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Oil Volatility Spillover on MENA Stock Markets: a DCC-GARCH Approach and Portfolio Analysis

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Abstract. This study examines the effect of oil volatility on MENA stock market return. We select four oil importer countries (Egypt, Lebanon, Morocco, and Tunisia) and four oil exporter countries (Oman, EAU, Qatar, and Saudi Arabia). The time horizon of the study is from January 2014 to August 2021. We use in the first step a univariate Threshold-GARCH (1,1) by employing the calculated oil volatility as an exogenous variable in the mean and variance equation of stock returns. In the second step, we employ a multivariate DCC-GARCH to compute the dynamic conditional correlation between oil and the stock market, the optimal portfolio and Hedge effectiveness index. The results indicate that oil volatility has a weak influence on stock market returns but has a very significant effect on stock market volatility for oil-importing (negative) and exporting (positive) countries. We also discover a strong correlation between the oil market and the stock market of oil-exporting countries. In addition, investing in oil assets is more efficient in terms of minimizing portfolio risk.

Keywords: oil volatility, stock return, oil-importing countries, oil-exporting countries, DCC-GARCH

1. Introduction

One of the main factors in the world economic development is energy, especially oil. This vital energy source is the basis of the industry for all countries. It represents 33.1% of the world's primary energy consumption in 2019 (statistical Review of World Energy*). Therefore, a change in the oil price can greatly affect the future economic growth and stability of developed and developing countries. The oil price had been highly volatile during the last two decades, rising from \$60 to \$145 between 2007 and 2009. A few years later, in 2014 and 2015, oil prices lost almost 75% of their value. Then, during the crisis of covid-19, it dropped to about 20 dollars a barrel. More recently, oil prices have risen from \$71 per barrel in December 2021 to \$130 in March 2022.

In addition to their impacts on the economy, oil price fluctuations have been linked to stock market movements (Arouri et al., 2011, 2012; Kang et al., 2014; Xu et al., 2019; Ashfaq et al., 2019, 2020; Cevik et al., 2020; Zhang & Hamori, 2021; Khalfaoui et al., 2019; Liu et al., 2020). Whereas understanding the correlation between oil price fluctuations and the stock markets is crucial for energy policy design, portfolio diversification, energy risk management etc. The investigation of this relationship remains poorly researched in developing countries, which is perhaps explained by the small size of these economies and the weakness of their stock markets in terms of trading volume and market capitalization. Our study seeks to fill this gap in the literature by examining this relationship in the MENA region by distinguishing between oil importing and exporting countries. It also offers portfolio implications as well as some recommendations for the design of an efficient portfolio for investors in this region. The MENA country is an emerging region that includes

* Bp oil company, Primary energy, "https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world energy/primary-energy.html"

both oil-imp and exporting countries. The oil-producing countries in this area are OPEC+ members and having a direct influence on oil price volatility.

Crude oil price shocks can affect stock markets by their impacts on monetary policy instruments, inflation, corporate earnings, and other economic activities (Gourène & Mendy, 2018). Tang et al. (2010) identified five pathways (stock valuation channel, monetary channel, output channel, fiscal channel, and uncertainty channel) through which oil prices and stock market returns are transmitted. First, oil price fluctuations can positively or negatively impact the discount rate and the company's future cash flow depending on whether the company is an oil producer or a consumer (stock valuation). In addition, higher oil prices lead to higher production costs. This rise will be transmitted to consumers, which will drive up retail prices and thus expected inflation Razmi et al. (2016). As a result, monetary authorities will raise the interest rate in response to high inflation, which will affect the discount rate and consumption, thereby depressing cash flows and stock prices (monetary). Furthermore, due to changes in retail prices (resulting from higher production costs), as well as higher gasoline and heating oil prices (Edelstein & Kilian, 2009), rising oil prices are expected to reduce household disposable income. The decline in income leads to a decrease in consumption and, consequently, in aggregate output, which can have a negative impact on the stocks prices (*output*). Only for oil-exporting countries, the rise in oil prices will boost the wealth of oil-exporting countries and their public spending, and consequently, household consumption and the level of corporate production will be increased, which in turn will have a positive impact on profitability, cash flow, and stock prices (Fiscal). Due to the obvious effects of rising oil prices on inflation, production, consumption, etc., uncertainty will increase in the real economy. As a result, rising oil prices will limit companies' interest in irreversible investments and slow down the economy (Chuku et al., 2010), lowering predicted cash flows (uncertainty).

For all the noise it makes, the relationship between oil and the stock market is not necessarily stable over time and remains ambiguous. Moreover, the impact of an oil price change on the stock market depends mainly on whether the country is an oil importer or exporter. The largest studies have found a negative impact of oil prices on international stock market returns (Xiao et al., 2018; Joo & Park, 2021; Alsalman & Herrera, 2015); Tchatoka et al., 2019). On the other hand, there is a positive relationship between oil prices and the stock prices of oil companies (El-Sharif et al., 2005; Urom et al., 2020; Bouri, 2015; Wanhai et al., 2017; Bouri et al., 2017). Furthermore, the recent health crisis has largely affected the stock markets of developed and developing countries. The crisis caused by the COVID-19 pandemic is exceptional in many respects: it is shaping up to be the deepest recession recorded in advanced economies since the Second World War (World Bank)[†]. Zhang and Hamori (2021) have documented that the impact of COVID-19 on oil and stock market volatility exceeds that of the 2008 global financial crisis.

