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THE IMPACT OF THE OIL AND GOLD PRICE SHOCK ON ISLAMIC AND CONVENTIONAL STOCK MARKET INDICES: EVIDENCE FROM THE DCC-GARCH MODEL

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Abstract:

This paper aims to explain the relation between gold, oil, and financial market indexes in the US. To do so, we applied the conditional dynamic correlation Generalized autoregressive conditional Heteroskedasticity DCC-GARCH model on tree indexes DJIM50US, DJIA, and S&P500 representing the US financial market, this model capture the dynamic correlations of the variance, covariance, and correlation coefficient of the time series, and help to reflect the long-run dynamic correlation between returns. Our results show that there is no significant correlation between gold and market indexes in the US (for Islamic and conventional indexes), on the other hand, oil has a significant correlation with all indexes, as well as the gold.

1. Introduction:

It is interesting and important for financial economists to observe and study movements in oil and gold prices because of their important role in the economy. For example, an increase in oil prices can be a source of inflationary pressure, which can predict the future of interest rates and investments, so gold is considered a safe investment for all economies. The relationship between oil prices and economic growth is believed to be a fact. The positive correlation between oil prices and economic growth should exist, especially in countries that depend heavily on oil revenues where it has a large share of GDP.

In Saudi Arabia, Russia, and Venezuela, one of the major oil-producing countries, the oil sector contributes about 45%, 30%, and 33% of their respective GDP. In a developed country such as the United Kingdom, where oil reserves are declining, its GDP is by far represented by the service sector such as banking, insurance, and other service companies. Besides, the service sector also accounts for about 76% of the GDP of the developed economy of the United States, while its imported oil accounts for two-thirds of its consumption. Although the United States obtains oil from its reserves, it chooses to import oil from foreign countries to conserve the owns for as long as possible. As a result, the relationship between oil and economic growth is expected to vary from a country to another depending on each country's dependence on oil and whether the country is an oil consumer or an oil supplier. The objective of this study is to examine how conventional and Islamic stock market indices respond to changes in oil and gold prices by applying the DCC-GARCH model. This paper is structured as follows: Section 2 deals with the literature review. Sections 3 contain the methodology and data used. Section 4 discusses the results and discussion. Finally, section 5 concludes our work.

2. Literature review

Since there is thought of a link between oil prices and economic output, studying the relationship between oil prices and stock market returns and volatility has become an attractive topic for researchers in finance and economics. The existence of inverse relationships between oil prices and economic activity was examined by Hamilton (1983; 1996), one of the first authors to estimate the impact of oil-price increases on the real income of the U.S. economy after the first oil-price shock in 1973.

Hamilton has shown that the historical correlation between rising oil prices and economic recession is not a statistical coincidence for the period 1948-1980. He found that an increase in oil prices had reduced output growth in the U.S. economy.

Gold is considered to be a precious metal with both commodity and monetary attributes. Due to the influences of common factors, many empirical studies indicate that crude oil and gold prices are positively correlated and have the co-movement mechanism of risk. Zhang et al (2008) and Ewing and Malik (2013) find that changes in gold prices can affect the volatility of crude oil prices and produce an occasional relationship between them. One possible reason for this is that both gold and crude oil are traded in U.S. dollars in international markets and are considered the world's active commodities.

