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Research Article

The Impact of COVID-19 Epidemic on the Hedging Islamic and Conventional Stock Markets with Financial Assets

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Abstract

This study investigates optimal hedging ratios for Islamic and conventional stock markets during the COVID-19 pandemic using the DCC (Dynamic Conditional Correlation), ADCC (Asymmetric Dynamic Conditional Correlation), and GO-GARCH (Generalized Orthogonal GARCH) models. The effectiveness of various financial assets as hedges is evaluated, and findings indicate that the DJCOM (Dow Jones Commodity), VISTOXX (Euro STOXX 50 Volatility Index), and VIX (Chicago Board Options Exchange Volatility Index) indices exhibit superior effectiveness across both market types, particularly DJCOM showing exceptional performance during the COVID-19 period. The hedging analysis indicates that the hedge ratios vary and depend upon the hedge instrument included in the portfolio. Furthermore, the empirical results indicate that the global impact of the pandemic diminishes the viability of one of the six assets as a safe haven instrument. In conclusion, these findings provide valuable insights for investors and portfolio managers aiming to utilize Gold, Brent, VISTOXX, VIX, CDS (Credit Default Swap), and DJCOM for portfolio rebalancing to mitigate risks associated with volatile Islamic and conventional stock returns. These conclusions contribute significantly to helping investors adjust their investment strategies more effectively and adapt to changing market conditions.

Keywords

COVID-19, Islamic and Conventional Stock Markets, ADCC and GO-GARCH Models, Rolling Estimation Procedure, Hedging Effectiveness

1. Introduction

The novel coronavirus (COVID-19) that started in early 2020 has led to global economic slowdown. Particularly, the production was reduced, consumers changed their behavior and companies were in serious financial burden. Such severe shifts in economy and business across the world are expected to affect stock markets. In addition, recent studies have observed plummets during the pandemic, but the reasons remain unclear (see, for example: [1, 3, 4, 6, 30, 12]).

Since the world health organization has declared the COVID19 as global health emergency, the pandemic has led to a turbulence of financial market [13]. The US stock market experienced circuit breakers twice in one week, and the cases in other markets were not much better. Further, the central banks and governments have immediately come forward with their policy instruments to restore confidence in the financial markets (see, for example: [8, 10, 25]).

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Although in general, stock markets have responded negatively to the pandemic and somewhat rebounded after the announcement of bailout programs, the exact direction and magnitude of stock markets responses to stimulus packages and announcements of coronavirus outbreak are yet to be explored. The COVID-19 pandemic is not over yet, from an investment perspective, there is a need to assess how COVID-19 affected efficiency in cryptocurrency and stock markets. However, for investors, the importance of portfolio diversification increases during periods of financial and economic turbulence. The optimal returns through effective diversification need a complete understanding of the risk and return characteristics of different securities in a portfolio, as well as the comovements between them.

In such a context, contemporary investment strategies, such as the financialization of securities, the advent of alternative investments [15], and the restructuring of financial markets, are some of the most practiced one. When it comes to alternative financial strategies, Islamic finance is emerging as a key area and is being debated by researchers and practiced by investors across global financial markets.

The principles of Islamic finance are based on Islamic rules and regulations (called Sharia) marked by socially responsible investments, an ethically oriented trade system, and sustainable banking and finance. It is also based on asset based investments in compliance with Islamic laws. In terms of returns, these are low-risk investments with modest returns or short to medium-term secured commodity finance and investments. The purpose of the current work is to examine any complexity traits in islamic and conventional stock markets before and during COVID-19 pandemic.

Indeed, this the first study to conduct a formal and robust empirical investigation on the effect of COVID-19 pandemic upon the efficiency of islamic and conventional stock markets, to the best of our knowledge. To date, investors still have time to adjust their decisions based on the current shifts of these markets. In fact, market agents and policy makers need a first assessment of current influences of the pandemic outbreak on stock markets to provide better decision making in the short run.

The COVID-19 pandemic is a source of systematic risk, therefore there is a need for further research on financial effects of coronavirus spread. The main purpose of this study is to investigate hedging effectiveness of six alternative assets such as: Gold, Brent, VISTOXX, VIX, CDS and DJCOM to reduce risk in emerging stock markets and whether hedging strategies differ when using conventional or Islamic emerging indices before and during the COVID-19 pandemic. In the best of our Knowledge, this is the first paper that study the impact of COVID-19 epidemic on optimal hedging strategy in emerging stock markets and that compare between conventional and Islamic indices in this context.

The remainder of this paper is organized as follows. Section 2 provide a brief review of existing literature. Section 3 explains the methodology employed in this study. Section 4 presents the data and empirical results. Section 5 reports the hedging effectives and risk management strategies for mixed-asset portfolios, while Section 6 concludes.

2. Literature Review

Previous research has focused on the effects of pandemics such as SARS and EBOLA on stock market performance. The current pandemic has been raging worldwide, and has had a traumatic impact on the global economy and financial markets. To minimize the impact of the COVID-19 pandemic on the global economy, researchers began to analyze their relationship. However, as stock markets are the global economy's driving force, this literature review focuses on the link between the stock markets and the COVID-19. Some of the important literature is summarized in Table 1.

Table 1. *Previous researches on the relationship between the stock markets and the COVID-19 pandemic.*

Authors (Year)	Timespan	Objective	Methodology	Finding Results
[8]	1999 - 2020	Examine the reaction of the US stock to the COVID-19 pandemic	Approach to quantify	The influence of the COVID-19 pandemic on the US stock market is unprecedented, and is comparable with the previous infectious disease outbreak, the Spanish Flu.
[1]	1979 - 2009	Examine to evaluate the COVID-19 pandemic effect on the Chinese stock market	Panel data	The daily increase in confirmed cases and the total number of deaths caused by COVID-19 have a significant negative impact on the stock returns of all companies.
[26]	2019 - 2020	Examines the impact of the COVID-19 pandemic and related deaths on the US stock market	GARCH	The reported number of deaths in Italy and France has a negative impact on US stock market returns, but has a positive effect on the VIX returns.
[27]	01/2020 -	Investigate the direct and indirect	Panel data	Their results show that Google-based anxi-

Authors (Year)	Timespan	Objective	Methodology	Finding Results
	04/2020	impact of the COVID-19 pandemic on implied stock market volatility across Europe, Asia, the US, and Australia		ety about the contagious effects of COVID-19 would lead to increased risk aversion in the stock market.
[29]	01/2020 - 03/2020	Examine the connectedness between the COVID-19 pandemic, oil price volatility shock, the stock market, geopolitical risk, and economic policy uncertainty in the US	Wavelet-based Granger causality tests	The unprecedented impact of the COVID-19 pandemic on these elements leads to the development of low-frequency bands, and the impact of the COVID-19 pandemic on the geopolitical risk is substantially greater than on the US economic uncertainty.
[24]	1995 - 2020	Examines the relative significance of COVID-19 infections and oil price news in influencing oil prices.	Panel data	They concluded that when oil prices are used as the threshold, news about the COVID-19 pandemic and negative oil price will affect oil prices under high volatility
[35]	2006 - 2020	Examine the return and volatility spillover between the COVID-19 pandemic in 2020, the crude oil market, and the stock market	Time-domain approach	The impact of COVID-19 on The results show that the oil and stock markets exceeds that of the 2008 financial crisis. The crude oil and stock markets changed pattern before and after COVID-19 was announced. companies and oil is 0.20.
[18]	2019 - 2020	Examine the direct effects and spill-overs of COVID-19 on stock markets	Panel data	The COVID-19 pandemic has negative impacts on stock market returns in the short term.
[3]	01/2020 - 04/2020	Examines the stock markets' response to the COVID-19 pandemic.	Panel data	Empirical results that the stock market returns continue to decline as the number of confirmed cases increase.
[22]	2019 - 2020	Investigate the stock market oscillations during the corona crash	Autoregressive model	The autocorrelation of the S&P 500 index returns increased in magnitude and remained negative in periods of extreme market volatility and when attention to the COVID-19 increased.
[16]	03/2020 - 04/2020	Examine the impacts of COVID-19 on the spillovers between US and Chinese stock sectors.	Copula functions	The risk spillover is higher from the US to China before COVID-19 and from China to the US during COVD-19 spread, which is significantly intensified between March 2020 and April 2020
[34]	02/2020 - 23/2020	Examine the impact of global pandemic of COVID-19 on financial markets	Correlation analysis	The global financial market risks have increased substantially in response to the pandemic. Individual stock market reactions are clearly linked to the severity of the outbreak in each country
[9]		Examine the effect of news shocks related to local epidemic conditions and information diffusion through Twitter	Panel data	Empirical results that a large market price of contagion risk.
[28]	2016 - 2020	Examine the role of gold as a safe haven or hedge against crude oil price risks	VARMA-GARCH	The gold is found to exhibit a significant safe haven against oil price risks. The optimal portfolio and hedging ratios support this evidence.
[23]	2018 - 20200	Examine the impacts of COVID-19 on the multifractality of gold and oil prices based on upward and downward trends	A-MF-DFA	Gold and oil markets have been inefficient, particularly during the outbreak. The efficiency of gold and oil markets is sensitive to scales, market trends, and to the pandemic

Authors (Year)	Timespan	Objective	Methodology	Finding Results
				outbreak, highlighting the investor sentiment effect.
[31]	03/2020 - 04/2020	Investigate the impact of COVID-19 on emerging stock markets	Panel data	The negative impact has gradually fallen and begun to taper off by mid-April. The highest impact is in Asian and the lowest in European emerging markets
[5]	01/2020 - 04/2020	Examine the effects of COVID-19 on the U.S. stock market volatility at the industry level.	Markov Switching (MS) regime AR	Changes in the volatility are found to be more sensitive to COVID-19 news than economic indicators. while changes in systematic risk vary across industry
[33]	01/2020 - 04/2020	Examine if government response to COVID-19 mitigates international stock market volatility	CAPM	significant increase in stock market volatility in countries where governments take rigorous actions to curb the spread of COVID-19, such as information campaigns and cancellation of public events
[17]	01/2020 - 04/2020	Investigate whether COVID-19 news coverage leads to shifts in volatility	GARCH	The majority of industries they examined did not exhibit significant shifts in volatility as a result of media coverage and news sentiment

Recent research objective is significant, given that the financial markets, including other markets as oil, gold, commodity are vulnerable to pandemics. With increased financialisation, the global financial and commodity markets have been empirically shown to be negatively impacted by COVID-19 pandemics.

3. Methodology

In this paper, the DCC model of [11], the ADCC model of [7] and the GO-GARCH model of [32] are used to model the volatility dynamics, conditional correlations and hedge ratios between conventional and Islamic markets stock prices, oil crude price, gold, VISTOXX, VIX, CDS and commodities prices. The choose of these versions is explained by their popularity in most recent previous works and the simplicity to provide time varying conditional correlation compared to other methods using R software.