By covering two major crisis periods, the oil crisis (2014-2016) and the health crisis (2020), this study aims to analyze in a first step the impact of oil price volatility on the stock market returns and volatility in the MENA region by using a T-GARCH model introduced by Zakoian (1991). Based on a DCC-GARCH model (Engle, 2002), we try to examine in a second step the dynamic correlation between stock markets and the oil market. Finally, we use the outputs of the DCC-GARCH model to compute the optimal weight of oil in a portfolio that contains two assets (stock/oil) and analyze the role of oil in hedging against risk according to the "Hedge Effectiveness" index introduced by Ederington (1979).

[†] The COVID-19 pandemic plunges the global economy into its worst recession since World War II. World bank. 2020. “https://www.banquemondiale.org/fr/news/press-release/2020/06/08/covid-19-to-plunge-global-economy-into-worst-recession-since-world-war-ii”

The remainder of this paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 is reserved for the methodology Then in section 4, we present the sample used in the study. The results are discussed in Section 5 and finally, section 6 provides a conclusion and future research perspectives.

2. Literature Review

Many studies have examined the relationship between oil prices and stock market indices. Jones and Kaul (1996) have used quarterly data to capture the response of stock market indices to oil shocks after World War II. They show the negative reaction of American, Canadian, British, and Japanese stock prices to oil shocks through the impact of the latter on real cash flows. Sadorsky (1999) discussed the asymmetric impact of oil price shocks and volatility on the economy (industrial production, interest rates) and US stock returns (S&P 500) using VAR (variance decomposition, impulse response function) and GARCH models. The results indicate that positive oil shocks depress real stock returns. Thus, oil price volatility shocks have asymmetric effects on the economy. Malik and Hammoudeh (2007) have studied the transmission of shocks and volatility between oil price (WTI), the US stock market, and the stock markets of the GCC countries (Gulf Cooperation Council) from 14 February 1994 to 25 December 2001. The results from the BEKK-GARCH model suggest that the GCC stock markets receive volatility from the oil market, except for Saudi Arabia, which is a transmitter of volatility in the oil market (an important role played by Saudi Arabia in the world oil market). Thus, shocks in the US stock market indirectly affect the stock markets of the Gulf countries. This shows the strong correlation between the two markets as a result of cross-coverage and information transmission (Ross, 1989). Morema and Bonga-Bonga (2020) have examined the impact of oil and gold market fluctuations on the South African stock market at the sectoral level. Using a VAR-ADCC-GARCH model, they find that the industrial and resource sector indices are most affected by past oil price volatility shocks while the financial sector is insulated from these shocks. Furthermore, the transmission of volatility is unidirectional from the commodity market (oil and gold) to the South African stock markets. Sarwar et al. (2020) show that oil price volatility has a negative spillover effect on the stock markets of three Asian emerging countries.

Other studies have investigated this transmission by distinguishing between oil importing and exporting countries. Bass (2017) have examined the effect of oil price uncertainty on stock returns in Russia; he uses the bivariate GARCH-M model and the IRF (Impulse Response Function) technique on weekly data to detect the asymmetric response of stock returns to oil shocks. On the one hand, he finds that in the case of oil-exporting countries (the case of Russia), a positive oil shock leads to a significant increase in stock returns and vice versa. On the other hand, the response of stock market returns to oil shocks is asymmetric, in the case of a negative shock, the effect is short-term and large, while when the shock is positive the effect is long-term but smaller. Ashfaq et al. (2019) found a bidirectional contagion effect between equity and oil returns for exporting countries while for importing countries the results are less significant. The stock markets of oil-exporting countries show a significant correlation with oil prices, but it is weak for the stock markets of oil-importing countries (Ashfaq et al., 2020). Furthermore, according to Gonzalez et al. (2021), volatility spillovers between the stock markets and the oil market vary considerably over time but are higher from the stock markets to the oil market than in the other way. Sarwar et al. (2019) have investigated the volatility spillover between oil and stock returns by retaining daily data for the three major oil-importing Asian countries. They found a bidirectional volatility spillover between the Nikkei index (Japan) and crude oil prices; however, a unidirectional volatility transmission was captured from the Nifty 225 (India) index to the oil market. They did not find any significant indication of volatility transmission in China. However, the contagion effect of returns and volatility extends from the international oil market to the Chinese stock market (Ahmed & Huo, 2020).

For a long time, the financial and oil markets have experienced several crises and major disturbances. However, in the last two decades, these markets have been affected more heavily and successively by major crises, which have drawn the attention of researchers to examine the link between the two markets during these crises. Studies have focused primarily on two major crises, the 2008 global financial crisis that resulted from systemic failure and the recent 2020 health crisis which affected the entire market (systematic). Arouri et al. (2011) have examined the return and volatility spillovers between global oil prices and GCC stock markets before and after the 2008 crisis. They use the VAR (1) -GARCH (1,1) model by taking daily data (Period: 06/2005-02/2010). Their results reveal that the volatility shocks and spillovers between oil and stock markets are considerable in most cases they increases especially during the crisis period. An increase in oil price volatility caused by shocks and policy changes affecting oil supply and demand would immediately boost the volatility of GCC stock markets. By using the VAR-GARCH copula model, Jaghoubi (2015) found that the dependency level between the GCC stock markets and the oil price (WTI) becomes stronger and turns from negative to positive when the financial crisis occurs. Cevik et al. (2020) show that there are no significant spillover effects of oil prices on the Turkish stock market in the whole sample except in 1993 (economic slowdown in Turkey) and 2008 (global financial crisis). The study presented by Zhang et al. (2021) made a combination between the TVP-VAR (time-varying parameter vector autoregression) model and the volatility spillover index proposed by Diebold and Yilmaz (2009, 2012, 2014). They concluded that the spillover effect between the energy market and the stock market has become higher compared to the pre-pandemic period. In addition, energy markets confronted many systemic risks from stock markets during the COVID-19 period. Wang (2020) has focused on the frequency dynamics in volatility spillover between crude oil and international stock markets (U. S, Europe, and Japan). Volatility spillover is time-varying, it is relatively significant during the global crisis and the European debt crisis (from 2008 to 2012). Additionally, the interest rate influences the volatility spillover in the short (negative effect) and long term (positive effect). Moreover, after the beginning of the Covid-19 crisis, a positive (negative) oil shock is better (worse) news for the stock market than an equivalent shock before the crisis.