For example, a depreciation of the U.S. dollar would lead to an increase in the nominal dollar price of crude oil and gold, which has been confirmed by Baur and McDermott (2010) and Reboredo (2013). Also, a violent surge in the price of crude oil will increase the demand for gold and support the rise in the gold price. To explain this phenomenon, Reboredo (2013) provides empirical evidence that gold can serve as a refuge from crude oil price fluctuations during the financial crisis. Numerous publications have expressed concern about the relationship between the price of gold and the price of crude oil Reboredo (2013); Jain and Biswal (2016). Reboredo (2013) uses copula to analyze the dependency structure between the price of gold and the price of oil, and they find that there is a positive and significant dependency between the gold market and the oil market. However, the dynamic linkages between the gold market, the U.S. dollar, and the crude oil market have not been much studied in the empirical literature. Lin et al. (2016) use wavelet analysis to examine whether the U.S. dollar can influence oil and gold prices. It is essential to study the impact of oil prices on the stock market. The important point is that it is to the advantage of investors, fund managers, and policymakers to understand the relationship between the two markets. Theoretically, the oil market can potentially exert significant effects on the stock market. Changes in oil prices cause changes in production costs and, therefore, oil price shocks empirically affect real output and expected profits, leading to changes in overall stock prices. This theoretical fact has been proven by previous studies. There is a build of literature that sheds light on the link between oil prices and stock returns. Hammoudeh and Aleisa (2004) examine the relationship between NYMEX oil futures prices, prices quoted for delivery at a specific quantity, time, and location on the NYMEX, and the Saudi stock market and other GCCs using daily data covering the period 1994 to 2001. Using cointegration, causality, and error correction techniques, and the main conclusion is that only Saudi stock market returns are predictive of oil futures prices, and they can also be predicted by oil prices. Maghyereh (2004) found that oil returns had no impact on 22 emerging markets using a generalized VAR approach. However, Maghyereh and Al-Kandari (2007) attempted to explore the possibility of finding a non-linear relationship between oil prices and stock markets in GCC countries. They concluded that there is a non-linear relationship between oil prices and stock market indices in the GCC countries. So far, the literature on the relationship between oil and the stock market simply says that oil returns can have some influence on stock market returns. However, Ross (1989) has also shown that the flow of information also affects the volatility of asset returns. Malik and Hammoudeh (2007: p. 360) state that: "*Since the flow of information and the time used to process it varies in individual markets, different volatility patterns can be expected in different markets*". They have contributed to the impact of volatility on cross-market hedging and changes in shared information. They find that the relationship between the stock market and the oil market can exist between the second moments. Therefore, the question to be answered here is whether stock market returns and their conditional variance are sensitive to oil price shocks and volatility. In other words, can oil market shocks and volatility explain average expected stock market returns and conditional volatility? and does this mean that oil volatility will continue if it can explain expected returns? Moreover, the accuracy of the oil market volatility measure is also important to see if it can help explain the average stock market return. The autoregressive conditional heteroscedasticity model (ARCH), originally developed by Engle (1982) and later generalized by Bollerslev (1986), is by far the most popular method for modeling the volatility of high-frequency financial time series data. Generalized multivariate autoregressive conditional autoregressive heteroscedasticity (GARCH) models have been popular for estimating volatility spillovers in different markets.

A negative sensitivity of US stock market returns to the volatility of oil returns is a conclusion drawn by Sadorsky (1999). His empirical study, using monthly U.S. data from January 1947 to April 1996, examined the links between oil prices and stock prices using an unrestricted VAR model that also included short-term interest rates and industrial production. It was evident that both the price of oil and a univariate GARCH measure of oil price volatility plays an important role in explaining stock returns. However, oil prices became more important in affecting stock returns after 1986 because of the increased turbulence in the oil market. Hammoudeh and Aleisa (2002), using monthly data from 1991 to 2000, used univariate two-stage GARCH models. In the context of markets in Bahrain, Indonesia, Mexico, and Venezuela, the results indicated that average spillovers from oil markets to equity markets. These results did not surprise us as some of these countries are major oil exporters and their economies are highly dependent on oil. Hammoudeh and Aleisa suggested that further research could test whether the relationship between oil and stock market returns exists in the second moment. In response to this suggestion, Malik and Hammoudeh (2007) examine the volatility and shock transmission mechanism between U.S. equities, the world crude oil market, and the stock markets of Saudi Arabia, Kuwait, and Bahrain, using a multivariate GARCH model on daily data from 14 February 1994 to 25 December 2001.

They found a significant transmission of volatility between conditional spreads in U.S. equities and world crude oil markets. The conclusion was that, in the Gulf markets, a significant spillover of volatility from the stock market to the oil market was found only in the case of Saudi Arabia, while other stock markets are the recipients of oil market volatility. Malik and Ewing (2009), using weekly returns covering the period from January 1, 1992, to April 30, 2008, used bivariate GARCH models to simultaneously estimate the mean and conditional variance between oil prices and five different U.S. sectoral indices; financial, industrial, consumer services, health care, and technology.

It was statistically evident that shocks and volatility were transmitted between oil prices and some of the market sectors examined. To summarize the literature presented above, the empirical evidence is reasonably consistent that there is a transmission of volatility between oil prices and the conventional United States and some emerging equity markets. However, it would also be interesting to see whether this applies to ISMI, given that the GCC, including some of the major oil-exporting countries, is an important source of capital for Islamic funds.

Studies using GARCH models that have examined Islamic markets to date have focused only on the risk/return relationship. They have not yet discussed the effects of oil volatility on Islamic markets. Hassan (2002), using a GARCH model, examined the time-varying risk-return relationship for the Dow Jones Islamic Index (DJIM) over the period 1996-2000. Empirical evidence showed that there is a significant positive relationship between conditional volatility and returns on DJIM stock market indices. However, a large literature has been devoted to the dynamic link between financial markets by studying the model dominated by Engle (2002), namely the conditional dynamic correlation (DCC) model.