3.1. Dynamic Conditional Correlation Model

The Engle, R. F. [11] proposed a dynamic conditional correlation (DCC) model, which is represented as follows:

$$H_t = D_t R_t D_t \tag{1}$$

where H_t is a $n \times n$ conditional covariance matrix, R_t is the conditional correlation matrix, and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag\left(h_{1,t}^{1/2}, \dots h_{n,t}^{1/2}\right) \tag{2}$$

$$R_t = diag\left(q_{1,t}^{-1/2}, \dots q_{n,t}^{-1/2}\right) \; q_t diag\left(q_{1,t}^{-1/2}, \dots q_{n,t}^{-1/2}\right) \tag{3}$$

The conditional variance h_{it} can be defined as a univariate GARCH model, as follows:

$$h_{i,t} = \omega_i + \alpha_i \; \varepsilon_{i,t-1}^2 + \beta_i \; h_{i,t-1} \tag{4}$$

Q_t is the conditional covariance matrix.

$$Q_t = \left(1 - \theta_1 - \theta_2\right) \; \overline{Q} + \theta_1 z_{t-1} z_{t-1}^{'} + \theta_2 Q_{t-1} \tag{5}$$

$\overline{Q}_t$ is the $n \times n$ unconditional correlation matrix of the standardized residuals $z_{i,t}\left(z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}\right)$. The parameters θ_1 and θ_2 are scalar parameters to capture the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation. These parameters are non-negative.

The DCC model is meaning reverting as long as $\theta_1 + \theta_2 < 1$. The correlation estimator is given as follows:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\ q_{j,j,t}}} \tag{6}$$

The DCC model is not linear, but may be estimated simply using a two-step method based on the likelihood function. In the first step, the univariate GARCH parameters are estimated. In the second step, the conditional correlations are estimated.

3.2. Asymmetric Dynamic Conditional Correlation Model

Cappiello, L. et al. [7] build on the DCC model and the asymmetric GARCH model of [14] by adding in an asymmetric term and create the Asymmetric DCC (ADCC) model.

The ADCC model for univariate GARCH (1, 1) is given as:

$$h_{i,t} = \omega_i + \alpha_i\ \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i\ \varepsilon_{i,t-1}^2\ I\left(\varepsilon_{i,t-1}\right) \tag{7}$$

The indicator function $I\left(\varepsilon_{i,t-1}\right)$ is equal to one if $\varepsilon_{i,t-1} < 0$ and 0 otherwise. For this specification, a positive value for d means that negative residuals tend to increase the variance more than positive ones. The asymmetric effect or "leverage effect" is designed to capture an often observed characteristic of financial assets that an unexpected drop in asset prices tends to increase volatility more than an unexpected increase in asset prices of the same magnitude. This can be interpreted to mean that bad news increases volatility more than good news.

The dynamics of Q for the ADCC model are given as:

$$Q_t = \left(\bar{Q} - A^{4}\bar{Q}A - B^{'}\bar{Q}B - G^{'}\bar{Q}^{-}G\right) + A^{'}z_{t-1}z_{t-1}^{'}A + B^{'}Q_{-1}B + G^{'}z_t^{-}z^{'-}G \tag{8}$$

where, A, B and G are n x n parameter matrices z_t^- and are zero-threshold standardized errors which are equal to z_t when less than zero and zero otherwise. $\bar{Q}$ and $\bar{Q}^-$ are the unconditional matrices of z_t and z_t^-, respectively.

3.3. Go-GARCH Model

The generalized orthogonal GO-GARCH model introduced by [32] has been associated with a set of independent univariate and conditionally uncorrelated GARCH processes, where a liner map uses marginal density parameters to relate these elements to the observed data that offers more flexibility in the estimation, compared to other MGARCH models.

Under the GO-GARCH model, residuals ε_t are modeled as follows:

$$\varepsilon_t = Af_t \tag{9}$$

where f_t denotes a set of unobserved independent factors ($f_t = (f_{1t}, f_{2t}, ..., f_{nt}$). A is an invertible and time-invariant n x n and can be decomposed into an unconditional covariance matrix Σ and an orthogonal matrix U.

$$A = \Sigma^{1/2}U \tag{10}$$

The rows of matrix A represent the factor weights assigned to each time series while the columns of matrix A represent the factors$f$. The specification of the factors f_t is as follows:

$$f_t = H_t^{1/2}u_t \tag{11}$$

Where u_t is a random variable satisfying $E[u_{it}] = 0$ and $E[u_{it}^2] = 1$. H_t is a diagonal matrix with elements h_{1t}, $h_{2t}, \ldots, h_{nt}$ being the conditional variances of the factors. The factor conditional variance h_{it} can be modeled using the GARCH process (i=1, 2,…,n). Furthermore, the unconditional distribution of the factors f satisfies $E[f_t] = 0$ and $E[f_t f'_t] = 1$. It follows that the returns r_t can be expressed as:

$$r_t = u_t + AH_t^{1/2}u_t \tag{12}$$

The conditional covariance matrix of the returns $r_t - u_t$ is:

$$\Sigma_t = AH_tA^T \tag{13}$$

In this equation, the two vital assumptions of the GO-GARCH are satisfied: first A is time invariant and second H_t is a diagonal matrix. In the case where A is restricted to be orthogonal we obtain OGARCH version as a special case of GO-GARCH. In addition, we apply the independent component analysis (ICA) to estimate the U matrix.

4. Data and Empirical Findings

4.1. Data

Our empirical analysis use prices indices daily data on Dow Jones emerging Islamic prices (DJIEMG), conventional Emerging market stock prices (EMRG), gold prices (GOLD), crude oil prices (Brent), EURO STOXX 50 Volatility index (VISTOXX), Chicago Board Options Exchange (CBOE) Volatility Index (VIX), Credit Default Swap Europe index (CDS) and Dow Jones Commodity index (DJCOM). All data are obtained from Thomson Reuters Datastream and cover the period from December 27, 2007 to September 24, 2020 (We have a sample of 3326 observations) to include the COVID-19 period and analyse its impacts on hedging strategy. The Islamic emerging market index contains a larger exposure to the oil gas, technology, basic materials and telecommunications sectors, compared to the conventional emerging markets index. The conventional emerging markets index has greater exposure to consumer goods and financials, consumer services sectors. The Islamic emerging market is less volatile than the conventional by more than 1%. The investment managers who manage Islamic emerging markets will have to quantify value adding by taking positions outside the index and be more active in quantitative research to obtain more consistent and more superior performance. Figure 1 shows that all price series are not stationary.

For each data series, continuously compounded daily returns are calculated as the difference in the logarithms of daily prices multiplied by 100: $r_t = \ln(p_t / p_{t-1}) \times 100$, where p_t is the closing price index and r_t is the level of return in percentage on day t. Such transformation permit to make data stationary.

4.2. Preliminary Statistics

Table 2 presents the summary statistics of the daily returns. The returns of the EMERG conventional stock indice range from 0.0032 to 0.016 and the mean returns of the DJIM indices are higher, ranging from 0.014 to 0.023 in each case over the sample period. However, VIX and VISTOXX have the largest variability and DJ commodieties has the least over the sample period.

Table 2. *Summary statistics for daily returns.*

Index	EMRG	DJIEMG	GOLD	Brent	VISTOXX	VIX	CDSEU	DJCOM
Observations	3325	3325	3325	3325	3325	3325	3325	3325
min	-9.002713	-9.165188	-9.811288	-64.36989	-43.43765	-35.05885	-71.44897	-8.466831
Max	9.457768	10.799563	8.588524	41.20225	47.06665	76.82450	70.71890	6.465763
Q1	-0.532325	-0.489329	-0.475257	-1.04343	-3.91658	-4.10659	-1.13978	-0.505258
Q3	0.604016	0.594403	0.564616	1.06612	3.12116	3.29005	1.04426	0.001855
mean	-0.000812	0.006543	0.024475	-0.02531	0.01304	0.01027	0.00922	0.544344
Median	0.054883	0.053588	0.007002	0.00000	-0.31299	-0.35921	-0.04274	0.000000
St. Dev.	1.21168	1.20007	1.13785	2.864475	6.722422	7.59118	5.496346	1.097497
Skewness	-0.631321	-0.5115845	-0.2117925	-2.583544	0.709325	1.09971	-0.09354688	-0.4977709
kurtosis	9.139432	9.610997	6.346226	101.2491	4.090621	6.581375	34.88968	5.411888
JB Test	11812	12963	5614.5	1425706	2602.2	6682.2	168871	4202.7
KPSS Test	0.07122	0.15241	0.1271	0.05027	0.016769	0.021951	0.27613	0.065877
Q(12)	175.93	158.33	30.0050	176.8	35.01	49.662	361.68	26.752
Q ²(12)	4687.5	3609	558.18	925.83	470.44	285.76	984.05	1466

Notes: Shaded numbers indicate the rejection of the null hypothesis of associated statistic tests at the 5% level.

The KPSS test indicate that the null hypothesis of stationary is accepted for all return series. Figure 2 depicts daily returns over time and show increase of incertitude and price fluctuations during the first quarter of 2020 caused by COVID-19. We can remark the presence of the phenomena of cluster volatility. In other terms, the large volatilities are followed by large ones, and the smallest one follows small changes. As shown in this table, the Kurtosis is greater than three for all variables, which means that the distributions are leptokurtic. The skewness is different from 0 (it is negative in all cases except for VIX and VISTOXX indexes) which means that all distributions are asymmetric, The JB statistics indicate that all series are beyond being normal. The Ljung-Box test applied to raw returns and and squared returns favors the rejection of the hypothesis of no autocorrelation for order lower than 12 and indicate the presence of dependence both of first and second order that will modeled by ARMA-GARCH model. On the other hand, the reported evidence on the ARCH (12) LM test, not reported her, indicates the presence of the ARCH effects. This means that available public information play a central rule in determining financial prices. Therefore, the DCC, ADCC and GO-GARCH methods are correctly specified to ascertain the dynamic dependence between the conventional and Islamice emerging stock indices on one hand and the hedging instruments such that Gold, Bren, CDSEU, VIX, VISTOXX and DJCOM on the other hand.

