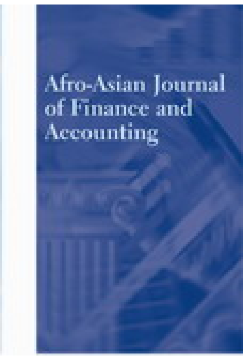

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Commodity sectors and emerging stock markets: is there any risk transmission?

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Abstract: The present work aimed to examine the risk spillover between three commodity sectors, namely energy, precious metals, and agriculture, and emerging stock markets. Asymmetric dynamic conditional correlation (ADCC) and conditional value at risk (CoVaR) were used to measure downside and upside risk spillovers between the studied markets. Our empirical results reveal that the downside and upside risk spillovers are significant. We also found an asymmetric two-way risk spillover in most cases, but the degree of asymmetry differs according to the application of the entire cumulative distributions or distribution tails. Downside and upside risk spillover magnitudes between precious metals and emerging stock markets are not significantly larger following the global financial crisis (GFC) compared to the pre-crisis period, except for the downside risk spillover below the 25th quantile. However, for the other pairs, downside and upside risk spillovers are significantly higher after GFC than before it. Our empirical findings have important implications for risk management among investors and policymakers, as they emphasise the prevalence of tail behaviour and the persistent asymmetric nature of both downside and upside risk spillovers.

Keywords: commodity sectors; emerging stock markets; risk spillover; ADCC-CoVaR approach.

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1 Introduction

The 2007–2009 global financial crisis (GFC) started in the USA and highlighted risk spillover internationally. Since this crisis, commodity and stock markets have gained momentum from investors and risk management agencies. Commodity markets are deemed the most well-received investment tool for hedging, diversifying, and avoiding portfolio risks (Kang and Yoon, 2020).

Furthermore, the relationship between commodity and traditional financial markets, namely stock and exchange rate markets, is relatively weak; thus, portfolio managers put more commodity markets with weak or negative interdependences with equity assets in their portfolios (Sadorsky, 2014; Bekiros et al., 2017). The interdependences and volatility spillovers between stock and commodity markets are essential for portfolio optimisation and risk management (Wen et al., 2021).

Theoretically, investors can diversify their risk and create an optimal portfolio using low-correlated markets. However, such diversification becomes invaluable in uncertain markets. Besides, each investor aims to understand and grasp the concept of interdependence among different markets and the various risk factors that can impact their portfolio. Nevertheless, in turbulent markets, the correlations between several equity markets intensify due to transmission effects (Longin and Solnik, 1995, 2001; Antoniou et al., 2007; Markwat et al., 2009). Furthermore, the turbulent financial market periods push portfolio managers to seek alternative ways to diversify their portfolios and reduce risk. Moreover, commodity markets have emerged as eligible financial assets for portfolio diversification. Over the last three decades, the demand for investing in commodity markets has increased significantly.

Therefore, good risk management can enhance the quality and performance of these markets. The prices of basic commodities have experienced considerable fluctuations over the past two decades. Accordingly, it is challenging to determine the extent to which the level and volatility of commodity prices are related to financial investments, such as equity markets.

Rare or extreme events, such as international crises, highlight the presence of correlations, particularly between multiple stock and commodity markets. As a result, the rapid and forceful transmission of shocks and crises can be attributed to increased levels of integration among global markets. Indeed, investors strive to develop their portfolios regularly without assuming excessive risk. However, they are sometimes exposed to the risk of a very sharp drop or rise in their assets' value. Therefore, studying the growing market instability is pertinent to investors and short- or long-term financial decision makers. Extreme events are characterised by a low probability of occurrence. Indeed, extreme events, such as GFC, the COVID-19 pandemic, and the Russian-Ukrainian war, have resulted in significant losses for investors primarily because conventional risk modelling fails to assess the impact of shocks during crises. Consequently, examining risk assessments and extreme dependencies has become a critical research area.

In other words, the dynamics of stock and commodity markets are among the most complex economic phenomena. Uncertainty is a driving force behind these dynamics and occupies a central position in most problems the modern financial theory addresses (Bollerslev et al., 1992). The GFC period evidences a significant interdependence between commodity and stock market returns (Tang and Xiong, 2012). The subsequent collapse of Lehman Brothers triggered a stock market crash, prompting investors to shift toward commodity markets. This investor reaction resulted in the emergence of a new transmission among stocks and commodity markets (Adams and Glück, 2015).

According to the literature, there has been a significant increase in the importance of commodities to investors over the past two decades, indicating a growing integration between commodity and stock markets (Tang and Xiong, 2012; Adams and Glück, 2015; Karyotis and Alijani, 2016) that results in augmented volatility spillovers. A shock to one market, commodity or stock market, may motivate investors to rebalance their portfolios by investing in the other market leading to volatility transmissions. Many previous studies have investigated volatility spillovers from commodity to stock markets and vice versa (Mensi et al., 2013, 2021a, 2021b; Vardar et al., 2018; Wen et al., 2021).

Based on this background, the current study contributes to the existing literature by addressing two specific questions: Firstly, how do the commodity sector and emerging stock markets move over time, and is there evidence of a significant correlation under extreme economic conditions caused by the global financial crisis? Secondly, what deductions can be made about the nature of the downside and upside risk spillovers across these markets given the dependence structures? Risk spillovers are computed using the estimation of the downside and upside conditional value at risk (CoVaR) through the asymmetric dynamic conditional correlation (ADCC), where downside (upside) risk denotes potential extremely long (short) position losses. The bootstrapped two-sample Kolmogorov-Smirnov (KS) test (Abadie, 2002) was used to assess the significance of risk transmission and potential asymmetries.

This study differs from previous studies in two aspects. First, to our knowledge, unlike the few papers focusing on the risk spillovers between commodity sectors and emerging stock markets, our paper is the first to study the nature of downside and upside risk spillovers across these markets, given the dependence structures. Second, it contributes particularly to the limited literature about the commodity sector markets.

The remainder of the paper is structured as follows: Section 2 reviews previous empirical studies. Section 3 outlines the methodology. Sections 4 and 5 present and discuss the data and estimation results. Finally, Section 6 concludes the paper.

2 Literature review

Value at risk estimation has become crucial for risk management and measurement for all financial institutions. The examination and analysis of the dynamic links between stock and commodity markets through several techniques have been contemplated in much of the previous empirical work. However, they focused mainly on risk transmission between equity and commodity markets.