Among this research, Joy (2011) applied the DCC model to assess the role of gold as a hedge and safe haven against the US dollar. He found a negative correlation between the price of gold and the U.S. dollar exchange rate and also suggested that gold behaves as a hedge against the U.S. dollar. Sensoy (2013) used Aielli's consistent conditional dynamic correlation (cDCC) model Aielli (2013) to study changes in the volatility of the returns of four major precious metals over the period 1999-2013 and found strong correlations between precious metals and a one-way contagion effect from the volatility of gold to all other precious metals, such as silver, platinum, and palladium.

Abul Basher and Sadorsky (2016) applied some correlation models, such as the DCC, asymmetric DCC (ADCC), and the generalized orthogonal GARCH (GO-GARCH) models, to compare the optimal coverage ratios obtained from the DCC-type models (DCC and ADCC) with those obtained from the GO-GARCH model by analyzing emerging market prices, oil prices, the VIX, gold prices, and bond prices. Sadorsky (2014) used a VARMA-AGARCH and DCC-AGARCH model to study the volatilities and behavior of conditional correlations of emerging market prices, copper prices, oil prices, and wheat prices. The author finds a significant increase in correlations after 2008. Tabak and Cajueiro (2007) studied the dynamic nature of crude oil prices (WTI and Brent) and volatility using the time-varying Hurst exponent approach. Their empirical results revealed that WTI crude oil prices exhibited a weaker form of efficiency than Brent crude oil prices over the period 16 May 1983 to 28 July 2014. Besides, the degree of long-term dependence measured by the Hurst exponent decreased over time for both average yields and volatilities. Wang and Liu (2010) extended the work of Tabak and Cajueiro (2007) and focused on analyzing the efficiency of the WTI crude oil market using relaxed fluctuation analysis.

3. Data and methodology:

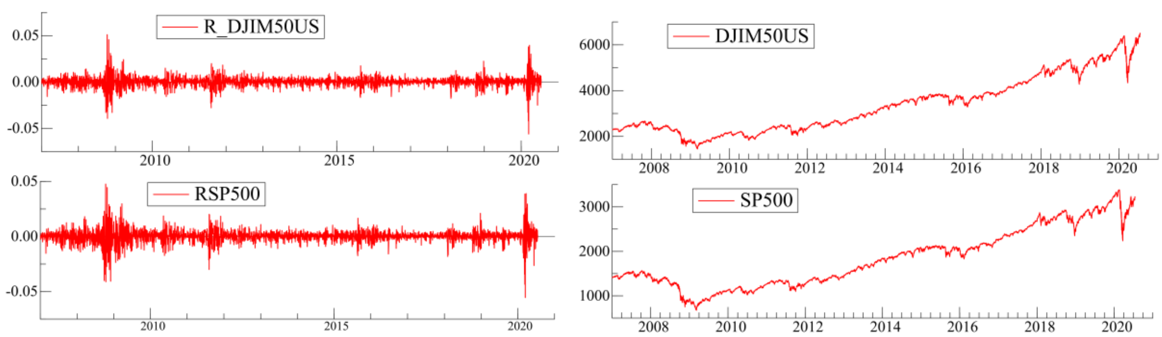
3.1. Data:

This chapter examines the relationship between oil prices, gold, and three stock market indices, two conventional and one Islamic; DJIM US 50, S&P 500, and DJIA. These three indices are deliberately chosen to be proxies for the US stock market, the data cover the period from 2007-01-03 to 2020-07-17.

Table 1: Descriptive statistics of the performance series of the three indices and the two commodities

	RSP500	R_OIL	R_GOLD	R_DJIM50US	R_DJIA
Mean	0.000122	5.75E-05	0.000125	0.000151	0.000112
Median	0.000286	8.16E-05	6.63E-05	0.000253	0.000238
Maximum	0.047587	0.171437	0.037537	0.051027	0.046749
Minimum	-0.055439	-0.143708	-0.042650	-0.055972	-0.060114
Std. Dev.	0.005725	0.012446	0.005000	0.005418	0.005499
Skewness	-0.529896	0.735612	-0.119765	-0.298594	-0.474063
Kurtosis	16.35522	33.06979	9.425659	17.71513	18.87194
Jarque-Bera	24746.52	124963.9	5700.644	29903.95	34857.19
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	3309	3309	3309	3309	3309

Financial time series are generally stationary at the first difference. The unit-root tests, presented in Table 2, confirm that by rejecting the null hypothesis of a unit root after the first difference indicating that all the series in this study are I (1). Therefore, the time-series data used are all in the form of returns using the first difference in log prices.



