only the Trace Test will be used.

The distribution of both Likelihood Ratio (L.R.) tests is not standard and critical values depends crucially on the presence of deterministic components included in the model. Hendry and Juselius (2001) and Ahking (2002) show that wrong model specification leads to biased results regrading the cointegration relationship because the asymptotic distribution of the Trace and Max Tests tend to depend on whether or not deterministic components are included in the model specification.

There are at least five different models specifications that are commonly used (Asteriou and Hall, 2016). In our analysis, we use the third model specification, where we include the impulse dummies unrestrictedly. The cointegrating equation has only intercepts, allowing for linear trends only in the level of data. Matrix $\boldsymbol{\Pi}$ can be decomposed into $\boldsymbol{\Pi}= \boldsymbol{\alpha\beta'}$, where $\boldsymbol{\alpha}$ is a matrix of adjustment coefficients, and $\boldsymbol{\beta}$ is a matrix of long-run coefficients. Then we can rewrite equation (10) as follows:

$$\Delta Z_t = \gamma + \alpha(\beta' Z_{t-1} + \mu) + \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \cdots + \Gamma_k \Delta Z_{t-k-1} + \Phi D_t + u_t \quad (13)$$
$$u_t \sim IIN\ (0,\Sigma)$$

Where $\boldsymbol{D_t}$ is a vector of impulse dummies, $\boldsymbol{\alpha}$ measures the speed of adjustments to equilibrium and $\boldsymbol{\beta}$ measures the long-run equilibrium relationships, $\boldsymbol{\gamma}$ is the constant coefficient in the short run model (VAR model), and $\boldsymbol{\mu}$ is the constant coefficient in the long run model (Cointegrating Equation).

c) The Gregory and Hansen Test:

One of the main pitfalls of the traditional cointegration tests proposed by Engle and Granger (1987) and Johansen (1988) is that they do not allow for structural breaks or any regime shifts in the cointegrating relationship; they assume that the cointegrating relationship is time-invariant. However, variables may be cointegrated over a long period, and then the cointegrating relationship shifts to a new long-run relationship at an unknown time, hence using the conventional tests of cointegration, in this case, would be inappropriate, as the presence of the break tends to reduce the power of these tests, thus resulting in unreliable conclusions regarding the cointegrating relationship. Gregory and Hansen (1996) show that not allowing for a structural break in the cointegrating relationship can falsely lead to accepting the null hypothesis of no cointegration. To account for structural breaks in the cointegrating equation, Gregory and Hansen (1996) develop a residual-based test for cointegration by extending the approach of Engle and Granger (1987) through incorporating a single structural shift at an unknown point in time. The Gregory–Hansen (G.H.) approach defines a dummy variable to model a structural shift:

$$DU_t = \begin{cases} 0, & if\ t \leq T_b \\ 1, & if\ t > T_b \end{cases}$$

Where T_b denotes the unknown breakpoint in the series that is determined endogenously. Gregory and Hansen (1996) propose four different models to account for the structural changes at a single unknown date in the cointegrating relationship. For simplicity, suppose that we have two variables y_t and x_t That are $I(1)$. The first model is a level shift (Model C):

$$y_t = \mu_1 + \mu_2 DU_t + \phi x_t + \varepsilon_t \quad (14)$$

Where DU_t is an indicator dummy taking the value of one when the break occurs and zero otherwise, ε_t is a white noise error term and $I(0)$. Model C allows for a change in the intercept only with the slope coefficient held constant. μ_1 is represent the intercept before the shift and $\mu_1 + \mu_2$ represent the intercept after the shift.

The second model is a level shift with a time trend referred to as (Model C/T) which extend the previous model by including a deterministic time trend:

$$y_t = \mu_1 + \mu_2 DU_t + \beta t + \phi x_t + \varepsilon_t. \quad (15)$$

Where β is the slope of the time trend.

The third model is a regime shift referred to as (Model C/S) :

$$y_t = \mu_1 + \mu_2 DU_t + \phi x_t + \delta x_t DU_t + \varepsilon_t \quad (16)$$

Model C/S includes both changes in the intercept and slope coefficients, with ϕ being the cointegrating parameter before and $\phi + \delta$ is the cointegrating parameter after the structural break, respectively. The final and the most flexible model is the regime and trend shift referred to as (Model C/S/T):

$$y_t = \mu_1 + \mu_2 DU_t + \beta t + \gamma t DU_t + \phi x_t + \delta x_t DU_t + \varepsilon_t \quad (17)$$

Model C/S/T extends Model C/S by incorporating changes in the slope parameter of the deterministic trend. Where β is the slope parameter before, and $\beta + \gamma$ is the slope parameter after the structural break, respectively.