Creti et al. (2013) tested the transmission of return volatility between the US stock market (S&P500) and the 25 commodities (precious metals, energy, agriculture, food, etc.) using the dynamic conditional correlation-generalised autoregressive conditional heteroskedasticity (DCC-GARCH) model. They showed that the correlation between commodity markets and US equities was very volatile at the start of the global financial crisis. Similarly, Sadorsky (2014) used the vector autoregressive moving average process with adaptive GARCH (VARMA-AGARCH) and DCC-AGARCH models to examine the impact of volatility on emerging stock markets and three commodity markets (oil, wheat and copper). They found a contagion effect between the considered markets. In the same vein, Mensi et al. (2015) used the DCC with fractionally integrated asymmetric power ARCH (DCC-FIAPARCH) model to investigate the relationship between the Saudi stock market (Tadawul) and major commodities, such as gold, silver, oil, rice, wheat, and corn. These authors found a non-significant DCC between commodity markets and the Tadawul index, except for silver.

Furthermore, Boldanov et al. (2016) investigated the conditional correlation between Brent crude oil prices and stock market volatility across six major oil-importing and exporting countries, namely Canada, Russia, and Norway as oil-exporting countries and the USA, China, and Japan as oil-importing ones from January 2000 to December 2014. Using a model from the Baba, Engle, Kraft, and Kroner (BEKK) family, the authors revealed that the correlation between equity and oil market volatility varies over time, showing positive and negative values throughout the study period. The correlations are sensitive to significant economic and geopolitical events, such as the GFC and the contraction of economic activity, which affected some stock markets in developed countries in the early 2000s.

Several studies (e.g., Boako and Alagidede, 2016; Boako et al., 2020; Bouri et al., 2020; Liu et al., 2020) have shown a negative relationship between stock and commodity markets. Moreover, Amar et al. (2021) examined the interdependence between equity and commodity markets during the COVID-19 outbreak. Their results demonstrate a significant effect of COVID-19 on the financial market and a strong co-movement between financial and commodity markets. Hung and Vo (2021) investigated the spillover effects and time-frequency correlations among the S&P 500, crude oil prices, and gold assets. They showed that, during the pandemic, return spillovers are more pronounced and that there are specific structures of dependence between the three market indices. Mensi et al. (2021b) showed that short-term transmissions between precious metals and stock markets in top precious-metal exporters and importers dominate the long-term ones. The hedging effectiveness is more significant in the short term for precious metals exporters.

It is also central to understand the dynamics of stock markets through their relationship to foreign exchange (FX) markets. The many studies investigating the relationship between FX and stock markets reached mixed findings (Jorion, 1991; Nieh and Lee, 2001; Smyth and Nandha, 2003; Inci and Lee, 2014; Bahmani-Oskooee and Saha, 2015; Tian et al., 2023) that could be attributed to the differences in methodologies, time, and countries.

The relationship between FX and stock markets has attracted researchers' attention, particularly if fluctuations in FX could spill over to equity markets. The direction of the FX-stock markets linkage has been explained using two theories, namely the stock-oriented model (from stock markets to FX) and the flow-oriented model (from FX to stock markets). The spillover from FX to the stock market is especially relevant in emerging countries. Besides, emerging countries have experienced several turbulent periods characterised by high FX rate volatility (e.g., the subprime crisis of 2007–2009).

According to Warshaw (2020), volatility spillovers between FX and European equity markets during the 2003–2019 period are bidirectional and asymmetric across the frequency domain in most cases. They revealed that the transmissions from equity to FX markets are significant at high, mid-range, and low frequencies, whereas only at lower frequencies in the opposite direction. The results also showed that the spillover significance and persistence increased during the GFC and remained impacted afterward.

Tian et al. (2023) explored risk spillovers from the FX to the stock markets and found an asymmetric behaviour in the spillover from FX to stock markets, with the downside risk transmissions being more prominent than the upside ones.

3 Methodology

Downside and upside CoVaR, used to evaluate risk spillovers between emerging stock markets and commodity sector markets, were calculated using a three-step ADCC-based methodology.

In the first step, the VaR of each market *i* was computed by estimating the threshold GARCH (TGARCH) model of Zakoian (1994), which is the first element. The returns r_t^i of an individual market *i* at time *t* are defined as:

$$r_t^i = \mu_t^i + \varepsilon_{i,t} \tag{1}$$

where $\mu_t^i = \alpha_0 + \alpha_1 r_{t-1}^i$ and $\varepsilon_{i,t} = z_{i,t}\sigma_{i,t}$. Then, $z_{i,t}$ is independent and identically distributed (iid) with zero mean and unit variance; then, the conditional variance has the TGARCH (1, 1) specification:

$$h_{i,t} = \beta_0^i + \beta_1^i \varepsilon_{i,t-1}^2 + \lambda_1 \varepsilon_{i,t-1}^2 D_{t-1} + \beta_2^i h_{i,t-1} \tag{2}$$

$$D_{t-1} = \begin{cases} 1, & \text{if } \varepsilon_{t-1} < 0 \\ 0, & \text{if } \varepsilon_{t-1} \geq 0 \end{cases} \tag{3}$$

where $h_{i,t-1}$ denotes the conditional variance at time $(t - 1)$, $\varepsilon_{i,t-1}$ represents the errors at time $(t - 1)$, while the coefficients β_0^i, β_1^i and β_2^i are not restricted to non-negativity and $\beta_1^i + \beta_2^i < 1$. Next, λ_1 is known as the leverage or asymmetry parameter. In this model, bad news ($\varepsilon_{t-1} < 0$) and good news ($\varepsilon_{t-1} > 0$) have a differential effect on conditional variance.

Moreover, after determining the distribution hypothesis for *z* and the q-quantile of the estimated conditional distribution, we can calculate the VaR of each institution j for each period.

Given the return r_t^i of an individual market *i* at time *t* with a confidence level of $(1 - \alpha)$, the downside and upside $VaR_{\alpha,t}^i$ are as follows:

$$\text{Downside:} \qquad \Pr\left(r_t^i \leq VaR_{\alpha,t}^i\right) = \alpha \tag{4}$$

$$\text{Upside:} \qquad \Pr\left(r_t^i \geq VaR_{1-\alpha,t}^i\right) = \alpha \tag{5}$$