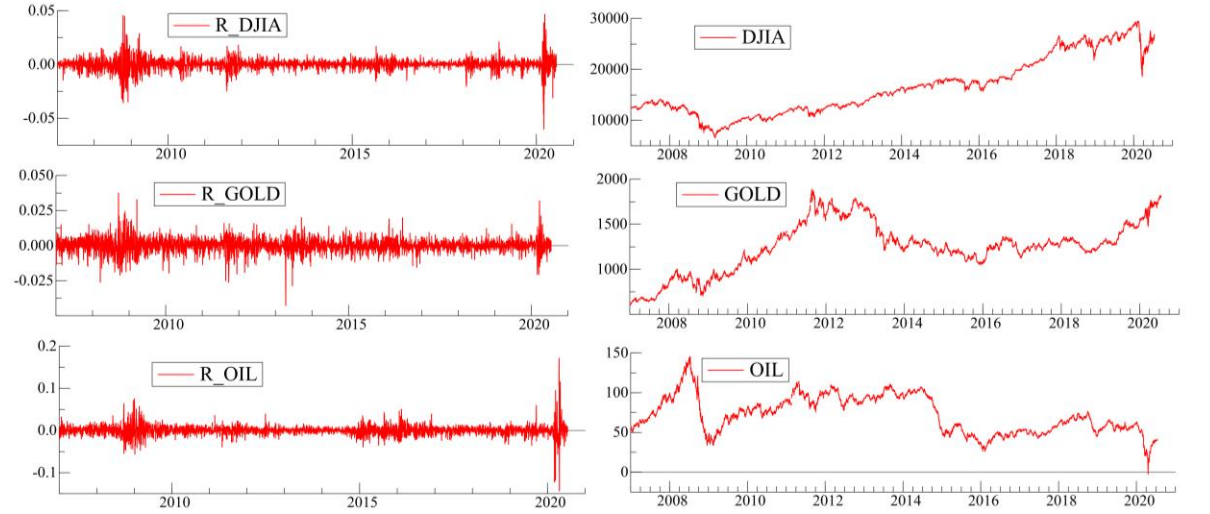


Figure 1: Change in closing values and returns of the series of variables

Figure 1 shows the evolution of prices and returns for the three DJIA DJIM50US and S&P500 indices and the two commodities Gold and Crude oil.

Table 2: Stationarity test of the series in our study

	RDJIM50US	RDJIA	RSP500	RGOLD	ROIL
ADF statistic	-72.06456	-66.61891	-71.16282	-61.11742	-33.49572
critical values 1%	-3.431898	-3.432146	-3.431898	-3.431898	-3.431899
critical values 5%	-2.862109	-2.862219	-2.862109	-2.862109	-2.862110
critical values 10%	-2.567116	-2.567175	-2.567116	-2.567116	-2.567117
Prob.*	0,0001	0,0001	0,0001	0,0001	0,0000
PP statistic	-72.36123	-66.57214	-71.31186	-61.26509	-57.71466
critical values 1%	-3.431898	-3.432146	-3.431898	-3.431898	-3.431898
critical values 5%	-2.862109	-2.862219	-2.862109	-2.862109	-2.862109
critical values 10%	-2.567116	-2.567175	-2.567116	-2.567116	-2.567116
Prob.*	0,0001	0,0001	0,0001	0,0001	0,0001
KPSS statistic	0.186506	0.134798	0.197767	0.252886	0.194869
critical values 1%	0.739000	0.739000	0.739000	0.739000	0.739000
critical values 5%	0.463000	0.463000	0.463000	0.463000	0.463000
critical values 10%	0.347000	0.347000	0.347000	0.347000	0.347000

Notes: ADF refers to the Augmented Dickey-Fuller test, PP to the Phillips-Perron test, and KPSS to the Kwiatkowski, Phillips. Schmidt, Shin-test, where the first two tests have the null hypothesis of non-stationarity, and the KPSS has the null of stationarity of the analyzed time series. *, **, and *** refer to the significance of the test statistics at 10, 5, and 1% risk levels. Percentage returns are calculated as log differences of daily price observations.

The stationarity test for all models shows that all the yield series are stationary at the level, the ARCH-LM heteroskedasticity test (Table 3) also shows that the yield series are heteroskedastic and that the ARCH and GARCH family models can be applied to all the series.

Table 3: Test of heteroscedasticity ARCH-LM test

	F.stat	Prob	nR²	Prob
RDJIA	427.2890	0.0000	378.4430	0.0000
RDJIM50US	499.4560	0.0000	441.2619	0.0000
RSP500	485.4696	0.0000	430.3148	0.0000
RGOLD	153.4400	0.0000	147.5174	0.0000
ROIL	199.4452	0.0000	189.2020	0.0000

3.2 Methodology

The objective of this article is to study the dynamic relationship between stock market indices, gold, and crude oil. Some researchers use GARCH-type models to study this relationship, but it has some limitations.