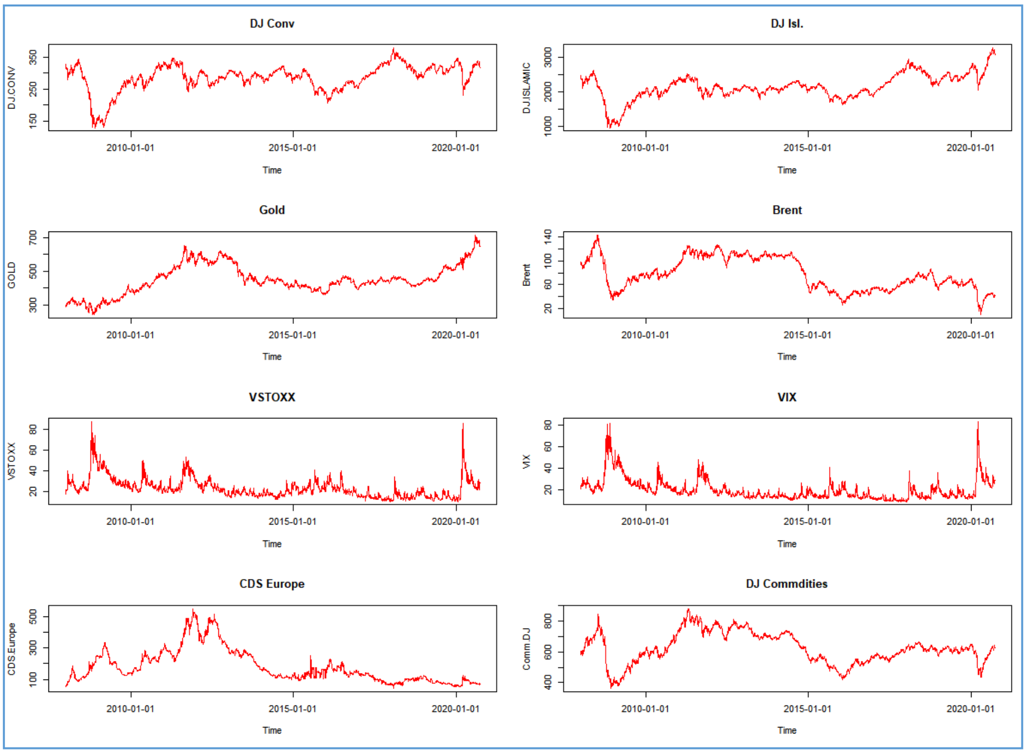

Figure 1. Plots of daily price indices (Period from December 27, 2007 to September 24, 2020).

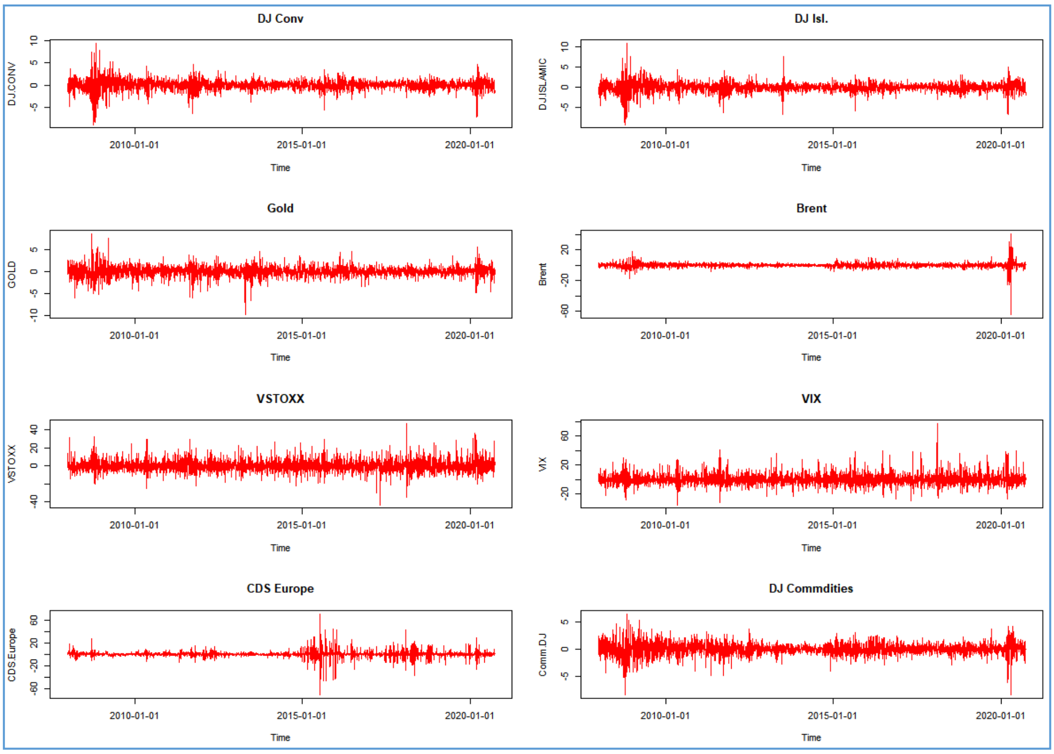

Figure 2. Plot of daily squared return of sample variables (Period from December 27, 2007 to September 24, 2020).

Table 3 reports the pair-wise unconditional correlations which indicate that both the conventional and Islamic dow jones stock indices show a similar and significant relation with the hedging instruments studied in this paper. Relation is positive with Gold, Brent and DJCOM indices but it is negative with VIX, VISTOX and CDS indices. The highest correlation coefficient is recorded between emerging markets and DJCOMM while the most negative is recorded with VISTOXX indice. These results have a strong implications on the position (short or long) to take investors on emerging stock markets to hedge their portfolios. The remainder of correlation are not important in this study as we limit to determine optimal hedging strategies on emerging stocks markets.

Table 3. *Pearson correlations matrix between daily returns.*

	EMRG	DJIEMG	GOLD	Brent	VISTOXX	VIX	CDSEU	DJCOM
EMRG	1,0000	0,9641	0,1297	0,3316	-0,5085	-0,3975	-0,1735	0,4991
DJIEM	0,9641	1,0000	0,1349	0,3208	-0,4850	-0,3742	-0,1675	0,4768
GOLD	0,1297	0,1349	1,0000	0,1574	0,0030	0,0119	-0,0037	0,3952
Brent	0,3316	0,3208	0,1574	1,0000	-0,2423	-0,1939	-0,0875	0,5925
VISTOXX	-0,5085	-0,4850	0,0030	-0,2423	1,0000	0,5437	0,1472	-0,3294
VIX	-0,3975	-0,3742	0,0119	-0,1939	0,5437	1,0000	0,0760	-0,3088
CDSEU	-0,1735	-0,1675	-0,0037	-0,0875	0,1472	0,0760	1,0000	-0,1107
DJCOM	0,4991	0,4768	0,3952	0,5925	-0,3294	-0,3088	-0,1107	1,0000

Shaded number indicates the reject of the null hypothesis at 95% confidence level.

Table 4 report Pearson correlations matrix for daily squared returns. Both the conventional and Islamic dow jones stock indices show a similar and significant relation with the hedging instruments except those between emerging stock market and CDSEU. The highest correlation coefficient is recorded between Stock markets and DJCOMM. Cross correlations coefficients between raw returns and between squared returns, no reported her, are statistically significant which give argument to model each bivariate data by AR-MGARCH model.

Table 4. *Pearson correlations matrix between daily squared returns.*

	EMRG	DJIEMG	GOLD	Brent	VISTOXX	VIX	CDSEU	DJCOM
EMRG	1,00000	0,93683	0,23279	0,08600	0,25563	0,20702	0,03998	0,45266
DJIEM	0,93683	1,00000	0,21065	0,07593	0,23011	0,17783	0,02963	0,40574
GOLD	0,23279	0,21065	1,00000	0,04859	0,06968	0,13239	0,01192	0,29272
Brent	0,08600	0,07593	0,04859	1,00000	0,06088	0,02279	0,00487	0,45868
VISTOXX	0,25563	0,23011	0,06968	0,06088	1,00000	0,33273	0,02446	0,19139
VIX	0,20702	0,17783	0,13239	0,02279	0,33273	1,00000	0,05131	0,12444
CDSEU	0,03998	0,02963	0,01192	0,00487	0,02446	0,05131	1,00000	0,00759
DJCOM	0,45266	0,40574	0,29272	0,45868	0,19139	0,12444	0,00759	1,00000

Shaded number indicates the reject of the null hypothesis at 95% confidence level.

4.3. Specifications of the Multivariate GARCH Models

In the rest of this paper, we model each bivariate data by one of three MGARCH versions: DCC, ADCC and GOG-ARCH. To make in consideration the presence of auto and cross correlation in raw returnseries, we propose also to add constant and AR(1) terms to the mean equation and to distinguish between various versions in term of innovations distributions. Eight MGARCH specifications are compared in table 5.

Table 5. DCC and ADCC parameter estimates.

Model / Parameters	AR DCC MVT				AR ADCC MVT			
[EMRG].mu	0.048445	0.016871	2.87142	0.004086	0.013129	0.017488	0.75078	0.452785
[EMRG].ar1	0.192489	0.016902	11.38831	0	0.202301	0.016382	12.34877	0
[EMRG].omega	0.012677	0.004038	3.13973	0.001691	0.013923	0.005896	2.36157	0.018198
[EMRG].alpha1	0.086566	0.013534	6.39593	0	0.06763	0.018585	3.63901	0.000274
[EMRG].beta1	0.903837	0.014397	62.77859	0	0.933397	0.019578	47.67578	0
[EMRG].eta11					0.759509	0.12365	6.14241	0
[EMRG].shape	8.596386	1.165556	7.37535	0	10.268792	1.616223	6.35357	0
[DJIEMG].mu	0.054954	0.016373	3.35628	0.00079	0.022377	0.019413	1.15265	0.249055
[DJIEMG].ar1	0.182782	0.017021	10.73856	0	0.192733	0.019448	9.91014	0
[DJIEMG].omega	0.01198	0.003712	3.22727	0.00125	0.014915	0.005311	2.80836	0.00498
[DJIEMG].alpha1	0.086087	0.012938	6.65371	0	0.077198	0.015605	4.94703	0.000001
[DJIEMG].beta1	0.905374	0.013355	67.79041	0	0.925401	0.016259	56.91636	0
[DJIEMG].eta11					0.674315	0.088121	7.65211	0
[DJIEMG].shape	7.660236	0.952307	8.04387	0	8.746924	1.243623	7.03342	0
[Gold].mu	0.038627	0.013266	2.91176	0.003594	0.041031	0.014416	2.8463	0.004423
[Gold].ar1	-0.033837	0.014426	-2.3456	0.018997	-0.035387	0.013526	-2.6162	0.008891
[Gold].omega	0.004985	0.001795	2.77641	0.005496	0.005898	0.001975	2.98705	0.002817
[Gold].alpha1	0.035426	0.002905	12.19453	0	0.051996	0.003287	15.82105	0
[Gold].beta1	0.963346	0.000509	1892.87488	0	0.958689	0.000399	2405.15399	0
[Gold].eta11					-0.163236	0.09512	-1.71611	0.086142
[Gold].shape	3.978882	0.283165	14.05147	0	3.968481	0.27861	14.24385	0
[brent].mu	0.030326	0.027266	1.11222	0.266042	0.006544	0.025507	0.25656	0.797516
[brent].ar1	0.014392	0.016324	0.88162	0.377985	0.01535	0.015496	0.99056	0.321901
[brent].omega	0.046606	0.014304	3.25816	0.001121	0.01835	0.005797	3.16524	0.00155
[brent].alpha1	0.086077	0.010185	8.45171	0	0.066044	0.009655	6.84023	0
[brent].beta1	0.910413	0.00963	94.53619	0	0.942755	0.008546	110.31571	0
[brent].eta11					0.534944	0.093381	5.7286	0
[brent].shape	5.028454	0.464343	10.82918	0	5.569366	0.569939	9.77187	0
[VISTOXX].mu	-0.370061	0.092188	-4.0142	0.00006	-0.233841	0.094043	-2.48654	0.012899