In the second step, we estimated a bivariate GARCH model with an ADCC model (Cappiello et al., 2006) to capture the correlation between the returns of two markets. Let $r_t = (r_t^i, r_t^j)'$, then, r_t is expressed as follows:

$$r_t = \mu_t + \varepsilon_t = \mu_t + H_t^{1/2} + z_t \tag{6}$$

where H_t represents the 2 × 2 covariance matrix of the residual ε_t, while μ_t is the 2 × 1 vector of conditional means. Then, the standardised innovation vector z_t is i.i.d. with a zero mean and identity matrix variance. Following the ADCC model proposed by Cappiello et al. (2006), the time-varying conditional covariance matrix (H_t) is presented as:

$$H_t = D_t^{1/2} P_t D_t^{1/2} \tag{7}$$

where $D_t^{1/2}$ is a diagonal matrix of time-varying standard deviations from univariate TGARCH models on the diagonal. Following the DCC-GARCH model (Engle, 2002), the conditional correlation matrix (P_t) is as follows:

$$P_t = diag\left(Q_t\right)^{-1/2} \times Q_t \times diag\left(Q_t\right)^{-1/2} \tag{8}$$

$$Q_t = \left(1 - \alpha_c - \beta_c\right)\bar{Q} - \gamma\bar{N} + \alpha_c u_{t-1}u'_{t-1} + \beta_c Q_{t-1} + \gamma_c n_{t-1}n'_{t-1} \tag{9}$$

where Q_t represents the covariance matrix of the standardised residuals u_t and $u_t = D_t^{-\frac{1}{2}}\varepsilon_t$; $diag(Q_t)$ defines the 2 × 2 matrix with Q_t on the diagonal and zero off-diagonal; $\bar{Q}$ denotes the unconditional covariance matrix of u_t. Then, parameters α_c, β_c and γ_c are elements in estimating the conditional correlation matrix P_t. Furthermore, let $n_t = I[u_t < 0] \circ \mu_t$, where $I[.]$ represents an indicator function that takes 1 if the argument is true and 0 otherwise. Then, '$\circ$' denotes the Hadamard product and $\bar{N} = E[n_t n'_t]$.

In the third step, we estimated the downside (d) and upside (u) $CoVAR_{\beta,\tau}^{1/j}$ as follows:

$$\text{Downside:} \qquad \Pr\left(r_t^i \le CoVaR_{\beta,t}^{i/j},\, r_t^j \le VaR_{\alpha,t}^j\right) = \alpha\beta \tag{10}$$

$$\text{Upside:} \qquad \Pr\left(r_t^i \le CoVaR_{\beta,t}^{i/j},\, r_t^j \ge VaR_{1-\alpha,t}^j\right) = \alpha\beta \tag{11}$$

As a result, we numerically solved the following double integral for downside and upside $CoVaR_{\beta,\tau}^{i/j}$ with VaR_t^j estimated in the first step as follows:

$$\text{Downside:} \qquad \int_{-\infty}^{CoVaR_{\beta,t}^{i/j}} \int_{-\infty}^{VaR_{\alpha,t}^j} pdf_t(x, y)dydx = \alpha\beta \tag{12}$$

$$\text{Upside:} \qquad \int_{-\infty}^{CoVaR_{\beta,t}^{i/j}} \int_{-\infty}^{VaR_{1-\alpha,t}^j} pdf_t(x, y)dydx = \alpha\beta \tag{13}$$

Moreover, the downside and upside risk spillover significance and that of potential asymmetries were tested by comparing the cumulative distribution functions (CDFs) for the VaR and CoVaR using the two-and one-sided bootstrapped two-sample Kolmogorov-Smirnov (KS) test developed by Abadie (2002). Then, the two-sided equal-distribution *KS* statistic is as follows (see Warshaw, 2019):

$$KS^{EQ} = \sqrt{\frac{mn}{m+n}} \sup_x \left|F_m(x) - G_n(x)\right| \tag{14}$$

where $F_m(x)$ and $G_n(x)$ denote the CDFs of the CoVaR and VaR, respectively, and the elements m and n represent the sizes of the two samples. The two-sided test is used to evaluate H_0: $F_m(x) = G_n(x)$ versus H_1: $F_m(x) \neq G_n(x)$. Similarly, for the dominance test, the one-sided test statistic is defined as follows:

$$KS^{FSD} = \sqrt{\frac{mn}{m+n}} \sup_x \left(F_m(x) - G_n(x) \right) \tag{15}$$

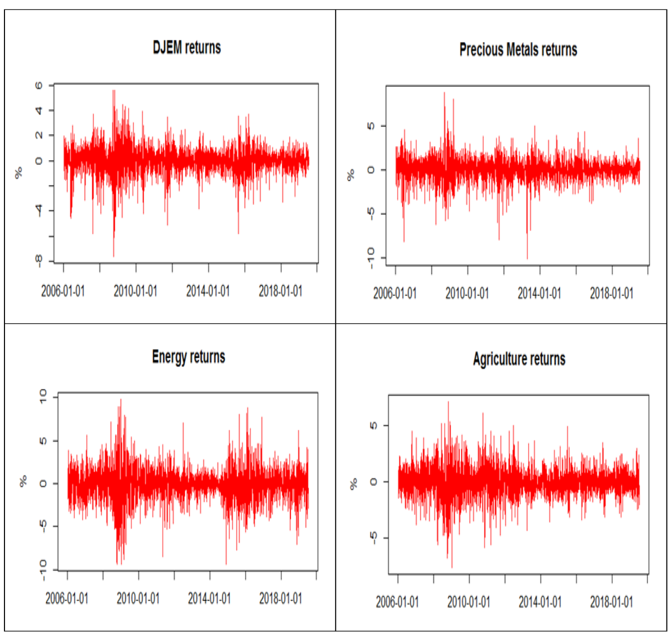
Here, the assumptions were defined as follows: H_0: $F_m(x) \leq G_n(x)$ versus H_1: $F_m(x) > G_n(x)$ or H_0: $F_m(x) \geq G_n(x)$ versus H_1: $F_m(x) < G_n(x)$.

4 Data and preliminary analysis

4.1 Data

The data used in this study were the daily series of the stock market indices for the different commodity sectors, namely agriculture (S&P GSCI Agriculture), precious metals (S&P GSCI Precious Metals), and energy (S&P GSCI Energy), as well as the global emerging stock market index [Dow Jones Emerging Markets (DJEM)]. The study spanned 30 December 2005 to 17 July 2019, with 3,534 observations. Our data were downloaded from the Data Stream database with all indices in dollars.

Figure 1 Dynamics of sample returns (see online version for colours)



4.2 Preliminary analysis

The graphical study of a statistical series is an essential step in the analysis of a statistical problem because it gives information on the shape of the observed distribution. Figure 1 presents the changes in the returns of the studied series (DJEM, precious metals, energy, and agriculture). Here, the daily returns were defined as $r_t = 100 * [\ln(P_t) - \ln(P_{t-1})]$, with P_t the price at time t. A cursory examination reveals similar behaviour patterns across the four markets over time, with distinct periods of clustered volatility. In addition, these fluctuations take both positive and negative values around the mean value. The curves show common extreme peaks in the volatilities of the considered indices, especially in 2009, which may be due to the subprime crisis.