To study the correlation between the performances of different assets over time, it is necessary to estimate the change in correlation over time. In the literature, several methods are proposed to study the variation of the correlation over time, particularly in the GARCH family. These methods are cumbersome to estimate and difficult to interpret. Engle (2002) proposed a pragmatic model to study the change in correlation over time between different asset returns, known as the dynamic conditional correlation model (DCC). On the one hand, the DCC-GARCH model retains the good features of the traditional GARCH-type model; on the other hand, it overcomes the computational complexity of the traditional model and helps to improve the accuracy of the model's estimation. As shown in Table 3, the yield series exhibit heteroskedasticity. These characteristics justify the use of DCC-GARCH to capture the dynamic correlations of the variance, covariance, and correlation coefficient of the time series, and it helps to reflect the long-run dynamic correlation between returns. Next, the correlation and conditional volatility plots of the DCC-GARCH models are presented to explore the contribution of oil and gold variation to the conditional variance of the data.

3.2.1. Model GARCH

The GARCH model is giving by the following equation:

$$\sigma_t^2 = \omega_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2.$$

Where ω is unconditional volatility, α_i is a parameter that governs the impact of past shock: the more important it is, the more volatility will increase after a shock. β_j is a parameter interpreted as the speed of getting back to minimum volatility ω. This equation refers to the conditional variance σ_t^2 . The conditional variance depends on lagged squared errors and lagged conditional variances. To be well-defined GARCH model necessitates that coefficient of the lagged squared errors and lagged conditional variances to be non-negative and their sum must be less than unity $\omega > 0, \alpha > 0 \; and \; \beta > 0$.

3.2.2. Model DCC-GARCH

The DCC-GARCH model has the following form:

$$r_t = \mu_{t-1} + a_t$$

With

$$a_t = H_t^{1/2} \varepsilon_t,$$

Where ε_t is a random vector k × 1 with a mean of zero and H_t is a positive defined matrix k × k. According to the matrix decomposition theory, the covariance matrix which can be decomposed into $H_t = D_t R_t D_t$

Where $D_t = diag(\sqrt{H_{11,t}}, \dots, \sqrt{H_{kk,t}})$ is the diagonal matrix (k × k) of the conditional standard deviations of the residuals, which are obtained by taking the square root of the conditional variance modeled by the GARCH (1,1) process, and R_t in Eq. (3) is a matrix of dynamic conditional correlations. Let $z_t = D_t^{-1}, \varepsilon_t$ then H_t can be updated by the Quarterly Standardized Residue (z_{t-1}),), the unconditional covariance matrix (H_0) and its first-order delayed value (H_{t-1}) according to the equation. (4).

$$H_t = (1 - a - b)H_0 + a\, z_{t-1} z_{t-1}^T + b\, H_{t-1}.$$

The parameters of the DCC-GARCH (1,1) model are generally estimated using the quasi-maximum likelihood (QML) method concerning the log-likelihood function and an ordinary two-step estimation procedure. We assume ε_t in Eq. (2) is the multivariate t-distribution normalized with $\mathcal{V}$ degrees of freedom and probability density function.

$$p(\varepsilon_t, \mathcal{V}) = \frac{\Gamma((\mathcal{V}+k)/2))}{[\pi(\mathcal{V}-2)^{\frac{k}{2}}\Gamma(\frac{\mathcal{V}}{2})]}[\, 1 + (\mathcal{V}-2)^{-1} {\varepsilon_t}^{T_{\varepsilon_t}}\ ]^{-(\mathcal{V}+k)/2}$$

In combination with the average equation of the equation. (1), we can obtain the conditional multivariate distribution of r_t that is to say,

$$r_t | \mathcal{F}_{t-1} \sim t(\, r_t, \mu_{t-1},\ H_t, \mathcal{V})$$

4. Results and discussions

The objective of this study is to estimate 3 models of stock market index series and their relationships with gold and crude oil. The results of the estimates are presented in Table 4.

Table 4: DCC-GARCH model estimation

		RDJIA	RDJIM50US	RS&P500
C_{M0}	Coefficient	0,000311	0,00029	0,00029
	p-value	0,000000	0,00000	0,00000
C_{V0}	Coefficient	0,48811	0,53551	0,46955
	p-value	0,000000	0,00000	0,00000
α_0	Coefficient	0,151683	0,13062	0,13080
	p-value	0,000000	0,00000	0,00000
β_0	Coefficient	0,830109	0,84529	0,85027
	p-value	0,000000	0,00000	0,00000
$\alpha + \beta$		0,981792	0,975903	0,98107
C_{MGold}	Coefficient	0,000105	0,00011	0,00011
	p-value	0,1499	0,10610	0,10610
C_{VGold}	Coefficient	0,188354	0,24504	0,24504
	p-value	0,0707	0,03720	0,03720
α_{Gold}	Coefficient	0,043769	0,04549	0,04549
	p-value	0,0707	0,00160	0,00160
β_{Gold}	Coefficient	0,949341	0,94326	0,94326
	p-value	0,000000	0,00000	0,00000
$\alpha + \beta$		0,99311	0,988746	0,988746
$C_{MCruid-oil}$	Coefficient	0,000165	0,00021	0,00021
	p-value	0,2235	0,09710	0,09710
$C_{VCruid-oil}$	Coefficient	0,008086	0,00012	0,00012
	p-value	0,0315	0,98120	0,98120
$\alpha_{Cruid-oil}$	Coefficient	0,081598	0,09741	0,09741
	p-value	0,0001	0,00000	0,00000