Model Parameters	AR DCC MVT				AR ADCC MVT			
[VISTOXX].ar1	-0.013765	0.017532	-0.78514	0.432369	-0.003403	0.017896	-0.19018	0.849172
[VISTOXX].omega	3.49017	1.092188	3.19558	0.001396	0.299425	0.078114	3.83317	0.000127
[VISTOXX].alpha1	0.109208	0.021902	4.98621	0.000001	0.07268	0.012207	5.95401	0
[VISTOXX].beta1	0.822107	0.039275	20.93233	0	0.89933	0.018775	47.9016	0
[VISTOXX].eta11					-0.999997	0.194851	-5.13211	0
[VISTOXX].shape	4.418959	0.333477	13.25118	0	4.642665	0.356682	13.01626	0
[VIX].mu	-0.42083	0.092353	-4.55674	0.000005	-0.244628	0.09754	-2.50797	0.012143
[VIX].ar1	-0.073668	0.017065	-4.317	0.000016	-0.072438	0.017361	-4.17257	0.00003
[VIX].omega	7.119345	1.353151	5.26131	0	0.494089	0.093281	5.29678	0
[VIX].alpha1	0.176969	0.02886	6.13198	0	0.106796	0.012436	8.58737	0
[VIX].beta1	0.718084	0.038646	18.58084	0	0.852163	0.019242	44.28732	0
[VIX].eta11					-0.999999	0.128811	-7.7633	0
[VIX].shape	4.034258	0.297853	13.54445	0	4.380689	0.351934	12.44746	0
[CDS.Europe].mu	-0.111316	0.028215	-3.9453	0.00008	-0.108217	0.028017	-3.86261	0.000112
[CDS.Europe].ar1	0.013576	0.014986	0.90594	0.36497	0.017239	0.012927	1.33363	0.182324
[CDS.Europe].omega	1.55403	0.585659	2.65347	0.007967	0.553858	0.160519	3.45041	0.00056
[CDS.Europe].alpha1	0.293871	0.07317	4.01627	0.000059	0.557251	0.124117	4.48973	0.000007
[CDS.Europe].beta1	0.705129	0.104753	6.73134	0	0.760249	0.052292	14.5384	0
[CDS.Europe].eta11					-0.166651	0.076833	-2.16901	0.030082
[CDS.Europe].shape	2.395906	0.080181	29.88139	0	2.1	0.000471	4459.08495	0
[DJCommodity].mu	0.013809	0.013283	1.03962	0.298518	0.00827	0.014135	0.58503	0.558525
[DJCommodity].ar1	-0.004118	0.017281	-0.23831	0.81164	-0.003423	0.022074	-0.15509	0.876754
[DJCommodity].omega	0.005734	0.002493	2.29975	0.021462	0.004267	0.001544	2.76376	0.005714
[DJCommodity].alpha1	0.058619	0.012184	4.81111	0.000002	0.056574	0.003026	18.69414	0
[DJCommodity].beta1	0.937775	0.01271	73.78257	0	0.953399	0.001258	757.92517	0
[DJCommodity].eta11					0.339999	0.072835	4.66807	0.000003
[DJCommodity].shape	6.476929	0.694829	9.32161	0	6.476799	0.671969	9.63854	0
[Joint]dcca1	0.014222	0.001788	7.95414	0	0.013506	0.001546	8.7378	0
[Joint]dccb1	0.973011	0.004817	201.98061	0	0.971798	0.004523	214.86176	0
[Joint]dccg1					0.001439	0.000827	1.73938	0.081968
[Joint]mshape	5.991387	0.186795	32.07468	0	5.715703	0.171173	33.39138	0

Following AIC, BIC Shibata, H-Q and Likelihood criteria, the best specification is VAR(1)-DCC (1,1) with innovations that follow multivariate t-student distribution. In the out of sample analysis, we maintain also the asymetric version of this model to an aim of comparison between models and as the asymetric phenomena in bivariate data can be more significant in out of sample period.

Table 6 presents the estimated results of the DCC and ADCC models. In the DCC model, all the coefficients alpha1 and beta1 are statistically significant, indicating that the volatilities of price returns of the emerging countries and alternatives assets are influenced by both their own past shocks and volatilities. The coefficients eta1 are statistically significant in all case except with Gold. The coefficients of mean equation are not statistically significant in all cases. All shape parameters are statistically significant which indicate that using multivariate t-student distribution to model innovations is more appropriate than the hypothesis of multivariate normal distribution. Coefficients estimated in second step are statistically significant with EMERG and ERMGI indices. Only the asymetric coefficient of ADCC specification is not statistically significant. As the estimation of alpha is larger than that of beta for all markets, the price returns are more sensitive to past volatilities than to past shocks. As the estimated results of DCC specification (dcc1a, dcc1b, dcc1g) are statistically positive and their sum is close to, but less than 1, the dynamic conditional correlations exhibit weak reversion. Figure 3 shows the GOGARCH news impact correlation surface.

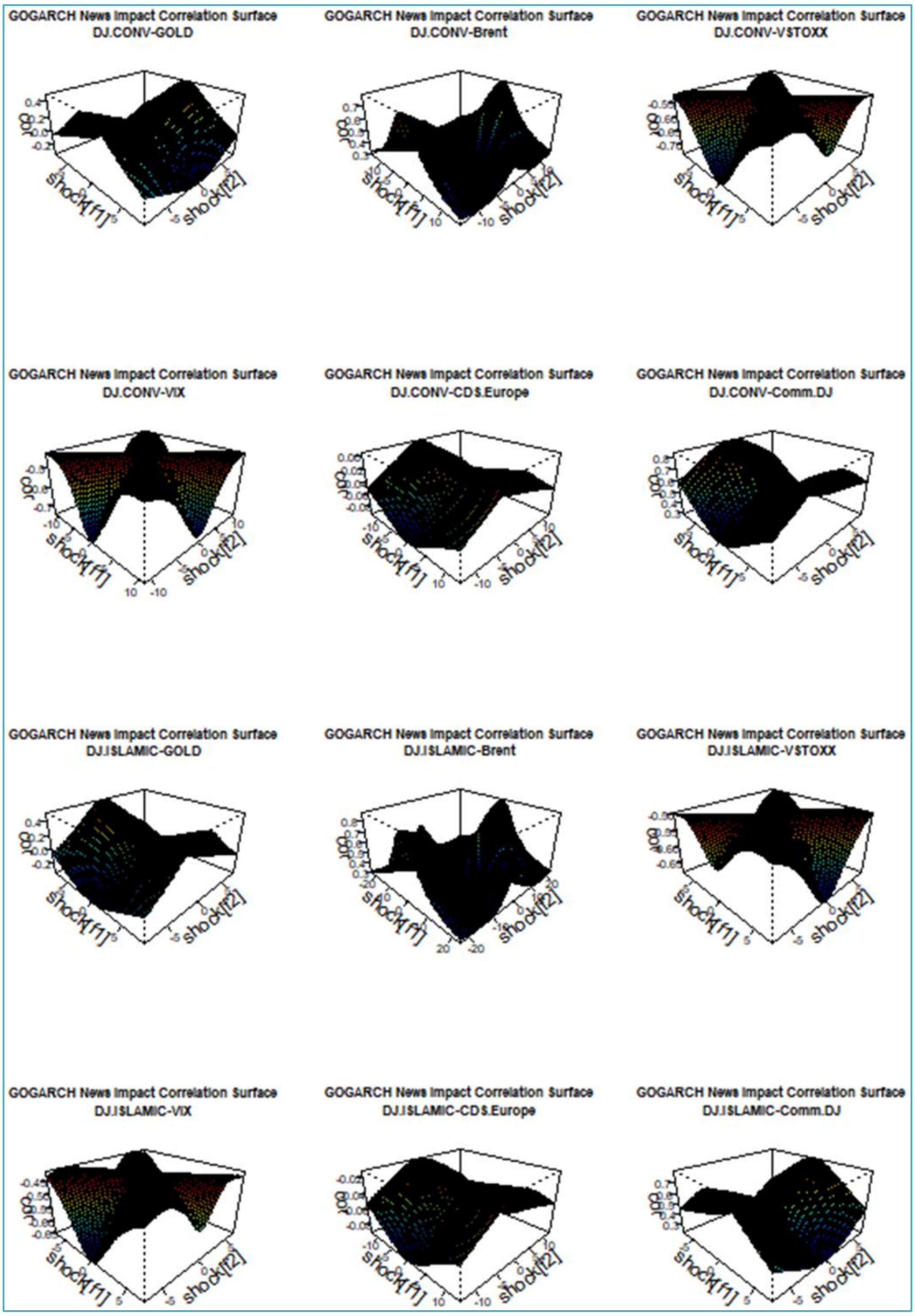

Figure 3. *News impact correlation surface (GOGARCH).*

5. Hedging Effectiveness and Optimal Portfolio

This section discusses the optimal portfolio weights and hedging effectiveness of Gold, Brent, VISTOXX, VIX, CDS and DJCOM for conventional or Islamic emerging indices using the conditional variance and covariance estimates obtained from the main estimation. The significant of returns and volatility spillovers between the Islamic and conventional stock markets and the six financial assets returns is suggestive of volatility and risk susceptibilities to investors' assets in the global financial and commodity markets. The outbreak of COVID-19 pandemic further amplifies these associated volatilities and risks susceptibilities. It is therefore imperative for investors to mitigate such risks by engaging in portfolio rebalancing and hedging, through engagement in future contract and without jeopardizing their expected returns.

We estimate the optimal portfolio weights to evaluate the optimal proportion of assets that should form a rational investor's portfolio. Following [20] and [2], we construct the optimal portfolio weight of holding the two assets using the conditional variance and covariances defined as:

$$\omega_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} + h_{ij,t} - 2h_{jj,t}} \tag{14}$$

Under the condition that

$$\omega_{ij,t} = \begin{cases} 0, & if\ \omega_{ij,t} \langle 0 \\ \omega_{ij,t} & if\ 0 \le \omega_{ij,t} \le 1 \\ 1, & if\ \omega_{ij,t} \rangle 1 \end{cases}$$

where is the weight on the first asset in a one dollar portfolio of two assets (assets and) at time t. The weight on the second asset is given by $\left(1-\omega_{ij,t}\right)$.

In setting up the hedging process, we need to consider the estimation of the optimal hedge ratio. We construct the optimal hedge ratio to evaluate the hedging effectiveness, which is based on the minimisation of the variance of the portfolio return [20, 19].

The risk minimising hedge ratio between asset i and asset j is given as;

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \tag{15}$$

where $h_{ij,t}$ is the conditional covariance between asset i and j at time t, and $h_{jj,t}$ is the conditional variance of asset j at time t. It is to be noted that a long position in one dollar in asset i can be hedged by a short position in $\beta_{ij,t}$ dollars of asset j.

Furthermore, following [21] we determinate the hedging effectiveness (HE) across the proposed portfolios. The hedging effectiveness (HE) is given as:

$$HE = \left(\frac{\mathrm{var}_{unheged} - \mathrm{var}_{hedged}}{\mathrm{var}_{unheged}}\right) \tag{16}$$

where, HE presents the hedging effectiveness of portfolio, $\mathrm{var}_{unheged}$ is the variance of unhedged assets and var_{hedged} represents the variance of portfolio. This method compares the variance of the hedged portfolio to that of an un-hedged portfolio. The three GARCH models are compared on the basis of the hedge ratios produced from each model which states that the higher the hedge ratio is, the higher the hedging effectiveness of the mode.