Table 1 Descriptive statistics

	DJEM	*Precious metals*	*Energy*	*Agriculture*
Mean (%)	0.013	0.027	–0.004	0.009
Median (%)	0.058	0.011	0.010	0.000
Minimum (%)	–7.579	–10. 105	–9.347	–7.634
Maximum (%)	5. 583	8. 758	9. 808	7.153
Q_1 (%)	–0.484	–0.501	–0.915	–0.710
Q_3 (%)	0.580	0.658	0.951	0.734
Standard deviation (%)	1. 060	1. 225	1.882	1.307
Skweness	–0.530	–0.436	–0 .160	–0.126
Kurtosis	4.319	5.759	3.080	2.614
Jarque-Bera (p-value)	2,917.6 (0.000)	5,003.6 (0.000)	1,415.1 (0.000)	1,018 (0.000)
Q(12) (p-value)	155.6 (0.000)	25.169 (0.014)	20.26 (0.062)	15.098 (0.236)
Q2(12) (p-value)	2,351.2 (0.000)	378.17 (0.000)	1,523.5 (0.000)	860.18 (0.000)
ADF (p-value)	–13.367** (0.01)	–15.075** (0.01)	–13.426** (0.01)	–13.786** (0.01)

Notes: The sample includes 3,534 observations for each series. The ADF are empirical statistics of the augmented Dickey and Fuller (1979); ***, **, and * indicate the rejection of the null hypothesis at 1, 5, or 10% levels, respectively; $Q(12)$ and $Q^2(12)$ denote the empirical statistics of the Ljung-Box test for the autocorrelation of the returns and the squared return series, respectively.

Table 1 presents descriptive statistics for the market returns series. As can be seen in this table, the average returns for the relevant series are close to zero. Furthermore, the energy market is more volatile than other markets. The skewness coefficient is negative for all return series. This result indicates that the returns are characterised by a longer left tail (extreme losses) than the right tail (extreme gains). We also note that the value of the kurtosis coefficient is different from 3 for all the studied series, indicating that they do not all follow the normal distribution. In addition, we note that all the Jarque-Bera statistics are significant, suggesting that the null hypothesis of the normality of the return series is rejected for all four series. The provided Ljung-Box statistics are significant, signifying the presence of an auto-correlation for all the squares of the returns and hence the existence of linear and nonlinear dependence in the return series and the utility of GARCH modelling. The augmented Dickey-Fuller (ADF) test results reject the null hypothesis of a unit root for each series, showing that the returns are stationary.

5 Results and discussion

5.1 Multivariate GARCH estimation

We used the ADCC-GARCH model to analyse the correlations and dynamic volatilities between the returns of all pairs of market indices (Table 2). Indeed, the choice of the optimal number of lags of the model is based on the Akaike information criterion (AIC). According to this criterion, the best model is the one with the weakest AIC value. Therefore, the estimated model is the ADCC-GARCH (1, 1) model. This model is estimated via maximum likelihood assuming the conditional multivariate normal distribution.

Table 2 Multivariate GARCH estimation

ADCC-GARCH(1,1)				
TGARCH Parameters				
Parameters \ *Data*	*DJEM*	*Precious metals*	*Energy*	*Agriculture*
μ	0.002 (0.864)	0.031 (0.056)	–0.020 (0.564)	–0.012 (0.536)
$ar1$	0.200*** (0.000)	–0.017 (0.300)	–0.006 (0.786)	0.037 (0.022)
w	0.014 (0.035)	0.009** (0.000)	0.012*** (0.000)	0.007* (0.007)
α_1	0.082*** (0.000)	0.050*** (0.000)	0.045*** (0.000)	0.058*** (0.000)
β_1	0.920*** (0.000)	0.955*** (0.000)	0.959*** (0.000)	0.949*** (0.000)
v	0.416*** (0.000)	0.003 (0.981)	0.649*** (0.000)	–0.004 (0.952)

ADCC parameters			
Parameters	*DJEM-precious metals*	*DJEM-energy*	*DJEM-agriculture*
dcca	0.039*** (0.001)	0.013*** (0.005)	0.006*** (0.001)
dccb	0.897*** (0.000)	0.979*** (0.000)	0.989*** (0.000)
Dccg	0.000 (0.999)	0.001 (0.554)	0.000 (0.643)

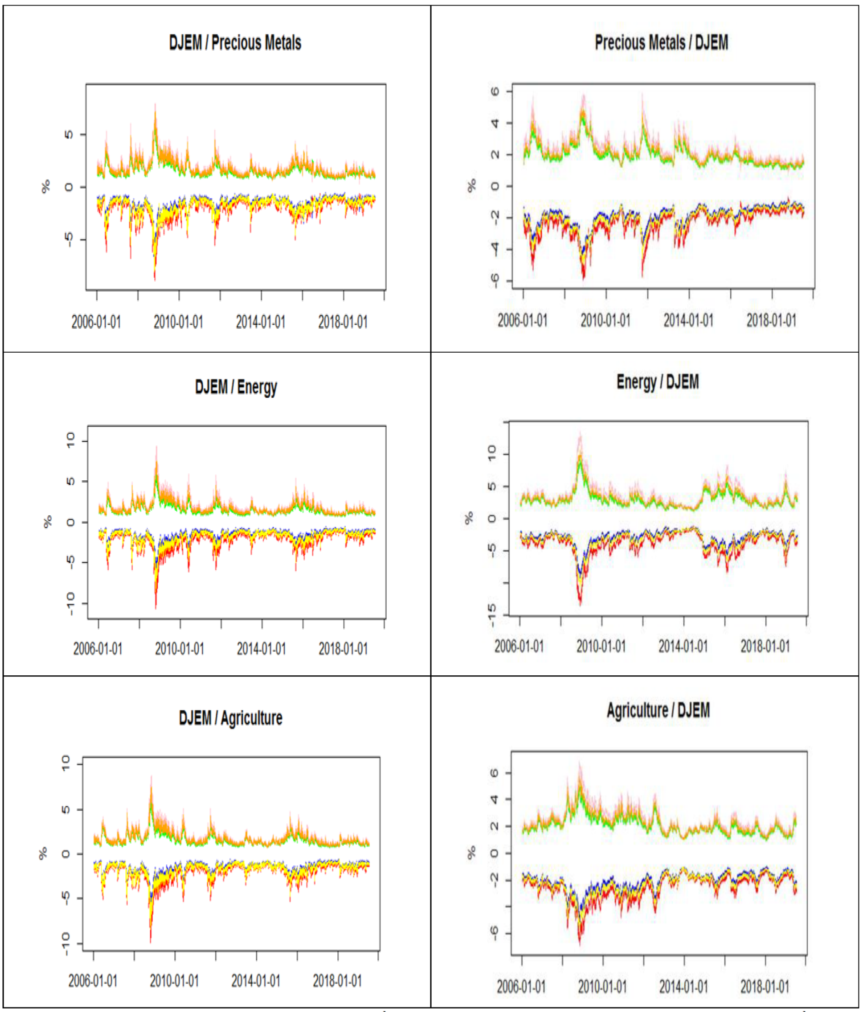
Notes: ***, **, and * indicate the rejection of the null hypothesis at 1, 5, or 10% levels, respectively. The p-values are given in parentheses.