$\beta_{Cruid-oil}$	Coefficient	0,914855	0,92605	0,92605
	p-value	0,000000	0,00000	0,00000
$\alpha+\beta$		0,996453	1,023452	1,023452
	Corrélation paramètres			
ρ_{IG}	Coefficient	0.015511	0.095544	0.067488
	p-value	0.7920	0.1474	0.2999
ρ_{IC}	Coefficient	0.264001	0.312417	0.312417
	p-value	0.0000	0.0000	0.0000
ρ_{CG}	Coefficient	0.213999	0.227097	0.227097
	p-value	0.0001	0.0010	0.0007
α	Coefficient	0.022522	0.024608	0.026567
	p-value	0.0005	0.0000	0.0000
β	Coefficient	0.966546	0.965903	0.301587
	p-value	0.0000	0.0000	0.0000
$\alpha+\beta$		0,989068	0,990511	0,328154

The DCC-GARCH model (1,1) shows a significant overestimation of oil and gold volatilities, in particular, the estimation of oil volatilities during periods of a global financial crisis (see Figures 2, 3, and 4).

For the DCC-GARCH model (1,1), we assume that the univariate conditional yields of crude oil or gold are significant. Next, we can decompose the DCC-GARCH (1,1) model into two parts, and the marginal model includes the following parameters:

$$C_{M0},\ C_{V0}\ ,\alpha_0\ ,\beta_0\ ,C_{MGold}\ ,C_{VGold}\ ,\alpha_{Gold}\ ,\beta_{Gold}\ ,C_{MCruid-oil}\ ,C_{VCruid-oil}\ ,\alpha_{Cruid-oil},\beta_{Cruid-oil}$$

and the dynamic correlation part has the parameters ($\rho_{IG},\rho_{IC}\ et\ \rho_{CG}$). As shown in Table 4, we find both $\alpha_0+\beta_0$, $\alpha_{Gold}+\beta_{Gold}$, $\alpha_{Cruid-oil}+\beta_{Cruid-oil}$Thus, it is implicit that the persistence of volatility exists indefinitely in the Brent oil and gold markets.

The values $\alpha+\beta$ are obtained between Brent oil and Gold for the three DJIA DJIM50US and S&P500 indices are respectively equal to 0.989068, 0.99051, and 0.328154. It can be explained that the variation of the correlation over time will be brought back to its average level between crude oil and the gold market.

We also note the absence of significant values for the correlation between gold and the indexes treated in our work, while it should be noted that the parameters of the DCC-GARCH model (1.1) are almost statistically significant at the 1% level, except for the constant parameters of the mean and variance models

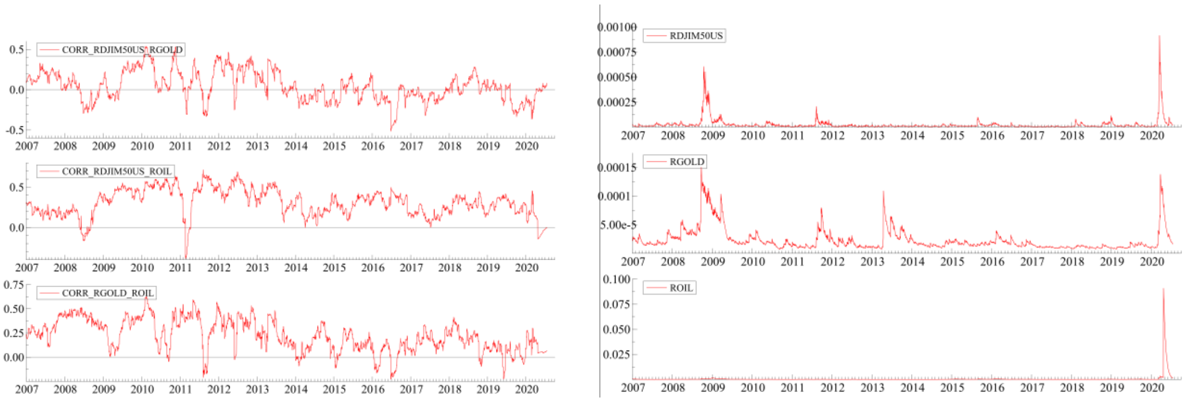


Fig. 2. Conditional variance and Dynamic correlation between DJIM50US Gold and Crude oil