5.1. Impact of COVID-19 on Hedging Strategy

We divide all sample in two period: in sample and out of sample period. The first period include the first 1000 observations of the data used to MGARCH specifications. The second one is the period of evaluation of hedging effectiveness of various instruments. To study to impact of COVID period, we divide this period in two sub periods: before (Before Decembre 30, 2019) and During COVID-19 (from Decembre 31, 2019 to the end of data). We use the rolling window analysis to construct rolling one step ahead forecast hedge ratios of the out of sample period. At time period t, a one-period-ahead conditional volatility forecast is made and these forecasts are used to construct a one-period-ahead hedge ratio. These forecasted hedge ratios are then used in constructing the hedged portfolio. A rolling window size of 1000 observations is used to construct 2326 one-period-ahead hedge ratios. However, the GARCH models are refit at every (20, 40 and 60 observations) to study whether the hedging effectiveness can be sensitive to horizon of investments.

Table 6 reports the correlation between optimal hedge ratios calculated from three MGARCH versions: DCC, ADCC, and GO-GARCH. We find that the hedge ratios obtained from DCC and ADCC models exhibit high correlation both before and during COVID-19 period, indicating that these models capture the properties of the data in the same way. The hedge ratios obtained from GO-GARCH model not exhibit always similar comovement with DCC and ADCC models as in previous works. Only in the case of Gold and CDS, GOGARCH offer hedge ratios that have the same comovement with DCC and ADCC models and both for EMRG and DJIEM indices. Correlation between hedge ratios obtained from GOGARCH and DCC model is more higher during than before COVID-19 periods for DJCOM. The correlation coefficient change of sign to become positive during COVID-19 period. Correlation coefficients between optimal hedge ratios obtained from GOGARCH and DCC during COVID-19 period are weaker than the same coefficients obtained before COVID-19 period.

Table 6. *Correlations between hedge ratios before and during COVID-19 period.*

EMRG	**Period**	**Gold**	**Brent**	**VISTOXX**	**VIX**	**CDSEU**	**DJCOM**
DCC/ ADCC	Before COVID	0.9997	0.9957	0.9999	0.9980	0.9994	0.9993
	During COVID	0.9990	0.9988	1	0.9998	1	0.9998
DCC/ GOGARCH	Before COVID	0.4399	-0.3972	0.7858	-0.4746	0.7574	0.5733
	During COVID	0.3153	-0.3092	0.9196	-0.5482	0.4271	0.9005
ADCC/ GOGARCH	Before COVID	0.4380	-0.4307	0.7863	-0.4720	0.7584	0.5667
	During COVID	0.2798	-0.3186	0.9196	-0.5490	0.4271	0.9029
DJIEM	Period	Gold	Brent	VISTOXX	VIX	CDSEU	DJCOM
DCC/ ADCC	Before COVID	0.9991	0.9954	0.9999	0.9967	1	0.9989
	During COVID	0.9965	0.9984	1	0.9999	1	0.9998
DCC/ GOGARCH	Before COVID	0.4359	-0.3049	-0.5048	-0.5225	0.7614	-0.2355
	During COVID	0.5275	-0.2172	-0.5358	-0.5421	0.4792	0.30496
ADCC/ GOGARCH	Before COVID	0.4151	-0.3417	-0.5056	-0.5377	0.7614	-0.2603
	During COVID	0.4731	-0.2330	-0.5358	-0.5377	0.4792	0.3107

Notes: Forecasts calculated from fixed width rolling analysis which produces 1000 one step forecasts. Models are refit every 20 observations

Table 7 reports the correlations between correlations obtained from three MGARCH models. It indicate that the correlation between DCC and ADCC are very high both before and during COVID-19 periods which confirm previous empirical results. The correlation between from DCC/GO-GARCH or ADCC/GOGARCH are largely less correlated. Correlation is more higher during than before COVID period when we use VISTOXX, VIX or DJCOMM as hedge alternative. Correlation is lower before COVID period if Brent and CDS are used as hedge instruments to reduce emerging stock markets risk.

The daily rolling one–step conditional correlation forecast between EMERG and EMERGI in one side and each altenatives assets in the other side obtained from the three MGARCH versions are presented in Figure 4 and Figure 5). We notice that correlation coefficients obtained from DCC and ADCC models tend to have similar pattern over time.

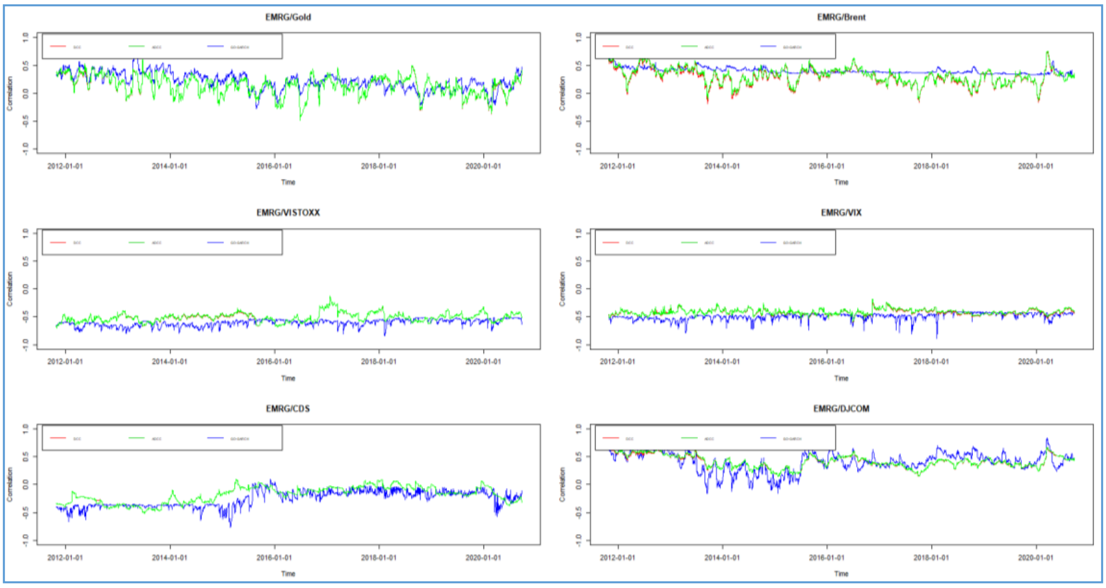

Figure 4. *Rolling one- step ahead Conditional correlation forecast between EMERG and each of alternatives assets obtained from DCC, ADCC and GOGARCH models.*

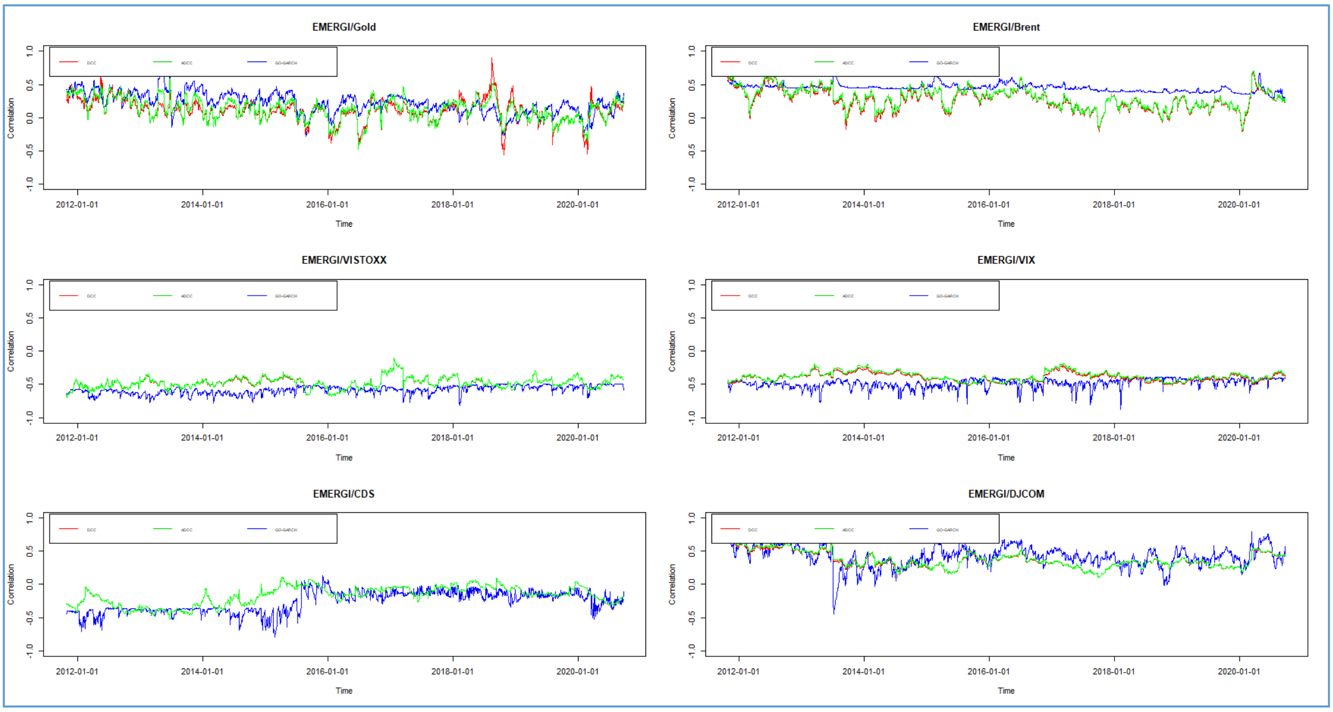

Figure 5. *Rolling one- step ahed Conditional correlation forecast between EMERGI and each of alternatives assets obtained from DCC, ADCC and GOGARCH models (refit=20).*

The average values of the hedge ratios as well as minimum and maximum values, for different refit and MGARCH versions, are reported in Tables 8 and 9. In the same tables, we can found the hedging effectiveness (HE) values for each models, each instruments and each refit. We determinate these statistics both for after and during COVID-19 period to examine eventual changes in hedging strategy after the emergence of COVID-19 epidemic.

The hedge ratios for each portfolio vary significantly over time in markets. This does not mean that the portfolio manager has to rebalance the portfolio at each point of time which may lead to increased transaction costs. Investors can look for average hedge of the constituents of a portfolio over a period of time and rebalance the portfolio. The average values of the hedge ratios showed in Tables 9 and 10 offers several insights for short hedgers. First, the low ratios suggest that stock (EMRG or EMERGI) investment risk can be hedged by taking a short position in market index used. Before COVID-19, the average value of the hedge ratio between EMRG (EMERGI) obtained with DCC model is 0.1254 (0.10905) indicating that a $1000 long position in EMRG (EMERGI) is hedged by taking short position for $125.4 ($109.05) in gold market. These amounts increase to $164.7 ($167.2) if the model used is GOGARCH.