Our work is divided into two parts. On the one hand, we estimate a univariate T-GARCH (1,1) model introduced by Zakoian (1991) by incorporating the estimated volatility of the oil price in the mean and variance in order to examine the spillover of oil price volatility on the stock markets of MENA countries. On the other hand, we adopt a DCC-GARCH approach Engle (2002), to analyze the dynamic conditional correlation between the stock market and the oil market. Then we compute from the output of the DCC model the two indices "optimal portfolio" kroner and ng (1998) and "Hedge Effectiveness" introduced by Ederington (1979). The DCC-GARCH model respects the flexibility of univariate GARCH models while simplifying parameterization and empirical estimation. It is an efficient tool for analyzing interactions between several assets, markets, and/or countries. It is therefore evident that this form of model is often used in previous studies to investigate financial market mechanisms: contagion, volatility spillovers, etc. (Arouri et al., 2011; Jouini, 2013; Morema & Bonga, 2020; Singhal & Ghosh, 2016).

3. Methodology

3.1 Threshold GARCH (1,1)

To examine the asymmetric impact of oil price volatility (Brent) on the return and volatility of MENA stock markets, we estimate a univariate TGARCH (1,1) model (Zakoian,

1991) for each index by including the calculated oil price volatility as an explanatory variable in the mean and variance equations (Mike et al., 2002; Hammoudeh & Yuan, 2007).
The model is presented below:

$$r_{it} = \theta_1 \, r_{it-1} + \phi_1 \varepsilon_{it-1} + \gamma \; vol_{oil}$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \lambda_1 vol + \psi_1 D_t \varepsilon_{t-1}^2$$

Where r_{it} is the stock market return, θ_1 and ϕ_1 are the estimated parameters of an ARMA model, vol_{oil} is the volatility of the oil price, σ_t^2 is the conditional volatility, α_1 and β_1 are the ARCH and GARCH coefficients, respectively, D_t is a "dummy" variable to capture the asymmetric impact of past shocks:

$$D_{t-1} = \begin{cases} 1 \; \varepsilon_{t-1} < 0 \\ 0 \;\; \varepsilon_{t-1} > 0 \end{cases}$$

The oil price volatility is obtained from a GARCH (1,1) process:

$$\sigma_n^2 = \gamma V_l + \alpha \mu_{n-1}^2 + \beta \sigma_{n-1}^2$$

V_l : unconditional variance
μ_{n-1}^2 : Lagged squared return

3.2 DCC-GARCH model

An extension of the CCC model is the DCC model introduced by Engle (2002) which, unlike the CCC model, does not assume that the correlations between the series are constant. In this way the model can take into account a possible time-varying Covolatility. The model is presented in the following equation:

$$H_t = D_t R_t D_t$$
$$D_t = diag\left(\sqrt{h_{11t}} \;\;,\;\; \sqrt{h_{22t}} \;\; \ldots \;\; \sqrt{h_{NNt}}\right)$$
$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t^{-\frac{1}{2}})$$

Where R is a symmetric, positive definite matrix with a dimension (NxN).

$$Q_t = (1 - \lambda_1 - \lambda_2)\bar{Q} + \lambda_1 \varepsilon_{t-1} \varepsilon_{t-1}' + \lambda_2 Q_{t-1}$$

With $\lambda_1 + \lambda_2 < 1$

The coefficients λ_1 and λ_2 provide a measure of the correlation persistence between two assets in the portfolio, and $\bar{Q}$ represents the unconditional variance-covariance matrix with a dimension (NxN), symmetric and positive definite.

3.3 Optimal Portfolio Weight

An efficient portfolio is one that offers the optimal risk/return combination for investors. According to Markowitz's (1952), the minimum variance of a portfolio containing two assets i and j is calculated as follows:

$$\sigma_p^2 = w_i^2 \sigma_i^2 + (1 - w_i)^2 \sigma_j^2 + 2 w_i (1 - w_i) \sigma_{ij}$$

The optimal portfolio weight according to Kroner and Ng (1998), is obtained by the following formula:

$$w_t^{AP} = \frac{\sigma_t^A - \sigma_t^{AP}}{\sigma_t^A + \sigma_t^P - 2\sigma_t^{AP}}$$

Where:

$$w_t^{AP} = \begin{cases} 0, si\ w_t^{AP} < 0 \\ w_t^{AP}, si\ 0 \leq w_t^{AP} \leq 1 \\ 1, si\ w_t^{AP} > 1 \end{cases}$$

The optimal weight of the stock in the portfolio is equal to (1- w_t^{AP}).

3.4 Hedge Effectiveness

There are several studies in the literature that have employed the hedge effectiveness index provided by Ederington (1979) to examine the performance of a hedged portfolio against an unheeded one (Arouri et al., 2011; Chkili, 2016; Basher & Sadorsky, 2016, Morema & Bonga-Bonga, 2020). A Hedge Effectiveness (HE) index is calculated as follows:

$$HE = \frac{variance_u - variance_h}{variance_u}$$

Where, $variance_u$ and $variance_h$ refers to the variance of an unhedged and hedged portfolio respectively. Indeed, if the value of HE is higher, it means that more variance (risk) is eliminated by the hedging strategy.