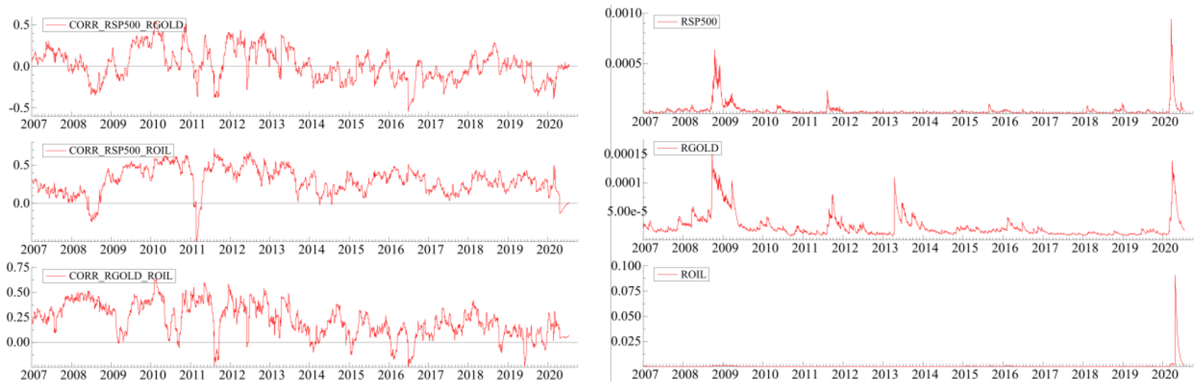


Fig. 3. Conditional variance and Dynamic correlation between S&P 500 Gold and Crude oil

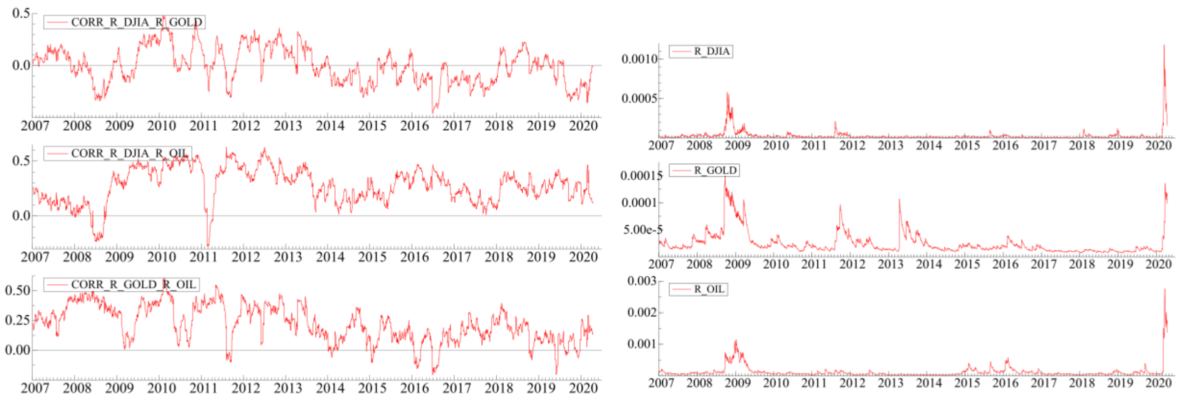


Fig. 4. Conditional variance and Dynamic correlation between DJIA Gold and Crude oil

From the perspective of dynamic correlation, the impact of the fallout from volatility can be understood intuitively. Based on the DCC-GARCH model, the dynamic correlations between indices, crude oil, and gold in the United States marked are shown in Figures 2, 3, and 4. There is generally a stable positive correlation between them.

4.1. Gold/oil dynamics

For commodities, the reasons for this positive correlation can be explained by both the commodity attributes and the financial attributes of oil and precious metals. First of all, oil and precious metals are important industrial commodities from the point of view of commodity attributes and, in general, they are related in a complementary way, with one increasing demand leading to another, which in turn leads to higher prices. Second, in the financial market, oil and precious metals are substitutes for each other in terms of financial and investment attributes. When the price of oil rises, yields increase, and precious metals as an investment alternative for oil, the expectation of increasing yields of precious metals will also be increased, leading to an increase in investment in precious metals.