Since G.H. approach is a residual-based test of cointegration, models in ((14),(15),(16),(17)) are estimated through OLS and residuals $\hat{\varepsilon}_t$ are then tested for unit root where the null hypothesis of a unit root in the residuals; hence no cointegration is tested against the alternative of stationary residua-ls, which indicates cointegration with a single structural break. Gregory and Hansen (1996) suggest the use of conventional ADF residual test and the Phillips and Perron (1988) Z_t tests statistics. In this study, we employ the ADF test statistics on the residuals obtained from models ((14),(15),(16),(17)). The critical values for the ADF test have been modified by Gregory and Hansen (1996) to account for the different model specifications. The ADF test statistics on the residuals $\hat{\varepsilon}_t$ is obtained from the following:

$$\Delta\hat{\varepsilon}_t = \lambda\hat{\varepsilon}_{t-1} + \sum_{i=1}^{k}\varphi_i\,\Delta\hat{\varepsilon}_{t-i} + \nu_t \qquad (18)$$

Where λ is then tested using the modified ADF t-statistics, for consistency, the lag length in (18) is determined by the AIC.

d) The Granger causality Test:

The Granger causality (G.C.) test allow us to detect short-run linkages between variables, even if variables are not cointegrated in the long run. However, when variables are cointegrated, Engle and Granger (1987) show that a causal relationship will exist in at least one direction. According to Granger (1969), a variable y_t is said to Granger causes another variable x_t, if the current variable value of x_t can be predicted with more accuracy using the lagged values of y_t than x_t alone. To investigate the short-run interdependence between stock markets, we construct a bivariate VAR in first differences. Suppose we want to test for Granger causality between y_t and x_t. Then we can set up a VAR (k) model:

$$\Delta y_t = \alpha_1 + \sum_{i=1}^{k}\beta_i\Delta\,x_{t-i} + \sum_{i=1}^{k}\lambda_i\Delta\,y_{t-i} + \nu_{1,t} \qquad (19)$$

$$\Delta x_t = \alpha_2 + \sum_{i=1}^{k}\phi_i\Delta\,x_{t-i} + \sum_{i=1}^{k}\delta_i\Delta\,y_{t-i} + \nu_{2,t}$$

Where $\nu_{1,t}$ and $\nu_{2,t}$ are uncorrelated white noise error terms. k represents the lag length for Δx_t and Δy_t.

After estimating the above VAR, there four cases that we want to test:

1. Case 1 unidirectional causality from Δx_t to Δy_t , this occur when the lagged terms of Δx_t in equation (19) are statistically different from zero as a group, hence $\sum_{i=1}^{k} \beta_i \neq 0$ and the lagged terms of Δy_t are not statistically different from zero as a group, therefore $\sum_{i=1}^{k} \delta_i = 0$. Under this case, we say that Δx_t Granger causes Δy_t.

2. Case 2 unidirectional causality from Δy_t to Δx_t, this means that lagged terms of Δy_t are statistically significant as a group, hence $\sum_{i=1}^{k} \delta_i \neq 0$, however the lagged terms of Δx_t are statistically insignificant $\sum_{i=1}^{k} \beta_i = 0$. Therefore, we can say that Δy_t Granger causes Δx_t.

3. Case 3 bi-directional causality between Δx_t and Δy_t, this occurs when the lagged terms of Δy_t and Δx_t are statistically significant, meaning that $\sum_{i=1}^{k} \delta_i \neq 0$ and $\sum_{i=1}^{k} \beta_i \neq 0$. Therefore both variables Granger causes each other.

4. Case 4 independence between Δy_t and x_t , this is the case when lagged terms of Δy_t and Δx_t are statistically insignificant, so $\sum_{i=1}^{k} \delta_i = 0$ and $\sum_{i=1}^{k} \beta_i = 0$. Hence no Granger causality.

To ensure the robustness of our result, the optimal lag length is determined by estimating equation (19) starting at the maximum lag set by set by Schwert (1989) rule and then reduced down by re-estimating the model with one lag less. In each of the models, we inspect the AIC and the diagnostics tests. The model with the lowest AIC and passes all the diagnostic tests will be used to test for Granger causality. When large outliers are detected, we include impulse dummies in the VAR equation (19) using the same technique outline in J.A. to satisfy the normality assumption.