4. Data

The objective of our empirical study is to analyze the interaction between the oil market and the MENA stock markets. The selection of the region is not arbitrary, as although there are several empirical studies that examine the conditional correlations and volatility spillovers between crude oil prices and stock returns, the focus of the literature is mostly on developed countries. There are few studies that analyze this relationship in the MENA region (Kyrtsou & Labys, 2006; Mensi et al., 2021; Bouri, 2015).

The period runs from 03/01/2014 to 30/09/2021. The number of observations differs from one country to another, depending on the availability of data (the minimum number of observations is 1813 for the BLS index). The period covers two major crisis periods that are both characterized by high volatility, the oil crisis of 2016 and the covid-19 crisis. Our database includes the "Brent Futures" oil price on which we measure the oil price volatility. We choose the Brent because it represents about 65% of the world oil production and it is the reference price for the oil produced in Europe, Africa, and the Middle East[‡]. We collect stock market indices for 8 MENA countries: MSM30 (Oman), ADX (UAE), EGX30 (Egypt), MASI (Morocco), BLS (Lebanon), QEAS (Qatar), TASEI (Saudi Arabia), and TUNINDEX (Tunisia). All data are taken from the “investing.com” website. The daily returns of the stock market indices are calculated as follows:

$$r_{it} = ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where rit is the stock return i at time t, Pt and Pt-1 represents the index value at time t and t-1 respectively.

[‡] Fioulmarket.fr, 2018. Cours du pétrole : le Brent, qu’est-ce que c’est ?

5. Empirical Results

5.1 Descriptive Statistics and Stationarity

Table 1. Descriptive statistics

	Mean (%)	*Median (%)*	*Maximum (%)*	*Minimum (%)*	*Std. Dev (%)*	*Skewness*	*Kurtosis*	*J-B*
BRENT	*-0,0149*	*0,079*	*19,077*	*-27,976*	*2,521*	*-0.9698*	*22.14*	*30828.69 ****
MSM30	*-0.0299*	*-0.017*	*5.369*	*-6.413*	*0.622*	*-1.1383*	*21.88*	*28438.14 ****
ADX	*0,0293*	*4,37*	*8,076*	*-8,406*	*1,091*	*-0,2855*	*15,39*	*12432.61 ****
EGX30	*0,023*	*7,02*	*6,488*	*-9,808*	*1,327*	*-0,5716*	*8,19*	*2225.86 ****
MASI	*0,0187*	*2,4*	*5,305*	*-9,232*	*0,684*	*-1,7100*	*33,08*	*73473.49 ****
BLS	*-0.0066*	*-1,54*	*4,409*	*-10,541*	*0,711*	*-2,5781*	*45,13*	*136113.4 ****
QEAS	*0,0167*	*2,34*	*7,272*	*-9,998*	*1,032*	*-0,812*	*14,92*	*11615.65 ****
TASEI	*0,0149*	*7,5*	*8,547*	*-8,684*	*1,151*	*-0,9254*	*13,99*	*10012.26 ****
TUNINDEX	*0,026*	*1,72*	*2,678*	*-4,186*	*0,461*	*-1,0067*	*13,7*	*9550.13 ****

Notes: *, ** and *** indicate rejection of the null hypothesis at 10%, 5% and 1% respectively.

Table 1 reports the main descriptive statistics and stochastic properties of the return series. We find that the ADX index has the highest average return with a medium risk level. Regarding risk (st.dev), the oil index is the riskiest. This high volatility can be explained by the effect of the turbulences related to oil production in the MENA zone given that the major oil producers in this area are members of OPEC+ and have a direct influence on the oil price volatility (the supply control). The skewness coefficient is negative in all cases, i.e., the tail of the distribution of returns is spread to the left, which means that negative returns are more frequent than positive returns. Therefore, the kurtosis coefficient suggests that all the returns are leptokurtic ($k > 3$), which means that the probability of being very close to the mean is high. Hence, the normality hypothesis is rejected for all the series according to the Jarque-Bera test, which leads us to check for the presence of heteroscedasticity in the series.

According to the White and ARCH tests (Table 2) of heteroscedasticity, all the returns series are heteroscedastic and include an ARCH effect. The results of the ADF and PP tests suggest that all the returns are stationary in level at the 1% significance level.

Table 2. Heteroskedasticity and stationarity tests of the return series

	Heteroscedasticity tests		***Stationarity tests at level***	
	ARCH (1) test	***White test***	***PP***	***ADF***
BRENT	*103.969 ****	*1.01E+26 ****	*-43.690 ****	*-43.576 ****
ADX	*324.358 ****	*1.05E+26 ****	*-42.772 ****	*-12.899 ****
EGX30	*78.453 ****	*5.25E+25 ****	*-33.848 ****	*-22.116 ****
MASI	*60.730 ****	*2.44E+26 ****	*-37.636 ****	*-10.748 ****
BLS	*3.522 ***	*7079.630 ****	*-40.103****	*-38.832 ****
MSM30	*152.187 ****	*9.63E+25 ****	*-31.620 ****	*-17.094 ****
QEAS	*89.952 ****	*8.87E+25 ****	*-40.156 ****	*-22.861 ****
TASEI	*323.728 ****	*7.13E+25 ****	*-38.716 ****	*-38.7718 ****
TUNINDEX	*584.432 ****	*7.53E+25 ****	*-33.994 ****	*-33.853 ****

Notes: *, ** and *** indicate rejection of the null hypothesis at 10%, 5% and 1% respectively.

The values shown in the table above for the heteroscedasticity and stationarity tests are Fisher’s and Student's statistics, respectively.