Their commodity and financial attributes together create this positive correlation. However, these correlations had a negative characteristic in 2007 and 2009, and this negative correlation appeared more frequently after 2011, particularly in 2014 and 2016. Specifically, the correlation between oil and gold increased in 2007 and 2008, but declined rapidly in early 2009 and eventually became negatively correlated. This negative correlation may be due to the sharp decline in international crude oil that occurred between July 2008 and early

2009, forcing investors to turn to other commodities, which led to an increase in the price of other commodities such as gold and silver. After May 2011, this negative correlation appeared more frequently. In the meantime, the price of oil has been back in the uptrend channel since the beginning of 2009 and fell sharply again in August 2014. The negative correlation of the international price of crude oil after major economic events such as the Great Financial Crisis (GFC) over the period 2007-2009, and the European sovereign debt crisis in 2011, which indicate the hedging function between crude oil and precious metals, will appear when the economic climate is uncertain.

Therefore, the macroeconomic shock is one of the main reasons for the negative correlation that is believed. And the negative correlation can be taken as a sign that the financial attributes of precious metals have increased, which may indicate that precious metals could represent a greater investment value during this period. It can be seen that the transformation of the positive and negative correlation is a reflection of the time-varying characteristic of the volatility ripple effects between international crude oil and precious metals.

4.2. Index/commodity dynamics

The literature has shown that certain asset classes are particularly important. The increased financialization of some commodity markets, such as oil and gold, has made these assets even more influential in equity markets than before (Basak and Pavlova, 2016; Adams and Glück, 2015). Also, there is evidence that the volatility of these markets interacts significantly with stock markets around the world (Mensi et al., 2017, 2013; Diebold and Yilmaz, 2012).

It should be noted that changes in crude oil and gold prices are often influenced by sudden external events, such as national politics, war, and natural disasters. These extreme movements in the modeling of crude oil and gold prices could generate structural instability.

Because of the negative correlation of these two commodities during times of crisis, gold can serve as a refuge from crude oil price fluctuations during the financial crisis period.

For example during the VIDOC pandemic-19, the price of oil was severely impacted, the shutdown of several sectors of economic activity led oil prices to very low levels, while gold gained value, this result coincides with that of Lee et al (2010), Wen et al (2016), and Wen et al (2018).

Regarding the difference between the conventional and Islamic market, the results of the models show that the Islamic market presented in our case by the DJIM 50 US is more volatile than the other two conventional indices S&P 500 and DJIA, the model parameters DCC-GARCH model confirms that the Islamic index has the lower which indicates that his response to shock is weak. The parameters $\alpha + \beta$ are ≤ 1 which confirms the stationarity of the models.

Table 5: Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
R_OIL does not Granger Cause RSP500	3042	6.88639	0.0010
RSP500 does not Granger Cause R_OIL		21.3186	6.E-10
R_GOLD does not Granger Cause RSP500	3046	8.46521	0.0002
RSP500 does not Granger Cause R_GOLD		1.47358	0.2293
R_DJIM50US does not Granger Cause R_OIL	3187	22.0228	3.E-10
R_OIL does not Granger Cause R_DJIM50US		8.07996	0.0003

R_DJIA does not Granger Cause R_OIL	3133	21.4736	5.E-10
R_OIL does not Granger Cause R_DJIA		9.24852	0.0001
R_DJIM50US does not Granger Cause R_GOLD	3191	1.97767	0.1386
R_GOLD does not Granger Cause R_DJIM50US		6.25649	0.0019
R_DJIA does not Granger Cause R_GOLD	3137	0.55532	0.5739
R_GOLD does not Granger Cause R_DJIA		9.48892	8.E-05

Granger's causality test results show a significant causal relationship. There is a two-way causal relationship between the returns of the S&P 500, DJIA, and DJIM50US indices and the oil price return. Also, the Granger causality test shows a significant causal relationship for gold returns on all three indices.

This result confirmed the co-movement between the variables and was consistent with the Granger causality results. The result has an important implication in the significant relationship, particularly for the impact of oil prices on the returns of Islamic assets, indicating the exposure of the Islamic stock market to external macroeconomic variables.

Conclusion

The originality of our work lies in the use of commodities (Gold and Oil) for the investigation of shocks on US capital market indices (in the form of conditional correlations). Using daily data, the estimated DCC-GARCH models reveal several significant results.

First, U.S. stock market returns have stronger correlations in times of crisis. Second, returns are most correlated with oil shocks, followed by equity market shocks, and are least correlated with gold shocks. At the same time, fluctuations in the price of gold do not always affect the decision making of equity market participants on US markets (p-value not significant for index/gold correlations). These results are essential for equity investors and fund managers. The negative correlations between equity markets and oil volatility suggest that investors should adjust their holdings when oil volatility increases, particularly during periods of turbulence (such as during the COVID-19 pandemic shocks). The low correlation between equity markets and gold volatility suggests the potential role of gold in portfolio diversification. Investors can react to gold price changes by considering gold to be a very good substitute for equities; because it is more available and they can hedge against inflation, when gold price changes occur, they have the greatest impact on the stock market.

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