Table 7. *Correlations between correlations obtained with three MGARCH versions before and during COVID-19 period.*

EMRG	Period	Gold	Brent	VISTOXX	VIX	CDSEU	DJCOM
DCC/ ADCC	Before COVID	0.9997	0.9961	0.9993	0.9798	0.9994	0.9988
	During COVID	0.9995	0.9979	1	0.9946	1	0.9994
DCC/ GOGARCH	Before COVID	0.6072	0.3270	0.1291	0.0415	0.6745	0.7255
	During COVID	0.5881	0.2102	0.4998	0.5431	0.2600	0.1653
ADCC/ GOGARCH	Before COVID	0.6084	0.3752	0.1196	0.0653	0.6750	0.7170
	During COVID	0.5756	0.2239	0.4998	0.5714	0.2600	0.1831
DJIEM	Period	Gold	Brent	VISTOXX	VIX	CDSEU	DJCOM
DCC/ ADCC	Before COVID	0.9994	0.9963	0.9995	0.9911	1	0.9987
	During COVID	0.9984	0.9985	1	0.9992	1	0.9997

EMRG	Period	Gold	Brent	VISTOXX	VIX	CDSEU	DJCOM
DCC/ GOGARCH	Before COVID	0.6183	0.4451	0.1084	-0.2003	0.5442	0.5092
	During COVID	0.6084	0.3162	0.4117	0.4115	0.3645	0.7108
ADCC/ GOGARCH	Before COVID	0.6105	0.4620	0.0981	-0.1774	0.5442	0.4877
	During COVID	0.5911	0.3319	0.4117	0.4191	0.3645	0.7126

Notes: Forecasts calculated from fixed width rolling analysis which produces 1000 one step forecasts. Models are refit every 20 observations

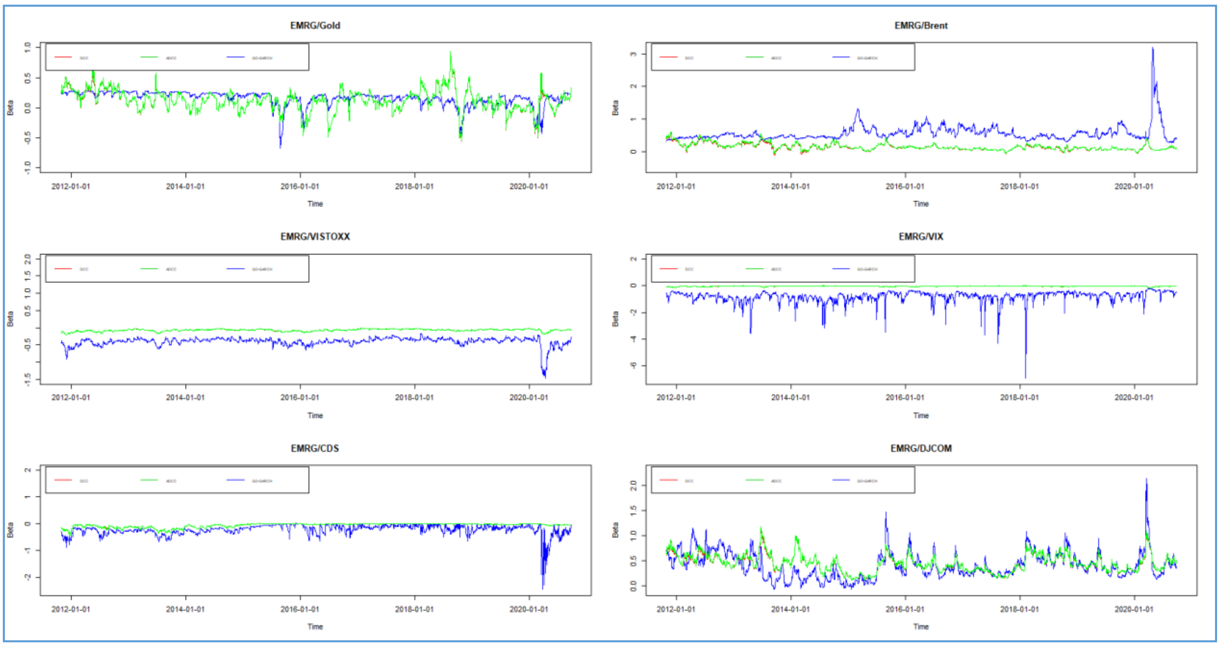

Figure 6. *Time series plot of optimal hedge ratio of various alternatives for EMER index obtained with three MGARCH versions.*

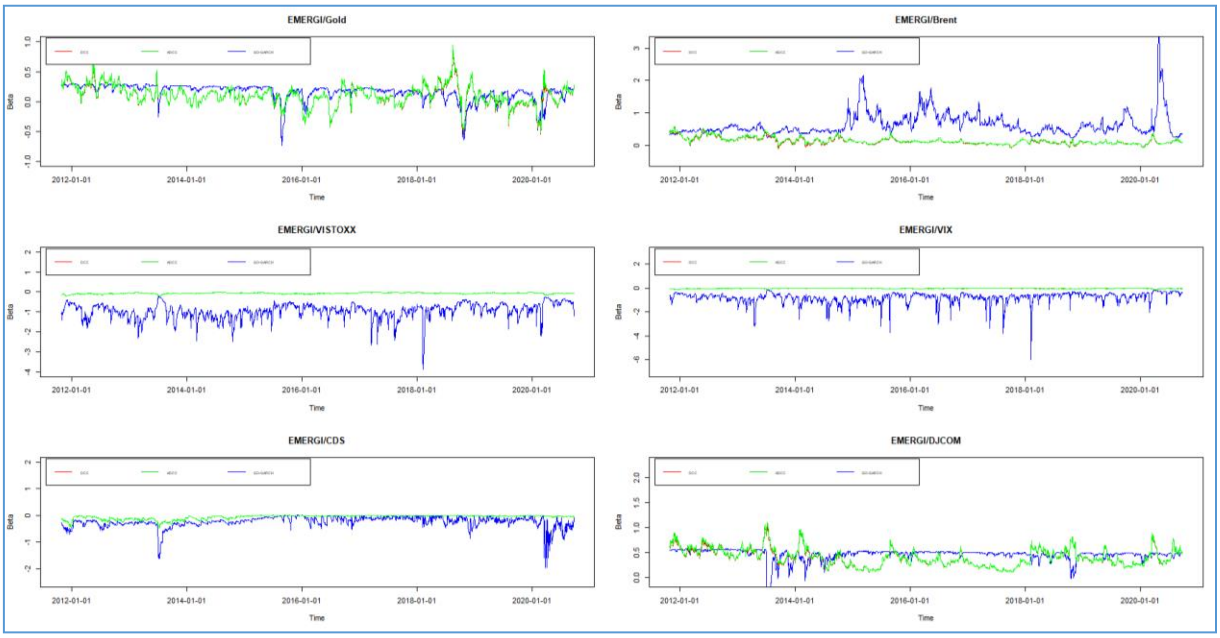

Figure 7. *Time series plot of optimal hedge ratio of various alternatives for EMERGI index obtained with three MGARCH versions.*

Table 8. *Summary statistics of hedge ratios (β) and hedge effectiveness (HE) for EMRG -MVT distribution.*

Period		Refit=20				Refit=40				Refit=60			
		mean	min	max	HE	mean	min	max	HE	mean	min	max	HE
EMERG /Gold													
DCC	After	0.1253935	-0.5575603	0.9237533	0.04954837	0.1253201	-0.5410122	0.9237533	0.04923517	0.1253824	-0.5410122	0.922848	0.04908256
	During	0.05656799	-0.4956466	0.5395996	0.03272476	0.05707719	-0.4956466	0.5453409	0.03264153	0.05837086	-0.4956466	0.5453409	0.03250792
ADCC	After	0.1273156	-0.5506768	0.9292186	0.05037021	0.1270794	-0.5330709	0.9292186	0.04997689	0.1271566	-0.5330709	0.9231039	0.04982197
	During	0.06389841	-0.4834687	0.5745333	0.03357669	0.06365808	-0.4834687	-0.4834687	0.03339999	0.06487872	-0.4834687	0.572112	0.03320575
GOGARH	After	0.1647109	-0.6770023	0.2818023	0.07517399	0.1650192	-0.6776378	0.2816662	0.07515297	0.3221641	-0.1091047	1.716869	0.07502418
	During	0.07041624	-0.4291153	0.2513056	0.0433674	0.0674483	-0.4658975	0.2501365	0.0430959	0.1766807	-0.1090858	0.8578254	0.04275875
EMERG / Brent													
DCC	After	0.1482027	-0.1181236	0.58407	0.1079452	0.1484365	-0.1181236	0.5811174	0.1078748	0.1484333	-0.1181236	0.5811174	0.108142
	During	0.1023957	-0.0489724	0.3969809	0.1330395	0.1016825	-0.0450557	0.3914664	0.1325385	0.102114	-0.04524345	0.3914664	0.1327833
ADCC	After	0.1580188	-0.0660094	0.6027581	0.1179227	0.1583303	-0.0660094	0.6027581	0.1179014	0.1582889	-0.06600948	0.6027581	0.1181526
	During	0.1065404	-0.0404016	0.4056502	0.1410226	0.1059835	-0.0366335	0.4002637	0.1416252	0.1063258	-0.03683126	0.4002637	0.1410931
GOGARH	After	0.544149	0.3056887	1.329559	0.1644118	0.544406	0.306984	1.32713	0.1644726	0.545266	0.3069238	1.32524	0.1647495
	During	0.7715292	0.2687125	3.211972	0.1322184	0.8865007	0.2703791	3.248455	0.1464095	0.7770776	0.2704375	2.885044	0.1294281
EMERG /VISTOXX													
DCC	After	-0.0727382	-0.2079442	-0.0119064	0.2658239	-0.0727995	-0.2077739	-0.0119064	0.2657156	-0.0729090	-0.2077739	-0.0138341	0.266136
	During	-0.0820221	-0.196254	-0.0216592	0.256139	-0.0822618	-0.196254	-0.0216592	0.255773	-0.0822959	-0.1937993	-0.0218531	0.2560182
ADCC	After	-0.0724855	-0.207944	-0.0119058	0.2639487	-0.0725453	-0.2077733	-0.0119058	0.2638442	-0.0726533	-0.2077733	-0.0138352	0.2642484
	During	-0.0820215	-0.1962523	-0.0216593	0.2561356	-0.0822614	-0.1962523	-0.0216593	0.2557708	-0.0822956	-0.1937993	-0.0218529	0.2560163
GOGARH	After	-0.3891325	-0.9140428	-0.1641372	0.3767996	-0.3894688	-0.9063057	-0.1642104	0.3774238	-1.032392	-4.107811	-0.4064148	0.3783915
	During	-0.5734326	-1.464668	-0.2167204	0.3131182	-0.5724954	-1.463568	-0.21676	0.313153	-0.6962901	-2.605662	-0.2720079	0.3131702