5.2 T-GARCH (1,1) Model Estimation

The estimation results of the model are presented in Table 3 below. For the conditional return generating processes, other than the EGX30, MASI, and BLS indexes, we note that lagged returns (***θ1***) significantly and positively affect their current values indicating some evidence of short-term predictability of oil price movements (Arouri et al., 2012). Overall, we find that the impact of oil market volatility on stock market returns (***γ1***) is weakly significant, while the oil price volatility positively affects the average return of the QEAS index, yet it has a negative influence on the BLS index return. This can be explained by the fact that the worst economic conditions in Lebanon can make investors very sensitive to an increase in the oil price uncertainty, while this negative effect can be offset by the economic expansion in Qatar and make investors very confident, despite oil price fluctuations. However, the stock index volatility of oil-exporting countries (MSM30, ADX, and TASEI) is positively influenced by the oil market volatility. This result highlights the potential for information processing from the oil market and cross-market hedging undertaken primarily by equity investors in these markets, implying that participants in the equity markets of these countries can potentially benefit by monitoring the global oil market and taking it as a signal of likely future changes in their own markets (Malik & Hammoudeh, 2007). On the other hand, the effect is negative for the oil-importing countries (EGX30, MASI, BLS, and TUNINDEX), i.e., a rise in oil volatility can lead to a drop in stock market volatility. In addition, the ARCH and GARCH coefficients are statistically significant (at the 1% level). There are 3 out of 8 stock returns whose conditional volatility is highly sensitive to the market (***α1*** > 0.1). These returns are MSM30 (***α1*** = 0.123), MASI (***α1*** = 0.251), and BLS (***α1*** = 0.12). These markets display an almost low Beta coefficient (***β1***) in other words the volatility in these markets tends to decrease rapidly following a crisis.

Table 3. T-GARCH (1,1) univariate model estimation

	MSM30	*ADX*	*EGX30*	*MASI*	*BLS*	*QEAS*	*TASEI*	*TUNINDEX*
Mean equation								
θ1 *(AR)*	*0.301 ****	*0.9 ****	*0.037*	*0,027*	*0,038*	*0.661****	*0.19 ****	*0.076 ***
ϕ1 *(MA)*	*0.029*	*-0.885 ****	*0.021*	*0.07 ***	*0,017*	*-0.579 ****	*0.071 ****	*0.087 ***
γ1 *(VOL)*	*-0.562*	*-0,031*	*-0.684*	*0,022*	*-0.269 ***	*1.595 **	*-0,343*	*0.07*
Variance equation								
α0 *(Cst)*	*2E-6 ****	*4E-5 ****	*9E-5 ****	*7E-6 ****	*4E-5 ****	*4E-6 ****	*2E-6 ****	*1E-5 ****
α1 *(ARCH)*	*0.123 ****	*0.031 ****	*0.03 **	*0.251 ****	*0.12 ****	*0.045 ***	*0.017 **	*0.042 ****
β1 *(GARCH)*	*0.693 ****	*0.805 ****	*0.557 ****	*0.564 ****	*0.578 ****	*0.836 ****	*0.819 ****	*0.554 ****
λ1 *(VOL)*	*0.008 ****	*0.024 ****	*-0.029 ****	*-0.005 ****	*-0.01 ****	*-3E-05*	*0.041 ****	*-0.003 ***
ψ1	*0.124 ****	*0.171 ****	*0.039 **	*-0,017*	*-0.089 ****	*0.154 ****	*0.241 ****	*0.078 ****
Residual diagnostic								
ARCH (10)	*0.603*	*0,556*	*15.116 ****	*1,198*	*0,555*	*0.38*	*0,179*	*10.74 ****
Q^2-Stat (20)	*11.404*	*14,124*	*285.85 ****	*23,678*	*7,3576*	*5.331*	*4,6192*	*182.36 ****

Notes: *, ** and *** indicate rejection of the null hypothesis at 10%, 5% and 1% respectively.

The lag associated with the AR and MA coefficients is fixed using the AIC (Akaike Information criteria). The Ljung-box Q^2-Stat (20) statistics represent a no autocorrelation test with h=20. The Lagrange multiplier ARCH statistics represent a no ARCH effect test.

In addition, the volatility for the other markets (ADX, EGX30, QEAS, TASEI, and TUNINDEX) is less sensitive to market shocks (***α1*** < 0.1) i.e., the conditional volatility varies slowly under the pressure of market innovations in performance, but it tends to fluctuate gradually over time and persist in the future, as shown by the high magnitude of their GARCH coefficients (Arouri et al., 2012).

Overall, the volatility convergence rate to the mean (***α1+β1***) for oil-exporting countries (MSM30, ADX, MASI, QEAS, and TASEI) is close to one (81%, 84%, 81%, 88%, and 84% respectively). Despite shocks, these markets tend to recover in the long term, making them more or less secure markets. Regarding the asymmetric effect of past shocks on conditional volatility (***ψ1***), the results provide evidence of asymmetric behavior in the stock markets. The coefficient ψ1 is statistically significant and positive for most indices which implies that bad news prevails over the good in these markets. However, good news prevails over bad news in the Lebanese market (the coefficient ***ψ1*** is negative). We can observe in Figure 1 that our study period is marked by two major crises (the oil crisis of 2014-2016 and the covid-19 crisis) on which the conditional volatility is boosted.