The results (Table 2) show that the coefficients α_1 and β_1 are positive and statistically significant at the 5% threshold. Moreover, the coefficient β_1 is close to 1 for all the used indices, indicating persistent long-term volatility for all the studied series. Besides, the coefficients (dcca and dccb) estimated from the ADCC model are also statistically significant at the 1% level, implying the presence of dynamic conditional correlations between each pair of markets.

5.2 Downside and upside risk spillover

Based on the estimation of the ADCC-GARCH model, downside and upside VaR and CoVaR were calculated for each pair of market indices. The following analysis assumes that $\alpha = \beta = 0.05$, focusing on the 95% confidence levels.

Figure 2 Downside and upside of the VaR_i, $CoVaR^{i/j}$, and $CoVaR^{i/j^b}$ (see online version for colours)



$-VaR_i(d)$ $-CoVaR^{i/j}(d)$ $-CoVaR^{i/j^b}(d)$ $-VaR_i(u)$ $-CoVaR^{i/j}(u)$ $-CoVaR^{i/j^b}(u)$

Figure 2 plots the downside and upside VaR_i, $CoVaR^{i/j}$, and $CoVaR^{i/j^b}$ estimates for each pair of market indices. $CoVaR^{i/j}$ indicates the conditional value at risk at the state of stress, and $CoVaR^{i/j^b}$ denotes the conditional value at risk in the normal state. Each sub-figure legend gives the direction of conditioning the $CoVaR^{i/j}$ and $CoVaR^{i/j^b}$. For example, 'DJEM/precious metals' denotes that the downside and upside $CoVaR^{i/j}$ for the

DJEM are computed under the condition of shock occurring in the precious metals market. Here, the downside and upside VaR_i correspond to DJEM returns. This figure shows a large trend of gains and losses in 2009 for each pair of markets, which can be attributed to the subprime crisis. Risk spillovers generally move together over time, exhibit heteroskedasticity, and are most prominent during the GFC in 2009. In addition, we notice that the downside and upside risk spillovers for the DJEM/energy, energy/DJEM, and DJEM/agriculture during the GFC are higher than the other market pairs.

We also observe that the downside (upside) $CoVaR^{i/j}$ generally exceeds the downside (upside) VaR_i and $CoVaR^{1/j^b}$, suggesting that when commodity sector markets are under stress, emerging equity market risk will be greater and vice versa. However, more rigorous testing is needed to confirm transmission significance.

Table 3 presents the results of downside (d) and upside (u) risk spillovers under the KS^{FSD} statistics with bootstrapped p-values to perform the following test (T1):

$$\text{T1:}\quad \begin{cases} H_0 : CoVaR_{\beta,t}^{i/j,d} \geq VaR_{\alpha,t}^{i} \quad vs \quad H_1 : CoVaR_{\beta,t}^{i/j,d} < Var_{\alpha,t}^{i} \\ H_0 : CoVaR_{\beta,t}^{i/j,u} \leq Var_{1-\alpha,t}^{i} \quad vs \quad H_1 : CoVaR_{\beta,t}^{i/j,u} > Var_{1-\alpha,t}^{i} \end{cases}$$

The rejection of the null hypothesis indicates that risk spillover is significant such that downside (upside) CoVaR is larger than downside (upside) VaR. Test (T1) is conducted for each equity market pair and direction of spillover conditioning. As shown in columns 3 and 6, which consider the entire cumulative distributions (denoted 'all'), downside and upside risk spillovers are significant at the 1% level in all cases.

For example, the KS^{FSD} statistic for the downside CoVaR for precious metals returns conditional on the downside VaR for DJEM returns versus isolated downside VaR for precious metals returns is 0.299, indicating that potential precious metals losses are higher when the DJEM has already experienced an extreme decline in value. In addition, the results presented above confirm the dynamic dependencies between commodity sectors and emerging stock returns and identify the dependence regimes in different periods, mainly during the GFC period. Furthermore, the results show that the downside CoVaR is significantly smaller than its corresponding VaR, while the upside CoVaR is significantly larger than its corresponding VaR for all markets. These results also show that the downside (upside) risk spillover between the energy sector and emerging stock markets is more significant than other market pairs. However, the lowest risk spillover is between the agriculture sector and emerging stock markets. Overall, all results indicate a substantial risk spillover for all pairs of market indices, confirming the presence of potential systemic risk in international markets.

Moving beyond the entire cumulative distributions, risk spillover significance is also studied below the 25th and above the 75th quantiles. For downside risk, below the 25th (above the 75th) quantile shows that the degree of risk in each market is currently high (low). For upside risk, the correspondence is reversed. Columns 4–5 and 7–8 of Table 3 present the downside and upside risk spillovers by quantile, respectively. We found similar results for the entire cumulative distributions. These results suggest that downside and upside CoVaR are higher than VaR even when possible long and short position losses are low. Neglecting these facts can lead portfolio managers to underestimate potential downside and upside risks during calm periods.

Table 3 Downside and upside risk spillovers.

CoVaR	*VaR*	*Downside*			*Upside*		
		All	*Lower 25th*	*Upper 75th*	*All*	*Lower 25th*	*Upper 75th*
Precious metals/ DJEM	Precious metals	0.299 (0.000)	0.633 (0.000)	0.604 (0.000)	0.309 (0.000)	0.614 (0.000)	0.640 (0.000)
DJEM/ precious metals	DJEM	0.249 (0.000)	0.510 (0.000)	0.604 (0.000)	0.266 (0.000)	0.602 (0.000)	0.506 (0.000)
Energy/DJEM	Energy	0.320 (0.000)	0.75 (0.000)	0.565 (0.000)	0.313 (0.000)	0.537 (0.000)	0.737 (0.000)
DJEM/energy	DJEM	0.300 (0.000)	0.656 (0.000)	0.674 (0.000)	0.315 (0.000)	0.685 (0.000)	0.634 (0.000)
Agriculture/ DJEM	Agriculture	0.245 (0.000)	0.699 (0.000)	0.486 (0.000)	0.241 (0.000)	0.483 (0.000)	0.681 (0.000)
DJEM/ Agriculture	DJEM	0.243 (0.000)	0.529 (0.000)	0.664 (0.000)	0.245 (0.000)	0.624 (0.000)	0.515 (0.000)

Notes: 'All' implies testing over the entire cumulative distributions, whereas the lower 25th and the upper 75th refer to below the 25th and above the 75th quantiles of each cumulative distribution, respectively.