5. Empirical Results:

a) Unit Root Test:

One of the main prerequisites for cointegration testing is to ensure that all variables are non-stationary and integrated of the same order. To investigate the integration order of the 11 stock indices, the ADF and DF-GLS were performed on the natural logarithm of stock indices and the first differences (monthly returns) under the two model specifications (constant, constant and time trend). In both tests, the lag length k has been selected by the AIC in Eviews 11, where the maximum k was set at 12 lags obtained from utilising the Schwert rule.

The results of the tests are presented in Table 4. Both tests suggest that the null hypothesis of a unit root cannot be rejected for the individual logarithmic stock indices at a 1% significance level, except in the case of Jordan and Tunisia. While the ADF test suggests that the stock index of Jordan is stationary with a deterministic trend (0), the DF-GLS supports the existence of a unit root; given the higher power of the DF-GLS test, we conclude that the stock index of Jordan follows a random walk process. Alternatively, the ADF and DF-GLS for the stock index of Tunisia show a rejection of the null hypothesis of a unit root at a 1% significance level, suggesting that the stock index of Tunisia is stationary around a deterministic trend, and is $I(0)$.

Applying the first difference on the logarithmic stock indices and computing the ADF and DF-GLS, we find that the null hypothesis of a unit root is now rejected for almost all indices at 1% significance level under both tests, which suggests that monthly returns follow a mean-reverting process, except for the stock index of Lebanon, which fails to rejects the null hypothesis of a unit root in monthly returns, this indicates that the stock index of Lebanon is integrated of an order higher than one. Hence, we can conclude that stock indices of Bahrain, Egypt, Jordan, KSA, Morocco, Oman, Qatar, the UAE and the U.S. are integrated of the same order $I(1)$. Because we had to take the first difference of the original series only once to obtain stationarity.

Table 4: Stationarity Test Results

Stock Market	Levels								First differences							
	ADF				DF-GLS				ADF				DF-GLS			
	k	Constant	*k*	Constant & Trend	*k*	Constant	*k*	Constant & Trend	*k*	Constant	*k*	Constant & Trend	*k*	Constant	*k*	Constant & Trend
Bahrain	[1]	-1.619	[1]	-1.899	[1]	-1.342	[1]	-1.390	[0]	-6.738***	[0]	-7.018***	[4]	-2.299***	[0]	-5.821***
Egypt	[1]	-2.699	[1]	-2.627	[1]	-1.507	[1]	-2.288	[0]	-9.233***	[0]	-9.226***	[0]	-8.340***	[0]	-8.930***
Jordan	[2]	-1.450	[1]	-3.965***	[2]	0.556	[2]	-2.497	[1]	-8.314***	[1]	-8.281***	[10]	-0.902	[0]	-7.089***
KSA	[1]	-2.312	[1]	-2.463	[2]	-1.267	[1]	-2.424	[1]	-7.538***	[1]	-7.499***	[1]	-7.440***	[1]	-7.530***
Lebanon	[9]	0.776	11	-1.190	[9]	1.579	[11]	-1.737	[12]	-0.641	[12]	-0.813	[12]	-0.733	[12]	-1.170
Morocco	[1]	-1.609	[1]	-1.388	[1]	-1.264	[1]	-1.392	[0]	-8.348***	[0]	-8.388***	[0]	-7.841***	[0]	-8.295***
Oman	[1]	-0.502	[1]	-1.580	[1]	0.072	[1]	-1.532	[0]	-9.191***	[0]	-9.202***	[8]	-1.474	[0]	-8.901***
Qatar	[5]	-2.486	[5]	-2.400	[5]	-0.722	[5]	-1.797	[4]	-3.688***	[4]	-3.747***	[4]	-3.700***	[4]	-3.705***
Tunisia	[1]	-2.344	[1]	-3.988***	[1]	-1.168	[1]	-3.983***	[0]	-6.872***	[0]	-6.848***	[0]	-6.896***	[0]	-6.906***
U.S.	[0]	-0.255	[0]	-2.860	[0]	2.300	[0]	-2.864	[0]	-9.928***	[0]	-9.885***	[7]	-0.917	[0]	-8.124***
UAE	[1]	-0.923	[9]	-2.612	[1]	0.164	[9]	-2.656	[0]	-8.746***	[0]	-8.710***	[0]	-8.641***	[0]	-8.757***