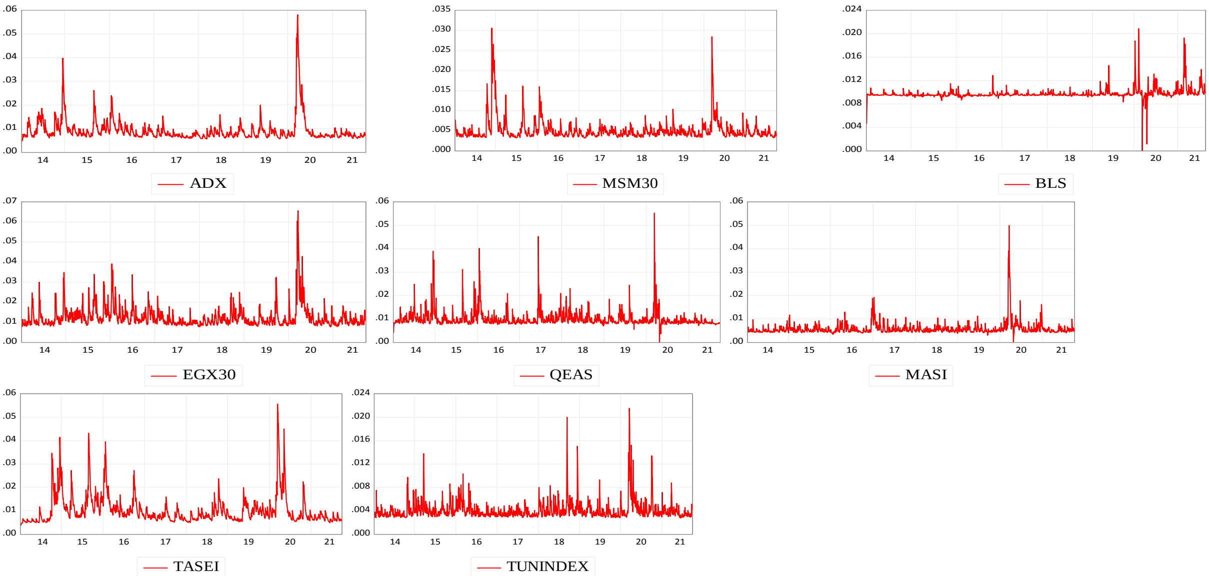

Figure 1. Conditional standard deviation obtained from the T-GARCH model (1,1)

5.3 DCC-GARCH model estimation

In this subsection we estimate a multivariate DCC-GARCH (1,1) model (Engle, 2002) to detect the interconnection between stock markets as well as their connectivity with the oil market. Our sample has been divided into two groups, oil-importing countries, and other exporters, for which we investigate five models to examine the relationship between the stock markets of importing countries (*Imp*), the stock markets of exporting countries (*Exp*), the stock markets of importing countries and the oil market (*Imp-Oil*), the stock markets of exporting countries and the oil market (*Exp-Oil*) and finally the stock markets of importing and exporting countries (*Imp-Exp*).

The results are reported in Table 4 below. The coefficients ***λ1*** and ***λ2*** are highly significant in both cases "*Exp*" and "*Exp-Oil*" which implies that the correlation between the stock markets of the exporting countries and the oil market is persistent over time, as well as for the correlation between the markets of exporting countries. Moreover, it is not the same thing for the correlation between the oil-importing countries and the oil market "*Imp-Oil*" which means that the correlation does not persist over time, the same remark for the cases "*Imp*" and "*Imp-Exp*" (Khalfaoui et al., 2019).

Table 4. DCC-GARCH (1,1) model estimation

	Imp	*Exp*	*Imp-Oil*	*Exp-Oil*	*Imp-Exp*
λ1	*0.0005*	*0.009 ***	*0.00*	*0.008 ***	*0.0003*
λ2	*0.62 **	*0.912 ****	*0.20*	*0.89 ****	*0.39*
AIC	*-29.20*	*-27.55*	*-34.11*	*-32.5*	*-56.61*
LLV	*26488*	*26026*	*30954*	*30706*	*51367*

Notes: *, ** and *** indicate rejection of the null hypothesis at 10%, 5% and 1% respectively

Since the coefficients λ1 and λ2 are insignificant for the importing countries, we present only, in Figure 2, the dynamic conditional correlation in the stock markets among themselves and their correlations with the oil market (Brent). Overall, in some periods the correlation becomes positive and in others it is negative. This relationship can be due to the transfer of news from the oil market to the stock market and also to the way investors react. We notice that during the health crisis in 2020, the correlation between the stock market and the oil has increased and then returned to its previous level. This strong increase indicates that the stock market returns of the MENA exporting countries move in the same direction as the oil return during the crisis of covid-19. Indeed, in this period, the closure of industries and the production suspension in lockdown led to a fall in stock prices and oil prices. On the other hand, for the correlation between the stock markets, it is noted that the strongest correlation is recorded between the QEAS index and TASEI (rho = 0.33). Thus we can observe the decrease of this correlation in 2017 which is caused mainly by the diplomatic crisis between the two countries when Saudi Arabia along with other countries broke their diplomatic relationship with Qatar.