Period		Refit=20				Refit=40				Refit=60			
		mean	min	max	HE	mean	min	max	HE	mean	min	max	HE
EMERG /VIX													
DCC	After	-0.0527599	-0.1539912	-0.0129938	0.1767879	-0.0528648	-0.1566418	-0.0131460	0.1769473	-0.0529334	-0.1566418	-0.0129938	0.1772304
	During	-0.0706809	-0.2004566	-0.0228395	0.1760439	-0.0708160	-0.2004566	-0.0228395	0.1758449	-0.0708803	-0.201622	-0.0228703	0.1763806
ADCC	After	-0.0519697	-0.1497146	-0.0125410	0.1716141	-0.0520389	-0.1512673	-0.0127442	0.171622	-0.0521855	-0.1512673	-0.0125410	0.1724517
	During	-0.0684743	-0.1955395	-0.0221866	0.1644959	-0.0686095	-0.1955395	-0.0221866	0.1643596	-0.0685506	-0.1953112	-0.0221801	0.1645275
GOGARH	After	-0.8412791	-6.939782	-0.3343132	0.2450262	-0.3152685	-0.6319149	-0.1127918	0.2454567	-0.3159241	-0.6309794	-0.1128476	0.2470849
	During	-0.497231	-2.149104	-0.226922	0.2195331	-0.5548234	-1.745479	-0.1741954	0.220251	-0.5572266	-1.745331	-0.1742133	0.219813
EMERG/CDS													
DCC	After	-0.0604298	-0.4564774	0.01157692	0.05124584	-0.0602432	-0.4564774	0.00993399	0.05082786	-0.0609028	-0.4317619	0.01157692	0.05156118
	During	-0.0330437	-0.0907255	0.001381608	0.05785379	-0.0324585	-0.0851274	0.001381608	0.05607442	-0.0327240	-0.09072553	0.001586288	0.0561486
ADCC	After	-0.0606921	-0.4564781	0.01157985	0.05153206	-0.0606228	-0.4564781	0.009929958	0.05134827	-0.0609002	-0.4317623	0.01157985	0.05155706
	During	-0.0330442	-0.0907256	0.00138160	0.0578543	0.03245848	-0.0851271	0.00138160	0.05607447	-0.0327239	-0.09072562	0.00158628	0.05614845
GOGARH	After	-0.2056799	-0.8881027	0.01283549	0.08619358	-0.2081404	-0.8836188	0.01483905	0.08788171	-0.4877729	-6.002909	0.7445222	0.08983233
	During	-0.4673315	-2.439468	-0.0111134	0.07272392	-0.4668329	-2.425539	-0.0111130	0.07219926	-0.1588782	-0.2445048	-0.1234449	0.06937778
EMERG / DJCOM													
DCC	After	0.4404277	0.1078664	1.139088	0.175865	0.4404082	0.1101507	1.120637	0.1759935	0.4386107	0.1078664	1.139088	0.175646
	During	0.4841356	0.2489972	1.06964	0.2305234	0.484931	0.2488555	1.083011	0.2294946	0.4886133	0.2511547	1.083011	0.230238
ADCC	After	0.4465692	0.1095779	1.169864	0.1810106	0.4467187	0.1116368	1.152013	0.181257	0.4452534	0.1095779	1.169864	0.1811691
	During	0.4897615	0.2517685	1.089403	0.2357125	0.4902504	0.2530267	1.09521	0.2345078	0.4936277	0.2555537	1.09521	0.2347869
GOGARH	After	0.3857491	-0.0726011	1.467995	0.1963463	0.3841245	-0.0632842	1.446893	0.1944028	0.5031068	0.1670578	1.238322	0.261998
	During	0.5245704	0.1217508	2.133469	0.2485045	0.5202301	0.1192563	2.176903	0.2447087	0.5297793	0.1329954	2.091725	0.2507806

***Table 9**. Summary statistics of hedge ratios (β) and hedge effectiveness (HE) for EMERGI -MVT distribution.*

Period		Refit=20				Refit=40				Refit=60			
		mean	min	max	HE	mean	min	max	HE	mean	min	max	HE
EMERGI/Gold													
DCC	After	0.1090521	-0.5584573	0.9042251	0.04301913	0.1091821	-0.5411037	0.9042251	0.04272829	0.1094117	-0.5411037	0.8994416	0.04250408
	During	0.05053687	-0.5452059	0.4676115	0.03099718	0.05063183	-0.5452059	0.4674059	0.03091046	0.05166628	-0.5452059	0.4674059	0.0308164
ADCC	After	0.1144333	-0.520215	0.9432188	0.04442046	0.1143198	-0.4998328	0.9432188	0.0440693	0.1146183	-0.4998328	0.9345973	0.04384985
	During	0.06473859	-0.5168169	0.5331401	0.03227069	0.0641584	-0.5168169	0.5250554	0.03206948	0.06512852	-0.5168169	0.5250554	0.03188764
GOGARH	After	0.1672197	-0.7267276	0.2947581	0.07807873	0.1676144	-0.7269752	0.2958532	0.07812925	0.3185111	-0.1099623	1.710215	0.07792813
	During	0.06516291	-0.4753626	0.2405457	0.03584738	0.06243263	-0.4734287	0.238185	0.03533289	0.148134	-0.1046194	0.6773584	0.03482657
EMERGI/ Brent													
DCC	After	0.1355979	-0.1115375	0.578278	0.09618132	0.1357971	-0.1115375	0.5768561	0.09613164	0.135912	-0.1115375	0.5768561	0.09655278
	During	0.09438912	-0.074127	0.3499186	0.1313219	0.09292833	-0.0699495	0.3374801	0.1282162	0.09304135	-0.06978898	0.3374801	0.1281579
ADCC	After	0.1463778	-0.0746724	0.5867216	0.106584	0.1466813	-0.0718266	0.5861432	0.1066308	0.1467184	-0.07172784	0.5861432	0.1070608
	During	0.1001269	-0.0653264	0.3638451	0.1420573	0.09864944	-0.0611167	0.3515256	0.139148	0.098803	-0.06089404	0.3515256	0.138852
GOGARH	After	0.6226952	0.2272767	2.166856	0.2063217	0.623915	0.2286328	2.169126	0.2069113	0.3797136	0.1853231	1.84579	0.2080019
	During	0.8178667	0.2415211	3.634977	0.1514792	0.9505528	0.2438711	3.739604	0.1743954	0.2773682	0.09053353	0.7716691	0.1546882
EMERGI/VISTOXX													
DCC	After	-0.0676959	-0.2120372	-0.0088755	0.235609	-0.0677876	-0.2120372	-0.0088755	0.2357443	-0.0678029	-0.2083173	-0.0098348	0.2357171
	During	-0.0759901	-0.1729815	-0.0252313	0.2270737	-0.0762037	-0.1729815	-0.0252313	0.2269169	-0.0761802	-0.1719136	-0.0253441	0.226832
ADCC	After	-0.0674776	-0.2110872	-0.0088765	0.234003	-0.067565	-0.2110872	-0.0088765	0.2341337	-0.0675842	-0.2083172	-0.0098347	0.234119
	During	-0.0252311	-0.1729813	-0.0759897	0.2270713	-0.0762033	-0.1729813	-0.0252311	0.2269151	-0.0761801	-0.1719131	-0.0253459	0.2268323
GOGARH	After	-0.9851581	-3.880605	-0.2432455	0.3504824	-0.9855668	-3.880668	-0.2432123	0.3511828	-0.3845946	-1.67563	-0.1786607	0.3521706
	During	-0.6127465	-2.195504	-0.2724677	0.2772851	-0.6128958	-2.195645	-0.2770663	0.2773269	-0.548929	-1.220483	-0.2277916	0.276857

Period		Refit=20				Refit=40				Refit=60			
		mean	min	max	HE	mean	min	max	HE	mean	min	max	HE
EMERGI/VIX													
DCC	After	-0.0494423	-0.1558218	-0.012523	0.1592096	-0.0496335	-0.1558218	-0.012523	0.1598795	-0.0496037	-0.1529795	-0.012523	0.1595965
	During	-0.0676679	-0.1766011	-0.0261365	0.1656378	-0.0678034	-0.1766011	-0.0261365	0.1656479	-0.0677088	-0.1768002	-0.0260693	0.1655693
ADCC	After	-0.0475119	-0.1513178	-0.0116341	0.1480236	-0.0476793	-0.1513178	-0.0116341	0.1485063	-0.0476554	-0.1448227	-0.0116341	0.1481624
	During	-0.0644872	-0.169118	-0.024955	0.1507272	-0.0646281	-0.169118	-0.024955	0.1508002	-0.0644833	-0.1687302	-0.0248419	0.1505505
GOGARH	After	-0.8377176	-5.959565	-0.187957	0.243772	-0.8377396	-5.954266	-0.1877426	0.2440667	-0.3171623	-1.250762	-0.1305108	0.245597
	During	-0.4536477	-2.063812	-0.191883	0.1864881	-0.4530088	-2.063757	-0.1941658	0.1867634	-0.5024366	-1.348443	-0.1980499	0.1859668
EMERGI/CDS													
DCC	After	-0.0578985	-0.4677504	0.01412011	0.04767914	-0.0580313	-0.4677504	0.0127981	0.04778934	-0.0582072	-0.4416967	0.01412011	0.04774828
	During	-0.0296534	-0.0740437	0.001017602	0.04437142	-0.0292489	-0.0703525	0.001017602	0.04311903	-0.0294363	-0.07404378	0.001292259	0.04358022
ADCC	After	-0.0578983	-0.4677505	0.01412043	0.04767921	-0.0580314	-0.4677505	0.01279814	0.04778944	-0.0582067	-0.4416968	0.01412043	0.04774807
	During	-0.0296531	-0.0740438	0.001017598	0.04437088	-0.0292477	-0.0703516	0.00101759	0.04311621	0.02943386	-0.07404385	0.001292274	0.0435742
GOGARH	After	-0.2155762	-1.615089	0.015997	0.09625207	-0.497818	-7.073178	1.362618	0.0980953	-0.5124872	-7.051554	1.074514	0.1009827
	During	-0.4696971	-1.957906	-0.0119884	0.07199738	-0.1555586	-0.2111425	-0.126121	0.07160619	-0.1540816	-0.1997818	-0.126121	0.06960183
EMERGI/ DJCOM													
DCC	After	0.3872718	0.0879061	1.024225	0.1429442	0.3871942	0.09136539	1.011351	0.1430415	0.3855939	0.09097076	1.024225	0.1429278
	During	0.4364399	0.2164672	0.8717894	0.1902203	0.4379817	0.2162639	0.891294	0.1905297	0.4393717	0.2188126	0.891294	0.1894795
ADCC	After	0.3946111	0.08787634	1.097266	0.1483376	0.394737	0.09135561	1.097266	0.1485609	0.393426	0.09097547	1.04762	0.1486701
	During	0.4397417	0.2164866	0.8814217	0.1936781	0.8928631	0.216444	0.4408137	0.1938112	0.8928631	0.2200192	0.4413857	0.1916031
GOGARH	After	0.4495758	-1.760897	0.5596919	0.1952896	0.4484473	-1.757034	0.559932	0.1942433	0.4466807	-1.115232	0.5594586	0.1941507
	During	0.4421234	0.2557971	0.4887852	0.2537099	0.4411454	0.2537975	0.4889719	0.2538102	0.4394398	0.2490086	0.4831024	0.2515211

During COVID-19, the average value of the hedge ratio between EMRG (EMERGI) obtained with DCC model decrease to 0.05656 (0.05054) indicating that a $1000 long position in EMRG (EMERGI) is hedged by taking short position for $56.56 ($50.54) in gold market. These amounts increase to $70.42 ($65.16) if the model used is GOGARCH. Minimum and maximum values of hedge ratio are of opposite sign indicate that hedging strategy is in alternance between long and short position when hedging conventional and Islamic stock indices by Gold. No considerable difference when change refit from 20 to 40 or 60 days. The only significant difference is observed when we use GOGARCH version with refit of 60 days. In this case, average hedge ratios are much greater than average hedge ratios with refit equal to 20 and 40 days.