5.3 Asymmetric risk spillover

Potential risk transmission asymmetries are presented along two dimensions. Firstly, downside and upside risk transmission magnitudes were compared. According to Warshaw (2019), downside and upside CoVaR are normalised by their corresponding VaR. The test (T2) is as follows:

$$\text{T2:} \quad H_0 : \frac{CoVaR_{\beta,t}^{i/j,d}}{VaR_{\alpha,t}^{i}} \le \frac{CoVaR_{\beta,t}^{i/j,u}}{VaR_{1-\alpha,t}^{i}} \quad vs \quad H_1 : \frac{CoVaR_{\beta,t}^{i/j,d}}{VaR_{\alpha,t}^{i}} > \frac{CoVaR_{\beta,t}^{i/j,u}}{VaR_{1-\alpha,t}^{i}}$$

The rejection of the null hypothesis indicates that downside risk spillovers from market *j* to *i* are significantly larger than upside risk spillovers in the same direction. Secondly, the conditioning direction was explored for potential downside and upside risk spillover asymmetry. The test (T3) is presented as follows:

$$\text{T3:} \quad \begin{cases} H_0 : \dfrac{CoVaR_{\beta,t}^{i/j,d}}{VaR_{\alpha,t}^{i}} = \dfrac{CoVaR_{\beta,t}^{j/i,d}}{VaR_{\alpha,t}^{j}} \quad vs \quad H_1 \dfrac{CoVaR_{\beta,t}^{i/j,d}}{VaR_{\alpha,t}^{i}} \neq \dfrac{CoVaR_{\beta,t}^{j/i,d}}{VaR_{\alpha,t}^{j}} \\ H_0 : \dfrac{CoVaR_{\beta,t}^{i/j,u}}{VaR_{\alpha,t}^{i}} = \dfrac{CoVaR_{\beta,t}^{j/i,u}}{VaR_{\alpha,t}^{j}} \quad vs \quad H_1 \dfrac{CoVaR_{\beta,t}^{i/j,u}}{VaR_{\alpha,t}^{i}} \neq \dfrac{CoVaR_{\beta,t}^{j/i,u}}{VaR_{\alpha,t}^{j}} \end{cases}$$

Here, the test examined whether the influence of market *j* on market *i* was of the same magnitude as that of market *i* on market *j*.

Potential asymmetries between downside and upside risk spillovers, for the entire cumulative distributions, below the 25th, and above the 75th quantiles, are shown in Table 4. For the cumulative distributions, downside risk spillover is significantly higher than upside risk spillover regardless of market pair and conditioning direction, except for the 'DJEM/precious metals'. For example, the value of the KS^{FSD} test (i.e., 0.031) for 'precious metals/DJEM' indicates an asymmetric effect between downside and upside risk spillovers. In other words, the downside risk spillover from emerging stock to precious metals markets is significantly higher than the upside risk spillover in the same direction. Contrariwise, from the precious metals sector to emerging stock markets, the results show that the downside risk spillover is not significantly higher than the upside risk spillover.

More importantly, these findings are consistent below (above) the 25th (75th) quantiles. As opposed to capturing the general level of risk, normalised values in the lower (upper) tail of the distribution imply that the severity of downside and upside risk spillovers is low (high). Downside risk transmissions are greater than upside ones even at relatively small transmission severity or degree; that is to say, investors should be warier of downside risk transmissions across a wide range of market conditions and not just when markets are already turbulent.

Table 4 Asymmetric risk spillover: downside versus upside

CoVaR	*VaR*	*All*	*Lower 25th*	*Upper 75th*
Precious metals/DJEM	Precious metals	0.031 (0.028)	0.426 (0.000)	0.000 (1.000)
DJEM/precious metals	DJEM	0.017 (0.325)	0.244 (0.000)	0.000 (1.000)
Energy/DJEM	Energy	0.028 (0.055)	0.662 (0.000)	0.000 (1.000)
DJEM/energy	DJEM	0.048 (0.000)	0.567 (0.000)	0.000 (1.000)
Agriculture/DJEM	Agriculture	0.026 (0.091)	0.504 (0.000)	0.000 (1.000)
DJEM/agriculture	DJEM	0.064 (0.000)	0.406 (0.000)	0.001 (0.998)

Notes: 'All' implies testing over the entire cumulative distributions whereas the lower 25th and the upper 75th refer to below the 25th and above the 75th quantiles of each cumulative distribution, respectively.

Table 5 Asymmetric risk spillover by conditioning direction

CoVaR	*Downside*			*Upside*		
	All	*Lower 25th*	*Upper 75th*	*All*	*Lower 25th*	*Upper 75th*
DJEM and precious metals	0.028 (0.105)	0.088 (0.074)	0.026 (0.306)	0.028 (0.124)	0.060 (0.440)	0.031 (0.153)
Energy and DJEM	0.072 (0.000)	0.137 (0.000)	0.077 (0.000)	0.030 (0.073)	0.081 (0.124)	0.040 (0.027)
Agriculture and DJEM	0.050 (0.000)	0.201 (0.000)	0.068 (0.000)	0.042 (0.003)	0.125 (0.003)	0.057 (0.000)

Notes: 'All' implies testing over the entire cumulative distributions whereas the lower 25th and the upper 75th refer to below the 25th and above the 75th quantiles of each cumulative distribution, respectively.

Spillover direction also plays a crucial role in determining the magnitude of risk spillover. Table 5 presents the results for each directional test. Considering the entire cumulative distributions for 'DJEM and precious metals' except for downside risk spillover below the 25th quantile, the null hypothesis is not rejected at the 10% level, indicating a symmetric risk spillover between the precious metals market and the emerging stock market, i.e., the level of risk remains unchanged. However, concerning the 'energy and DJEM', the null hypothesis is rejected at the 10% level, except for upside risk spillover below the 25th quantile, indicating an asymmetric risk spillover between energy and emerging stock markets. Likewise, the downside and upside risk spillovers from agriculture to DJEM are not equivalent to those from DJEM to agriculture. Ultimately, the degree of conditional asymmetry is positively related to the difference in size and development of the chosen equity market pair. This result holds over the entire cumulative distributions and below (above) the 25th (75th) quantiles.

5.4 Risk spillovers before and after the global financial crisis

In this section, we will examine the effect of the GFC on the risk spillover structure between commodity sectors and emerging stock markets. The test (T4) was implemented to study whether the downside and upside risk transmission magnitudes are significantly high following the global financial crisis:

$$\text{T4:}\quad \begin{cases} H_0 : \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},d}}{VaR_{\alpha,t}^{i}}(before) \geq \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},d}}{VaR_{\alpha,t}^{i}}(after) \;\; vs \\ \qquad H_1 : \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},d}}{VaR_{\alpha,t}^{i}}(before) < \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},d}}{VaR_{\alpha,t}^{i}}(after) \\ H_0 : \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},u}}{VaR_{1-\alpha,t}^{i}}(before) \geq \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},u}}{VaR_{1-\alpha,t}^{i}}(after) \;\; vs \\ \qquad H_1 : \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},u}}{VaR_{1-\alpha,t}^{i}}(before) < \dfrac{CoVaR_{\beta,t}^{\frac{i}{j},u}}{VaR_{1-\alpha,t}^{i}}(after) \end{cases}$$

where 'before' refers to 30 December 2005 to 3 August 2007, and 'after' refers to 3 July 2009 to 17 July 2019. Furthermore, *d* and *u* denote the downside and upside risk spillover, respectively.