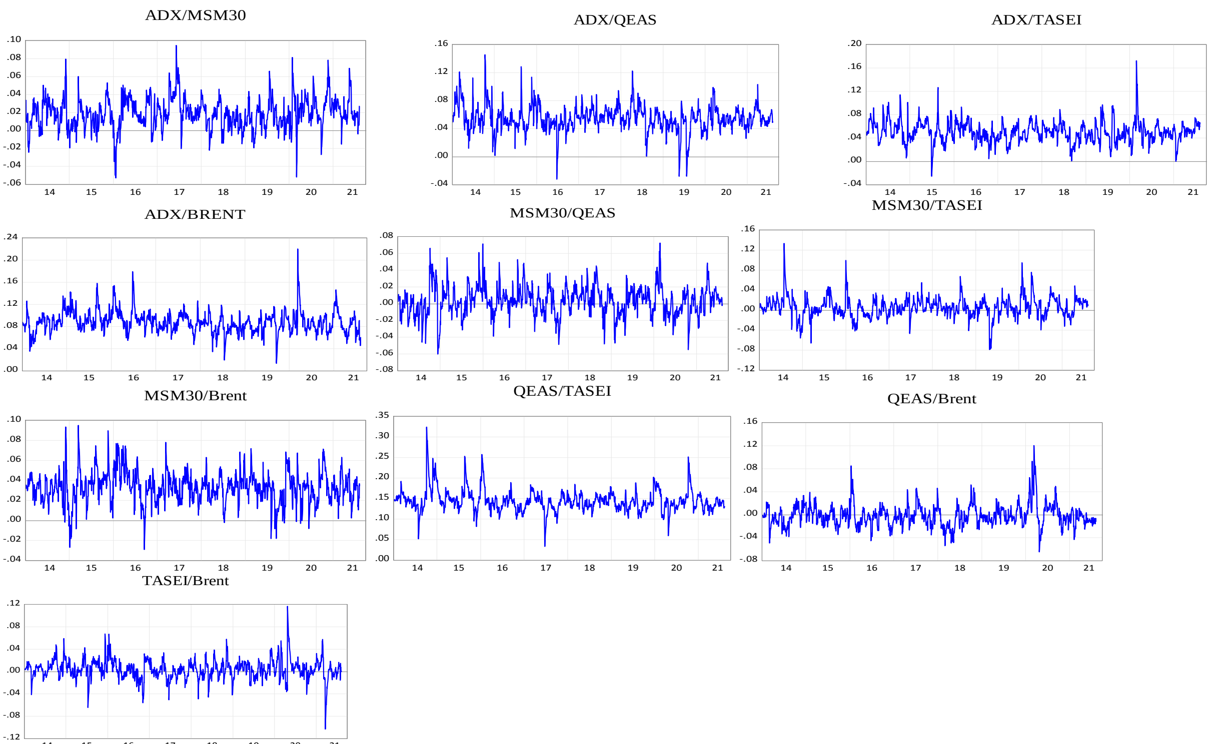

Figure 2. Dynamic conditional correlation between exporting countries' stock markets and the oil market

5.4 Optimal Weight

From the results mentioned in the previous two sections, it is interesting to notice the contagion effect from the oil market to the stock markets and the connections among them.

Investors in these countries may need to hedge more effectively against oil risk by diversifying their portfolios. The investor's strategy is to minimize the risk of his portfolio without reducing his expected returns. To show the implications of our results on optimal portfolio composition, we calculate the optimal weight of oil in a portfolio composed of two assets (oil and stock). Figures 3 and 4 illustrate the optimal weight of the oil asset in the portfolio. We can note that during the covid-19 crisis, the weight of oil is very near to be equal to zero for both oil-exporting and oil-importing countries. This is due to the historical drop in the oil price in April 2020 and its effect on the investor's behavior. However, in periods when economic activity is almost stable, the oil share exceeds 0.5 in most cases, which indicates that oil is more efficient for an investor who is looking to minimize his portfolio risk.

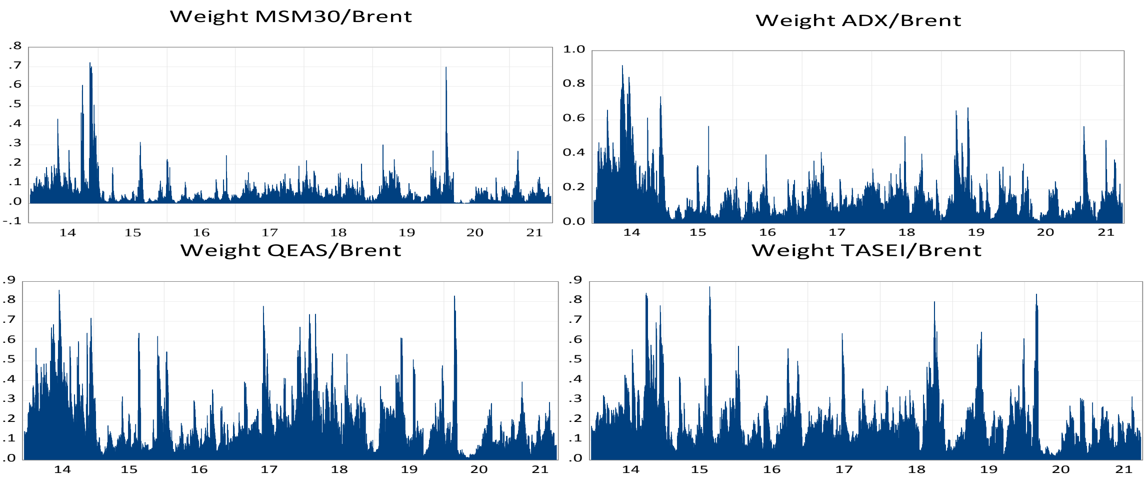

Figure 3. The optimal weight of oil assets in the portfolio (case of exporting countries)