Notes: For each stock market index, the unit root test is computed on levels, and the first differences using the ADF and the DF-GLS unit root testing procedure, by including a constant and a constant and trend in the regression. *k* represent the lag length selected using the AIC. *** and ** indicate a rejection of the null hypothesis of a unit root at 1% and 5% levels, respectively.

b) Unit Root Test Allowing for Endogenous Breaks:

Since conventional unit root tests of the ADF and DF-GLS do not incorporate structural breaks, the results found in Table 4 may be biased towards the non-rejection of the null hypothesis of a unit root. Thus, to allow for the possibility of a structural break in the natural logarithm of stock indices, we employ the Zivot and Andrews (1992). Using the Z.A. unit root test, we can obtain more reliable results regarding the integration order of the stock indices. Each loged stock index is now subject to one structural break in the intercept and the time trend slope.

Allowing for a structural break in the stock indices, results in Table 5 show that not all stock indices are non-stationary as claimed by the ADF and DF-GLS. The Z.A. test confirms the ADF and DF-GLS tests, finding that Tunisia's stock index is trend stationary. However, the Z.A. reveals further evidence which suggests that the stock index of KSA is also trend stationary since the null hypothesis of a unit root with no structural break is rejected at a 5% significance level

Table 5: The Zivot and Andrews Unit Root Test Results: Break in Both Intercept and Trend

Stock Market	Levels		
	k	t-statistics	Break point
Bahrain	[1]	-2.631	2015m9
Egypt	[1]	-3.632	2013m7
Jordan	[1]	-4.903	2017m2
KSA	[2]	-5.353**	2015m8
Lebanon	[3]	-3.772	2017m12
Morocco	[1]	-3.205	2016m8
Oman	[1]	-4.102	2013m3
Qatar	[2]	-3.014	2013m5
Tunisia	[1]	-5.779***	2018m1
U.S.	[1]	-4.242	2015m8
UAE	[1]	-4.415	2013m1

Notes: For each stock market index, the Z.A. unit root test is performed on levels allowing for one structural change in the constant and the time trend. The t-statistics are the minimum ADF unit root test. The break point is determined endogenously and represents the date of the most significant structural break in the stock index level. k represent the lag length selected using the AIC. *** and ** indicate a rejection of the null hypothesis of a unit root and no structural break at 1% and 5% levels, respectively.

According to the Z.A. test results in Table 5, the stock indices of KSA and Tunisia are $I(0)$, this suggests that stock indices fluctuate upwards and downwards and over time will revert to its trend path; hence future returns can be predicted using historical prices, which violates the weak form of the EMH. Finally, by linking the three test results of unit root, we can conclude that nine out of the eleven stock indices are non-stationary. However, only eight of them are integrated of the same order $I(1)$ which are stock indices of Bahrain, Egypt, Jordan, Morocco, Oman, Qatar, the UAE and the U.S. Since cointegration testing requires variables to have the same order of integration, only these eight indices will be considered for the subsequent analysis of cointegration and Granger causality.

c) Cointegration Test:

As we have determined that only eight of the eleven stock indices considered are $I(1)$, cointegration test on these stock indices can now be executed. We procced by testing for a long-run equilibrium by performing the J.A. The test of cointegration is divided into two parts; in the first part, we investigate the diversification opportunities for U.S. investors wishing to invest in the MENA region by considering a bivariate J.A. between the U.S. stock market and the seven MENA stock markets. In the second part, we examine the long-run relationship within the MENA stock markets for investors who are concerned about diversifying their portfolio within the region.

Table 6 displays the results obtained from applying the J.A. of cointegration between the U.S. stock market and the seven MENA stock markets in a bivariate form. The first column indicates the stock market that is being tested for cointegration with the U.S. stock market, and the second and third column shows the null and the alternative hypothesis under the J.A. The fourth column shows the Trace statistics, where if the value is larger than critical value then a long-run relationship exists. The final column shows the lag length used in the VAR model based on the AIC.