The rejection of the null hypothesis indicates that risk spillover magnitudes after GFC are higher than before for a given tail end and conditioning direction. Table 6 presents the results of the test (T4). Downside and upside risk spillover magnitudes between precious metals and DJEM are not significantly higher after the GFC than before, except for downside risk spillover below the 25th quantile. However, downside and upside risk spillover magnitudes are significantly higher after GFC for the (Energy and DJEM) and (Agriculture and DJEM) pairs. Consequently, risk management practices need to adjust risk measurement and management strategies to take into account significant changes in the downside and upside risk spillovers between each pair of markets.

Table 6 Risk spillovers before and after the global financial crisis

CoVaR	*VaR*	*Downside*			*Upside*		
		All	*Lower 25th*	*Upper 75th*	*All*	*Lower 25th*	*Upper 75th*
Precious metals/ DJEM	Precious metals	0.001 (0.997)	0.258 (0.000)	0.001 (0.999)	0.001 (0.998)	0.033 (0.816)	0.100 (0.164)
DJEM/precious metals	DJEM	0.001 (0.999)	0.164 (0.007)	0.001 (0.999)	0.000 (0.999)	0.092 (0.216)	0.004 (0.996)
Energy/DJEM	Energy	0.487 (0.000)	0.595 (0.000)	0.155 (0.013)	0.487 (0.000)	0.270 (0.000)	0.759 (0.000)
DJEM/energy	DJEM	0.425 (0.000)	0.476 (0.000)	0.157 (0.011)	0.462 (0.000)	0.316 (0.000)	0.702 (0.000)
Agriculture/ DJEM	Agriculture	0.612 (0.000)	0.722 (0.000)	0.298 (0.000)	0.609 (0.000)	0.319 (0.000)	0.986 (0.000)
DJEM/ agriculture	DJEM	0.528 (0.000)	0.559 (0.000)	0.429 (0.000)	0.552 (0.000)	0.487 (0.000)	0.870 (0.000)

Notes: 'All' implies testing over the entire cumulative distributions whereas the lower 25th and the upper 75th refer to below the 25th and above the 75th quantiles of each cumulative distribution, respectively.

6 Conclusions

The present work examined risk spillover between commodity sectors and emerging stock markets using ADCC-GARCH and CoVaR models. The data cover the period between December 30, 2005, and July 17, 2019, including the global financial crisis period. The CoVaR of each market was used to measure the downside and upside risk spillovers and the asymmetric effect between commodity sectors and emerging stock market indices. The results of the ADCC-GARCH model show the presence of dynamic conditional correlations between each pair of markets. Furthermore, a sharp increase in CoVaR in 2020 for all market pairs implies that they become riskier and more sensitive to risk and extreme events that occur in other markets. Indeed, the results show significant downside and upside risk spillovers between all market pairs and over the entire cumulative distributions, below the 25th, and above the 75th quantiles. These findings suggest that downside and upside CoVaR are higher than VaR even when potential long and short position losses are low. Neglecting these facts can lead portfolio managers to underestimate potential downside and upside risks during calm periods.

Downside risk spillovers are higher than upside ones even when the transmission severity, or degree, is relatively small; that is to say, investors should be warier of downside risk spillovers across a wide range of market conditions and not just when markets are already turbulent.

Considering the entire cumulative distributions, we found symmetric downside and upside risk spillovers by the conditioning direction between emerging stock and precious metals markets. However, there were asymmetric downside and upside risk spillovers by the conditioning direction, especially between emerging stock markets and the other commodity markets (i.e., Energy and Agriculture). Furthermore, except for the downside risk spillover below the 25th quantile, downside and upside risk spillovers between the precious metals and emerging stock markets are not significantly higher after the GFC than before. For other cases (i.e., energy/DJEM, DJEM/energy, agriculture/DJEM, and DJEM/agriculture), downside and upside risk spillovers after the GFC are significantly higher than those before, indicating that potential losses caused by extreme events, such as GFC, tend to increase. As a result, risk management strategies need to be updated to account for higher risk spillover.

Our empirical results have implications for both institutional and retail investor risk management. They are also useful for economic and financial policies, highlighting the prevalence of tail behaviour and the persistent asymmetric nature of downside and upside risk transmission. Thus, empirical findings draw two main managerial implications. First, international market regulators for emerging stock and commodity sector markets should monitor the international market to support the market immediately when fear and apprehension become pervasive. In this context, market crash risk can be managed in extreme cases. Second, investors and regulators should implement hedging or safe haven strategies.

Indeed, given the enormity of the global financial crisis, it is crucial to implement dynamic measures to mitigate systemic risk during times of significant upheaval and to develop international markets' resilience to various challenges. As a result, supervisory measures should be developed to minimise excessive risk shocks from the global markets, particularly if further periods of international distress, such as the COVID-19 pandemic and the Russia-Ukraine conflict, persist.

Future works can use other methodologies, such as bivariate VaR for VaR for each pair market or multivariate VaR for VaR for all markets simultaneously, to examine risk spillover and evaluate the time response of markets in terms of risk during international crises, such as the COVID-19 pandemic and the Russia-Ukraine war, using impulse response functions. It is possible to calculate systemic risk accurately by exploiting the multiscale nature of data and applying a wavelet to estimate CoVaR.

References

Abadie, A. (2002) 'Bootstrap tests for distributional treatment effects in instrumental variable models', *Journal of the American statistical Association*, Vol. 97, No. 457, pp.284–292.

Adams, Z. and Glück, T. (2015) 'Financialization in commodity markets: a passing trend or the new normal?', *Journal of Banking & Finance*, Vol. 60, pp.93–111.

Amar, A.B., Belaid, F., Youssef, A.B., Chiao, B. et al. (2021) 'The unprecedented reaction of equity and commodity markets to COVID-19', *Finance Research Letters*, Vol. 38, p.101853.

Antoniou, A., Pescetto, G.M. and Stevens, I. (2007) 'Market-wide and sectoral integration: evidence from the UK, USA and Europe', *Managerial Finance*, Vol. 33, No. 3, pp.173–194.

Bahmani-Oskooee, M. and Saha, S. (2015) 'On the relation between stock prices and exchange rates: a review article', *Journal of Economic Studies*, Vol. 42, No. 4, pp.707–732.