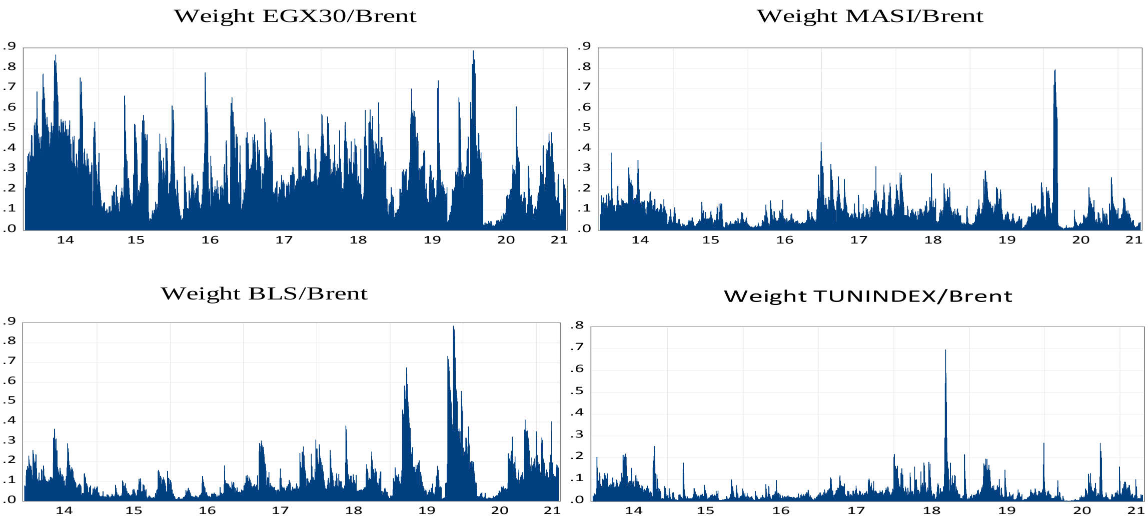

Figure 4. The optimal weight of oil assets in the portfolio (case of importing countries

5.5 Hedge Effectiveness

Hedging in finance refers to investment protection. A hedge is an investment position, in which the investor tries to mitigate potential losses suffered by an associated investment.

Hedging is frequently used by investors who invest in market-related instruments[§]. In our study, we calculate the portfolio risk-adjusted return and the "Hedge effectiveness" index introduced by Ederington (1979). We follow Arouri et al. (2011), Morema and Bonga-Bonga (2020).

To assess the contribution of the oil asset to the hedging, we construct two portfolios P1 (Stock-oil) and P2 (Stock):

$$P_1 = w * return_{oil} + (1 - w) * return_{stock}$$
$$P_2 = 1 * return_{stock}$$

Where we and (1-*w*) are the optimal weight of oil and stock in the portfolio respectively, obtained in the previous subsection. A positive hedge ratio indicates the number of future contracts that must be sold (short) in the oil market if the investor has a long position in the stock market. A negative hedge ratio occurs when investors take a long or short position in both the stock and the oil market (Bonga-Bonga & Umoja, 2016). The results in Table 5 show that the P2 portfolio is better than the P1 portfolio in terms of risk-adjusted return except for the Lebanese market, i.e., the addition of the oil asset in a portfolio containing stocks can reduce its risk-adjusted return. Our results are in contrast with those of (Arouri et al., 2011).

Table 5. Risk-adjusted return and hedging effectiveness

	Mean (%)		***St. dev (%)***		**Risk-adjusted return (%)[**]**		***Variance (%)***		***HE (%)***
	P1	***P2***	***P1***	***P2***	***P1***	***P2***	***P1***	***P2***	
Oil exporters									
MSM30	-0.042	-0.030	0.575	0.623	-7.325	-4.800	0.003	0.004	14.817
ADX	-0.002	0.027	1.026	1.100	-0.194	2.445	0.011	0.012	13.086
QEAS	-0.031	0.015	0.926	1.040	-3.396	1.478	0.009	0.011	20.696
TASEI	-0.027	0.017	1.037	1.160	-2.594	1.499	0.011	0.013	20.151
Oil importers									
EGX30	-0.015	0.025	1.061	1.340	-1.382	1.894	0.011	0.018	37.228
BLS	0.001	-0.007	0.640	0.711	0.093	-0.939	0.004	0.005	18.927
MASI	0.004	0.015	0.631	0.693	0.628	2.228	0.004	0.005	17.206
TUNINDEX	0.023	0.026	0.452	0.470	5.098	5.511	0.002	0.002	7.523

6. Conclusion

The purpose of our study is to investigate the effect of oil price volatility on the return and volatility of MENA stock markets, to explore the dynamic conditional correlation between the stock and oil markets, and to show the performance of the oil asset in the portfolio.

In a first step, we employ a univariate T-GARCH (1,1) model by incorporating the calculated oil price volatility (Brent) as an exogenous variable in the mean and variance, in order to illustrate the impact of the Brent volatility on the return and volatility of each stock market. The results show that oil volatility has a positive influence on stock market volatility for oil-exporting countries, while it negatively affects volatility for importing countries. Thus, the results show an asymmetric impact of past shocks on the volatility of stock market indices. Indeed, in most cases, negative shocks have a greater effect on volatility than positive shocks.

[§] What Is a Hedge? By THE INVESTOPEDIA TEAM, Updated September 30, 2021, Reviewed by GORDON SCOTT “https://www.investopedia.com/terms/h/hedge.asp”.

[**] the risk-adjusted return of a portfolio is obtained by dividing the average return (mean) by the risk (St. dev).

In a second step, we examine the dynamic conditional correlation between the stock markets and the oil market by referring to a multivariate DCC-GARCH model. The results show that the stock markets of exporting countries are significantly correlated with each other and with the oil market, this correlation is more remarkable during the Covid-19 crisis and it persists over time. However, the results are different for oil-importing countries. We compute the optimal weight of the oil asset in the portfolio and the Hedge Effectiveness Index from the output of the DCC-GARCH model. We find that the oil asset is a good instrument for risk minimization in tranquil periods, but during the financial crisis, it is regarded as a contributor to the portfolio risk increase.

Our results are useful for building efficient models for asset pricing, predicting future stock market volatility and will help to better understand the linkages between MENA stock markets and the oil prices. Thus, this work provides investors with an overview of the link between oil volatility and stock market returns in order to maximize the expected return by reducing the risk level of their portfolios.

Finally, an extension of our work would be to introduce some variables such as the economic policy uncertainty (Daily Infectious Disease Equity Market Volatility Tracker) which has become very high in the countries of our sample due to wars and political instability and especially in the period of the coronavirus pandemic. As well, we can even introduce the variables that increase and decrease the uncertainty such as Corona Virus and its vaccine.

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