Overall, the results in Table 6 are interestingly do not suggest any evidence of a cointegration relationship between the U.S. stock market and the MENA stock markets. Except for Jordan's stock market, the results indicate a significant cointegration relationship between the stock market of Jordan and the U.S. The Trace Test rejects the null hypothesis of no cointegration at a 5% significance level, suggesting the existence of one cointegrating vector linking the stock markets in the U.S. and Jordan, indicating that there is one common stochastic trend driving both series, which imply that when the stock indices drift away from the common trend, the internal dynamics will force both series to revert to the long-run equilibria. As a result, both indices will generate the same return in the long term. Therefore, such a close relationship between the two stock markets suggests that portfolio diversification for the U.S. investor in Jordan's stock market will not provide risk reduction benefits in the long run as the market share common risk factors with the U.S. market. However, the other six MENA markets still present desirable opportunities for portfolio diversification in the viewpoint of the U.S. investor, as these markets fail to reject the null hypothesis of no cointegration.

For investors wishing to diversify their portfolio across the MENA markets, the results are reported in Table 7. In each bivariate VAR under the J.A., we report the Trace statistics and the number of lags used in the bivariate VAR model; when the Trace statistics are larger than the null hypothesis's critical values of no cointegration can be rejected.

The results in Table 7 are interesting because they suggest that even regionally, the MENA stock markets are not cointegrated; the only case of cointegration is observed between stock markets of Bahrain and the UAE. Therefore, this suggests that there are potential benefits from diversifying across the MENA markets from an investment perspective. Investors need to avoid either Bahrain or the UAE stock market in their portfolio construction as these markets share a common stochastic trend.

The results in Table 6 and Table 7 contradicts the findings by previous studies; for instance, Almohamad *et al*. (2018) suggest that most stock markets in the MENA region become cointegrated regionally and with the U.S stock market. Hassan (2003) and Al-Khazali *et al*. (2006) provide evidence of long-run comovement across the GCC stock markets. However, our results suggest otherwise. We argue that the MENA stock markets still offer investors diversification opportunities and that the previous evidence regarding cointegration of the MENA stock markets with the U.S. stock market and regionally is due to the use of weekly data, rather than selecting other lower frequency data. Weekly data, especially data on stock prices, suffers from serial correlation, heteroscedasticity and nonnormality, leading to misspecified VAR model and biased cointegration results. Juselius (2006) argues that these issues can lead to the over-rejection of the null hypothesis of no cointegration. Juselius (2006) suggests that the VAR model must at least satisfy the normality assumption to draw reliable conclusions regarding the cointegrating relationship.

Therefore, we argue that the failure of previous results to account for these issues may explain the apparent finding of cointegration relationship, after controlling for these issue through the use of monthly data and including impulse dummies to account for large residuals which represent essential information that must be included in the VAR model and satisfy the normality assumption. We can conclude that our results in Table 6 and Table 7 are robust and consistent.

Table 6: The Johansen Approach Results Between the U.S. and MENA Stock Markets

Stock Market	Null	Alternative	λ_{Trace}	k
Bahrain	r=0	r=1	4.302	[3]
Egypt	r=0	r=1	4.708	[1]
Jordan	r=0	r=1	17.135**	[3]
Morocco	r=0	r=1	4.684	[2]
Oman	r=0	r=1	11.506	[3]
Qatar	r=0	r=1	3.915	[3]
UAE	r=0	r=1	4.412	[1]

Notes: Each stock market index from the MENA is tested for cointegration with the U.S. stock index using a bivariate VAR model. The reported trace statistics represents the value of testing the bivariate cointegrating relationship. k represent the lag length selected using the AIC. *** and ** indicate rejection of the null hypothesis of no cointegration at 1% and 5% levels, respectively.

Table 7: The Johansen Approach Results Between MENA Stock Markets

1	2		3		4		5		6		7	
Stock Market	Egypt		Jordan		Morocco		Oman		Qatar		UAE	
	λ_{Trace}	k	λ_{Trace}	k	λ_{Trace}	k	λ_{Trace}	k	λ_{Trace}	k	λ_{Trace}	k
Bahrain	8.986	[7]	8.571	[2]	6.351	[2]	5.499	[2]	11.167	[2]	15.848***	[2]
Egypt			8.661	[2]	6.481	[2]	8.848	[2]	15.406	[2]	9.366	[2]
Jordan					4.540	[2]	8.801	[2]	10.501	[2]	10.533	[2]
Morocco							4.793	[2]	11.852	[2]	10.533	[2]
Oman									6.619	[6]	4.961	[2]
Qatar											7.063	[2]

Notes: Column 1 illustrates the stock markets tested for cointegration relationship with stock markets in columns 2 to 7. The reported trace statistics represents the value of testing the bivariate cointegrating relationship. k represent the lag length selected using the AIC. *** and ** indicate rejection of the null hypothesis of no cointegration at 1% and 5% levels, respectively.

d) Gregory and Hansen Cointegration Test:

The results obtained above using the J.A. assumes that there is no structural break in the DGP; however, when a structural break is detected, the cointegration relationship results are biased and inconsistent. Therefore to ascertain that our previous results are consistent, we employ the Gregory and Hansen (1996) cointegration test. The test's main advantage is that it permits us to detect cointegration if there is a single structural break in the DGP and detect the time of the break.