Before COVID-19, the average value of the hedge ratio between EMRG obtained with DCC model is -0.05276 (-0.04944) indicating that a $1000 long position in EMRG (EMERGI) is hedged by taking long position for $52.76 ($49.44) in VIX market. These amounts increase to $841.27 ($837.71) if the model used is GOGARCH. During COVID-19, the average value of the hedge ratio between EMRG (EMERGI) obtained with DCC model decrease to -0.07068 (-0.06766) indicating that a $1000 long position in EMRG (EMERGI) is hedged by taking long position for $70.68 ($67.66) in VIX market. These amounts increase significantly to $497.23 ($453.64) if the model used is GOGARCH. Minimum and maximum values of hedge ratio are al negative indicate that long position must be considered during all out of sample period when hedging conventional and Islamic stock indices by VIX. No considerable difference when change refit from 20 to 40 or 60 days. The only significant difference is observed when we use GOGARCH version with refit of 60 days. In this case, average hedge ratios are much greater than average hedge ratios with refit equal to 20 and 40 days.

The mean value of the hedge ratios between brent and the Islamic stock index is lower (greater) than the mean value of the hedge ratios between brent and the conventional stock indices when using DCC or ADCC (GOGARCH) models to compute hedge ratio. The mean value of the hedge ratios between DJCOM and the Islamic stock indices is lower than the mean values of the hedge ratios between brent and the conventional stock indices when using MGARCH models to compute hedge ratio. The mean hedge ratio between the islamic Stock indices and DJCOM is greater than mean hedge ratio between DJCOM and islamic stock indices only in the case of GOGARCH model applied before COVID-19 period. In the majority of cases and specially when using DCC and ADCC models, mean value of hedge ratios between Islamic stock indice and each instrument is lower than the mean value of the hedge ratios between conventional stock index and each instrument indicating that these instrument provide an economical hedging to Islamic stock portfolios and they has higher diversification benefits with the Islamic stock indices, compared to the conventional stock indices. These findings confirm that the development of the Islamic stock indices provides alternative opportunities to diversify portfolios globally. These results have important implications for investors who seek higher yields from the Islamic stock index, while hedging their tail risk through portfolio construction. The DJCOMM, VSTOXX and VIX indices have the highest hedging effectiveness for both the Islamic and conventional stock indices with more superiority to DJCOM specially during COVID-19 period compared with other instruments. Risk reduction can be higher than 17% and can go to 37% when investors hedge his portfolio with VISTOXX for exemple. Hedge using CDS and Gold is less effective as the HE values are between 3.2% and 8.9%.

5.2. Impact of COVID-19 on Hedge and Safe Haven Properties

To study the extent to which the six altenative assets may stand as diversifiers, as hedging or safe haven instruments for conventional and islamic emerging stock indices, we follow the same methodology adopted. Hence, ρ_t are initially extracted and transferred from the VAR-DCC models with innovations assumed follow bivariate t-student distribution, to be subsequently regressed on dummy variables representing market turmoil to test whether there are changes in hedge and safe haven properties of altenatives during COVID-19 period. We have willingly considered to adopt the regression models for the simple reason that we have realized it a bit odd to carry out an analysis dealing with the impact of presence of extreme returns on the correlation. We estimate and test the significance of the parametrers of the following linear regression model:

$$\rho_t = \gamma_0 + \gamma_1 D\left(r_{equity} q_{10}\right) + \gamma_2 D\left(r_{equity} q_5\right) + \gamma_3 D\left(r_{equity} q_1\right) \quad (17)$$

where D represent dummy variables that capture extreme movements in the underlying stock markets at the 10%, 5% and 1% quantiles of the most negative stock returns.

Accordingly, alternative asset is considered as diversifier against movements in the stock market if is significantly positive, while it is considered as weak hedging tools against movements in the other asset if (γ_0) is zero, or might also represent strong hedging instruments if (γ_0) is statistically significante and negative. In the other hand, alternative asset is considered as a weak safe haven tools against movements in the other asset if the (γ_1), (γ_2) and coefficients are not significantly different from zero. Asset is a Strong safe haven if these coefficients turn out to be statistically significant and negative. A negative correlation of asset and stock in extreme market conditions implies that the price of asset increases in such conditions thereby compensating investors for losses incurred with stock investments.

Table 10. *Hedge and safe haven properties of alternatives with emerging markets.*

	EMERG						EMERGI					
	Gold	**Brent**	**VISTOXX**	**VIX**	**CDS**	**DJ COMM**	**Gold**	**Brent**	**VISTOXX**	**VIX**	**CDS**	**DJ COMM**
Before COVID-19												
γ_0	0.1325***	0.3183***	-0.5219***	-0.4336***	-0.2096***	0.4264***	0.1195***	0.3038***	-0.4904***	-0.4118***	-0.2091***	0.3930***
γ_1	0.0073	0.0129.	-0.0084*	-0.0341*	0.0043	0.0123*	-0.0038	0.0148.	-0.0106**	-0.0111***	0.0061	0.01617*
γ_2	0.0529	-0.0121	0.0081.	0.0023	0.0121	-0.0008	0.0228*	-0.0052	0.0043	0.0064.	0.0093	-0.0008
γ_3	-0.005	-0.0136.	0.0097*	0.0063***	0.0191*	-0.0174**	-0.0114	-0.0223**	0.0147***	0.0052.	0.0190*	-0.0236***
During COVID-19												
γ_0	0.0620***	0.3296***	-0.5214***	-0.4349***	-0.2700***	0.4864***	0.0637***	0.3150***	-0.4901***	-0.4225***	-0.2341***	0.4465***
γ_1	-0.0342	-0.0163	-0.0068	-0.0023	0.0106	-0.0076	-0.0108	-0.0381	0.0078	0.0084	-0.0027	-0.015
γ_2	0.0720.	-0.0328	0.0331**	0.0178*	-0.0247	-0.0118	0.0254	-0.0147	0.031.	0.0134	0.0055	-0.0035
γ_3	-0.0519.	-0.0007	-0.0105	-0.0035	0.0119	0.0004	-0.0231	0.011	-0.0211	-0.0081	-0.0068	0.0046
Test de Show	44.56***	17.54***	0.9287	8.2189***	40.6925***	86.3413***	29.8364***	3.4981**	0.9343	14.93002***	16.0074***	40.2937***

Note: ***,**,* indicates statistical significance at the 1%, 5% and 10% levels, respectively.

Accordingly, alternative asset is considered as diversifier against movements in the stock market if is significantly positive, while it is considered as weak hedging tools against movements in the other asset if (γ_0) is zero, or might also represent strong hedging instruments if (γ_0) is statistically significante and negative. In the other hand, alternative asset is considered as a weak safe haven tools against movements in the other asset if the (γ_1), (γ_2) and coefficients are not significantly different from zero. Asset is a Strong safe haven if these coefficients turn out to be statistically significant and negative. A negative correlation of asset and stock in extreme market conditions implies that the price of asset increases in such conditions thereby compensating investors for losses incurred with stock investments. Zghal et al. (2018) and Zghal and Ghorbel (2020) analysis the impact of data frequency on safe haven and hedge properties of various assets among which we can cite VIX, Bitcoin and CDS.

The estimated results on the role of the six hedge alternatives as a safe haven and hedge on emerging stock markets are reported in Table 10. Empirical results are similar for conventional and islamic stock indices. We found that Gold and Brent are a diversifier instruments and there is not a non linear relationship between these two markets and emerging stock markets. CDS and VISTOXX are a hedge instruments for both conventional and islamic stock indices. Any alternative can play the rule of safen haven instrument during COVID-19 period on emerging stock markets. No significant changes are detected in the properties of instruments. The propagation of COVID-19 on the world reduce the chance to use one of the six assets as a safe haven instruments.

6. Conclusion

This paper use different MGARCH Models to estimate time varying optimal hedge ratio and determinate whether investors in emerging stock markets will take short or long position in each of the six alternatives instruments and with how much amount to reduce their portfolio risk. We study the sensitivity of results to change of investment horizons as we estimate hedge ratio with various refits: 20, 40 and 60. We compare between optimal strategies adopted by investor on conventional emerging stock markets and another that have portfolio composed of EMERGI index. We test equally impact of COVID-19 on hedging strategy of this two investors and this is the main contribution of this paper.

Many results in this paper have various implications for investors. First, the hedging analysis indicates that the hedge ratios vary and depend upon the hedge instrument included in the portfolio, the conditional correlation between markets and model used to estimate this correlation. Investor can change daily his position from long to short or from short to long over time to best hedge against risk. Second, DJCOM is the best hedge instrument for both Islamic and conventional stock portfolios because the EMRG/DJCOM and DJIEM/DJCOM hedges have the highest hedging effectiveness coefficients. Third, DCC and ADCC give similar results and similar Hedging effectiveness while hedge ratio obtained from GOGARCH don’t have the same pattern and volatility. It is not in all cases that GOGARCH offer hedge ratios more volatile than DCC and DCC one. Fourth, impact of COVID on hedge and safe haven properties of instruments studied is not clear. Finally, impact of COVID-19 is most clear when compare between average hedge ratio and between HE. In the majority of cases, average hedge ratio decrease with the appearance of COVID-19 epidemic. Some instruments become more effective in hedging emerging stock markets during COVID-19 period than before such as: Brent and DJCOM. Both Gold and CDS are less effective than before appearance of COVID-19. These findings provide relevant information to agents with respect to the stock market in which they need to invest at the current situation of acute distress caused by the pandemic in an effort to mitigate risks.

Future researches can introduce the second wave of COVID-19 in analysis and can improve optimal hedging strategy by take into account two instruments simultaneously instead of one instrument to improve hedging effectiveness using trivariate MGARCH versions or time varying vine copula or GAS copula. It is evident to show mathematically that hedging with two instruments is more effective than hedge with one instrument.

Abbreviations

DCC: Dynamic Conditional Correlation
ADCC: Asymmetric Dynamic Conditional Correlation
GO-GARCH: Generalized Orthogonal GARCH
DJCOM: Dow Jones Commodity
VISTOXX: Euro STOXX 50 Volatility Index
VIX: Chicago Board Options Exchange Volatility Index
CDS: Credit Default Swap

Conflicts of Interest

The authors declare no conflicts of interest.

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