Bekiros, S., Nguyen, D.K., Sandoval Jr., L. et al. (2017) 'Information diffusion, cluster formation and entropy-based network dynamics in equity and commodity markets', *European Journal of Operational Research*, Vol. 256, No. 3, pp.945–961.

Boako, G. and Alagidede, P. (2016) 'Global commodities and African stocks: a 'market of one?'. *International Review of Financial Analysis*, Vol. 44, pp.226–237.

Boako, G., Alagidede, I.P., Sjo, B. et al. (2020) 'Commodities price cycles and their interdependence with equity markets', *Energy Economics*, Vol. 91, p.104884.

Boldanov, R., Degiannakis, S. and Filis, G. (2016) 'Time-varying correlation between oil and stock market volatilities: evidence from oil-importing and oil-exporting countries', *International Review of Financial Analysis*, Vol. 48, pp.209–220.

Bollerslev, T., Chou, R.Y. and KRONER, K.F. (1992) 'ARCH modeling in finance: a review of the theory and empirical evidence', *Journal of Econometrics*, Vol. 52, Nos. 1–2, pp.5–59.

Bouri, E., Shahzad, S.J.H., Roubaud, D. et al. (2020) 'Bitcoin, gold, and commodities as safe havens for stocks: new insight through wavelet analysis', *The Quarterly Review of Economics and Finance*, Vol. 77, pp.156–164.

Cappiello, L., Engle, R.F. and Sheppard, K. (2006) 'Asymmetric dynamics in the correlations of global equity and bond returns', *Journal of Financial Econometrics*, Vol. 4, No. 4, pp.537–572.

Creti, A., Joëts, M. and Mignon, V. (2013) 'On the links between stock and commodity markets' volatility', *Energy Economics*, Vol. 37, pp.16–28.

Dickey, D.A. and Fuller, W.A. (1979) 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association*, Vol. 74, No. 366a, pp.427–431.

Engle, R. (2002) 'Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models', *Journal of Business & Economic Statistics*, Vol. 20, No. 3, pp.339–350.

Hung, N.T. and Vo, X.V. (2021) 'Directional spillover effects and time-frequency nexus between oil, gold and stock markets: evidence from pre and during COVID-19 outbreak', *International Review of Financial Analysis*, Vol. 76, p.101730.

Inci, A.C. and Lee, B.S. (2014) 'Dynamic relations between stock returns and exchange rate changes', *European Financial Management*, Vol. 20, No. 1, pp.71–106.

Jorion, P. (1991) 'The pricing of exchange rate risk in the stock market', *Journal of Financial and Quantitative Analysis*, Vol. 26, No. 3, pp.363–376.

Kang, S.H. and Yoon, S-M. (2020) 'Dynamic correlation and volatility spillovers across Chinese stock and commodity futures markets', *International Journal of Finance & Economics*, Vol. 25, No. 2, pp.261–273.

Karyotis, C. and Alijani, S. (2016) 'Soft commodities and the global financial crisis: implications for the economy, resources and institutions', *Research in International Business and Finance*, Vol. 37, pp.350–359.

Liu, F., Shao, S. and Zhang, C. (2020) 'How do China's petrochemical markets react to oil price jumps? A comparative analysis of stocks and commodities', *Energy Economics*, Vol. 92, p.104979.

Longin, F. and Solnik, B. (1995) 'Is the correlation in international equity returns constant: 1960–1990?', *Journal of International Money and Finance*, Vol. 14, No. 1, pp.3–26.

Longin, F. and Solnik, B. (2001) 'Extreme correlation of international equity markets', *The Journal of Finance*, Vol. 56, No. 2, pp.649–676.

Markwat, T., Kole, E. and van Dijk, D. (2009) 'Contagion as a domino effect in global stock markets', *Journal of Banking & Finance*, Vol. 33, No. 11, pp.1996–2012.

Mensi, W., Beljid, M., Boubaker, A. et al. (2013) 'Correlations and volatility spillovers across commodity and stock markets: linking energies, food, and gold', *Economic Modelling*, Vol. 32, pp.15–22.

Mensi, W., Hammoudeh, S. and Kang, S.H. (2015)' Precious metals, cereal, oil and stock market linkages and portfolio risk management: evidence from Saudi Arabia', *Economic Modelling*, Vol. 51, pp.340–358.

Mensi, W., Shafiullah, M., Vo, X.V. et al. (2021a) 'Volatility spillovers between strategic commodity futures and stock markets and portfolio implications: evidence from developed and emerging economies', *Resources Policy*, Vol. 71, p.102002.

Mensi, W., Vo, X.V. and Kang, S.H. (2021b) 'Time and frequency connectedness and network across the precious metal and stock markets: evidence from top precious metal importers and exporters', *Resources Policy*, Vol. 72, p.102054.

Nieh, C-C. and Lee, C-F. (2001) 'Dynamic relationship between stock prices and exchange rates for G-7 countries', *The Quarterly Review of Economics and Finance*, Vol. 41, No. 4, pp.477–490.

Sadorsky, P. (2014) 'Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat', *Energy Economics*, Vol. 43, pp.72–81.

Smyth, R. and Nandha, M. (2003) 'Bivariate causality between exchange rates and stock prices in South Asia', *Applied Economics Letters*, Vol. 10, No. 11, pp.699–704.

Tang, K. and Xiong, W. (2012) 'Index investment and the financialization of commodities', *Financial Analysts Journal*, Vol. 68, No. 6, pp.54–74.

Tian, M., El Khoury, R. and Alshater, M.M. (2023) 'The nonlinear and negative tail dependence and risk spillovers between foreign exchange and stock markets in emerging economies. Journal of International Financial Markets', *Institutions and Money*, Vol. 82, p.101712.

Vardar, G., Coşkun, Y. and Yelkenci, T. (2018) 'Shock transmission and volatility spillover in stock and commodity markets: evidence from advanced and emerging markets', *Eurasian Economic Review*, Vol. 8, pp.231–288.

Warshaw, E. (2019) 'Extreme dependence and risk spillovers across north american equity markets', *The North American Journal of Economics and Finance*, Vol. 47, pp.237–251.

Warshaw, E. (2020) 'Asymmetric volatility spillover between European equity and foreign exchange markets: evidence from the frequency domain', *International Review of Economics & Finance*, Vol. 68, pp.1–14.

Wen, F., Cao, J., Liu, Z. et al. (2021) 'Dynamic volatility spillovers and investment strategies between the Chinese stock market and commodity markets', *International Review of Financial Analysis*, Vol. 76, p.101772.

Zakoian, J-M. (1994) 'Threshold heteroskedastic models', *Journal of Economic Dynamics and Control*, Vol. 18, No. 5, pp.931–955.