Since the main focus of our analysis is on the viewpoint of the U.S. investor, we only use Gregory and Hansen (1996) to examine the long-run relationship between the U.S. stock market and the MENA stock markets, and so to draw reliable conclusions, we consider the different regime change models of (14),(15),(16),(17) to detect possible cointegration relationship.

As the Gregory and Hansen framework is a single equation model, the U.S. stock index has been set as the independent variable. In contrast, the other stock indices of the MENA enter equation one at a time as a dependent variable. Again the lag length for the test has been detected by the AIC by setting the maximum lag by using the Schwert rule, and the ADF statistics are used. Results are depicted in Table 8.

Table 8: The Gregory and Hansen Test Results Between the U.S. and MENA Stock Markets

Stock Market		ADF	*k*	Break point
Bahrain	Model C	-4.480	[12]	2018m4
	Model C/T	-3.700	[1]	2012m3
	Model C/S	-4.350	[12]	2014m6
	Model C/S/T	-3.690	[1]	2013m10
Egypt	Model C	-3.220	[1]	2016m2
	Model C/T	-3.670	[1]	2014m4
	Model C/S	-3.260	[1]	2013m8
	Model C/S/T	-4.080	[1]	2013m11
Jordan	Model C	-4.330	[3]	2011m11
	Model C/T	-5.090**	[3]	2016m4
	Model C/S	-4.550	[3]	2017m7
	Model C/S/T	-5.400	[3]	2016m4
Morocco	Model C	-3.900	[9]	2013m4
	Model C/T	-3.850	[1]	2017m2
	Model C/S	-4.100	[12]	2014m4
	Model C/S/T	-4.460	[12]	2013m4
Oman	Model C	-4.190	[1]	2013m4
	Model C/T	-4.730	[1]	2017m8
	Model C/S	-4.000	[12]	2015m10
	Model C/S/T	-5.120	[1]	2016m3
Qatar	Model C	-3.800	[5]	2016m6
	Model C/T	-4.050	[1]	2017m1
	Model C/S	-4.730	[12]	2015m12
	Model C/S/T	-4.680	[0]	2017m6
UAE	Model C	-4.300	[1]	2013m7
	Model C/T	-4.800	[2]	2013m8
	Model C/S	-4.250	[1]	2013m7
	Model C/S/T	-4.590	[3]	2013m5

Notes: Each stock market index from the MENA markets is tested for cointegration with the U.S. stock market allowing for four different structural breaks. The reported ADF is the unit root test on residuals under the four different structural breaks. The break point is the determined endogenously and represents the date of the most significant structural break in the cointegrating relationship. *k* represent the lag length selected using the AIC. *** and ** indicate rejection of the null hypothesis of no cointegration with no structural breaks at 1% and 5% levels, respectively.

Still, after accounting for all possible regime shifts, the Gregory and Hansen test shows no sign of cointegration between the U.S. stock market and the MENA stock markets. However, it is worth noting that allowing for a break in the intercept and including a time trend (Model C/T), we can reject the null hypothesis of no cointegration at a 5% significance level between stock markets of the U.S. and Jordan, which is consistent with the finding under the J.A. obtained previously.

On balance, we can conclude that Gregory and Hansen test results confirm the results under the J.A. in Table 6, which suggests that there are still potential benefits from diversifying in the MENA markets for the U.S. investors.

e) Granger Causality Test:

The existence of no long-run relationship between the MENA markets regionally and the U.S. does not imply that there are no short-run linkages. To detect whether a short-term relationship exists between the eight stock markets, we employ the Granger causality (G.C.) test. The main intuition behind running this test is to determine short-run portfolio strategies for investors who are only interested in investing over the short-term horizon across the eight stock markets. In the case where changes or shocks in one stock market are transmitted to another stock market, then reaping the benefits of short-run diversification is limited; alternatively, if these shocks do not influence the other market, then we can say that such a market is immune to these shocks and is more independent; hence benefits of diversification, in this case, will rise.

The G.C. test is based on the VAR model in (19), and so for each stock market, we perform a pairwise G.C. analysis with other stock markets in the study. One requirement of the G.C. test is that all variables in the VAR model are stationary and integrated of the same order; therefore, the test will be performed on the first differenced stock price indices (monthly returns).

Table 9 displays the results from the pairwise G.C. tests; for each pairwise test, we report the differenced explanatory variable's chi-squared value and the lag length used based on the AIC. The reported chi-squared represents the value obtained from excluding the lags of the stock market that is believed to G.C. the other market. If the chi-squared value is significant, then we can reject the null hypothesis of no G.C.

Beginning with the pairwise G.C. test between the U.S. stock market and the MENA stock markets, results in Table 9 indicate that there exist no causal relationships between the stock markets of the U.S. and the MENA. These results suggest that changes in the U.S. stock market index do not explain the changes in the MENA stock market indices and vice versa. In other words, this means, for instance, arbitrageurs in the MENA markets cannot predict current movements regarding returns of the stock indices in the MENA markets by observing information about price changes of the U.S. stock index. Whether these changes are positive or negative, the MENA markets are not affected by such changes in the U.S. stock index, which further consolidate the evidence that the MENA markets are indeed segmented and still offer plausible diversification opportunities.

Concerning the pairwise G.C. tests on the MENA markets regionally, results indicate unidirectional G.C., which runs from the Moroccan stock market to the Egyptian and Jordanian stock markets. Since we can reject the null hypothesis of no G.C. at a 1% significance level, this suggests that changes in the stock markets of Morocco will have immediate spillover effects on the Egyptian and Jordanian stock markets, which can be explained by the long-standing history of the stock market in Morocco compared to other MENA markets (Almohamad *et al*. 2018). Additionally, we find unidirectional G.C. from the Egyptian to Bahraini stock markets, which indicates that movements in Egypt stock market are transmitted and affect the Bahrain stock market.

Surprisingly, no other G.C. relations were found between the MENA markets; in particular, we found no short-run relations among the GCC markets;

given the high integrity between these markets, one would assume that short-run relations would exist at least in one direction. The only sign of G.C. was observed between the Omani and Qatari stock markets. Results suggest unidirectional G.C. from the stock market in Qatar to the Oman stock market. These results indicate that the effort to uniformise GCC region stock markets has not resulted in a fully integrated market. From an investment perspective, these results highlight that possible regional portfolio diversification opportunities are still available even across the MENA markets, especially within the GCC region.

Table 9: The Granger causality Test Results

1	2		3		4		5		6		7		8		9	
Dependent Variable	*ΔBahrain*		*ΔEgypt*		*ΔJordan*		*ΔMorocco*		*ΔOman*		*ΔQatar*		*ΔU.S.*		*ΔUAE*	
	χ^2	k	χ^2	k	χ^2	k	χ^2	k	χ^2	k	χ^2	k	χ^2	k	χ^2	k
ΔBahrain	-		4.095**	[1]	0.448	[1]	3.520	[1]	0.969	[1]	1.471	[1]	0.400	[2]	1.477	[1]
ΔEgypt	2.700	[1]	-		1.064	[2]	6.988***	[1]	0.052	[1]	1.354	[5]	0.019	[1]	0.682	[1]
ΔJordan	0.272	[1]	2.848	[2]	-		13.056***	[1]	0.033	[1]	1.097	[1]	3.395	[2]	1.363	[2]
ΔMorocco	0.700	[1]	0.210	[1]	0.002	[1]	-		1.684	[1]	1.438	[1]	1.341	[1]	1.218	[1]
ΔOman	0.055	[1]	1.659	[1]	0.207	[1]	0.941	[1]	-		10.921**	[3]	2.140	[3]	2.685	[1]
ΔQatar	0.180	[1]	3.470	[5]	0.553	[1]	0.127	[1]	5.136	[3]	-		1.974	[2]	0.619	[1]
ΔU.S.	0.532	[2]	0.026	[1]	3.032	[2]	0.745	[1]	5.680	[3]	0.903	[2]	-		0.115	[1]
ΔUAE	2.794	[1]	0.099	[1]	1.716	[2]	0.012	[1]	0.490	[1]	1.197	[1]	0.412	[1]	-	

Notes: ***∆Bahrain, ∆Egypt, ∆Jordan, ∆Morocco, ∆Oman, ∆Qatar, ∆U.S., ∆UAE*** are the value of the first difference of stock price indices of **Bahrain**, **Egypt**, **Jordan**, **Morocco**, **Oman**, **Qatar**, **the U.S.** and **the UAE,** respectively. Column 1 illustrates the stock market under consideration as a dependent variable in the pairwise Granger causality test in the bivariate VAR. Columns 2 to 9 show the variable on the RHS of the bivariate VAR equation and the Chi-squared statistics from excluding the variable on the RHS. k represent the number of lags used in the bivariate VAR model. *** and ** indicate rejection of the null hypothesis of no Granger causality at 1% and 5% levels, respectively.

6. Conclusion:

The purpose of this study is to investigate whether stock markets in the MENA are cointegrated regionally and with the U.S. stock market. In doing so, two different methods of cointegration testing were used, the Johansen approach based on the work of Johansen (1988), Johansen and Juselius (1990), and the Gregory and Hansen approach proposed by Gregory and Hansen (1996). We also tested for short-run relationships by utilising the Granger causality test based on the work of Granger (1969). The study also aims to fill the gaps in the literature and provide consistent evidence regarding the integrity of the MENA financial markets regionally and with the U.S. market by considering model specification issues ignored by previous studies.

Using monthly data from 2010 to 2020, the analysis shows that there is little evidence of long-run relationships between the MENA stock markets and the U.S. stock market. According to both cointegration testing approaches, only Jordan stock market out of the MENA markets cointegrates with the U.S. S&P 500 index, implying that Jordan's stock index is not independent and is predictable through using the information of the S&P 500 index and vice versa. However, regarding the regional cointegration of the MENA markets, the J.A. results show no evidence of cointegration; the only case of cointegration was observed between the stock markets of Bahrain and the UAE.

The empirical findings that emerge from this study highlight the fact that MENA markets and the U.S. market are more likely to move in different directions in the long-run. Hence MENA markets do still provide long-run risk reduction benefits for U.S. investors. Additionally, even within the region, investors can reap benefits by diversifying across the MENA markets.

These results are consistent with the fact that the existence of cointegration would imply strong form predictability of stock indices with certainty in the long run, which violates the EMH. In contrast, short-run predictability may exit due to behavioural biases and markets frictions; however, that does not imply anything about the long-run behaviour of stock indices.

Since stock indices are calculated as a weighted sum of the individual stock prices which represents the index, each of the individual stocks listed on the index contains global, local and stock-specific stochastic trends when using cointegration analysis to investigate the long-run relationship between stock indices at a national level; only the global stochastic trend will be eliminated, leaving the local and stock-specific stochastic trends uncancelled, which in turn precludes cointegration from existing between international stock indices. For cointegration to exist, it would require both stochastic trends of local and stock-specific to be offset by similar shocks, which is rather unlikely since stock markets in different countries would have different industrial structure and respond differently to economic shocks. Therefore, one could argue that such existence of local and stock-specific stochastic trends in the national stock indices suggests that international portfolio diversification is still possible for investors in the long run.

Using the Granger causality approach, we were able to detect short-run relationships between stock indices in the study. The findings suggest unidirectional Granger causality from Morocco's stock market to Egypt and Jordan stock markets; these findings suggest that return variations in the stock index of Morocco significantly affect stock indices returns of Egypt and Jordan. Moreover, variations in Egypt and Qatar's stock index are transmitted to Bahrain and Oman stock indices, respectively. Therefore, returns on Egypt and Qatar's stock indices significantly influence those in Bahrain and Oman, respectively. However, using the Granger causality approach does not allow us to investigate whether the changes in one stock index affects another positively or negatively and how long these changes last. Therefore, future research could employ an Impulse response analysis to answer these questions.

Finally, the implications and recommendations of this study are clear, for U.S. investors and in particular asset managers wishing to diversify abroad, the MENA markets present opportunities for further diversification as these markets do not share a long-run equilibrium and exhibit low correlations and no causality with the U.S. market, and the same is true for investors wishing to diversify across the MENA markets.

Notes:

1. Skewness is a measurement of asymmetry of a series distribution around its mean.

2. Kurtosis is a measurement of the peakedness or fatness of a series distribution. The Kurtosis value for the normal distribution is 3.

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